Acoustic Flow Perception in Bats and Applications in Navigation

By

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Acoustic flow is the change in acoustic parameters in an acoustic scene induced by the relative motion between the observer (source) and the scene. This work investigates how bats may perceive acoustic flow through echolocation and use it to navigate. This is explored through both physical observations on bats’ response towards an induced acoustic flow, and computational simulations of how acoustic signals (specifically bat calls) behave in dynamic and complex acoustic scenes. The physical experiment studied whether free-flying wild pipistrelles were able to perceive a change in acoustic flow velocity by manipulating the motion of the acoustic background while the bats flew down a woodland corridor. It was found that the bats changed their speed proportionally to the relative velocity induced. To determine what flow information the bats may have processed, computational simulations were used to study acoustic flow in the context of bat flight. Frequency changes (or Doppler shift) proved to be the acoustic property that was most robust in estimating acoustic flow velocity. The simulations were then used to estimate flow induced frequency changes in complex environments and process the information for navigation. The Wideband Ambiguity processing method was used, which is a cross correlation of the echo signal with artificially Doppler shifted versions of the original signal (matched filtering) to extract the frequency changes. The simulation study manipulated different variables (signal properties, environment complexity and processing methods) to fully understand the limitations and potential of using Doppler to estimate flow velocity for bat-like signals. An algorithm was developed for processing a single signal-echo response to obtain lateral position as well as azimuth to a ‘wall’ of objects. The robustness of this algorithm for simple autonomous navigation scenarios, such as parallelly following a wall at a safe distance and turning a corner was then explored using computational simulations.
Some of the work in the thesis has been affected by the pandemic, as the nationwide lockdowns prevented the planned research activity for the final chapter of the thesis. This was a physical experiment, intended to test the proposed signal processing method with artificial bat signals in measuring the frequency changes (or Doppler shift) in echoes of these signals from moving structures. This experiment would have complemented the results from the simulation studies, as a proof of concept that the extraction of Doppler shift for acoustic flow navigation was possible. However, instead of this physical experiment, a simulation chapter on how to use the would-be extracted Doppler information for autonomous navigation is presented in its place as the final study of the thesis.
ACKNOWLEDGEMENTS

Throughout my time as a PhD student, I have received a continuous and an outpouring of support from various individuals. I would first like to thank my supervisors, Dr. Shane Windsor, and Prof. Marc Holderied, for their expertise, which were invaluable in the formulation of my research and the methodologies to accompany it; and for their strong, continuous, and kind support throughout the entire research process.

I wish to express my utmost gratitude for all the support I received from my colleagues and friends in the Bio-Inspired Flight (BIF) lab, the Behavioural, Acoustic and Sensory Ecology (BASE) lab, and the Flight Lab, who have helped me with my work in numerous ways, especially when it came to volunteering with field work experiments, which involved many long nights to help set up the experiments with me. In that, I would also like to extend my thanks to the many student volunteers and friends, who volunteered to help with the field work as well.

I wish to thank various people within the CAME engineering department, who have helped with the design and manufacturing of my experimental setup, specifically Mr. Clive Rendall and Mr. Mike Fitzgerald, of the dynamics lab and electronics workshop respectively.

Last but not in the slightest bit least, I am deeply grateful to my family and friends, who supported me through all this with patience, love, and encouragement. Specifically, my parents, who have been my pillar of support throughout my entire academic career. I only hope I have made them proud in my achievements.
AUTHOR’S DECLARATION

I declare that the work in this dissertation was carried out in accordance with the requirements of the University’s Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate’s own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

SIGNED: Athia H Haron

DATE: 27/11/2020
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<td>Pulse Repetition Rate</td>
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<td>STFT</td>
<td>Short Time Fourier Transform</td>
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<td>WAF</td>
<td>Wideband Ambiguity Function</td>
</tr>
<tr>
<td>WAFCORR</td>
<td>Wideband Ambiguity Function Correlation Image</td>
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<tr>
<td>SA</td>
<td>Single object, Ahead</td>
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<td>SL</td>
<td>Single object, Lateral (at angle)</td>
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<tr>
<td>ML</td>
<td>Multiple objects, Lateral (at angle)</td>
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<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
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<td>DR</td>
<td>Doppler shift ratio</td>
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<td>FM</td>
<td>Frequency Modulated signal</td>
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<td>SPL</td>
<td>Sound Pressure Level</td>
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<td>IFFT</td>
<td>Inverse Fast Fourier Transform</td>
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<td>SNR</td>
<td>Signal to Noise Ratio</td>
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<td>FMCF</td>
<td>Frequency Modulated with Constant Frequency signal</td>
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<td>CF</td>
<td>Constant Frequency signal</td>
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<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
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<tr>
<td>GPS</td>
<td>Global Positioning Satellite</td>
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<td>PID</td>
<td>Proportional, Integral and Derivative controller</td>
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<td>SONAR</td>
<td>Sound navigation ranging</td>
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<td>IMU</td>
<td>Inertial Measurement Unit</td>
</tr>
<tr>
<td>NDT</td>
<td>Non-Destructive Testing</td>
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<tr>
<td>CTFM</td>
<td>Continuous Time Frequency Modulated</td>
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<td>EKF</td>
<td>Extended Kalman Filter</td>
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<td>TOF</td>
<td>Time of Flight</td>
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<td>DC</td>
<td>Direct Current</td>
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<td>MATLAB</td>
<td>Matrix Laboratory, a proprietary multi-paradigm programming language and numerical computing environment developed by MathWorks</td>
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<td>CSAPS</td>
<td>Cubic Smoothing Spline</td>
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<td>NAC</td>
<td>Night-Averaged Correction</td>
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<tr>
<td>NO</td>
<td>Night Order</td>
</tr>
<tr>
<td>TONC</td>
<td>Time of Night-Averaged Correction</td>
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<td>WAV</td>
<td>Waveform Audio file format</td>
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<td>ANOVA</td>
<td>Analysis of variance</td>
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<td>TL</td>
<td>Transmission Losses, dB</td>
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<td>ISO</td>
<td>International Organisation for Standardisation</td>
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<td>TS</td>
<td>Target Strength, dB</td>
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<td>NL</td>
<td>Noise Losses, dB</td>
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<td>DI</td>
<td>Directionality Index</td>
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<td>DFT</td>
<td>Discrete Fourier Transform</td>
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LIST OF SYMBOLS

The list of unique symbols used in the thesis is presented here. Note: some symbols that are commonly used in literature and are repeated in multiple chapters in the text are not included in this list or are defined once.

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<tr>
<td>(-)</td>
<td>Slow down condition for experiment</td>
<td>n/a</td>
<td>2</td>
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<tr>
<td>(x)</td>
<td>Control condition for experiment,</td>
<td>n/a</td>
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<td>$V_{AC}$</td>
<td>Average-Corrected Velocities</td>
<td>m/s$^{-1}$</td>
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<tr>
<td>$x_q$</td>
<td>Query points for statistical analysis</td>
<td>m</td>
<td>2</td>
</tr>
<tr>
<td>s</td>
<td>Displacement</td>
<td>m</td>
<td>3</td>
</tr>
<tr>
<td>c</td>
<td>Speed of sound in air</td>
<td>m/s$^{-1}$</td>
<td>3</td>
</tr>
<tr>
<td>$p$</td>
<td>Sound pressure</td>
<td>Nm$^{-2}$</td>
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<tr>
<td>$\rho$</td>
<td>Density of a medium</td>
<td>kg/m$^3$</td>
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<td>$v_w$</td>
<td>Speed of wave that the sound travels within</td>
<td>m/s$^{-1}$</td>
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<tr>
<td>$l$</td>
<td>Sound intensity</td>
<td>W/m$^2$</td>
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<td>r</td>
<td>Reference radius of a spherical sound wave</td>
<td>m</td>
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<td>$\theta, \phi$</td>
<td>Specified angles of sound directivity</td>
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<td>3</td>
</tr>
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<td>f</td>
<td>Frequency of a sound wave</td>
<td>Hz</td>
<td>3</td>
</tr>
<tr>
<td>T</td>
<td>Period of a sound wave</td>
<td>s</td>
<td>3</td>
</tr>
<tr>
<td>$V_r$</td>
<td>Velocity of a sound receiver</td>
<td>m/s$^{-1}$</td>
<td>3</td>
</tr>
<tr>
<td>$V_s$</td>
<td>Velocity of a sound emitter or source</td>
<td>m/s$^{-1}$</td>
<td>3</td>
</tr>
<tr>
<td>$\bar{V}_F$</td>
<td>Flow velocity</td>
<td>m/s$^{-1}$</td>
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</tr>
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<td>$\tau(x)$</td>
<td>Tau function of a parameter</td>
<td>n/a</td>
<td>3</td>
</tr>
<tr>
<td>$x_n, y_n$</td>
<td>Position of sensor relative to object</td>
<td>m</td>
<td>3</td>
</tr>
<tr>
<td>$\theta_n$</td>
<td>Relative angle of sensor to object</td>
<td>deg</td>
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</tr>
<tr>
<td>$E$</td>
<td>Echo train</td>
<td>n/a</td>
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</tr>
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<td>$y_s(t)$</td>
<td>Emitted signal as a function of time</td>
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<td>Heading angle of sensor to object</td>
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<tr>
<td>$\theta_{rel}$</td>
<td>Relative angle of sensor to object</td>
<td>deg</td>
<td>4</td>
</tr>
<tr>
<td>$x_{ob}, y_{ob}$</td>
<td>Position of sensor relative to object</td>
<td>m</td>
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</tr>
<tr>
<td>$T$</td>
<td>Signal length</td>
<td>s</td>
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</tr>
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<td>H</td>
<td>Atmospheric humidity</td>
<td>%</td>
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<tr>
<td>$K_p$</td>
<td>Controller proportional gain</td>
<td>n/a</td>
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</table>
Chapter 1

Introduction

1.1 Chapter Introduction

This chapter serves to introduce the main purpose of the thesis, and as a summary of what to expect from the work presented in this thesis. The chapter begins with presenting the necessary background information for the work, to provide the global context of the work and why the specific studies that followed were carried out. The background information highlights the gaps in the research topic, as well as the current development on the topic. The chapter then introduces the main aim (or motivation) for the work, as well as the corresponding objectives or specific questions derived from the aim. To conclude, a thesis outline is presented, describing the specific studies in the following chapters and as a summary of the thesis structure and how the work is presented.

1.2 Background Information

For most animals, the process of motion perception infers the speed and direction of objects in the observer’s environment based on visual, proprioceptive (sense of self-movement and body position via mechanosensory neurons in muscles, tendons, and joints), and vestibular inputs (sense of balance mediated by the inner ear). A combination of these inputs is often used to give the complete sense of movement, either of their surroundings, or of themselves. For some animals, however, a single sensory modality, like visual inputs, can often be sufficient for simple tasks of motion estimation. Visual perception, which is the ability to perceive the environment using light reflected by the objects within the environment, is usually the main sensory modality used for the control of locomotion. This was why for some animals, the manipulation of visual cues can result in the animal’s change in motion or behaviour [1, 2], even if the perceived motion did not match the actual motion of the animal or its environment. This is evident in many optic flow experiments on different animals.

1.2.1 Optic Flow

Optic flow is the perception of motion caused by the relative motion of the observer and the objects in a visual scene [3]. Since the concept’s introduction in the 1940s by James J. Gibson, that was used to describe one’s ability to detect possible one's actions (or affordance perception), the role of optical flow stimulus in navigation has been studied by many, including biologists and roboticists. This is because
optic flow and its perception was observed to be a simple and elegant image processing solution to self-
motion estimation [4]. Self-motion perception is one’s ability to estimate their own motion parameters,
like speed, and relative position in their environment, without needing measurements from an external
system or sensor. The estimation of self-motion not only gives motion information for the sensing
system, but also a segmentation of the scene into independently moving or rigid elements [5, 6]. In
biology, the neuroprocessing and the associated behavioural responses of animals perceiving optic flow
gives insight on how some animals, even without the high visual acuity of other species, can
successfully navigate. A well-referenced example is how bees use perceived optic flow velocities to
balance flight position and speed [1, 7]. For example, one experiment [2] showed that the bees reduced
their speeds when the perceived optic flow was higher (i.e. moving light and dark gratings in the
opposite direction of their flight), and vice versa when the perceived optic flow was lower (Figure 1.1).
This gave insight on how bees can use their low visual acuity (~1/100th of human visual acuity[8]) for
efficient navigation tasks.

For roboticists, the computational efficiency of image processing techniques using low resolution
images [9-11] is attractive for the development of optic based navigation systems, especially for
autonomous navigation. Another advantage roboticists can reap from optic flow navigation techniques,
is the ability of motion estimation within a moving system, without external guidance of sensors or
waypoints (e.g. in GPS-denied environments). Optic flow navigation has been shown to succeed in
tasks such as automated braking [12, 13], position centring [14], path perception [15], and obstacle
avoidance[16], to name a few. These techniques simply estimated motion (or flow velocities) from
tracked image pixels between two successive images. Brightness (or intensity) of the pixels can be
tracked for example, between two well-contrasted images, and the optic flow velocity can be estimated
from the change of pixel position over time [17]. These changes can be determined via different
methods, such as phase correlation, block-based (or maximising normalised cross-correlation of the
differences), and differential methods of estimating optic flow (e.g. Lucas-Kanade [18], Horn-Schunck [19],
Buxton-Buxton [10] and Black-Jepson [20] methods). All these methods require two or more images
to estimate optic flow velocities.
Figure 1.1 Illustration of the optic flow experiment in bees [2], adapted from [1], and used with permission of The Royal Society (U.K). The image showed that bees inferred their range from the apparent image speed due to the motion of the walls. The larger, outer arrows indicated the movement of the walls, while the smaller, inner arrows, indicated the flight path of the bees. The spacing of the light and dark gratings were also indicated and interchanged in the image to remove the possibility that the bees were balancing the contrast of the images. The results showed that the bees flew closer to the side perceived as lower optic flow (b),(e) and away from the higher optic flow (c),(f). This experimental setup was the inspiration for our experimental setup in the following Chapter 2, where we studied acoustic flow perception in bats.

### 1.2.2 Acoustic Flow

In acoustics, the motion of the surroundings is perceived actively; that is, the reflection of the emitted signal is recorded and processed to obtain motion information (e.g. SONAR ranging). The use of sound for navigation has historically been to obtain motion and positional information of the surrounding objects, often to complement navigation information from other sensors or sources (optical, lidar, accelerometers, inertial measurement units (IMU), Global Positioning Satellite images (GPS) etc.) in a moving system. Motion perception caused by the sensor’s own motion (acoustic flow) however, is not as unambiguously defined or understood as its optic flow counterpart and can be described differently for various uses. For example, in medical ultrasonic imaging, each pixel on an ultrasound image is
assigned a flow vector, which is essentially the same as optic flow estimation in images. In ultrasonic flow meters, used mainly for non-destructive testing (NDT), the velocity of flow is estimated from the difference in transit time of ultrasonic pulses that propagates with or against flow direction [21, 22]. The average velocity of a fluid can also be measured using the Doppler shift of the ultrasound pulses propagating into and along the flow. In reference to optic flow (and optic flow navigation) acoustic flow can be described as the changes of acoustic parameters in a reflected signal, caused by the relative motion of the signal emitter and its environment.

The ‘image’ in acoustic flow navigation, is described by the combination of echoes from the surrounding objects, which depicts their position and relative motion. In an acoustic signal, this can be described by the specific power, frequency, and phase contribution of each echo. Like brightness (intensity) in optic flow, a comparable parameter in acoustic signals can be used to describe acoustic flow. In optic flow navigation, brightness is often used as the ‘tau’ parameter [23, 24] of the general tau theory, which is the guidance of bodily movements. The tau parameter is a dimensionless quantity that can be used to perform navigation tasks like braking, without explicitly computing information about distance and velocity [25, 26]. Studies in tau theory suggested that acoustic parameters such as azimuth, echo delay (or time-of-flight), or intensity can be used as this tau parameter for the control of braking [23]. In fact, the same study carried out an experiment to show that bats use echolocation to regulate this tau parameter for braking, by keeping the rate of change of tau constant. In this experiment, bats were flown in a tunnel to fly through a variable square aperture which can be dilated to make the bats’ approach to the aperture appear closer in time. The experiment successfully showed that the bats regulated deceleration (or braking) by keeping a constant tau. However, when varying the aperture while the bat was in motion to make the aperture seem closer, the bats did not conclusively change their behaviour or tau regulation. This indicated that the change in aperture may not have introduced a change of acoustic flow. This may be because the bats were more likely integrating the distance to the aperture, than reacting to the velocity change in the dilation of the aperture. The study acknowledged that future experiments were needed to investigate the bats’ response to different and separable combinations of distance and velocity, to determine whether bats perceive the two differently. In addition to this, a study on the particularly responsive cells in the auditory cortex of the mustached bat to echo-delay and Doppler shift [27], showed that in order to definitively manipulate the velocities of the bats, distance information may need to be separated from velocity information. Therefore, the parameters suggested in the study may not be the suitable tau parameter, in that it does not fully encompass all aspects of motion control. Future work is needed that considers the different contributions of the parameters within an acoustic signal to the perceived acoustic flow, and consequently, how animals (like bats) respond to them.
1.2.3 Bat Sonar and Navigation

Echolocating bats are known to excel in navigating via sound, even preferring this sensory modality to other modalities like vision in some cases [28]. Bats emit high frequency calls and listen to the reflected echo off their surroundings. These echoes contain temporal and spatial information that gives them navigational and hunting cues. Their long-evolved sonar capabilities also enable them, amongst other things, to detect landmarks [29] and water sources [30], locate and isolate prey from dense forests [31], and communicate with or filter out other bats in a large group [32]. These capabilities can be attributed to their fine control over their call vocalisations. Echolocating bats can control the loudness, duration, frequency, beam width (and directionality) and bandwidth [33-37] of their calls, all of which are adapted for their environment and foraging habits. For example, bats that forage in dense and cluttered environments emit short frequency modulated (FM) calls whereas bats that forage in open spaces emit longer constant frequency (CF) calls [31]. These call shapes were found to be advantageous in their specific habitats, as shorter FM calls give better target acuity whilst long CF calls give better ranging [38]. The shorter calls also avoid the call-echo overlapping, which is helpful when navigating in dense environments or when in close contact with prey. Some bats emit a combined logarithmic call shape with both FM and CF components (known as FMCF calls) that may allow them to reap the benefits of both call types (e.g. pipistrelle bats). These bats forage in similar dense habitats as FM bats, which is where the short (~5ms) call and FM component of the call would prove to be advantageous. The specific use of the CF component of FMCF call, however, is still unclear for these bats. Bats have also been known to completely change their call shapes in different scenarios. A noctule (Nyctalus noctula) bat shifts from a CF call when commuting to shorter FM sweeps when approaching a target to increase acuity [39, 40]. Horseshoe bats can change the frequency of their calls to compensate for shifts in frequencies due to motion, to ensure they receive echoes within the optimal range of hearing frequencies (Doppler shift compensation [41]). Doppler information also allows a bat to detect the flutter of insect wings, showing as modulations in frequencies in their brains [42]. Therefore, for the FMCF bat, the CF component may be used to estimate target velocity. To implicitly prove this, behavioural studies combined with neurobiology experiments are necessary. These controlled call adaptations contribute to half of the task of obtaining such diverse and complex sound information, as the other half lies within the processing of the echoes in their brain. Studies on the neurobiology of echolocating bats have revealed that a bat’s brain has specific components that allow them to systematically process different parameters of their echoes [43, 44]. For example, the mustached bat’s auditory midbrain contains neurons that are selective for specific delays (‘delay-tuned’) between the FM components of the pulse and echo [27]. The mustached bat also has a CF section in the auditory midbrain that is tuned to detect frequency changes (Doppler) of echoes.

The adaptations in both the signal type and neural processing of bat calls have shown that bats are more than capable to both detect prey and avoid obstacles. These can be categorized as adaptations for sound
acuity which allows them to clearly distinguish objects around them (much like clarity in vision). In terms of self-motion estimation, where performance in object detection may not necessarily be prioritized, much of how bats use sonar for this specific task is yet to be thoroughly investigated.

1.2.4 Acoustic Flow Perception in Bats

Although the previously mentioned study [23] showed that the bats regulated their deceleration to keep the tau parameter constant for different aperture sizes, the experiment did not clearly differentiate whether the bats were simply integrating the sizes of the aperture (or distance), instead of subsequently adjusting for the change of flow, as the experiment could not obtain clear evidence when the dilation of the aperture was introduced. A more recent study, showed that bats responded to perceived echo-acoustic flow, produced by the salience of lateral or horizontal structures [45]. In the experiment, bats flew in a tunnel lined with horizontal or vertical ridges (of various spacing), in which a horizontal ridge would produce weaker echo-acoustic flow compared to the vertical ridge that was oriented perpendicular to the flight resulting in time-variant echoes. The experiment, while successfully proving that the bats flew along the lower perceived flow (horizontal ridges, smaller spacing), also did not obtain velocity changes from the bats. It can be argued that these bats, instead of responding to the dynamic information of the echoes from its relative motion to the ridges, could have been perceiving the density of their immediate surroundings. The vertical ridges that returned time-separated echoes could be perceived by the bats as a lower density environment. Regardless, following the study, it was found that *Phyllostomus discolor* bats have neurons that encode echo-acoustic flow information of the relative geometry of the target and the bats’ flight trajectory, rather than echo delay [46]. The study showed that the cortical map of the bat’s target range was not fixed, changing according to the acoustic flow information, as the effect became stronger when the flight trajectories were simulated at higher speeds. These results further confirm that acoustic flow information, can be perceived, at least in the neural processing of these bats.

A contradictory experiment claimed that bats may not rely on acoustic flow for navigation, or even landmark recognition, instead favouring path integration or internal self-motion cues to estimate motion [47]. The study trained pipistrelle bats (*Pipistrelle kuhli*) to fly along a linear flyway aligned with vertical poles and land on a platform. The search responses of the bats when the platform was removed for three environments of different pole density (or acoustic flow) was recorded. The hypothesis was that the increased acoustic flow environment from the ‘denser poles’ would cause the bats to underestimate their position and search at a shorter distance. However, the results did not show any differences between the acoustic flow manipulated environments. The study also suggested two types of acoustic flow, statistical and analytical. For statistical flow, a specific flow amount corresponds to a distance travelled, mapping flow to learned distances, whereas for analytical flow, an absolute change
in distance can be estimated from the flow changes. To test whether the bats were using analytical acoustic flow, they removed the poles and the bats still searched where the platform was, suggesting they did not rely on the analytical acoustic flow induced by the poles. When introduced to wind in the absence of the poles, the bats underestimated the position of the landmark, suggesting that the bats were relying on the internal self-motion cues of path integration. This experiment, although confirming that bats indeed can integrate their surroundings to make motion estimation, did not explicitly test environments with induced acoustic flow that is independent on distance or density cues. Seeing as bats can use echolocation to estimate distance, to wholly determine whether bats perceive acoustic flow for self-motion estimation, an experiment with actual moving environments could remove the influence or preference of distance estimation from bats.

1.2.5 Acoustic Autonomous Navigation

Despite the novelty and uncertainty surrounding the perception of acoustic flow in bats, many have already tried to utilize acoustic flow for navigation in autonomous systems. Studies have shown that it is possible to obtain motion information from the pulse-echo of acoustic signals. For example, a biomimetic platform made of a sonarhead emitting constant frequency signals, a mobile platform, and a signal processing module based on a filterbank model of processing by the mammalian cochlea, showed that Doppler shifts can be extracted in a simple navigation of a robot heading towards a wall or reflected off a single object at a bearing [48]. The study discussed the issue of processing multiple targets and provided a simple analysis to show that even in dense foliage, specific acoustic signatures can be distinguished, and the problem becomes a problem of system identification rather than resolving different scatterers. However, the effect of multiple targets on obtaining Doppler shift or acoustic flow for the robotic platform was not studied. In this case, the acoustic ‘flow’ was estimated from the changes in frequency (or Doppler). Another study estimated motion of a moving pendulum from extracting changes in range (or time-of-flight) using a Continuous Transform Frequency Modulated (CTFM) sensor [49]. The CTFM sensor produces range information from the associated echo returned from an emitted FM signal. The experiment proved to be successful in obtaining the pendulum velocity although the processing required the range differential of two or more successive echoes.

Some authors have shown that autonomous navigation is possible using Doppler shift estimates. For example, a robot equipped with Doppler-radar estimated its position and heading from the measured Doppler shifts of echoes from static landmarks at known locations [50]. Although the platform was able to self-localise, the technique used an Extended Kalman-Filter (EKF) which required a series of measurements observed over time. The technique also required the positional information of known, largely spaced landmarks as it was essentially a feature-based mapping technique of self-localisation.
All of these, while positively showing the possibility of obtaining flow information, do not fully address how acoustic flow can be perceived in a realistic environment faced by a bat. In these environments, the combined echoes of the multiple objects of different properties and orientation may require a different approach of processing flow information. This, however, requires some measurement or expectation of the acoustic flow returned from these environments, either through physical measurements or simulation.

1.3 Thesis Motivation

Three main research questions were identified for the study on acoustic flow in the thesis. This thesis aimed to answer these as well as any derived question-specific objectives, which were:

1. Whether echolocating bats perceive acoustic flow velocities induced by relative motion
   a. How did they respond to the flow?
   b. What specific cues could they be responding to?
   c. Why did they respond as observed?
2. What parameters in sound can be extracted and perceived for acoustic flow navigation, and how to process the information for navigation (specifically for self-estimation of motion)
   a. Which sound parameter can be used to perceive acoustic flow (or acoustic flow velocities) in complex environments (e.g., multiple objects, or without estimation of distance to objects)?
   b. Whether different bat signals can return accurate estimations of acoustic flow velocity, and what the specific designs of the signals contributed to their success?
   c. If existing processing methods can successfully process the acoustic flow information determined in the study
3. How this information can be successfully used for autonomous navigation in complex environments
   a. What signals should be used with the signal processing method (determined from 2(c), above)?
   b. What are the limitations of the proposed navigation algorithm, and how to extend its capabilities to form a fully autonomous system?

These were mainly answered through a physical observation on free-flying pipistrelle bats’ response towards an induced acoustic flow, computational simulations of how acoustic signals (specifically different bat call types) behave in dynamic and complex acoustic scenes, and a simulation experiment to implement the autonomous acoustic flow navigation algorithm derived from the studies in the thesis. The question-specific objectives were also addressed within the studies.
Chapter 1. Introduction

1.4 Thesis Outline

The information presented in the thesis followed the overarching theme of the three research questions. Each chapter is a stand-alone chapter, with specific study aims, methods, results, discussions, and conclusions. Following this introductory chapter, where the background information (in the form of a literature review), thesis motivation, and outline is introduced, the rest of the chapters are presented as follows:

Chapter 2: Acoustic Flow Velocity Perception in Pipistrelle Bats

This chapter presents the physical experiment that studied whether free-flying common pipistrelles were able to perceive a change in acoustic flow velocity, in which it was found that the bats increased or decreased a proportion of their speed according to the relative velocity induced. The results of this chapter drove further investigations on how and what information was perceived by the bats in this experiment.

Chapter 3: Theory of Acoustic Flow and the Acoustic Flow Parameter

To determine what flow information the bats may have processed, computational simulations were used to study acoustic flow in the context of bat flight. Comparison to optic flow parameters were made to obtain the equivalent parameters for acoustic flow. This chapter studied the basic properties of dynamic acoustic signals, which was described via a simple simulation experiment on the behaviour of the properties (amplitude, time and frequency) of bat signals in the dynamic environment, similar to that of the bats in the physical experiment. Frequency changes (or Doppler) proved to be the acoustic property that was robust in estimating acoustic flow induced velocity in the complex environments, especially when the distance integration of the bats’ surroundings remain constant. As a result of the study, frequency was determined to be the acoustic flow parameter for the context of the thesis, and the following investigations focused on Doppler-Acoustic flow.

Chapter 4: Computational Simulation of Doppler-Acoustic Flow in Bats and Artificial Systems

This chapter studied how to successfully extract flow induced frequency changes (or Doppler-Acoustic flow) from a single echo train (or single signal-echo image) in complex environments and process the information for navigation. Echoes from these environments were computationally modelled and processed through different signal processing methods of obtaining spectral information of the echoes. The Wideband Ambiguity Function (WAF) processing method was introduced, which is a cross correlation of the echo signal with artificially Doppler shifted versions of the original signal to extract the frequency changes. The study manipulated different variables (signal design, environment complexity and processing methods) to explore the limitations and potential of using Doppler to estimate flow velocity for bat call-like signals. The result of which, produced an algorithm combining the WAF signal processing introduced with a template matching technique to obtain speed, lateral position and heading of a sensor from a single signal-echo response.
Chapter 5: Doppler-Acoustic Flow Navigation Simulation of Heading, Position, and Speed and Control

The penultimate chapter tested the robustness of this algorithm to obtain speed, lateral position and heading in simulated semi-realistic 2D environments using two types of bat-inspired signals for simple navigation scenarios. Open-loop tests were carried out for both speed and heading changes to infer the behaviour of the sensing system, the results of which were used to obtain a closed-loop navigation algorithm for turning away from or keep parallel to a wall. The closed-loop navigation analysis focused on fine-tuning the gains of a basic P controller (Proportional) to successfully perform the navigation tasks within the requirements and specifications of the system.

Chapter 6: Summary and Future Work

The final chapter concludes with the findings of the overall study and the potential work that needs to follow to both investigate the extent of bats’ perception of acoustic flow and fully study the potential of using acoustic flow for autonomous navigation in real world scenarios. The specific contributions and implications of the individual studies within the work is highlighted in this chapter as well.
Chapter 2

Acoustic Flow Velocity Perception in Pipistrelle Bats

2.1 Chapter Abstract

This chapter presents the behavioural experiment that investigated the response of wild, free-flying pipistrelle (genus Pipistrellus) bats towards an induced motion in the acoustic background of their commuting corridor. A lateral structure consisting of rotating panels with densely spaced naturalistic acoustic reflectors attached, were placed on either side of the bats’ path in the corridor (to mimic the natural ‘hedgerows’ in the corridor). These were rotated in the same or opposite to the direction of flight of the bats. The rotation was to induce a change in the relative velocity, that could be perceived by the bats in the echoes of the bats’ calls reflected from the moving panels (i.e. to induce an ‘acoustic flow’ velocity change). As expected, the bats flew slower when the panels were moved in the opposite direction of their flight, or when the perceived flow velocity was higher than expected by the bats, and sped up when the panels were moving in the same direction of the bats’ flight (i.e. lower flow velocity). The bats also increased their pulse repetition rates (PRR) only when the panels were moving, which indicated that they were responding to the motion of the panels. The bats, however, only changed a proportion of their flight speed from the expected velocity change, which indicated that the flow information was potentially dampened from the influence of the other, non-moving objects in the background of their flight corridor. The bats also adjusted their speeds before entering the area with moving panels, indicating that they perceived the flow velocity changes ahead of them. The recorded changes in speed is a significant result, as this was the first known study to show this type of response in bats towards acoustic flow manipulation.

We speculated that since the lateral structure was stationary, and the acoustic reflectors on the rotating panels were densely spaced, flow information from changing amplitude and time-of-flight of the echoes cannot possibly be perceived by the bats. This was because to track the flow information, the bats would have to track the motion of individual acoustic reflectors, which was determined to be a difficult task as they were all similar in size and very densely spaced (<5 cm apart). Therefore, frequency changes (or Doppler shift) from the relative motion of the panels, was suggested as the acoustic parameter that the bats were perceiving as flow velocity. The rationale of this was further explained in the conclusion, as well as the suggestion of future experiments to investigate which acoustic parameter could give reliable estimates of flow velocity in this scenario.
Chapter 2. Acoustic Flow Perception in Pipistrelle Bats

2.2 Introduction

When navigating in darkness, echolocating bats rely on their ability to process echoes with complex acoustic information returned from their surroundings. A single bat call will return echoes from multiple objects coming from different directions in their surroundings. These echoes contain position and motion data of the surroundings, which is also constantly changing relative to the motion of the bat. The motion-induced changes in the acoustic parameters, such as Time of Flight (TOF) or the time span of the bat’s call-echo, frequency, and amplitude of the echoes can be described as acoustic flow. Acoustic flow, named after its visual counterpart, optical flow[3, 51], allows for the estimation of self-motion, without needing explicit information of global position. The changes in flow could be used to estimate relative velocity, helpful in braking and keeping constant distances to a surface or object. The perception of optic flow has long since been observed in animals [1, 7, 52], and techniques for using optic flow for navigation has been well established [53-55]. In acoustics, however, only a handful of experiments on the flow perception has been observed with bats [23, 45, 47] and even fewer on how to effectively use it for sonar navigation. Few experiments have fully shown that bats manipulate acoustic flow the same way optic flow can be manipulated, that is to regulate flow velocity. Acoustic properties also return different information compared to optics, thus rendering it difficult to directly compare acoustic flow with optic flow, as more than one acoustic parameter can be used to perceive the flow.

Echolocating bats already exhibited braking regulation by controlling tau, a dimensionless quantity used in regulating optic flow [23]. The study, however, was not successful in changing the bats’ velocities and did not observe any behavioural changes according to their flow manipulation and thus it was unclear whether the bats were simply integrating the TOF to the obstacle instead. The first experiment to successfully show that bats physically responded to acoustic flow (or echo-acoustic flow as referred to in the study) was made in 2016 [45]. The study showed that the bats’ flight path changed according to the echo-acoustic salience of stationary vertical and lateral structures and moved toward a lower perceived echo-acoustic flow. The study was not able to show changes in flight velocity, indicating that the bats perhaps were not using the ridges to extract self-motion information, instead favouring less busy (i.e., less dense, lower amplitude echoes) routes which bats would still be able to perceive if they were scanning their environment whilst being stationary. These claims of acoustic flow manipulation were further refuted by a study that showed bats rely on path integration instead of statistical or analytical acoustic flow [47], however the study also did not introduce flow velocity manipulation, as they studied whether the bats overestimated or underestimated the position of a stationary feeding landmark in the presence of varying vertical structures (poles) density.

To investigate whether bats use acoustic flow to estimate and regulate relative velocity, an experiment manipulating the perceived relative velocities from the returned echoes is necessary. In one of the
earliest optic flow perceptions observed in bees, one of the manipulations was to move the walls surrounding the bees in the same or opposite direction of flight [7]. The walls moving in the same direction reduced the optic flow velocity perceived by the bees, which resulted in them flying faster to compensate their lower perceived velocity. Thus, to obtain a response similar to the balancing of optic flow velocity in bees, an experiment inspired by the experiment in [7] was conducted, to test whether free-flying, wild pipistrelle bats use echolocation to regulate their velocity. Like the moving walls in the optic flow experiment, the ‘walls’ were recreated in the acoustic context by rotating panels lined with naturalistic acoustic reflectors in the same or opposite direction to the bats’ flight. We hypothesized that the bats would reduce their flight velocity when the panels are moving in the opposite direction of their flight, as there would be a higher perceived acoustic flow, and vice versa. If the bats were perceiving the moving panels differently than a stationary environment, this would be reflected as an increase in their pulse repetition rates like how some bats respond to noise, or areas of uncertainty [31, 56].

A theory was presented in the study, that the bats balanced the Doppler shift in their echo frequencies by changing their flight speed, therefore the flow parameter for bats in this case is in the frequencies of the returning echoes. This was suggested, as theoretically, this is the only parameter that can be extracted reliably from a single call in naturalistic scenarios i.e. in highly complex situations with many overlapping echoes of similar amplitude. In these situations, it would be difficult if not impossible to track or discern changes in amplitude or time of flight of individual reflectors from call to call. Thus, the only reliable motion information available for the bats to process was from the Doppler shift in their call frequencies because it can be extracted from echoes from single echolocation calls.
2.3 Materials and Methods

2.3.1 Experimental Setup

Moving Wall
The experimental setup was located on a public path next to a brook [Ashton Brook, 51°25'32.4"N 2°39'31.9"W], that is a known commuting corridor for many bat species including members of the pipistrelles (genus Pipistrellus) and mouse-eared bats (genus Myotis) [M. Holderied, personal communication]. The test section was a 4.5 m x 8 m x 3 m (width x length x height) flight tunnel (Figure 2.1, A) surrounded by hedgerows on either side of the path and tree canopy above them. The section was lined with four 2 m x 1.8 m (length x height) rotating panels (rotated via a belt and pulley mechanical system). The panels were made of black lycra sheets (four sheets of lycra fabric skin thin polyester spandex, 5 m x 2 m each, 180gsm) with approximately 8000 individual plastic ivy leaves attached onto them (Figure 2.1, C). The panels were attached onto the rotating belt via Velcro pieces (VELCRO Brand Black Stick-On Tape Roll, 20 mm x 20 m, cut into smaller 20 mm x 20 mm pieces). The panels could rotate either in the same direction of the bats’ flight direction or in the opposite direction. Four DC motors (Parvalux UK motors, 24V, 10Nm torque, 300rpm maximum), powered by two 12V lead acid batteries moved the walls at a belt speed of 1.8 m s⁻¹ in both directions. The speed of the walls was recorded using four encoders (Bourns 5V DC 100 Pulse Optical Encoder with a 3.175 mm Plain Shaft, Bracket Mount, Axial PC Pin), each attached onto the motor shaft and synced in real time (managed and recorded via MATLAB and Arduino) to obtain real time speed measurements of the rotating walls. All electronics and the moving DC motors were tested on whether they emitted ultrasonic noise using a heterodyne bat detector. The DC motor, emitted a faint noise at 25 kHz, which was classified as negligible because it was not audible at a distance of more than 1 m.

Recording Software
Audio was recorded using two sets of four ultrasonic microphones (Knowles FG-O, Avisoft Bioacoustics, Berlin, Germany) positioned between 0.95 m to 1.27 m from the end of the panels (see Figure 2.1, A). Each group of four microphones was arranged in a three-armed symmetrical star with a central microphone (Figure 2.1, A, bottom image). The plane of the microphones faced the flight corridor between the panels and was tilted backwards by 45° with the central microphone approximately 1 m from the ground. Microphone outputs were recorded at 16-bit resolution at either 250 kHz or 330 kHz sampling rate using a 12-channel recorder (Ultrasoundgate 1216H) with recording software (Recorder, both Avisoft Bioacoustics, Berlin, Germany).
Figure 2.1 Experimental setup schematic. A) A schematic drawing of top (upper) and side (bottom) views of the experimental setup, showing positions and areas of the panels (green dashed line), microphones (red circles, mounted on the microphone arrays) relative to the test section (area of blue dashed line) and the surrounding environment (hedgerows, ground, and tree canopy). Positive x,y,z directions are indicated as blue arrows. Distance to central microphone from the ground is denoted as d = 1 m, and tilt at 45° was indicated in the image. The panel start and end positions are indicated in the bottom schematic as well. B) Flight direction of bats relative to the experimental setup. C) A small area of the panels showing the density of the leaves (≤5 cm between each plastic ivy).
2.3.2 Experimental Procedure

To induce changes in acoustic flow velocity, the panels were moved in the same or opposite direction to the bats’ flight direction. The panels moved at 1.8 ms\(^{-1}\) in both directions, with the expected increase in flow velocity if the panels moved in the opposite direction of flight and a lower flow velocity if the panels were moved in the same flight direction. Since the expectation was that the bats would balance the flow change by increasing or decreasing their velocity, the tests were named according to the hypothesised response. For example, if the panels were moved in the opposite direction and the flow velocity increased, the bats would be expected to reduce their velocities, thus this test was referred to as the slow down (\(-\)) condition.

For three different nights between June to August 2019 (each night separated approximately a month apart), three experimental conditions were conducted each night. These resulted in 9 sets of data collected overall. The conditions were to speed up (\(+\)) or slow down (\(-\)) the bats by manipulating the panel direction, and a control (\(x\)) condition where the panels were stationary. Each condition was tested and changed after 15-20 recorded flight passes could be seen in the recording software. The order of the conditions was rotated over the three nights to obtain a complete, non-time-biased set of data.

Table 2.1 Order of conditions for the three nights. (\(+\)) Speed up, (\(-\)) slow down and (\(x\)) control conditions. Each condition was rotated in order of the night to obtain a complete set of data (i.e. each condition was tested at every time of night for non-time-biased data).

<table>
<thead>
<tr>
<th></th>
<th>Night 1</th>
<th>Night 2</th>
<th>Night 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>First condition</td>
<td>(+)</td>
<td>(x)</td>
<td>(-)</td>
</tr>
<tr>
<td>Second condition</td>
<td>(-)</td>
<td>(+)</td>
<td>(x)</td>
</tr>
<tr>
<td>Third condition</td>
<td>(x)</td>
<td>(-)</td>
<td>(+)</td>
</tr>
</tbody>
</table>

2.3.3 Data Acquisition

For all three nights of data acquisition, the same recording procedures were kept. Calibration procedures would precede any bat flight recording, such as keeping track of the night conditions (temperature, humidity, moon phase, wind direction) and the positions for the panels relative to the central microphones. Recording would start if the first bats were seen passing through the test section (complemented by listening to the response of a bat heterodyne detector, placed at the microphone arrays, and tuned to the frequency of pipistrelle bats, \(~50\) kHz). A pass was validated either as a clear recording seen on the recording software, or if the bats were visually seen passing through the corridor. Only bats that were flying in the corridor were analysed, and this was confirmed if the calls could be
seen at similar sound levels across all eight channels in the recording software indicating that the bats flew somewhere within the middle of the test section. After 15-20 passes (varied range due to the activity levels of the night), the recording software would be paused to allow for changing of conditions. For moving panel conditions (-, +), recording was resumed after all four panels were moving at a constant velocity of 1.8 ms\(^{-1}\), which was determined from the measurements of the encoders attached to the rotating shaft of the panels.

### 2.3.4 Data Analysis

**Position and Velocity Data**

Only trajectories that had calls recorded more than the length of the test section (i.e., ≥ 8 m, Figure 2.1) and passed through the panels were used in the analyses. Bats that flew in the test section but not through the panels were discarded. The bats encountered across all three nights represent the fraction of the local bat population using the commuting corridor at the times of the recording. In each night, recording started after the first bat passes through the test section. Passes that were reversed (i.e., bats flying back to the roost location, identified from the trajectory analysis as an increased distance from the microphone array with increasing recording time) were not considered in the analyses. Only pipistrelle bats were used in the analysis. Other species identified in the recording software (e.g., mouse-eared bats) that flew in the corridor were recorded but were too few to analyse.

All data were analysed using multiple custom written MATLAB programs that processed the sound recordings into 3D trajectories, echolocation behaviour, and statistical analyses. 3D flight trajectories were made by triangulating calls from each channel in the recording to obtain a relative position (x,y,z) and time (t) of the bat calls to the microphones. These trajectories were calibrated from the nightly measurements of the panels’ location to the central microphones. From the position and time data, average flight velocity can be calculated between two calls.

The position data were smoothed before carrying out velocity calculations, to remove any effects of data noise that would affect the velocity calculations. Different smoothing algorithms (moving mean, moving median, Gaussian, linear regression, robust linear regression, Savitzky-Golay filter, and cubic smoothing splines (CSAPS) were tested on an artificial 3D trajectory with random position errors (up to 50 cm), and the CSAPS [57] method of smoothing returned the lowest error. The CSAPS function returns the cubic smoothing spline interpolation, for a given data (x,y,z) given a smoothing parameter, p. These were queried at original time data as call times could not be interpolated due to the irregular nature of the bats’ Pulse Repetition Rate, PRR. The smoothing parameter in the analysis was chosen using the formulation recommended by [57] that showed the sensitive range for p is:
\[ p = \frac{1}{1 + \epsilon} \]  
\[ \text{Eqn. 2.1} \]

Where \( \epsilon = \frac{h^3}{16} \) and \( h \) is the average difference between neighbouring points which in this case, were the average time difference between calls. Each trajectory had an individual smoothing parameter, depending on the average time difference of their calls.

Given the smoothed positions \((S_x, S_y, S_z)\) relative to the microphone position at \((0,0,0)\), time \(t\) recording for each call \(n\), velocity can be calculated using the equation of motion:

\[ \text{Velocity, } V = \frac{S_{n+1} - S_{n-1}}{t_{n+1} - t_{n-1}} \]  
\[ \text{Eqn. 2.2} \]

Where displacement, \( S \), is the shortest distance from the microphone to the bat, i.e. \( S_n = \sqrt{S_{x_n}^2 + S_{y_n}^2 + S_{z_n}^2} \) in metres, m.

The velocities were then linearly interpolated (from the data of smoothed positions), at query points \((x_q)\) or sampling distances of \(x_q = 0.5\) metre intervals from the microphones. This sampling distance was calculated from dividing the average velocity for the pipistrelles in the corridor (at 6.16 ms\(^{-1}\)) by the Pulse Repetition Rates (PRR) (~12 Hz) for when the panels were stationary. This PRR rate was chosen to calculate \(x_q\), as higher sampling distances would not be representative of the actual position of the bats in this condition and could result in wrongly interpolated positions. This analysis was carried out for the preparation of statistical analysis, as the regular position intervals would allow the uniform calculations of statistics along the trajectory.

**Combining Data from Different Nights**

We used the relative position of the panels to the microphone collected for each night to re-calibrate the trajectories relative to the bottom right corner of the end panels as the origin. This allowed us to combine the trajectories for all nights for positional analysis.

To combine the velocities and make a fair comparison for the different days and times, the velocities were averaged and corrected. These corrections were to remove effects of different days (night average correction) and effects of different times for the conditions (time of night correction). To correct for the effect of day, we calculated a velocity average for all conditions in a night to give a night average correction value \((\text{NAC}_{\text{Night}}, \text{Night} = 1, 2, 3)\). We then subtracted the \(\text{NAC}_{1,2,3}\) values from the calculated velocities to give velocities that were night averaged.

As the order of conditions were rotated every night, each condition needed to be corrected for the time of night effect. For example, the condition velocities of the first order of the night were first subtracted from the night average (see Table 2.6, night mean). This gives a value that indicated whether the first
condition was faster or slower than the night average. The calculation was repeated for the first conditions of all three nights and then averaged, giving the time of night correction value (TONC<sub>NO</sub>, NO = 1) for the first order of the night. This was then repeated for the second (TONC<sub>2</sub>) and third (TONC<sub>3</sub>) orders. We then subtracted the TONC<sub>NO</sub> values from the night averaged velocities to obtain a final, average-corrected velocities (V<sub>AC</sub>) for analysis. Positive averaged-corrected velocities meant that the bats’ velocities were faster than average whilst negative velocities were slower, and zero values indicated no change from the velocity average.

\[
V_{AC} \left( \text{ms}^{-1} \right) = \text{Recorded Velocity} - \text{TONC}_{NO} - \text{NAC}_N
\]

Eqn. 2.3

Where N = 1,2,3 are the different nights and NO = 1,2,3 for first, second and third order of the night.

**Pulse Repetition Rate, PRR**

Another custom MATLAB script was used to calculate PRR. This script allowed the user to recover calls from the original audio files (.WAV files) that were not successfully interpolated (or deleted due to high noise), to represent a more accurate biological behaviour. PRR were calculated for every call as below:

\[
PRR_{n+1} = \frac{1}{t_{n+1} - t_n}
\]

Eqn. 2.4

Like the velocity calculations, we then linearly interpolate the PRR data and query at \( x_q = 0.5 \) m for statistical analysis.

**Statistical Analysis**

A test for normality was done for each dataset (height and lateral displacement trajectories, velocity, call-rates) before deciding on a probability test for the variances of the conditions. The normality test decided the type of tests to follow, i.e., whether the tests were parametric or non-parametric. Normality was tested using the Anderson-Darling test, which returns a test decision for the null hypothesis that a data sample comes from a normal distribution.

For the normality test, the data were classified into two types of test populations. Type I was to populate every call from every trajectory within a test condition into one test population N. For example, the slowing down (-) condition had a total of 595 calls from 35 individual trajectories and thus the Anderson-Darling test was made with a population of N. = 595. Type II was to set every 0.5 m interpolated bins of the trajectories in the conditions as a test population. For example, the slowing down condition population would be N. = 35 for every 0.5 m bin as there were 35 individual flight trajectories for that condition.
After determining normality, we tested the data to determine whether each condition comes from the same distribution (i.e., whether the population means or medians from each condition was the same). If the data was parametric, the test for variance made was a one-way analysis of variance (one-way ANOVA). If the test rejected the null hypothesis that the conditions had the same mean, a post-hoc two-sample t-test was then made to determine which combination of two conditions significantly differ. Whereas if the data was non-parametric, a Kruskal-Wallis test was made in place of the ANOVA to test the medians of the conditions, followed by a post-hoc test via a Wilcoxon rank-sum test. The tests were made at every data query position ($x_q$) of 0.5 m Y-position intervals with the significance level of 5% for all tests, and variances were not assumed to be known. For the velocity data, the t-test (or rank-sum test) was tailed (one-sided) due to the expectation that there would be a lower value for every comparison between two conditions (e.g., slow down (-) vs. speed up (+), labelled as [-+]). Likewise, for the PRR and height data, the predicted differences of one condition having a lower value than the other is confirmed using a tailed test.

2.4 Results

2.4.1 Summary of Recordings and General Data

Over the three nights, a total of 181 pipistrelle flight trajectories were recorded, of which 104 were analyzed. The 104 trajectories were bats flying through the panels in the test section and had recorded calls of at least 8m from the panel start (long trajectories). The remaining discarded trajectories were short, potentially because the bats stopped calling or the calls were not successfully triangulated before they entered the panels. These trajectories could also have been bats that simply did not enter the panels and have turned around. Detailed breakdowns of the trajectories for the different nights and conditions are shown in Table 2.2 and Table 2.3.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Total Trajectories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed Up (+)</td>
<td>28</td>
</tr>
<tr>
<td>Slow Down (-)</td>
<td>35</td>
</tr>
<tr>
<td>Control (x)</td>
<td>41</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>104</strong></td>
</tr>
</tbody>
</table>
Table 2.3 Breakdown of trajectories that were successfully analysed, divided into the different night orders of each night. Unsuccessful trajectories (short, reversed and out-of-panel trajectories) are not included.

<table>
<thead>
<tr>
<th>Condition Order</th>
<th>Night 1</th>
<th>Night 2</th>
<th>Night 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>+</td>
<td>13</td>
<td>x</td>
</tr>
<tr>
<td>Second</td>
<td>-</td>
<td>13</td>
<td>+</td>
</tr>
<tr>
<td>Third</td>
<td>x</td>
<td>3</td>
<td>-</td>
</tr>
</tbody>
</table>

Although the analyses to follow were only on pipistrelles, we recorded a total of 11 mouse-eared bats that flew in the corridor. However, these were too low in numbers to be able to run a fair analysis. The nightly weather, light and general summary of the experiment days were also recorded and are presented in Error! Reference source not found.

Table 2.4 Weather, illumination (*or cloud cover), and general summary of the days of the experiments. Weather data extracted and cross-checked from publicly available sources of past-weather:

<table>
<thead>
<tr>
<th>Night</th>
<th>Date</th>
<th>Sunset</th>
<th>Avg. Temperature (ºC)</th>
<th>Avg. Humidity (%)</th>
<th>Moon Phase</th>
<th>Illumination* (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>06/06/2019</td>
<td>21:22</td>
<td>13</td>
<td>60</td>
<td>Waxing Crescent</td>
<td>31</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>18/07/2019</td>
<td>21:18</td>
<td>15</td>
<td>65</td>
<td>Waning Gibbous</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>22/08/2019</td>
<td>20:19</td>
<td>14</td>
<td>88</td>
<td>Last Quarter</td>
<td>31</td>
</tr>
</tbody>
</table>

The three nights were spaced about a month apart, to prevent the bats from getting used to the moving panels. The bats’ flight behaviour was assumed to be unaffected by the atmosphere of the nights since they were similar across the nights (in average temperature and average humidity, apart from the final night where the humidity was higher). These parameters, however, are not known to affect flight speeds, or echolocation of bats. The only effect these had on the corresponding bat behaviour, was the emergence of the first bat as they tended to emerge a few minutes after sunset. Moonlight intensity and effects of light levels (illumination) has been known to affect bat activity [58]. The activity levels, however, were not different between the three nights (note that the total successful trajectories in Table
2.3 did not indicate bat activity, as these were determined from whether the trajectories were successfully analysed.

### 2.4.2 Normality Tests

The results for all conditions, for type I normality test are shown in Table 2.5. The population would be normally distributed if all the tests did not reject the hypothesis (h = 0). As there were some tests that rejected the hypothesis (h = 1), the data was confirmed to be not normally distributed. Similarly, for the second type of normality test (Type II, APPENDIX A), some of the results rejected the hypothesis, and thus the data was determined as not normally distributed.

**Table 2.5** Type I test of distribution for data set. The normality tests for most of the data rejected the hypothesis (h =1) and thus the data was not normally distributed. ** Type II is included in APPENDIX A.**

<table>
<thead>
<tr>
<th>TYPE I</th>
<th>Slow Down (-), N = 595</th>
<th>Speed Up (+), N = 476</th>
<th>Control (x), N = 697</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>Unit</td>
<td>Mean</td>
<td>h</td>
</tr>
<tr>
<td>Average-Corrected Velocity</td>
<td>ms$^{-1}$</td>
<td>0.13</td>
<td>1</td>
</tr>
<tr>
<td>Height Displacement</td>
<td>m</td>
<td>1.8</td>
<td>1</td>
</tr>
<tr>
<td>Lateral Displacement</td>
<td>m</td>
<td>2.6</td>
<td>1</td>
</tr>
<tr>
<td>Pulse Repetition Rate</td>
<td>Hz</td>
<td>14</td>
<td>1</td>
</tr>
</tbody>
</table>

### 2.4.3 Trajectories

For all conditions, the bats exhibited a pulling up response (or increase in height, z) as they entered the panels (Figure 2.2, A). When the panels were moving (+, -), the bats flew between 0.3 - 0.5 m higher than when the panels were stationary (Wilcoxon rank-sum test, p < 0.05 for conditions [x+] and [x-] at all Y positions except at 8 m for [x+], Figure 2.2, A). However, there was no significant difference in height between the slow down (-) and speed up (+) conditions at any Y position in the test section.

In the lateral direction, the bats generally flew on the right side (of their flight direction) of the approximated test section midline (Figure 2.2, B). The bats significantly changed their lateral positions only when entering the panels (p<0.05, -+: Y = 0 to 2 m; x+: Y = 0 to 3.5 m; x-: Y = 2 to 4 m), with the control (x) condition maintaining a similar right-offset from the midline (between 2.3 and 2.5 m) as before entering the panels. In the moving panels condition ((+) and (-)), the bats converged towards the midline. Bats that were sped up (+) moved toward the midline around 2 m from the panel end whereas the slowed (-) bats converged earlier at the start of the panels (4 m) and kept that lateral position until the panel end. There was no significant difference in lateral position between the two moving panel conditions [+-] except for when the bats start to leave the panels at Y = 1 m.
Figure 2.2 Trajectory analyses of the bats. (A) Side-view of the trajectories showing changes in height of the bats entering the panels from right to left. Both (A) and (B) data are median and interquartile ranges (IQR) of the conditions. The location of the panels in the test section is indicated as dashed black lines. Coloured horizontal bars are the positions of significant differences between a combination of two conditions (p<0.05, tailed Wilcoxon rank-sum test, variances assumed unknown.). The data in (A) show that the bats fly upwards and out of the panels, starting as they entered the panels. There were significant differences in height between the moving panels and stationary panels (x+ and x- tests). (B) Top-view of the trajectories showing the lateral displacement from the midline of the test section. Data show that the bats were flying on the right side of the midline. Bats in moving panels converged toward the midline in the panels.
2.4.4 Velocities

The final *average-corrected* velocities presented in Figure 2.3, A, showed the general trend that the bats were flying faster in the speed up condition than the control and slow down condition at all y positions. However, the bats only had significant differences in speed before entering the panels (p<0.05, [-+]: Y = 3.5 m to 8 m). The bats flew fastest in the speed up (+) condition at all y positions, followed by the control (x) and the slow down (-) conditions. There was a significant difference in velocity between the slow down and control conditions just before the bats entered the panels at Y = 4 to 5 m.

Table 2.6 Mean of bat speeds for each night. Average across all three nights was 6.16 ms⁻¹

<table>
<thead>
<tr>
<th>Night</th>
<th>Night Mean (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.0055</td>
</tr>
<tr>
<td>2</td>
<td>5.8764</td>
</tr>
<tr>
<td>3</td>
<td>5.6013</td>
</tr>
</tbody>
</table>

2.4.5 Call Rates (Pulse Repetition Rates, PRR)

The bats kept a constant PRR value of ~12 Hz when the panels were not moving (x). The bats increased PRR as they approach moving panels (p<0.05, [x+]: Y = 0.5 m – 8 m; [x-]: Y = 2 m - 8 m), peaked (up to ~16 Hz for (+) condition) before entering the panels at Y = 5 m, then gradually decreased their PRR all the way through the panels (Figure 2.3, B). The recorded PRR for the moving panels were 1.33 times higher (16 Hz) than the PRR when the panels were not moving, at Y = 5 m. There were no significant differences between the moving panel conditions and both conditions had similar PRR values. The slow down (-) condition PRR however, decreased faster than the speed up (+) condition, as the PRR value returned to the control (x) value of 12 Hz at Y = 2 m.
Figure 2.3 Velocity (A) and Pulse Repetition Rate (B) analyses of the bats. (A) Graph shows the average-corrected velocity of the bats and their position as they fly into the panels (right to left). Data for both (A) and (B) are both median and interquartile ranges. Bottom horizontal bars show the significant changes between two conditions (p<0.05, Wilcoxon rank-sum test, tailed, unknown variances). (A) Bats reduce their velocities from the control average when panels moved in the slow down condition and increase velocities for the speed up condition. There is a significant difference (p<0.05) in velocities between the speed up and slow down condition. (B) Bats increased their PRR as they approach the panels (right to left), peaking at Y = 5 m, then
reduced their PRR as they exit the panels. There was a significant increase in PRR between the control and the moving panels ([(x+), (x-)]) at almost every Y-position for [x+], [x-].

## 2.5 Discussion

### 2.5.1 Velocity

Throughout the test section, the bats kept a velocity difference (up to 0.5 ms\(^{-1}\)) between the slow down (-) and speed up (+) conditions, with the significant differences recorded before they entered the panels (p < 0.05, y ≥ 3.5 m). This meant that they only strongly responded before entering the panels. To try to explain this behaviour, the acoustic parameter the bats most likely responded to needed to be determined. In optic flow, it is easier to estimate flow velocities from images with distinctive brightness patterns compared to images that had similar brightness across all pixels [58]. Similarly, in acoustic flow, there would have to be a parameter the bats could easily track the flow velocity from. There are three main parameters in sound that the bats could be tracking for flow velocity. They are amplitude or loudness, time of flight (TOF) or the time it takes for the reflected object echoes to return to the bats, and frequency or pitch.

Amplitude of sound changes from position change; that is, if an object is closer, the amplitude of the echo is higher as less sound energy is lost through propagation in the air or attenuated by the object’s reflective properties. If the bats were perceiving the flow velocity of the amplitudes returned from the panels, one would expect the bats to respond strongest within the panels (i.e., when the panels were closest and there were lesser echoes returned from the background environment). In this case, individual echo amplitudes from the panels were possibly more difficult to distinguish from background echoes at a further distance. The plastic ivy (acoustic reflector) on the panels had similar reflective properties as an ivy leaf found in the corridor (from comparing target strengths from a separate tomography measurement of real leaves and the plastic ivy, e.g. Chapter 3, Section 3.2.1, Figure 3.3). As the leaves were densely placed on the panels (<5 cm separation), the panels could be assumed to reflect sound like the dense surrounding vegetation. This makes it harder to distinguish the plastic ivy echo amplitudes with background vegetation at a similar distance. If we also consider factors like object backscatter, directionality and absorption, amplitude levels could be an unreliable parameter to track unless the influence from background echoes can be minimized. The same argument could be made with time of flight (TOF), as it would be difficult to extract and follow the TOF of the specific echoes from the ivy leaves. Even if the moving panels were considered as a single object (i.e., all leaves reflecting a collective summed amplitude, and is a perfect reflector), the amplitude flow velocity would not change. There would be a constant amplitude return as the resultant panel position would not have changed, regardless of the panel rotation.

A parameter that the bats could be tracking in the experiment was frequency. Some bats can track prey from a stationary environment, due to the fluctuations in frequency in echoes of their calls due to the
relative motion of their prey [42], and some bats even have specific components in their auditory cortex to process frequency changes [27]. These were bats with constant frequency (CF) components in their call signal. Pipistrelle bats also have a CF component in their signal, though it is usually combined with a short frequency modulated (FM) component in the beginning of the signal (FMCF, ~40-50 kHz constant frequency tail), and would suggest that these bats could also perceive frequency changes. Frequency changes is only dependent on relative velocity. A change in velocity between a sound source and the surrounding leads to the compression or rarefaction of the sound waves, changing the pitch or frequency (Doppler shift). If there were two objects at the same distance, but one of them has a different velocity (i.e., Doppler shifted), an amplitude-time analysis would not be able to differentiate the two objects clearly whereas a frequency-time analysis would show the two frequency components (one from each echo).

If the bats were flying at a constant velocity, the corresponding echoes from a stationary environment would return an expected amount of Doppler shift. Therefore, if the panels were moving in the opposite direction of flight, there would be a higher doppler shift than expected compared to panels moving in the same direction. Assuming the bats directed their heads in the direction of flight, which is common in commuting and search phases in echolocation for smaller bat species that emit broadband frequency calls (i.e., calls with frequency modulation) [59], we can estimate the relative velocities of objects at any distance and azimuth to the bat in the corridor. Using 2D trigonometry, when the object has a 90º azimuth, or the object is right next to the bat, the relative velocity is zero (cos(90º) =0). Conversely, the relative velocity increases up to the actual velocity of the bat, as azimuth approaches 0º or when the object is in front. As frequency is dependent on relative velocity, the largest shift in frequency would come from objects farthest away from the bat. If the bats were balancing the frequency shifts of their echoes, the bats would adjust their velocities to compensate for the perceived frequency shifts before they enter the panels. As the perceived changes in frequency decreases when they enter the panels, the bats would then readjust velocity back to the ‘normal’ values, which can be seen in the results as both the speed up and slow down condition speeds converged to the control speeds as they exit the panels.

The maximum detection range of the emitted FMCF call, can be roughly estimated, from calculating the maximum distance the sound can travel before being completely absorbed in the air. For average temperature of 14ºC and humidity of 71%, sound absorption coefficient loss, for a constant peak frequency of FMCF bats at ~ 50 kHz, is -1.54 dB/m (calculated at normal standard pressure, [60]). If the emitted signal was omnidirectional, (i.e. propagates from the source uniformly in all directions), the spreading loss is spherical, and is around -6 dB per doubling distance [61]. If the pipistrelle emitted a ~130 dB SPL signal, considering absorption and spherical spreading loss, the minimum detection range of the returning echo from the plastic ivy (maximum target strength, TS = -10 dB SPL from tomography measurement, Chapter 3, Section 3.2.1, Figure 3.3) before being completely lost in the air is approximately 10.5 m ahead of the bat (see APPENDIX B, B.1 for calculations). This would mean that
it was entirely possible for the bats to detect the moving panels at a further distance and adjust their velocities before entering the moving panels section. This analysis does not, however, consider other sound losses or effects of directionality, which may reduce the detection range. The combination of higher Doppler shifts ahead of the bat and the theoretically detectable echoes at far ranges, suggest that the response seen in this experiment may be due to changes in their expected call frequencies from the relative motion.

At 1.8 ms\(^{-1}\), the panels were expected to introduce a relative velocity change of between ±30% to 40% if the bats were flying at the expected mean velocity of between 5 ms\(^{-1}\) - 6.5 ms\(^{-1}\). Of the expected 1.8 ms\(^{-1}\) change, the bats only changed up to 0.5 ms\(^{-1}\) between slow down and speed up conditions, and even less if we compared the moving panels with the control (+,-) (0.42 ms\(^{-1}\), significant p<0.05 between x- at Y = 4 - 5 m). That is, the bats only changed velocities up to 28% of the expected change. This could be because of the competing echoes from the background environment, weakening the influence of the moving section of the bats’ environment. Another reason may be in the delay of the bats’ flight control and inertia, as it takes time to accelerate or decelerate, and is not an instantaneous response. However, this would have resulted in observing the speed changes as the bats flew through the panels, which was not the case.

The geometric proportion of the moving panels relative to the flight corridor may give another reason why the bats’ speed response was not as high as expected. For the test section of 4.5 m x 8 m x 2.5 m (width x length x height) (see Figure 2.1), the minimum surface area of background echoes (from hedgerows, ground and canopy) reflected to the bat was approximately 87.6 m\(^2\), if we ignore the echoes of objects behind the first surface of reflectors (areas behind trees, etc.) and assumed the canopy covered only half of the area above the test section. The surface area covered by the panels was up to 14.4 m\(^2\) which returns only 16.4% of the object echoes with a higher Doppler shift if the panels were moving. This percentage was likely lower if we considered the actual area of the background (i.e., including areas behind trees). This is a reasonable assumption if the density (or separation) of the leaves on the panels were comparable to the density of the shrubbery in the natural environment. This percentage shows that the small area covered by the panels compared to the overall environment (and thus amount of perceived Doppler shift) could have resulted in a lower chance of the bats detecting the flow changes. The bats were also flying at an average velocity of 5.6 to 7 ms\(^{-1}\). For the test section of 8 m in length and an even shorter panel length of 4 m, it would be difficult to obtain a significant and longer maintained change of velocity throughout the section as the bats passed through the section in less than two seconds.
2.5.2 Flight Corridor – Vertical and Lateral Displacement

The bats’ pulling up response when they entered the panels (Figure 2.2, A) is a natural response to unfamiliar territory or obstacles, usually to reduce flight speed and turn away from the area [62]. This was present in all three conditions, although there is a significant height offset (<0.5 m higher) between stationary (x) and moving panels (+, -). This suggested that the bats were responding more to the changes created by moving the panels. These changes were most likely noise-related, rather than specific acoustic flow responses, as there were no differences in height between the two moving panel conditions (where the significant velocity difference was observed). The offset in height, starting at the beginning of the test section (y = 8 m) further confirms that the bats were aware of the moving panels at that distance.

The bats generally flew slightly towards the right of their flight path in the test section. This could be because there were denser hedgerows on the left-hand side of the entire flight corridor (fenced with growing vegetation) whereas the right side had more sparse trees in some areas in the corridor. From previous studies, bats generally preferred to fly along sparser spaces [45]. When they entered the panels, however, the density of both sides of the panels were comparable, which could be why they tended to move closer to the midline. This however was only evident in the moving panel conditions. The bats may have been stimulated by the moving panels and responded by keeping a tighter distance between the moving panels.

2.5.3 Echolocation

When the panels were moving, the turning of the fabric around the shafts may have induced noise. As expected, the bats changed their PRR in response to the moving panels, a common response for bats when met with unfamiliar territory, obstacles, or anthropogenic noise ([63]). This increase in PRR (Figure 2.3, B) is common as the increased PRR would return clearer information to the bats (bats increase PRR when targeting prey [31]). The increase in PRR was evident from the beginning of the test section, further consolidating the fact that the bats were aware of the panels that far ahead of the panels. The bats decreased their PRR as they enter the panels, indicating that the influence from the panels has diminished as the bats obtain background echoes from beyond the panels.

2.6 Conclusion

This experiment suggested that FMCF bats perceived the relative motion induced (or acoustic flow velocity change) and that they responded according to the change in motion. The experiment suggested that the small (but significant) change in velocity between the speed up and slow down conditions were likely because the induced flow only covered a small portion of the bats’ acoustic range, and thus the
effects of the stationary, background echoes dampened the effects from the induced flow velocity section. The velocity change’s proportion to the bats’ average speed, however, was consistent with the simple calculation of the geometric proportion of the moving panels to the surrounding environment. Future experiments should consider a longer test section, with a higher flow velocity (faster moving panels) to achieve a bigger response in speeds from the bats. These can also extend to investigate whether the bats can balance acoustic flow between either side of their ears, by moving panels in opposite directions from each other. Since bats can already determine angles from balancing binaural cues from either side of their ears [64], this may shed light on some other abilities for bats in binaural hearing.

From the experiment, we speculated that the bats were perceiving the changes in acoustic flow velocity from the Doppler shifted echoes due to the relative motion, since it was unlikely that changes in amplitude and distance to the moving panels were easily tracked by the bats. This was further supported in simple analyses that the highest change in Doppler would be when the panels were ahead of the bats, and combined with the echolocation range of the bats, it was possible for the bats to perceive the flow at a distance before entering the panels. The significant response of the bat velocity change before they entered the panels, gave further confidence to our theory.

Future work will have to investigate how the acoustic flow velocity can be perceived by the bats. This could be from different experiments of manipulating flow velocity in different bats, for example. An experiment to investigate whether CF bats (horseshoe bats) and FM bats (mouse-eared bats) perceive acoustic flow velocities and regulate flight speed, could give insight as to whether the bats are perceiving Doppler shifts, since CF bats are known to be attuned to Doppler changes (Doppler shift compensation, [41]) and FM bat calls may be Doppler tolerant [65].
Chapter 3

Theory of Acoustic Flow and the Acoustic Flow Parameter

3.1 Chapter Abstract

In this chapter, a simulation experiment was conducted to determine a suitable acoustic flow parameter that is robust in extracting acoustic flow velocities in complex environments. In the experiment, a sensor moving at constant velocity, emitted bat calls in three 2D environments that comprised of either a single object placed directly ahead of the sensor or placed at a bearing angle to the sensor; or densely spaced multiple objects arranged laterally along the flight path of the sensor (mimicking a ‘hedgerow’). The emitted bat calls tested were real recorded signals of pipistrelle (*Pipistrellus pipistrellus*), mouse-eared (*Myotis daubentonii*), and horseshoe (*Rhinolophus ferrumequinum*) bats. The changes of the echo parameters (amplitude, time-of-flight (TOF) and frequency) were extracted, from which the relative flow velocity was estimated. These were compared for the different environments, and it was found that frequency was the only parameter that could extract flow velocity information for the densely spaced multiple object environment. As such, the experiment proposed that frequency changes (or Doppler shift) were the acoustic flow parameter that the bats in Chapter 2 were perceiving when responding to the moving panels. This was because both the bats’ environment in Chapter 2 and the multiple object environment tested here separated the changes in integrated distance to objects from relative velocity. The experiment then suggested for the following acoustic flow velocity investigations to consider frequency changes as the acoustic flow parameter (or ‘Doppler-Acoustic flow’), especially in realistic scenarios where distance-related parameters cannot extract flow-induced changes. The advantage of using frequency in extracting information other than relative velocity was also explored in the study, as frequency changes can be used to produce a 2D spatial map of objects.

Although the flow velocity information was present in tracking frequency changes, the accuracy of the flow velocity varied with the bat signals used. The fully frequency modulated (FM) signal of the mouse-eared bat returned the highest accuracy, followed by the partially frequency modulated and constant frequency signal (FMCF) of the pipistrelle bat, and the fully constant frequency signal (CF) of the horseshoe bat. This suggested that the signal properties affected the overall frequency estimation of the returned echoes. However, a more thorough investigation was needed to determine how the different signal properties (duration and frequency sweep) affected the estimation of Doppler in this scenario. This was explored further in the following Chapter 4.
3.2 Introduction

In acoustic flow, the flow information is derived from the relative motion between the source of sound and the acoustic scene. The relative motion information is apparent in the changes of acoustic parameters between one acoustic scene and the next and is usually depicted as flow velocity. Flow velocity can be estimated in some form of change of displacement to the object over time. As such, most studies on acoustic flow have suggested that the flow could be estimated from changes either in azimuth, echo delay (or time of flight, TOF) and the intensity of the echo (or amplitude) [23, 49], which are all range-dependent. Frequency changes in sound, however, give an estimation of velocity from the Doppler phenomenon (in which sound undergoes compression or rarefaction resulting in changes in pitch), that can be irrespective of range if the relative angle to the object is zero (i.e., no bearing component). Only few authors have proposed frequency changes as the acoustic flow parameter for flow velocity estimation. Models of acoustic flow due to Doppler shift have been developed for constant frequency (CF) signals [66, 67], and can provide estimates of localisation that are sufficient for tasks where high accuracy is not needed, such as obstacle avoidance. Physical experiments on artificial systems extracting acoustic flow have used both frequency and range-dependent acoustic parameters (e.g., echo delay) with varying successes [49, 68]. These experiments, however, were determining flow changes from single moving objects, often a significantly reflecting target (or perfect reflectors). In reality, a naturalistic acoustic scene is made up of many objects of different reflecting properties returning multiple overlapping echoes. These overlapping echoes coalesce and become a single echo signal reflected to the source, which is termed in this study, and the following chapters (or studies), as the echo train.

So far, all of the acoustic flow behavioural studies in animals (namely bats) have failed to show velocity regulation from their proposed flow manipulations [23, 45, 47]. These experiments however, manipulated acoustic flow by varying the density of the perceived environment, and did not actually induce changes in relative velocity (i.e., stationary targets). All but one experiment manipulated flow in this way, and the experiment that did not [23], varied the size of a square aperture with the bats’ approach, from which they also could not obtain any noticeable changes from the bats. The experiments, without inducing actual relative velocity changes in the environment, could suggest that the bats’ range estimation of the combined objects in their environment, took precedence over any perceived flow velocity changes in this way.

Therefore, a separation between distance estimation and relative velocity estimation is required, to determine whether bats can perceive acoustic flow velocity. Between TOF and amplitude, only the latter can potentially be manipulated irrespective of object distance, that is if the object somehow returned manipulated amplitudes of the echo for each pulse (i.e., larger amplitude differences between each pulse, than the proportional change of amplitude with distance). For frequency changes (or Doppler
motion perception can still theoretically be manipulated for a stationary object, by artificially shifting frequencies of the returned echoes. For example, hypothetically, if an object is rotating with various rotational velocities at a stationary position, amplitude (assuming the rotation did not affect the directionality of the returned echo) and TOF of the reflected echo remains the same for every returned echo, but the frequency of the echo varies with the rotational velocity. Even for moving objects, if the integrated distance to the objects remained the same, as is the case for most dense environments within which bats navigate, it would be difficult to obtain flow velocities from the distance-related parameters. This is because the movement of individual objects and their associated echo between calls would need to be tracked.

To illustrate this effect and determine whether acoustic flow velocities can still be extracted from the various parameters in such complex (or naturalistic) environments faced by bats, a simulation experiment was conducted. This involved computational simulations of extracting flow velocities in different environments of increasing complexity. As the objective was to postulate which parameter bats may utilise for acoustic flow estimation, the study simulated the three main bat call types (FM, CF, and FM-CF) emitted by a moving sensor in multiple 2D environments. The environments were modelled after environments that a bat may encounter, i.e., approaching an object or flying along a hedgerow. The increasing complexity of the environments was defined as both increasing the number of objects and separating the influence of distance of objects to the extracted parameters. The objects, however, were modelled as perfect reflectors (i.e., the echoes were not dispersed or backscattered by the objects) and other effects of noise and directionality were not considered. The aim of this experiment was to first determine what parameter the bats in Chapter 2 was attuned to in regulating flow velocity. Secondly, this experiment aimed to identify acoustic flow parameters which could be used in subsequent simulations to obtain reliable estimates of flow velocity, which would then be used to form an acoustic flow navigation algorithm.

3.2.1 Background Information on Acoustic Parameters

This section introduces the acoustic parameters available in a sound signal, and how the information varies when the source emitting the signal is in motion. The known properties of the acoustic parameters are described, and how the parameters can be perceived for acoustic flow is presented.

In optic flow, an image that contains pixels of different intensities is compared with another image that has the same combination of pixel intensities but have moved slightly due to relative motion of the sensor and the environment. Therefore, the pixel intensity (or brightness) is the optic flow parameter and the changes in the pixel-intensity position between one image frame and the next can be divided by framerate to give the optic flow velocity. In an acoustic ‘image’, information, often in the form of distance to sensor, can be described by different parameters. Both amplitude (energy) and time taken
Chapter 3. Theory of Acoustic Flow and the Acoustic Flow Parameter

for sound to reflect off an object are direct measures of distance. The closer an object is to the sensor, the higher the amplitude and the lesser time the sound has travelled. Amplitude also gives information of the size of the object, as the object covers a larger surface area for the signal to reflect off. A sound signal also contains frequency information that changes with motion, from which the relative sensor velocity can be obtained. Any of these three parameters can be used to estimate acoustic flow.

**Time of Flight (TOF)**

In sonar, the time taken for the sound to be reflected by each object, known as Time of Flight (TOF), gives positional information of the objects. TOF is the measure of distance between a sensor and an object. The time taken for the emitted signal from the sensor to reflect from the object gives the measured distance if the signal velocity is known (refer to Figure 3.1).

For active sonar, the sound travels towards and is then reflected by the object over a total time \( t \), giving displacement \( s \) as

\[
\text{Eqn. 3.1: } s = \frac{ct}{2}
\]

Where \( c \) is the speed of sound (343 ms\(^{-1}\), in air at sea level) and the time is halved to account for the sound travelling to and from the object. TOF is then, \( \text{TOF} = \frac{2s}{c} \).

**Figure 3.1** Illustration of how sound is reflected off an object to the source (bat), and what the displacement, \( s \), is between them.

**Amplitude, Intensity and Power**

Luminance (or subjectively termed, brightness) in an image is comparable to the amplitude in a sound signal in the way that both are measures of signal intensity (or energy) and returns energy that are dependent on the target it encounters. Thus, amplitude of a sound signal is the most analogous parameter to the optic flow parameter of brightness [17, 69].
A sound wave in air is a longitudinal pressure wave which can be described as air particles propagating in a sinusoidal oscillation. The amplitude is a measure of the displacement of air particles from its equilibrium position, or in a sinusoidal function (Figure 3.2), the magnitude of an oscillation. The amplitude of sound is proportional to the measure of the energy in the moving air particles in the sound wave and experienced as the loudness of sound. Energy is lost as heat as sound propagates in the air and is dampened, reducing the amplitude. Amplitude in this case is expressed as the physical quantity, sound pressure $p$.

![Figure 3.2 Sound wave described in terms of amplitude both physically (against displacement, x) and spectrally (against time, t). In the physical representation, the sine wave represents the moving particles of air in a sound wave. In the spectral representation, the sine wave represents changes of amplitude in the moving air particles over time.](image)

In sonar, sound power (or loudness) is usefully described as intensity, $I$. Intensity is the power ($P$) per unit area ($A$, m$^2$) carried by the sound wave, and power is the rate at which energy is transferred by the wave in decibels (dB). Equations Eqn. 3.2 and Eqn. 3.3 [61] describe the relationship between amplitude (pressure amplitude), intensity and power:

$$I = \frac{P}{A} \quad \text{Eqn. 3.2}$$

$$I = \frac{p^2}{\rho v_w} \quad \text{Eqn. 3.3}$$
where $\rho$ (kgm$^{-3}$) is the density of the medium which the sound travels within and $v_w$ (ms$^{-1}$) is the speed of the wave (speed of sound). The unit of intensity, $I$ is Wm$^{-2}$. Intensity is dependent on the pressure amplitude ($p$) which has units of Pascals (Pa) or Nm$^{-2}$. In sonar, power (or intensity) is expressed in terms of decibels (dB) which is a logarithmic scale.

$$\text{Power Gain (dB)} = 10\log_{10} \left( \frac{P_{\text{out}}}{P_{\text{in}}} \right)$$  \hspace{1cm} \text{Eqn. 3.4}$$

$$\text{Intensity Level, } \beta \,(\text{dB}) = 10\log_{10} \left( \frac{I}{I_0} \right)$$  \hspace{1cm} \text{Eqn. 3.5}$$

$I_0$ in equation Eqn. 3.5 is the reference intensity, which, for measurements relevant to human hearing, is usually set at the lowest intensity of sound that can be heard, $I_0 = 10^{-12}$ Wm$^{-2}$.

For active sonar sensors, in which a system transmits a pulse and listens to the echo reflected (like echolocating bats), the sonar equation is the systematic way of estimating the signal-to-noise (SNR) ratio of the system. The equation gives a measure of the power and resultant energy losses returned in an echo, considering source level, transmission losses from sound spreading and absorption, target backscatter or reflection losses, noise, and receiver characteristics.

The sonar equation for active sonar in the simplest form is [61]:

$$\text{SNR} = \text{SL} - 2\text{TL} + \text{TS} - \text{NL} - \text{DI}$$  \hspace{1cm} \text{Eqn. 3.6}$$

where SNR is the signal-to-noise ratio in dB, SL is the Source Level, TL are the Transmission Losses through sound absorption and attenuation, NL is the Noise Level and DI is the Directionality Index.

An active sonar device that both produces or transmits sound (by converting electrical energy into acoustic energy) and receives it is called a transducer. The output of a transducer is measured as Sound Pressure Level (SPL) and gives the Source Level (SL) component in the equation. SPL, which is the logarithm of intensity decreases with distance from the transducer, as the total power output is distributed over a larger area with increasing range. Thus, SPL is measured relative to a standard distance from the transducer to make consistent and meaningful comparisons. This is usually at one metre from the transducer (in SONAR or other practical uses). This is sometimes indicated when noting SPL values like SPL = 100dB, ref = 1µPa at 1 m. For bats, power measurements are usually made at 10 cm from the mouth (Sound Pressure Level, ref = 20 µPa at 0.1 m, [33]). For consistency, the rest of the study will use ‘dB SPL’ as the signals used are recorded bat calls. A typical SL for some bats can be between 100 and 140 dB SPL [33, 70].

Sound energy is lost through spreading in propagation, as well as from being absorbed by the medium it propagates through [61]. These are losses in power (or reduction in intensity) due to propagation or Transmission Losses (TL). Power is distributed equally in all directions and the total power, $P$, does not
change with range. For a spherical wave, energy is distributed across each crossing sphere of increasing radius and from Eqn. 3.2:

\[
\text{Power} = \text{Intensity} \times \text{Area} = I_1 4\pi r_1^2 = I_2 4\pi r_2^2 = \cdots = I_r 4\pi r_r^2 \tag{Eqn. 3.7}
\]

If the reference radius \(r_1\) is at 1 m, the spreading losses to range \(r\) can be described as

\[
\text{Spreading Loss} = 10\log_{10} \left( \frac{I_1}{I_r} \right) = 10\log_{10} r^2
\]

Spherical Wave Spreading Loss = 20\log_{10} r \tag{Eqn. 3.8}

Through a similar analysis, for a cylindrical wave, the spreading law gives a cylindrical spreading loss equation of:

\[
\text{Cylindrical Wave Spreading Loss} = 10\log_{10} r \tag{Eqn. 3.9}
\]

Sound is absorbed in the medium it propagates through various mechanisms. In sea water, sound is absorbed through two principal mechanisms: viscosity and molecular relaxation (only in salt water) where the molecules are reduced to ions induced by the pressure of sound [71]. In air, sound gets similarly absorbed through these mechanisms as well as via heat conduction [72]. The attenuation coefficient \(\alpha\) for absorption is dependent on frequency, temperature, humidity, and pressure. This can be calculated using the equations for predictions of atmospheric sound absorption for frequencies up to 100 kHz [60]. Sound absorption is significant in higher frequencies, which is why bats emit loud calls (>100dB SPL) [33, 70, 73] to ensure maximum range is achieved.

The total Transmission Loss (TL) is therefore the sum of the spreading loss and absorption losses. This is multiplied by two for the case of active sonar as the sound has travelled to and from the reflected object.

Target Strength (TS) is a measure of the area of the signal reflecting off an object (or target). The total amount of energy reflected by the object depends on the target shape, size and backscattering cross section. For most objects, TS can be estimated by directly measuring the intensity of sound returned from the echo reflected off the object. This can be made via acoustic tomography, in which the tomography images are made from transmitting a broadband wave across a section of the target at different angles. The tomography image contains the target strengths (in dB SPL) of sound at a specific frequency and direction (angle) to the object (Figure 3.3).
Noise Level (NL) describes the various noise sources attenuating the sound. These can be from the internal noise of the transducer or ambient noise from the environment. For underwater sonar, there is even noise from the vessel (from machines, flow noise over sonar dome and hull, propeller noise, etc.) [61]. A comparable external noise source between a bat’s sonar and artificial sonar is the biological ambient noise. These are usually noises in the low ranges of frequencies, such as the rustling of leaves or rain. They can be modelled as pink noise where the power spectral density (power per frequency interval) is inversely proportional to the signal frequency [74].

An omnidirectional source produces sound that has the same sound pressure level (SPL) for a given distance and direction from the source. Most sources do not necessarily have the same SPL at a distance and a direction from its centre. This is a sound property called directionality, and the changes in SPL with direction of sound emitted from a source is called its directivity [75, 76]. Whilst SL of a source does not give specific information about the directivity of the signal, a directivity index (DI) describes the gain (dB) for a given direction or angle to the source. The DI is the difference in decibels between the SPL in an angle or direction to the source, and the average SPL from an omnidirectional source:

$$DI(\theta, \varphi) = L_p(\theta, \varphi) - \bar{L}_p$$  \hspace{1cm} Eqn. 3.10
Where $DI(\theta, \phi) = \text{directivity index at a given direction (in dB)}, L_p(\theta, \phi)$ is the SPL for a given direction (dB), $\bar{L}_p$ is the SPL averaged over all directions (dB) and $(\theta, \phi)$ is the specified angle.

The sonar equation thus returns the estimation of sound power reflected by an object. From the equation, sound power (amplitude) is not only dependent on the range to the object, but on noise levels, sound directionality, and the object properties as well. Even in a perfect reflector case, where sound is not attenuated by the backscattering of an object, as well as neglecting directionality effects, sound is still attenuated through transmission losses which is proportional to the object range. An acoustic ‘image’, in this case, could be described as a combination of echoes with varying amplitudes returned from objects at various ranges.

Frequency

Frequency of a sound wave is the number sound waves produced in a single unit of time. This can also be described as $f = \frac{1}{T}$ where $T$ is the period of the wave. Frequency is often depicted as the pitch of sound, where a higher pitched sound contains a higher frequency. Bats emit high frequency calls which are in the ultrasonic range of frequencies (> 20 kHz). Frequency information has the added advantage that the changes in its value are directly proportional to the relative speed of the source and the object the sound is reflected by. This phenomenon is known as the Doppler shift, in which sound waves undergo compression or rarefaction and shifts in value depending on the speed and direction of the source or the object the sound hits. When a sound source moves towards the receiver, the compressed sound will have a higher frequency compared to when it is stationary and will have a lower frequency when it moves away from the receiver and had undergone rarefaction.

The relationship between observed frequency $f_{\text{observed}}$ and emitted frequency $f_{\text{emitted}}$ is given by the equation

$$f_{\text{observed}} = \left(\frac{c}{c \pm V_r} \mp \frac{V_s}{c}\right) f_{\text{emitted}}$$

Eqn. 3.11

Where $c$ is the velocity of waves in a medium, i.e., sound velocity (343ms$^{-1}$ in air). $V_r$ is the velocity of the receiver relative to the medium and is positive if the receiver is moving towards the source (or negative if moving in the opposite direction). $V_s$ is the velocity of the source relative to the medium and is positive if the source is moving away from the receiver (or negative if moving in the opposite direction). Since the sound waves are Doppler shifted twice, as the sound moves towards an object and is reflected to the source, for each direction the equation changes as the referenced source and receiver changes.
Figure 3.4 Sound wave reflected to and from the source (bat) with the conventions and definitions of the source and observer for each way the sound travels (a) Sound emitted from the bat (source) to the object (receiver). (b) Sound reflected to the bat (receiver) from the object (source).

When the sound is first emitted in the outward direction (Figure 3.4, a), sound is emitted from the source (bat) and is received by the object. Therefore, $V_s = V_b$ and $V_r = V_o$; where $V_b$ is the bat velocity and $V_o$ is the object velocity. The direction of the object velocity is accounted for in the sign (positive in the same direction as the bat velocity). Substituting the receiver and source velocities in Eqn. 3.11 (considering direction of flight in the sign assignment), for an emitted call frequency from a bat $f_b$, the resulting received frequency at the object $f_1$ is

$$f_1 = \frac{c - V_o}{c - V_b} f_b \quad \text{Eqn. 3.12}$$

Sound is then reflected (Figure 3.4, b) from the newly referenced source (object) and is received by the bat. The source and receiver velocities are now the opposite from the first emission (or outward direction), $V_s = V_o$ and $V_r = V_b$. The final frequency (i.e., frequency of the echo $f_e$) is

$$f_e = \frac{c + V_b}{c + V_o} f_1 \quad \text{Eqn. 3.13}$$

And substituting $f_1$ from the forward direction gives

$$f_e = \frac{c + V_b}{c + V_o} \left(\frac{c - V_o}{c - V_b}\right) f_b \quad \text{Eqn. 3.14}$$
The received echo frequency equation Eqn. 3.14 is valid for all cases, i.e., for when an object is moving towards \((V_o < 0)\) or away \((V_o > 0)\) from a source (or bat) moving towards it. From the echo frequency, a Doppler shift factor (or Doppler ratio) \(DR\) can be calculated, which is the ratio of the returned echo frequency \(f_e\) to the emitted bat call frequency \(f_b\)

\[
DR = \frac{f_e}{f_b}
\]

**Flow Estimation and the Tau Parameter**

In the simplest sense, acoustic flow velocity (for a constant source velocity) can be estimated as the changes of the measured parameter between two consecutive pulse-echoes, multiplied by the pulse repetition rate (PRR, in Hz). For distance-related parameters like amplitude (\(A\)) and TOF, the flow velocity \(\overline{V_F}\) can be calculated as:

\[
\overline{V_F}_A = (A_2 - A_1) \times PRR \quad [dB \ per \ second]
\]

Eqn. 3.16

For amplitude flow velocity \(\overline{V_F}_A\), or for time-of-flight flow velocity \(\overline{V_F}_{ToF}\),

\[
\overline{V_F}_{ToF} = (ToF_2 - ToF_1) \times PRR \quad [unitless]
\]

Eqn. 3.17

These flow velocities, however, are not equivalent to the source velocity and if required, can be related to the source velocity by a proportional factor, \(k\). The factor can vary depending on the type of motion (e.g. object directly ahead, or with bearing angle to the object) and the parameter change with distance. For example, if the object is directly ahead the source, flow velocity estimated from TOF is proportional to the source velocity \((V_s)\) as:

\[
\overline{V_F}_{ToF} = -\frac{2}{V_c} \times V_s
\]

Eqn. 3.18

where \(V_c\) is the speed of sound (343\,ms\(^{-1}\) in air at sea level). Therefore, the proportional factor in this case is \(k = -\frac{2}{V_c}\) (see APPENDIX B, B.2 for calculations). The proportional factors can be difficult to estimate, especially when considering factors like bearing angle to objects and acceleration or deceleration of the source.

Frequency of the emitted signal from a source moving at constant velocity would remain constant between the two pulse-echoes. Therefore, the method of estimating flow velocity mentioned earlier may not be useful in this case, as the flow velocity would be zero. However, relative velocity can be estimated from the Doppler shift equation, and if the object were directly ahead of the sensor, the
Doppler shift would be a constant value. For all parameters discussed, when an object is at a bearing angle to the sensor, the relative velocity would cease to be a constant value, due to the cosine relationship of the angle ($V_{relative} = V \cos(\text{bearing angle})$), and therefore an estimation of the bearing angle would be necessary to relate the flow velocity to the true sensor velocity. However, obtaining the accurate estimation of sensor velocity may be unnecessary in most cases, as the control for relative speed could just be to proportionally control $\vec{V}_F$, like in optic flow image velocity estimation and control [77, 78].

The \textit{tau function} of a parameter ($\tau(x)$) provides an alternative method of control of flow, that does not constantly require the computation of distance, velocity, and acceleration for navigation [25]. The function is defined as the ratio of the parameter $x$, to the rate of change of $x$ over time ($\dot{x}$)

$$
\tau(x) = \frac{x}{\dot{x}}
$$

Eqn. 3.19

The function can be used for controlled braking, with any sensory variable that is a power function of distance to aperture. The ratio of distance to speed of the approach to an object (termed the \textit{tau-margin}) provides a first order estimation of the sensor’s time-to-contact to the object. For a constant velocity, the ratio provides an accurate estimate, but if the sensor is accelerating or decelerating, the ratio over/underestimates the time-to-contact. This has been used in many successful optic flow robotic navigation experiments of controlled braking [12-14, 16, 79].

\textbf{Flow Estimation from a Single Pulse-Echo}

For most studies in acoustic (or optic) flow, flow velocities are estimated as the changes between one signal echo to the next echo coming from the second, emitted signal [49, 80]. While this is the traditional method of flow estimation, acoustic signals may contain flow information within a single echo (or ‘echo train’, as the echo is usually a combination of echoes from multiple objects). The fact that frequency changes are only dependent on relative velocity, can be used to create a unique set of frequency information purely dependent on the location and orientation of objects in the environment. This gives a direct relationship between the spatial information of the surroundings and frequency (as explored in Figure 3.5).
Figure 3.5 Doppler ratios from individual objects in specific layouts (2D environment) for a source moving at $V = 5\text{ms}^{-1}$ emitting a signal. (a) Objects arranged in a straight line along the path of the moving source with varying lateral ($x$) displacements. (b) Objects arranged in a straight line (along the lateral displacement) at varied forward ($y$) distance from the source. (c) Objects at different ‘corner’ arrangements, varying in radial configuration and distance to source. (a)-(c) Source is
moving along the y axis (0° heading angle). (d) Objects at the same displacement to source, but with different heading angle (from y-axis) of the source (0°, 30° and 60°).

From these theoretical environments, not only is relative velocity information present in one echo train, but the spatial information also (or lateral information in the 2D case) can be clearly defined as well. The theoretical evidence that these spatial-frequency information are present in the echoes can be used to process flow information in a different manner, mitigating the need for multiple signal-echo processing.

For the study to follow in this chapter, since the main aim is to determine which acoustic flow parameter could be reliably used for flow estimation, the study focuses on obtaining flow velocity between two consecutive pulse-echoes. The appropriate parameter is then used in the later chapters as the acoustic parameter of choice, where the potential of estimating flow from a single pulse-echo is explored.

### 3.3 Methods and Materials

The entire simulation experiment was conducted in MATLAB, a programming language and numerical computing environment developed by MathWorks. Three main bat call types were tested: constant frequency (CF), frequency modulated (FM) and composite ('hockey-stick', FM-CF) calls (Figure 3.6). The signals used in the simulation were imported from recorded bat audio signals (WAV files recorded by Danielle Linton at the Wildlife Conservation Research Unit at Oxford University [81]). These were single calls during search phases of greater horseshoe (*Rhinolophus ferrumequinum*), mouse-eared (*Myotis daubentonii*) and Nathusius’s pipistrelle (*Pipistrellus nathusii*) bats.

![Figure 3.6](image-url) Recorded calls of bats in Great Britain, by Danielle Linton (Wildlife Conservation Research Unit at Oxford University) with an UltraSoundGate 116-200 recorder. Top: spectrogram of calls. Bottom: Normalised [-1, 1] calls in the temporal domain.
These signals (assumed omnidirectional) were emitted by an active sensor (i.e., both source and receiver) in the simulation, navigating through three 2D environments that consisted of ‘perfect’ reflector objects, where the signal energy reflected to the sensor is not lost through dispersion or absorption by the object. These objects \( (n) \) were placed in the environment at a relative \((x_n, y_n)\) position to the sensor, where \(x\) is the lateral position from the sensor and \(y\) is the forward position parallel to the flight path of the sensor. The first environment (Figure 3.7, a) comprised of a single object placed \(x = 0\) m and \(y = 15.5\) m from the sensor, thus labelled SA (Single object, Ahead) as the object is in the direction of the sensor flight path. This is to mimic the scenario where a bat is flying towards a single obstacle. The second environment (SL, Figure 3.7, b) had a single object placed at \(x = 2\) m and \(y = 15.5\) m from the sensor. This laterally \((x)\) displaced position gives a relative bearing angle \((\theta)\) of the object to the sensor. The angle can be calculated from the \(x_n, y_n\) position as

\[
\theta_n = \tan^{-1} \left( \frac{x_n}{y_n} \right)
\]

Eqn. 3.20

The final environment (ML, Figure 3.7, c) was made up of multiple objects consistently placed \(x = 2\) m from the sensor, with \(0.1\) m separation in the \(y\)-direction between each object up to an infinite \(y\) value (although the maximum range of the sensor is \(17\) m, limited by the set pulse repetition rate value). This environment was made analogous to a bat flying parallel to a hedgerow or dense foliage.

The sensor speed \(v_s\) was \(5\) ms\(^{-1}\) for all three environments, and the pulse repetition rates (PRR) were kept constant at PRR = 10 Hz. This was taken as a comparable average pulse repetition rate for mouse-eared, pipistrelle, and horseshoe bats when in the search phase of their echolocation [82, 83].

**Simulation Environment**

![Figure 3.7 Simulation environment of the experiment for the three tests (SA, SL and ML). The source (or sensor) was moving at a constant velocity of 5ms\(^{-1}\) along the y-axis (i.e., constant heading angle of 0°). (a) Sensor moving directly towards the](image-url)
object (no bearing angle). (b) Sensor moving towards the object at a bearing angle $\theta$. (c) Sensor moving parallel to an ‘infinite’ path of multiple objects (0.1 m spacing), laterally (x) displaced from its path by 2 m.

### 3.3.1 Echo creation

To simulate an echo train of an emitted signal, comprising echoes reflected off multiple objects from an emitted signal, a single echo reflected off an object was first developed. The emitted signal $y_s(t)$ is a recorded sound signal (bat call) with amplitude and sampling rate $f_s = 441$ kHz. The emitted signal is first Doppler shifted relative to the velocity of the sensor. Using the equation for Doppler shift (Eqn. 3.14), and as the objects in the study were stationary, $V_o = 0 \text{ m/s}$, the Doppler shifted frequency ($f_e$) for a signal that travels to the object and back to the signal is

$$f_e = \left( \frac{c + V_o}{c - V_o} \right) f_s$$  \hspace{1cm} \text{Eqn. 3.21}

where $f_s$ is the emitted signal frequency and as the objects that had a lateral displacement (x-direction) to the sensor, the objects had a relative angle ($\theta$) component to the sensor flight direction. Thus, the relative velocity of the sensor to the bat was $V_x = v_s \cos \theta$, and the final equation for Doppler shifted echo frequency then became

$$f_e = \left( \frac{c + v_x \cos \theta}{c - v_x \cos \theta} \right) f_s$$  \hspace{1cm} \text{Eqn. 3.22}

And the final Doppler ratio used for artificially shifting the signal

$$DR = \frac{f_e}{f_s} = \left( \frac{c + v_x \cos \theta}{c - v_x \cos \theta} \right)$$  \hspace{1cm} \text{Eqn. 3.23}

Where $DR > 1$ indicated that the sensor was approaching the object, $0 < DR < 1$ indicated that the sensor was moving away from the object and $DR = 1$ had no Doppler component (i.e., there was no relative velocity between the sensor and the object).

Since any frequency and period ($T$) of a signal is related by $f = \frac{1}{T}$, the Doppler shifted echo signal will have a time period $T_e = T_s \left( \frac{f_s}{f_e} \right)$, or $T_e = \frac{T_s}{DR}$ which indicates that the original signal is compressed in time if $DR > 1$, and undergoes rarefaction if $0 < DR < 1$. This time compression or rarefaction can be made artificially by interpolating the signal $y_s(t)$. The interpolation estimates new data points from the discrete set of known data points at the new Doppler shifted times. For simplicity, we used a linear interpolation, that assumes a linear relationship between the data points (i.e., the interpolant is located along a linear line between the points closest to it).

To manipulate the sound parameters in the signal and perform changes in power (dB) of the signal, the signal was then decomposed into components of different frequencies via the fast Fourier Transform.
(FFT). An FFT is a fast computation of the discrete Fourier Transform (DFT) that converts a signal from its original time (or space) domain to a representation in the frequency domain. The DFT is defined in the MATLAB function used [84], for the Fourier transform $Y_{FFT} = fft(y_s)$ and the inverse Fourier transform $y_s = ifft(Y_{FFT})$, and signal length of $n$, as:

\[
Y_{FFT}(k) = \sum_{j=1}^{n} y_s(j)W_n^{(j-1)(k-1)}
\]

\[
y_s(j) = \frac{1}{n} \sum_{k=1}^{n} Y_{FFT}(k)W_n^{-(j-1)(k-1)}
\]

where

\[
W_n = e^{(-2\pi n)/n}
\]

While the analysis is in the frequency domain of the signal, changes in power for each frequency component can be made. The power from each echo can be estimated from the sonar equation, Eqn. 3.6. For perfect reflectors, there is no component of Target Strength (TS) and in a perfect case here there was no background or self-made noise in the simulated environment (i.e., $NL = 0$). The signal is also assumed to be omnidirectional, thus losses from directionality were not considered ($DI = 0$). The equation then simply becomes:

\[
SNR = SL - 2TL
\]

The atmospheric loss coefficient for sound absorption in air is frequency, temperature ($T$, °C), and humidity ($H$, %) dependent. For simplicity, a single value of $T = 15$ °C and $H = 60$ % is used, giving a loss coefficient within 0.516 dB/m to 2.98 dB/m for a frequency range of 20 to 100 kHz. As the signal was omnidirectional (i.e., spherical wave) the geometric spreading loss for an ideal case (no background noise or interference, perfect reflectors) is 6 dB per doubling distance. The total transmission loss (TL) is thus frequency dependent and doubled to consider the signal moving to and from the object. The SNR for every frequency was then

\[
SNR(f) = SL(f) - 2TL(f)
\]

$Ys(f)$ now had frequency components that have been reduced in power from the transmission of the signal. The signal was then reverted to the time-domain $Ys(t)$ via an inverse FFT to allow for the addition of time of flight (TOF) of the transmission. Since the sensor velocity $V_s$ was a lot slower than the speed of sound, $c = 343 ms^{-1}$ (i.e., $V_s \ll c$), TOF is calculated as (from Eqn. 3.1)
Chapter 3. Theory of Acoustic Flow and the Acoustic Flow Parameter

\[ \text{TOF} = \frac{2s}{c} \quad \text{Eqn. 3.27} \]

where \( s \) was the displacement of the object to the sensor \( s = \sqrt{x^2 + y^2} \) in m. The final echo signal \( (Y_s) \) from a single object at \((x,y)\) was then the Doppler shifted and power attenuated emitted signal \( (y_s) \), with the added TOF component

\[ Y_s(t + \text{TOF}) \quad \text{Eqn. 3.28} \]

For the case of multiple echoes (number of objects, \( N > 1 \)), the final echo train, \( E \), or the echo signal with the combined echoes from multiple objects can be calculated as

\[ E = \sum_{n=1,2,...N} Y_{sn}(t + TOF_n) \quad \text{Eqn. 3.29} \]

which is the summation of echo signals from the different objects at different \((x_n, y_n)\) positions.

3.3.2 Echo Parameter Extraction

For each emitted signal \( Y_s \), the echo train \( (E) \) from that signal can then be analysed to extract the parameters needed for flow velocity estimation. For consistency, the maximum power values of each parameter were extracted and tracked. For amplitude, the maximum value was extracted from the envelope (absolute of a Hilbert function) of the echo train signal. The maximum value of the envelope was the tracked amplitude \( (A_t) \) where the subscript \( t \) denotes the consecutive pulse-echo analysis, i.e., \( t_1 = \) first echo for single object case, or echo train for multiple objects case, and the time between the signal maximum amplitude and the echo train maximum amplitude was the time of flight \( (\text{TOF}_t) \). For the frequency flow parameter, the maximum frequency was obtained by analysing the signal in the frequency domain (FFT) and obtaining the frequency component in the signal with the highest magnitude. This was calculated for both the emitted signal and the echo train, to obtain the Doppler ratio \( (\text{DR}) \) which was then used to estimate flow velocity, \( VF \).
Figure 3.8 Example parameter extraction from echo train, (red) reflected off a single object, 1 m ahead of the sensor emitting a pipistrelle signal (blue). The top graph is the signals in the time domain, and the bottom, in frequency domain. The black line (time domain) outlining the signals is the absolute value of the Hilbert function of the signals. TOF\textsubscript{11} was measured as the time between the maximum amplitude of the emitted signal (blue) and the time at the maximum amplitude (A\textsubscript{11}) of the echo train (red). Maximum frequency of both signal and echo (F\textsubscript{t1}) were extracted using the FFT and divided to obtain the Doppler shift ratio (DR\textsubscript{t1}).

VF can then be calculated as the change between these extracted values (A\textsubscript{t2} – A\textsubscript{t1}, TOF\textsubscript{t2} – TOF\textsubscript{t1}, and DR\textsubscript{t2} – DR\textsubscript{t1}) divided by the time elapsed between the emitted signals (t\textsubscript{2} – t\textsubscript{1}, or simply the Pulse Repetition Rate, PRR). The amplitude and TOF flow velocities were then standardised for both the SA and SL environments as well as normalised to the velocity of the sensor (V\textsubscript{s}) to make fair comparisons amongst each other and with the actual relative velocity of the sensor. For the SA environment, the flow velocities were translated to centre at 5 ms\textsuperscript{-1}. For the SL environment, the maximum for the normalisation range was set to the mean of the corresponding flow velocities in the SA environment (determined as the maximum, steady state flow velocity), and the minimum was set to the minimum flow velocity of the SL environment.

\[
\bar{V}_F_{SL\text{norm}} = \left( \frac{\bar{V}_F_{SL} - \min(\bar{V}_F_{SL})}{\text{mean}(\bar{V}_F_{SA}) - \min(\bar{V}_F_{SL})} \right) (\max(\bar{V}_s) - \min(\bar{V}_s)) + \min(\bar{V}_s) \\
\text{Eqn. 3.30}
\]

49
where \( \bar{F}_{SL\text{norm}} \) was the normalised version of the flow velocity extracted by a parameter in the SL environment (\( \bar{F}_{SL} \)). \( \text{mean}(\bar{F}_{SA}) \) was the mean flow velocity (steady state) of the SA environment.

### 3.3.3 Theoretical Vs. Computed Velocities

A theoretical flow velocity was calculated to compare with the computed flow velocities. The theoretical velocities were calculated relative to the theoretical displacement of the objects in the simulation. For a single object, the sensor approached an object at a constant speed \( v_s = 5 \text{m/s} \) and at a relative angle \( \theta_n \) to the object (Eqn. 3.20). The theoretical relative velocity, can simply be calculated as

\[
V_n = v_s \cos \theta_n \tag{Eqn. 3.31}
\]

For multiple objects, an estimation of the theoretical velocities cannot be made without considering the effects of summating the echoes and thus the comparison will only be made with the constant sensor speed \( v_s = 5 \text{ms}^{-1} \). The root mean squared error (RMSE) can then calculated between the theoretical and computed velocities (notation for the different parameter RMSEs are: Amplitude = RMSE\(_A\), TOF = RMSE\(_{TOF}\), and Frequency = RMSE\(_F\)).
3.4 Results

As a general reference, the FFT of the emitted signals are presented in Figure 3.9. This was to show how the power was distributed across the frequencies in the signal (before emission). The peak frequencies were FM = 43.84 kHz, FMCF = 40.75 kHz, and CF = 81.82 kHz.

![FFT of Signals](image)

Figure 3.9 Single-sided fast fourier transform (FFT) of the emitted signals. All signals were normalised in magnitude prior to the transform and divided by the length of the signal in the transformation.

For both the CF and FMCF signals, the peak frequencies were distinct from the other frequencies in the signals. These were the constant frequencies of the signal. The FMCF signal however, had a wider spread of power, as the power was also distributed in the FM components of the signal. The pure FM signal, however, had a more evenly distributed power across all frequencies. This, as well as the signal power distribution in time, affected the results of the flow velocities presented in the following section.
3.4.1 Single Object Analysis

![Graph of flow velocities extracted for single object analysis of objects ahead of the sensor (left) and at an angle to the sensor (right). Flow velocities were normalised to the ranges of the expected velocity and the smoothed flow velocity (Savitsky Golay) to allow for comparison between the signal types and ensure the normalisation was not affected by outliers.](image)

**Figure 3.10** Flow velocities extracted for single object analysis of objects ahead of the sensor (left) and at an angle to the sensor (right). Flow velocities were normalised to the ranges of the expected velocity and the smoothed flow velocity (Savitsky Golay) to allow for comparison between the signal types and ensure the normalisation was not affected by outliers.

**Single Ahead, SA**

For this environment, the flow velocity measured from changes in TOF were the most accurate compared to the amplitude (A) and frequency (F) flow velocities. The errors (Table 3.1) were small for these (RMSE$_{TOF}$ ≤ 4.89E-04 ms$^{-1}$), although larger errors can be seen in the FMCF signal. These were deemed too small to conclusively state that the signal would have behaved as poorly in other occasions or environments. Larger differences can be seen in the flow velocities calculated from the change in maximum amplitudes (A), with the CF signal obtaining the lowest errors, followed by the FMCF signal and FM signal, respectively. These errors were, firstly, because of the spherical spreading loss of the signal. Since the losses (in dB) over distance were logarithmic (-6dB per doubling distance), the
expected velocity should not have been constant, and instead will have a logarithmic increase as the sensor approached the object. All signals exhibited this behaviour, with a highest increase seen in the FM signal.

From the signal design perspective, these varying errors were likely caused by the different signal power distributions and frequency content (see Figure 3.6, Figure 3.9). In the temporal distribution of power (amplitude vs. time), the CF signal had an almost equal power distribution throughout the signal, whilst the FM signal had an increasing power distribution. The CF signal also mainly comprised a single distinct frequency throughout the signal, whilst the FM signal consisted of a frequency sweep from ~100 kHz to ~30 kHz. This could affect the resulting amplitude envelope of the echo signals, as the signals traverse in air and are attenuated and absorbed. Higher frequencies were absorbed in air more than lower frequencies (α loss coefficient range from 0.516 dB/m to 2.98 dB/m for a frequency range of 20 to 100 kHz, 3.3.1). This created a distortion of the amplitude envelope in the resulting FM signal, as some of the higher signals were absorbed (or lost in power, dB) more than the lower signals. This, in turn, introduces a linear decrease in relative velocity, and combined with the logarithmic loss of the signal through spherical spreading, resulted in the flow velocity decreasing at a faster rate than the CF signal. Therefore, the effect can be seen to reduce as the signal becomes more constant in frequency (i.e., from FMCF to CF). The TOF flow velocities, however, were not as affected between the signals, indicating that ranging was not affected by the atmospheric effects or the signal design. This analysis, however, did not consider call-echo overlap, which would have made ranging more difficult to estimate for longer signals.

As expected, the frequency flow velocities measured in the SA environment were most accurate for the CF signal (RMSE$_F$ = 3.33E-03 ms$^{-1}$), followed by FMCF (RMSE$_F$ = 0.0498 ms$^{-1}$) and FM signals (RMSE$_F$ = 0.0812 ms$^{-1}$), respectively. The frequency flow velocities for the FM signal increased linearly as the sensor approached the object. This was likely because the higher frequencies of the signal were absorbed in air at further distances, leaving the echo with more power distributed in the lower frequencies, and thus returning underestimated values of the Doppler ratio. As the sensor approached the object, more high frequencies can be detected, increasing the Doppler ratio and the flow velocity measured. This can also be seen in the FMCF signal frequency velocities. The maximum power frequency of the FM signal was a constant measured at the lower end of the broadband spectrum, and the power across frequencies were more evenly distributed in the FM signal. Therefore, the increasing maximum frequency measured in the echo signal caused by the return of the higher frequencies to the echo signal, resulted in the overestimation of Doppler ratio as the sensor approached the object. This effect also explains why velocities measured in the FMCF signal were not overestimated, as the signal had more power concentrated for a single frequency at the tail end (long, CF component) of the signal.
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<table>
<thead>
<tr>
<th></th>
<th>Single Object, Ahead (SA)</th>
<th>Single Object, Lateral (SL)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>RMSE&lt;sub&gt;TOF&lt;/sub&gt;</td>
</tr>
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</tr>
<tr>
<td>Pipistrelle, FMCF</td>
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</tr>
<tr>
<td>Horseshoe, CF</td>
<td>0.0167</td>
<td>3.59E-06</td>
</tr>
</tbody>
</table>

Table 3.1 Root mean squared error (RMSE) of flow velocities from different parameters for the two single object tests. RMSE units are in ms<sup>-1</sup>.

Single Object, Laterally displaced (SL, or at an angle)

For the environment with an object at a lateral (x) displacement to the sensor (SL), the relative angle of the sensor to the object gives a relative velocity that decreases as the sensor approached the object (Vs = 0 when the sensor is right next to the object, as cos(90°) = 0). In this environment, the changes in displacement to object were no longer constant, giving an irregular change in the amount of signal power attenuation. This may cause the peak amplitudes to fluctuate in temporal position within the signal giving irregular TOF estimates. Given that the time difference between a signal echo to the next is small (0.1 s), a small fluctuation in TOF can cause large errors. Since amplitude and TOF changes were extracted via locating peaks (in time), the power distribution of the emitted signal significantly affected the consistency of locating the same peaks in the echo signals. If the signal had a more temporally distinguishable peak amplitude in the original signal, like the FM signal, small changes in the signal would still allow for the same peak amplitude to be extracted at the same time in the echo signal, as most of the signal power will be attenuated by the same ratio throughout the signal. As the power distribution in the CF signal was more evenly distributed, the peak amplitude measured was not distinct and therefore it would be even more difficult to obtain consistent time delays in the echo signal, especially when the signal has been subjected to inconsistent changes during transmission.

In most TOF estimation today, this can be improved using a combination of peak analysis and thresholding, where TOF is measured above a certain amplitude value to ensure that the peak is not a noisy feature in the signal [85, 86]. This technique is specially developed for non-destructive testing and evaluation (NDT) where the highest accuracy in TOF is required to obtain small features in an object (like cracks). As noise was not simulated in the study, and the comparison only considers the simplest form of parameter extraction, further action on extracting more accurate TOF was not implemented.
The results showed that for the SL amplitudes, the velocities measured followed the trend especially well when the sensor was further away from the object, but the measured velocities decreased earlier than expected as the sensor approached the object. This was also likely due to the absorption of the higher frequencies at further distances, affecting the expected power distribution of the returned echo, especially for signals with varied frequency components (FM) and power distribution.

In the frequency flow velocity measurements (SL), the CF signal returned the most accurate flow velocity. Since the CF signal had most of the signal power concentrated at one frequency, the maximum frequency can be accurately and consistently measured at the expected Doppler shifted value. This was why the FMCF signal also managed to obtain accurate frequency flow velocity, with its CF tail in the signal, and the pure FM signal returned fluctuated flow velocities.

### 3.4.2 Multiple Objects Analysis

For the multiple objects’ environment (ML), as expected no changes in amplitude or TOF can be measured, returning no flow velocity estimation. This is because although the sensor is moving, the relative distance to the objects were constant. However, since the sensor still had a velocity component, the signal was still Doppler shifted, giving an estimation of the relative velocity (Figure 3.11). Due to the large number of objects, the effects of the summation of echo signals from the objects altered the frequency profile of the overall echo train, making it difficult to obtain the accurate peak frequency, and thus Doppler shift. The larger overlap of the echo signals in time, especially for signals dominated by one frequency (i.e., CF and FMCF signals), the greater the effects of the summation and the larger the Doppler shift error.

![Figure 3.11](image)

*Figure 3.11* Flow velocities from frequency changes (Doppler shift) for the three signals in a multiple object environment.
3.5 Discussion

In the simplest case, where a sensor is approaching an object directly in front of it, all the parameters can be made a reliable estimator for acoustic flow velocity for any of the three signal designs. Careful consideration on how the parameters change with distance is required to obtain accurate expectations of flow changes (e.g., amplitude changes logarithmically with distance from attenuation and absorption in air, TOF changes linearly with distance and Frequency is dependent on relative velocity). This is consistent in studies on how the acoustic parameters may change for CF bats [66]. The signal design also affected how these parameters change, depending on the power distribution and frequency content or spread in the signal. For example, frequency sweep changes (between FM and FMCF signals) in this scenario can underestimate or overestimate the flow velocities, when combined with the effect of absorption of high frequencies in air.

When the object is at an angle to the sensor and the flow velocity is no longer constant, the absorption of sound affected the estimation of maximum amplitude, and in turn, the estimation for both the amplitude and TOF flow velocities. The logarithmic decrease of amplitude from sound absorption and attenuation decreased the flow velocity more than in the direct approach, resulting in the earlier decrease in flow velocities for the amplitude. The TOF flow velocity was affected by the duration of the signals, as the longer CF signal allowed for a bigger margin of time error. In this scenario, the frequency flow velocities followed the expected decrease in relative velocity, with low errors for signals with CF components (FMCF, pure CF signals). This was also proven to be achievable in some simple experiments of obtaining velocity from CF signals via Doppler shift, for objects at a bearing angle [68].

With the multiple objects’ scenario, as expected, neither the amplitude nor TOF parameters can give estimation of flow velocity, as the distance to the objects remained the same. Frequency changes were still present in all three signals, however, with underestimated flow velocities. The overlapping of echoes from longer signals (CF) returned higher errors and thus a larger underestimation of the Doppler shift (or relative velocity). The wide range of frequencies in the FM signal made the signal more Doppler tolerant, which in radar terms, meant that there is a wider range of Doppler shifted signal that has a high enough SNR to be obtained through correlation [65]. The Doppler tolerant FM signal that has lesser overlap between echoes may result in the more accurate estimation of Doppler shift in this case. This overlap effect is also a known sonar adaptation for FM bats, as shorter broadband signals are used by bats foraging in denser environments, to increase their sonar acuity to locate small prey [31]. The FM component of their signal allows them to differentiate the small fluctuations in wing-flapping of insects and the duration of their call avoids echo overlap. Bats also decrease their signal duration at the terminal phase of catching prey for the same reason. The analysis also showed that an FMCF signal could also return flow velocity estimates that were comparable to the FM signal (~1 ms\(^{-1}\) less). This was likely due to the same reasons as why the FM signal was successful. The underestimated values
could also explain why the bats in Chapter 2 only changed a fraction of their speed in response to the velocity changes.

It is important to note however, that although the long CF bat calls clearly suffered from the overlapping effects in extracting flow velocities in this analysis, this does not affect the bats’ natural ability to distinguish prey. Some CF bats rely on a finely tuned auditory system to differentiate prey from their surroundings [41]. These bats compensate for the flight-induced Doppler shift of their calls by adjusting the frequency of their calls to always be within the narrow bandwidth of the frequency their auditory systems are attuned to [42, 87]. Since the shorter duration and wideband frequency of calls led to better estimates of Doppler and flow velocity in this analysis, one might question whether pure CF bats with long calls would favour these call adaptations if they were to perceive acoustic flow velocity. Therefore, any further behavioural studies on whether bats perceive acoustic flow velocities, should pay close attention to whether call adaptations or plasticity are adopted by the bats.

3.6 Conclusion

For simple, single object cases, where distance to object varies with time, all the parameters studied returned adequate flow velocities estimations. The distance-dependent parameters were more accurate than frequency estimates, especially when the change of distance was linear. This analysis, however, did not account for target attenuation or directionality, both of which would affect the changes in amplitudes and TOF. Frequency, however, was only dependent on relative velocity, and in turn would only be proportional to the changes in speed. When extended to the case with multiple objects and the distance to the objects were constant, only frequency changes returned flow velocity estimates. This could explain why most of the acoustic flow behavioural experiment in bats so far (apart from the study in Chapter 2), did not observe velocity changes from the bats, as distance to objects were constant.

The experiment clearly showed that frequency is the only parameter that could extract flow velocity in the dense environment proposed, where distance to objects remained constant. Therefore, frequency changes should be considered as the only reliable cue for bat acoustic flow velocity perception, especially in dense environments where the environment features ‘blend’ together (e.g., dense foliage, or hedgerows).

The findings from this chapter motivated the investigation and development of methods to extract frequency changes more accurately, which are explored in the following Chapter 4. In the investigation, different signal processing methods can be compared to the FFT method used in this analysis, for the different signal types proposed here. This can give a better indication of why some signals gave better estimations in Doppler over others, and how the signal can be optimised for extracting Doppler. This chapter also proposed a method of extracting Doppler in a single pulse-echo, to analyse the Doppler
ratio vs. time (‘Doppler evolution’) in the signal. The Doppler evolution analysis suggested, could provide a 2D spatial map as well as motion estimates. This is also explored in the following chapter.

Future behavioural experiments on acoustic flow velocity perception should investigate the neural processing of the changing frequency parameters to determine whether the change in motion stimulates the Doppler sensitive parts of the auditory cortex [27]. As emphasised in the chapter, future experiments on acoustic flow velocity perception will have to separate the influence of distance estimation on the induced relative motion, to determine which parameter the bats are attuned to for flow estimation.
Chapter 4
Computational Simulation of Doppler-Acoustic Flow in Bats and Artificial Systems

4.1 Chapter Abstract
This chapter studies how frequency changes (or Doppler shift) in a single pulse-echo emitted by a moving source can be extracted to determine the source’s speed, heading angle, and position produced by the relative motion of the source and its environment (Doppler-acoustic flow). The chapter expanded on the idea presented in Chapter 3: that the resulting Doppler shift from each individual object over time (or ‘Doppler evolution’) in a single pulse-echo, can be related to a 2D spatial map. The studies presented here, focused on how to extract accurate Doppler shifts from a lateral structure made up of individual objects with varied spacing; similar to a hedgerow in a bat’s commuting path. This was a three-part study, where firstly (Part A), a suitable signal processing method was determined to obtain accurate Doppler ratios from three signals emitted by Pipistrellus nathusii, Myotis daubentonii, and Rhinolophus ferrumequinum bats (used in the analyses of previous chapters). A novel method of using the wideband ambiguity function (WAF) combined with an image processing (template matching) algorithm was developed for this study and obtained more accurate estimates of Doppler ratios compared to standard Fourier transform methods (Short Time Fourier Transform, STFT). The signal processing method proposed was able to estimate heading angles and lateral distances of the source to the lateral structure for some of the bat signals. Following this, the second part (Part B) studied the robustness of the proposed method with artificial bat-inspired signals. This was to determine whether specific characteristics of the bat-inspired signals led to better estimations of Doppler shift, and in turn, the source’s heading angles and distances to the environment. The method and combined signals were tested in more realistic environments, that included object properties and noise, in order to determine the optimal signal to be used with the method in real-world scenarios. The final part (Part C) tested the same artificial signals with the proposed method, in obtaining speed estimates for these realistic environments. The results of both Part B and C, showed that short (<5.5 ms) signals with a constant frequency (CF) component (either purely CF, or partly combined with a frequency modulated component, FMCF) could be used with the proposed signal processing module to obtain accurate estimates of the moving source’s heading, distance, and speed, within acceptable error margins (e.g., angle errors ≤ 10° for most heading angle and distance tests of the FMCF signal in noisy and dispersed echoes). Thus, the study proved that a single pulse-echo can return Doppler-acoustic flow information when processed with the proposed signal processing module and signals.
4.2 Introduction

As emphasized in the previous chapters, determining which acoustic parameter to extract acoustic flow velocities requires an experiment that separates the influence of distance estimation. This was important, as realistic environments are made up of multiple objects, surfaces or elements that are rarely distinguishable in the reflected sound. This is due to the coalescing of these object echoes into a single reflected echo (or ‘echo train’). This led to the preliminary study of extracting flow velocity from different acoustic parameters in a multiple-object environment in Chapter 3. From the experiment, the frequency changes (or Doppler shift) produced velocity flow information that, although underestimated, showed that the information of relative motion was present. In addition to this, the environment that the pipistrelle bats faced in Chapter 2 comprised multiple objects that were densely spaced (hedgerows, dense foliage, etc.), and yet the bats were still able to perceive the section of introduced motion (that was also made up of densely spaced leaves, or reflectors). This indicated that some flow velocity information, which was hypothesised as the resulting frequency changes in the echoes from the introduced motion, could be perceived by the bats in that environment. Therefore, this chapter aims to determine methods on how to extract the frequency changes, in environments like the previous chapters, and how to use the information for navigation.

Some Doppler based experiments for autonomous navigation, managed to extract accurate Doppler estimates (and thus, velocity) for simple environments (e.g., single objects), or objects with a distinct acoustic return (e.g., smooth wall) [67, 68]. Others experimented with extracting Doppler for navigation in a multiple-object environments, although the methods suffered from requiring multiple pulse-echo information for the system to estimate flow velocity [49], or calibration from known landmarks or features [50].

The analysis in this chapter expands on the theory that acoustic flow (and acoustic flow velocities) in complex environments, could be estimated from extracting Doppler ratios, and aptly termed ‘Doppler-Acoustic flow’ (from Chapter 3). Since the FFT method used returned underestimated values of Doppler (and thus flow velocity), this analysis focused on whether a different processing method could be used to extract the flow velocities. The study in Chapter 3 also suggested that the distribution of Doppler ratio over time (or ‘Doppler evolution’) within the reflected echo train may also present 2D spatial information. The advantages of this were twofold, that is, multiple information can be extracted from frequency shifts, and all the information is present in a single pulse-echo. Therefore, two main questions were identified for this study. They were, for Doppler-Acoustic flow:

(a) Whether speed, heading, and distance could be extracted from analysing a single echo train from the emitted pulse of a bat-inspired signal.
(b) Whether accurate Doppler shifts could be extracted using the standard methods of frequency processing (i.e., FFT), or another modified signal processing method is required.
In answering these questions, the analysis was divided into three parts, A, B and C. Part A investigated the signal processing methods required to successfully obtain Doppler ratios from echoes returned by real bat signals (from three species: *Pipistrellus nathusii* or pipistrelle bats, *Myotis daubentonii* or mouse-eared bats, and *Rhinolophus ferrumequinum* or horseshoe bats) reflected off the objects in the environment. These tests mimicked a bat travelling at a constant velocity, 5ms⁻¹, along a lateral structure (or ‘hedgerow’) with different object density, at various heading angles to the structure. The ‘Doppler evolutions’ from a single echo train reflected off these environments were then extracted using the different signal processing methods. This section introduces the use of the Wideband Ambiguity Function (WAF, commonly used in radar pulse compression [88]) to process the resulting echo train from the environment. The method is a cross-correlation between the echo train and the ‘match filter’, which comprises artificially Doppler shifted versions of the emitted signal. The WAF returns the distortion of the echo train in terms of Doppler and time. Comparisons are then drawn between the Doppler ratios obtained from a Short Time Fourier Transform (STFT) and the WAF, extracted via peak finding and template matching.

The bat calls used in this analysis were the same signals from Chapter 3 (Figure 3.6), to determine which signals and respective signal properties could be successfully used with the proposed signal processing methods. The signals were: a long (~65 ms) constant frequency (CF) horseshoe signal; a short (~5 ms), frequency modulated (FM) mouse-eared bat signal; and a short (~5.5 ms) combined frequency modulated and constant frequency signal (FMCF). It was hypothesized that the shorter bat signals (FM, 5 ms and FMCF, 5.5 ms) would perform better than the longer signal, as these signals were short enough to avoid the overlapping effect of the object echoes. However, since long CF signals are used by bats to detect Doppler shift [87], and CF bats perceive even the smallest Doppler shifted velocity (0.1ms⁻¹) [89], it was expected that the signals with the CF components would also return better Doppler shift estimates. Therefore, when used in the proposed signal processing methods to obtain the ‘Doppler evolution’ for motion estimates, the effect of both the signal duration and frequency sweep was observed.

Part B extended the study of the proposed signal processing module in part A, determined to have returned the most accurate estimations of Doppler ratio to obtain the motion information in part A. To determine the robustness of this method, this section tested the processing module with different artificial bat-inspired signals for varying environments, whilst considering realistic environment effects of object properties (attenuation from target strengths, uneven surfaces or dispersion effects) and background noise (pink noise). In this section, the results from the different signal properties (signal frequency sweep and duration) between the artificial signals were discussed in depth, and the signals that performed well in these tests were highlighted. Similar results from part A were expected for most of these tests, in that shorter signals would perform well in the analysis. The effects of frequency sweep, however, could not be easily predicted, because while FM signals are Doppler tolerant [65], CF signals
tend to obtain more consistent estimates of Doppler for simple cases [67, 68]. The tests aimed to determine whether there was an optimum signal duration or frequency sweep combination to use with the signal processing module to obtain the source’s heading angle and distance.

The final part of the analysis used the same tests in part B to obtain estimates of speed. This was conducted with templates of different speed combinations. In this part, the same signals as part B were used for the same tests, to obtain the corresponding conclusion of which signals were robust in determining speed using the proposed processing module.

### 4.3 Methods and Materials

The simulations were created within MATLAB using custom-made scripts and functions along with the existing functions within MATLAB (e.g., fft.m). Artificial (e.g., object positions) and real (e.g., measured object target strengths) data served as inputs to create the simulation environment, from which the echo response was obtained and was then processed to obtain Doppler-acoustic flow information.

#### 4.3.1 Simulation Environment

The analyses were made in a 2D environment (Figure 4.1), with a global coordinate system \((X_g, Y_g)\), in which the ‘bat’ or sensor \((X_{bg}, Y_{bg})\) and objects \((x_{og}, y_{og})\) were located. The sensor had a local coordinate system \((X_b, Y_b)\) with a heading angle, \(\varphi\), relative to the \(Y_g\) axis of the global coordinates. From the global positions of the sensor and objects, relative positions \((x_{ob}, y_{ob})\) between the objects and the sensor can then be calculated as

\[
(x_{ob}, y_{ob}) = (x_{og} - x_{bg}, y_{og} - y_{bg}) \tag{Eqn. 4.1}
\]

Assuming the direction of the emitted signal was the same as the direction of motion of the sensor, relative angles \((\theta_{rel})\) of the object to the sensor with a heading angle \(\varphi\) can then be calculated as

\[
\theta_{rel} = \varphi - \theta_{ob} = \varphi - \tan^{-1}\left(\frac{x_{ob}}{y_{ob}}\right) \tag{Eqn. 4.2}
\]

where \(\theta_{ob}\) was the angle between the object and the sensor position calculated from global coordinate relative positions (i.e., irrespective of heading direction of sensor)

\[
\theta_{ob} = \tan^{-1}\left(\frac{x_{ob}}{y_{ob}}\right) \tag{Eqn. 4.3}
\]

If the object appeared to be behind the sensor (i.e., if the relative \(y_{ob}\) position is negative and \(\theta_{ob}\) is also negative), then the relative angle would be
\[ \theta_{rel} = (90 - \varphi) + (90 + \theta_{ob}) \]  
\text{Eqn. 4.4}

If the sensor was facing the object headfirst, there was no relative angle between them, or \( \theta_{rel} = 0 \). The relative angle calculations were important to define consistently within the simulation, as they were used to estimate Doppler shift in the echoes reflected from objects. Note that to keep an ‘omnidirectional’ emission of the signal but only obtain echoes ahead of the sensor, the experiments assumed a beam divergence of 90° or beamwidth of 180°, which meant that the sensor beam was wide (i.e., -90° to 90° from the heading direction) and the sensor could only detect objects within this range.

Figure 4.1 2D Coordinate system of the simulation environment. Black filled circle is the object in the environment with global positions \( (x_{og}, y_{og}) \) whereas the bat silhouette is the sensor with global position \( (x_{bg}, y_{bg}) \). The heading angle \( (\varphi) \) is read as zero from the global Yg axis, positive in the clockwise direction from the axis (indicated by the arrowhead), whereas the relative angle \( (\theta_{rel}) \) is zero at the heading angle (red) line, positive in the clockwise direction from the heading line.

In part A, three main environments were tested, each increasing in ‘complexity’ over the one before it. The complexity of the environment was increased by increasing the number of objects and changing the relative angles of the sensor to the objects (i.e., including a sensor heading component). All environments had objects arranged as a 2D line of reflectors with the sensor moving in a parallel sense alongside it, analogous to a bat flying along a hedgerow. For all environments, only a single signal-echo response was studied, as per the experiment aim of extracting the evolution of Doppler shift over time in a single echo train from an emitted signal. This was much like a ‘snapshot’ of the acoustic scene at an instant of time.

As mentioned in the introduction, all environments were designed to mimic a bat flying along a hedgerow. The first environment (Figure 4.2, A) comprised reflectors aligned at a constant lateral distance from the sensor with \( N = 6 \) reflectors increasing with distance in the \( Y_g \) direction (starting at \( Y_g = 0 \, m \), and ending at \( Y_g = 10 \, m \)), with an object separation of \( \Delta Object = 2 \, m \). The second
environment (Figure 4.2, B) was like the first, except with a smaller separation between the objects, $\Delta Object = 0.1 \text{ m} \ (N = 101 \text{ objects})$. The sensor motion and direction of emitted signal were the same at $\varphi = 0^\circ$ (i.e., moving forward along the $Y_g$ axis). The final environment (Figure 4.2, C) was designed to study whether the Doppler shifts can be extracted for when the sensor heading is angled towards the line of reflectors at $\varphi = 45^\circ$.

![Environment Diagram]

**Figure 4.2** Simulation environments and their respective theoretical Doppler ratios calculated for a sensor moving at $v_s = 5\text{ ms}^{-1}$. A) Sparse environment and the corresponding Doppler ratios, well-spaced in time due to the large object separation. B) Dense environment ($\Delta Object = 0.1 \text{ m}$) and the corresponding Doppler ratios which are closer in time ~ 3 ms. C) Similar dense environment as B, except with the sensor now moving and emitting the signal in the direction of the heading ( $\varphi = 45^\circ$).

A similar dense environment (0.1 m object separation) was used for the two latter parts of the analysis, parts B and C. These tested the extraction of Doppler ratios for combinations of different sensor headings ($\varphi$) ranging from $0^\circ$ to $45^\circ$ (in $5^\circ$ increments), and a range of relative lateral ($x_{ob}$)
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displacements from the objects between 1 to 10 m (in 1 m increments). In these tests, the number of objects was increased to 1001 (from $y = 0$ m to $y = 100$ m) and the sensor was placed at $Y_g = 50$ m. This was to maintain a comparable number of objects that were within range of the sensor for all heading angles and all lateral displacements. There were 100 tests in total (10 angles x 10 lateral displacements).

Figure 4.3 Dense 2D environment to test multiple heading and lateral displacement combinations. The source (or sensor) emitted a signal in the direction of the heading, and the beamwidth is $180^\circ$.

4.3.2 Signal Design

For Part A, the same three types of bat calls as in Chapter 3, were used as the emitted signals in the analysis. They were FM (Myotis daubentonii), FMCF (Pipistrellus nathusii) and CF (Rhinolophus ferrumequinum) calls (Figure 3.6). The calls were recorded calls of bats in Great Britain, by Danielle Linton (Wildlife Conservation Research Unit at Oxford University) with an UltraSoundGate 116-200 recorder. These are made available and can be downloaded from the animal sound recordings repository in the Avisoft website [81].

Part B and C tested artificial calls that were inspired from the bat calls. The objective of this was to determine the specific characteristics of the signals that would return better estimates of Doppler shift from a dense environment for a range of sensor heading angles and lateral displacements (Figure 4.3) Eleven artificial signals were tested, of which nine were a combination of three different signal durations ($5$ ms, $25$ ms and $45$ ms) and three different frequency sweep ranges; decreasing from $100$ kHz to $20$ kHz and $40$ kHz and also a ‘no-sweep’ call with a constant frequency of $80$ kHz (see example, Figure 4.4, A). This created a range of artificial signals that mimicked an FM (mouse-eared bat) signal on one end and a CF (horseshoe bat) call on the other end of the range. Of the other two signals tested (Figure 4.4, B), the first was a custom FMCF signal with a frequency modulated sweep from 100-40
kHz for 1.5 ms combined with a 40 kHz constant frequency tail of 4.5 ms (6 ms in total), like a pipistrelle bat call. The second, was a long 65 ms signal mimicking more of the horseshoe bat call, that is by including short frequency modulated tails (80-100 and 100-80 kHz, 2.5 ms) at the beginning and at the end of the signal, with an intermediary long section (60 ms) with a constant frequency of 80 kHz (labelled FM-CF-FM). For all these signals except the FM-CF-FM, the amplitude distribution was the same, in that they followed a normal distribution with a mean of half the signal length $T$, ($\mu = T/2$), and standard deviation of 20% of the signal length ($\sigma = T/5$). The FM-CF-FM signal amplitude distribution followed the real horseshoe signal example (Figure 3.6), modelled as a steep ramp-up and ramp-down amplitude distribution (Figure 4.4, B, right-hand side image).
4.3.3 Signal Processing

Echo Train Generation

In every part of this analysis, the echo trains from the combined objects were created in the same way, starting with developing the echo from a single object in the environment, similar to the echo creation in Chapter 3 (Section 3.3.1). The emitted signal $y_s(t)$ frequencies were Doppler shifted due to the relative motion of the sensor to the object. The amount of Doppler shift was dependent on the relative angle of the object to the sensor, $\theta_{rel}$. The Doppler shift is presented as a Doppler ratio ($DR$), from Eqn. 3.23

$$DR = \frac{f_e}{f_s} = \frac{c + v_s \cos \theta_{rel}}{c - v_s \cos \theta_{rel}}$$

Eqn. 4.5

where $v_s$ was the speed of the sensor, kept constant at 5 ms$^{-1}$, $f_s$ were the frequencies in the emitted signal and $f_e$ were the Doppler shifted frequencies.

The signal was then Doppler shifted by this amount, as a compression ($DR > 1$) or rarefaction ($DR < 1$) in time (derived from the relationship of frequency and time period of the signal $f = 1/T$). As the sensor was always approaching the object, the signal was always compressed in time (i.e., $DR > 1$). This can be artificially made through a linear interpolation of the signal, where the new compressed times were estimated from the discrete set of known time-data, and the relationship between the points were assumed to be linear.

The Doppler shifted signal, now $Y_s(t)$, was then attenuated from its transmission in air and from being scattered by the object. To make these changes, the signal was first transformed from the time-domain to the frequency-domain using the Fast Fourier Transform (FFT). In the frequency domain, the signal was divided into frequency components of different magnitudes ($Y_s(f)$). As sound absorption and target backscatter are a function of frequency, this allowed for the attenuation of magnitudes for specific frequencies to be made. Note that in this section, the magnitudes of the frequencies were first converted and normalised to the dB scale with a maximum of 130 dB SPL comparable to average loudness in some bat calls [90]. Using the active sensor sonar equation (Eqn. 3.6), and ignoring attenuation from noise levels (NL) and directionality index (DI), the final intensities (or power) for each frequency in the signal can be determined as the signal to noise ratio, $SNR(f)$

$$SNR(f) = SL(f) - 2TL(f,H,T,s) + TS(f,\theta_{rel})$$

Eqn. 4.6

Figure 4.4 Artificial signals in the spectral (spectrogram) and temporal (normalised amplitude [unitless] vs. time) graphs. (A) 5 ms example of the various frequency sweeps used in the analysis. (B) Signals modelled after actual pipistrelle (left) and horseshoe (right) signals.
Transmission losses (TL) were from geometric spreading and atmospheric absorption, where an absorption coefficient was calculated as a function of frequency, at constant temperature, $T_{atm} = 15^\circ C$ and humidity, $H = 60\%$. For part C where the objects were not perfect reflectors, the attenuation from targets (TS) were taken from the acoustic tomography at every frequency for the calculated relative angle $\theta_{rel}$ (TS = 0 dB for parts A and B). The signal $Y_s(f)$ with attenuated magnitudes of frequency can then be transformed back to the time domain via the inverse of the FFT where the time of flight (TOF) or time-to-object component of the echo can be added. TOF, from Eqn. 3.1, for the object of displacement $s_{ob} = \sqrt{(x_{ob}^2 + y_{ob}^2)}$ was calculated as

$$\text{TOF} = \frac{2s_{ob}}{c}$$

Eqn. 4.7

The final echo signal has now been Doppler shifted and attenuated through the transmission and can be denoted as

$$Y_s(t + \text{TOF})$$

From the echo of a single object, the same calculations were then made for every object within the range of the sensor. These were then summated into a single echo train, $E$, which was simply

$$E = \sum_{n=1,2,...N} Y_{s_n}(t + T\alpha F_n)$$

Eqn. 6

where $N$ was the number of objects in the environment. An example of how a single echo was created is depicted in Figure 4.6.

Signal-Echo Overlap

To ensure that there was no signal-echo (or call-echo, in terms of real bat signals) overlap for the longer signals (25 ms, 45 ms) at close distances, the final echo train only considered signals returning after the signal has been fully emitted. This meant that the system only ‘listened’ at times after the signal duration and before the next pulse (a.k.a. timed ‘hearing’). The echo train was truncated by only having values after the signal emission has ended (Figure 4.5). In the simulation, if the echo train had values within the duration of the signal emission, the values were then replaced with zeros.
Figure 4.5 Signal-Echo Overlap and the resulting truncated echo. The images represent an amplitude vs. time plot of the signals. This was considered the simplest case of avoiding overlap. Artificial sonar systems have used both the separation of echo in time and in frequency to prevent signal-echo overlap [85, 91, 92]. Bats, however, are known to have a unique processing method of echoes that is robust to the overlap. This is evident in Doppler shift compensation in some horseshoe bats, where the hearing is only tuned to certain frequencies, like a high-pass filter [87]. In this simulation analysis however, since all bat signal types were used to design artificial signals (both FM and CF types), the practice of timed ‘hearing’ of the sensor was used to remove the complexity of filtering multiple frequencies. This is because in the FM case, a single frequency could not be used as the high-pass threshold as this may remove the other frequencies in the signal.
Figure 4.6 Single object echo generation process example using an FM signal. A) Spectrogram of the emitted signal. B) FFT of the signal with magnitudes (arbitrary units, a.u.) for each frequency in the signal and peak power frequency of 43.8 kHz. C) Atmospheric losses coefficients for constant temperature at varying humidity (left, red axes); and for constant humidity at varying temperatures (right, black axes). D) Example acoustic tomography of a leaf with target strengths (dB SPL). C-D were used in the power attenuation of the frequencies in the signal. E) The echo was inversed (IFFT) to obtain the final echo signal.
(red signal) and with time of flight (TOF) added to the time signal. F) FFT of the emitted signal and echo signal with a peak frequency that had now been Doppler shifted and attenuated (note: tomography effect is not depicted in this echo).

**Short Time Fourier Transform, STFT**

The echo train was then analysed to obtain Doppler shift over time (time-frequency signal processing) via two methods. The first, was to use the short time Fourier transform (STFT) to obtain the phase and sinusoidal frequency content of local sections in the signal. Essentially, a Fourier transform was made on the echo train signal that had been divided into shorter (time) segments of equal lengths. The results of which were then plotted as a changing spectrum over time, known as a spectrogram. This was done using the ‘spectrogram’ function in MATLAB with a hamming window (or segment length) of 256 samples, an overlap of 250, $2^{13}$ number of DFT points, and the signal sampling frequency of 44100 Hz. The combination of parameters for the STFT gave a frequency resolution of ~54 Hz and time resolution of 0.013 ms. These resolutions were kept consistent throughout the simulations and used for the second method as well to make fair comparisons in the results. An example of the STFT results from a single echo train is shown in Figure 4.7.

![Figure 4.7 STFT processing of echo train example. A) Example environment of three objects, with 0.5m separation, of emitted FM signal with no heading component and the sensor moving at 5 ms$^{-1}$. B) Spectrogram and time-domain representation of the signal and echo train of the environment. The three objects can be clearly seen as separated signals in the spectrogram. C) STFT Freq. Resolution = 53.8 Hz STFT Time Resolution = 0.013 ms](image-url)
FFT of the signal and echo train with the peak power frequency at 44.4 kHz. No other peaks can be distinguished in the FFT signal. D) STFT of the echo train with distinct peaks.

**Wideband Ambiguity Function, WAF**

The second method was, in essence, a cross correlation method. The method expands on the concept of an ambiguity function, which is a 2D representation of phase and frequency (Doppler) of the correlation between an echo signal and the signal match filter [93, 94]. As the frequency band of the signals used in the simulation were wideband (20 kHz to 100 kHz), the signal analysis then uses the wideband ambiguity function (WAF).

To obtain the WAF, a match filter was first created by artificially Doppler shifting the original emitted signal over a range of Doppler ratios \( DR = 1: 0.001: 1.05; \) i.e., ranging from zero to five percent shift, where \( DR = 1 \) indicated zero shift. This range only covered an upwards shift (\( DR > 1 \)), which represented the source approaching the objects. The Doppler resolution for this method was thus 0.1% of the frequencies in the signal, where for around 50 kHz frequency, the smallest frequency change that can be detected was 50 Hz (comparable to the 54 Hz resolution of the STFT method). The signal shifted higher in frequency (upwards shift, since the DR range were >1), was artificially compressed in time using the same method of linearly interpolating the signal in the echo train generation. The match filter signals can be denoted as

\[
MF_n = ys(t^*DR_n) \quad Eqn. 4.8
\]

where \( n \) is the number of artificially shifted signals in the match filter, which for the defined range, were 51 signals. The echo train, \( E \), was then cross correlated with the signals in the match filter. Since both signals were continuous functions, the cross-correlation can be defined as [95, 96]

\[
(MF_n \ast E)(\tau) \triangleq \int_{t_0}^{t_0+T} MF_n(t)E(t+\tau) \, dt \quad Eqn. 4.9
\]

where \( MF_n(t) \) denotes the complex conjugate of \( MF_n \), and since both signals were continuous periodic functions with period \( T \), the integration is over any interval \([t_0, t_0 + T]\) of length \( T \). To simplify, the cross-correlation gave estimates of the correlation lag (time shift, \( \tau \)) and correlation coefficient (\( \alpha \)) between the two signals:

\[
(\alpha, \text{lag}) = MF_n \ast E \quad Eqn. 4.10
\]

From the values of correlation lag and coefficients (calculated using the ‘corr’ function in MATLAB), the maximum coefficient, obtained from the signal envelope created by the Hilbert function of the
correlation coefficients vs. lag plot, were extracted for every match filter used in the correlation. These values were then stored in a coefficient matrix, $WAF_{CORR}$

$$\begin{bmatrix}
\alpha(t, \text{max})_1 & \cdots & \alpha(t_{\text{end}}, \text{max})_1 \\
\vdots & \ddots & \vdots \\
\alpha(t, \text{max})_n & \cdots & \alpha(t_{\text{end}}, \text{max})_n
\end{bmatrix}$$

Eqn. 4.11

where $\alpha(t, \text{max})_n$ is the maximum correlation coefficient for the correlated signals at the nth match filter and time t of the signal. This matrix was then presented as an image with scaled colours, where the maximum value corresponds to the expected Doppler shift value. For the echo train, the maximum values can then be seen as time-separated maximum-coloured pixels in the image (Figure 4.8, C).
Figure 4.8 WAF processing of the echo train from the same example analysis in Figure 4.7. A) Match filter examples made up of artificially Doppler shifted versions of the emitted signal from 0 - 5% shift [a.u. = arbitrary units]. A was then cross-correlated with (B) which is the echo train, giving the correlation coefficients WAF\text{CORR} in (C).
4.3.4 Doppler Extraction

Peak Finding

From the STFT and WAF\textsubscript{CORR} results of the echo train, the Doppler shifts in time can be extracted, firstly, via peak finding. The spectrogram (STFT) calculates the power spectral density of the frequency spectrum. This can be used to obtain the frequencies at maximum power for various times in the STFT. Theoretically, the maximum power frequency of the emitted signal will correspond with the maximum power frequency of the echoes returned from the objects, that had been attenuated and shifted in frequency value during transmission. Therefore, the Doppler shift values could then be calculated as the ratio of the maximum frequencies in the echo train to the maximum frequency of the emitted signal.

To obtain the peak frequencies in the power spectrum, the ‘\texttt{findpeaks}’ function was used, which calculates the local maxima of an input signal. The local peak in the signal is either larger than the two neighbouring data samples or is equal to infinity (non-infinity data endpoints are excluded). If the peak is flat, only the lowest index point is returned by the function. The function was used in conjunction with the ‘\texttt{minpeakdistance}’ threshold, which is the minimum distance between a peak and its neighbours. This was set according to the separation distance (or time separation) of the objects in the environment, and to reduce the chances of obtaining false peaks.

In the STFT results, the peaks had to be time-corrected. The maximum power frequency of the signal was rarely in the beginning of the signal, therefore the time to the maximum power frequency was also extracted to correct for this offset in the final comparison of Doppler shifts vs. time (‘time corrected’). This was simply a subtraction of the TOF of the echo train with the time to the maximum power frequency. For the WAF\textsubscript{CORR} image result, the peaks were also located using the ‘\texttt{findpeaks}’ function with the same peak distance threshold. The peaks were located at every time of the WAF\textsubscript{CORR} image, and correspond to a Doppler ratio value, thus no extra steps to calculate Doppler ratio or to correct for time-offsets were necessary. An example of the results for the extracted peaks is shown in Figure 4.9.

![Figure 4.9](image-url) First three peaks from the peak finding method on the STFT (Figure 4.7, D) and WAF\textsubscript{CORR} (Figure 4.8, C) results. STFT peaks were ‘time-corrected’ remove misalignment offsets.
**Template Matching via Image Masking**

The second method of extracting Doppler Shift essentially used a template matching algorithm. Since there was a clear definition of the Doppler evolution in time in the echo train for a line of objects (wall) at a distance and angle to the sensor, these can be used to create a library of templates for the different combinations of lateral displacements ($x$) and heading angles ($\varphi$) of the sensor to the objects.

The templates (Figure 4.10) were saved as a matrix of expected Doppler shift of the objects over time, for a defined lateral ($x$) displacements between 1 m and 10 m (1 m resolution) and heading angles ($\varphi$) between 0° and 45°, to a wall with object separation density of 0.1 m (like the ‘dense’ environment analysis in Figure 4.3, for objects only within the beamwidth of the signal, beam divergence = ±90°). These were then used to create a template ‘image’ which would be used to mask over the WAF$_{CORR}$ or the STFT echo train Doppler image. The template image was a binary image of unity values at the expected Doppler ratios and zero everywhere else in the image (Figure 4.11).

![Heading and Lateral Distance Templates](image1.png)

![Speed Templates](image2.png)

**Figure 4.10** Heading, Lateral Distance and Speed Templates. The heading and lateral distance templates were calculated for a constant sensor speed of 5 m·s$^{-1}$ at 5° angle increments (from 0° to 45°) and 1 m increments (from 1 to 10 m). The speed templates were calculated for a sensor with specific heading at 0° and at 2 m lateral distance to the ‘wall’, at 1 m·s$^{-1}$ increments (from 2 to 10 m·s$^{-1}$)
Figure 4.11 Template image creation. The dense (or resampled to 0.1 m distance between objects) environment (left) for a specific lateral (in x) displacements and heading angle (zero in this example), from which the expected Doppler shift (middle) were calculated. The final binary image saved as the template image (right) contained unity values at the expected Doppler shift, and zero elsewhere.

As the $\text{WAF}_{\text{CORR}}$ result was already an image that describes the Doppler shift content in the echo train over time, only the STFT results needed to be converted into a similar image. This is done by simply converting the STFT results into a Doppler ratio matrix over time. The frequency values of the STFT results of the echo train were divided by the emitted signal’s maximum power frequency, that converted the frequencies to a Doppler ratio that was then comparable to the $\text{WAF}_{\text{CORR}}$ echo train image. The plot of Doppler ratio over time of the STFT echo train was then the final image. The resulting image can then be resized to match the $\text{WAF}_{\text{CORR}}$ image in which both were termed as the echo train Doppler images (Figure 4.12).

This method of image masking hides some portions of the echo train Doppler images, to reveal only the portions where the Doppler shifts were expected. To create the image template, the templates of Doppler shift over time can be repopulated and resampled (for higher image resolution) in a larger matrix that is the same size as the echo train Doppler image, and given unity pixel values where the Doppler shift is expected and zero-pixel value elsewhere in the image. When this template image is multiplied with the echo train Doppler image, the result is the masked image with pixel values at the expected areas of Doppler shift, which could then be summated (weighted) and compared with another masked image from a different image template. The masked image with the highest weight then theoretically gives the lateral displacement and heading angle.
This method of template matching can also be used to obtain speed changes of a signal. Since the heading angle and lateral displacement templates were specific to a velocity (i.e., 5 m/s⁻¹), these templates could be repeated for multiple velocities. This, however, was impractical as the size of the templates would then be too large for a reasonable processing time. In the simplest test of velocity changes, velocity templates can be created for specific heading angles and lateral displacements and only tested with varying range of velocities. Therefore, a speed template was also created for the ranges of 2 m/s⁻¹ to 10 m/s⁻¹ with a template resolution of 0.1 m/s⁻¹ for the dense environment without varying the sensor heading component (i.e. 0º heading for all speeds, Figure 4.10). This was used to test speeds between 2 m/s⁻¹ to 10 m/s⁻¹ at 1 m/s⁻¹ increments.

**Template Matching Mismatch**

To determine the sensitivity of the template resolution (in both lateral displacement and angles), tests of slight position or angle mismatch were made for the environment with perfect reflectors. The mismatch was set to 25% offset of the resolution for each variable tested, and the angle and distance mismatch were tested separately. First, the lateral displacements of the sensor tested were +0.25 m (25% of the 1 m resolution) from the lateral displacement templates of 1 m, 2 m…10 m (i.e., at 1.25 m, 2.25 m, …10.25 m), whilst keeping the heading angles the same as the angles of the templates (0º, 5º… 45º). The second test was to mismatch the angle templates by +1.25 ° (25% of the 5 ° resolution), whilst keeping the lateral displacements at the same positions of the templates (i.e., testing heading angles at 0.25º, 5.25º, … 45.25º, for 1.0 m, 2.0 m, … 10 m).

**Figure 4.12** Template image masking (or multiplication) with the STFT and WBA images. The STFT image is divided (in frequency axis) by the emitted signal frequency peak to obtain a Doppler ratio as the y-axis. This was then resized to the size of the template image, prior to multiplication.
4.3.5 Noise, Reflector Properties and Echo Dispersion of Objects

For part C, to investigate the effects of object properties, the objects were given target strength values depending on their angle to the source. The target strength of an object is a measure of how much of the signal energy (or intensity) is reflected to the source, as the object scatters or absorbs the signal according to its properties. This energy is measured along different incidence angles to the object, that gives a directionality component to the amount of reflected sound energy. In this experiment, an acoustic tomography of a plastic ivy (Figure 4.6, D) was used, where the reflected intensity of a broadband signal was measured along a range of incidence angles (-80° to 80°) to the object, and the target strengths (dB SPL) were calculated for each frequency in the signal.

As real objects often have uneven surfaces, dispersing the returned signal to the objects in the analysis creates a more realistic object surface. A final environment was then created to include this effect, by adding a random orientation of ±45° to the angles of the returned object echoes whilst keeping the relative displacement to the objects constant. This test was repeated for 10 times, from which the mean and standard deviation values were calculated.

Finally, noise was added to the echo train signal. Pink noise was used as it is one of the most common signals in natural environments [74, 97], usually coming from rustling leaves or rainfall. Pink noise consists of all audible frequencies, with higher power distributed at lower frequencies. The pink noise used in the analysis was generated using the pinknoise.m function in MATLAB, for a duration of 1s with the same sample rate (fs) as the emitted signal used. This returned a noise of SNR = 3.84 dB (see Figure 4.13 for example), which more than represented the usual SNR of bat calls to rustling leaves of about 6.5dB (~130 : ~20 dB SPL) [90, 98].

![Pink Noise](Image)

**Figure 4.13** Pink noise (left) added to the echo train (right, top), with the resulting signal with noise (right, bottom) with SNR = 3.84 dB.
4.4 Results

4.4.1 Part A: Signal Processing of Real Bat Signals

WAF<sub>CORR</sub> images

In the WAF<sub>CORR</sub> results, the image of maximum correlation coefficients between the echo train signal and the match filter showed the temporal distortion of the echo train signal in frequency (represented as Doppler ratio) of the echo signal. The maximum power of the correlation coefficients (yellow color scale, or normalized power of 1, in the WAF<sub>CORR</sub> image) should correspond to the expected Doppler ratio of the objects in the signal, Figure 4.14).

In the WAF<sub>CORR</sub> images, the Doppler ratio for each of the objects in the environment were clearly separated in time for the short signals with FM components (mouse-eared and pipistrelle bat signals), even in the dense environments. A larger range of frequencies in the FM signal (between ~10 kHz - 30 kHz, refer to Figure 3.6) compared to a narrower range in the FMCF signal (~80 kHz - 40 kHz) resulted in high correlation values at a wider range of Doppler ratios. This was simply because a larger range of frequencies in a more broadband signal would have high correlation values with more of the artificially Doppler shifted emitted signals in the match filter. This also resulted in a wider distribution of power of the correlation values for the FM broadband signal across the Doppler ratio axis, and a narrower distribution across the time axis in the image compared to the FMCF. This was why for the long CF signal, the power of the correlation coefficients was very narrowly distributed in the Doppler ratio axis and widely distributed in the temporal axis. This analysis is illustrated in the supporting Figure 4.15, with the image of the FMCF signal in the dense and angled environment taken as an example.

For the sparse environment, the temporal separation of the objects in the echo train can be clearly seen for the FM and FMCF signals, compared to the CF signal. For both FM and FMCF signals, the maximum correlation values were at the expected Doppler ratios, whereas for the CF signal, only the first doppler ratio (of 1) was close to the maximum correlation value in the image. The effects of overlapping object echoes combined with the temporally-wide distribution of power of the CF signal, already affected the resulting correlation values of the WAF<sub>CORR</sub> image even in the sparse environment, and can thus be expected to suffer from the same effect in the other denser environments.

In the first dense environment (at 0° heading to the Yg axis), only the FM signal maximum correlation values consistently showed agreement with the expected Doppler ratio in the WAF<sub>CORR</sub> image throughout the entire echo train, with the FMCF signal only showing agreement to the expected values
for some of the objects in the echo train (Figure 4.14). This can be attributed to the wider frequency range of the FM sensor and its the narrower power distribution of correlation coefficients in time, resulting in lesser temporal mixing of the overall correlation values with the other objects in the echo train.

Figure 4.14 Wideband ambiguity function correlation coefficients WAF\textsubscript{CORR} results for the echo trains of all bat signals and environments, presented as a colour-scaled image (Doppler ratio vs time) with the colourmap representing the coefficient.
values. The coefficient values were normalised to represent ‘normalised power’ of the correlation. The theoretical Doppler ratios of the objects in the environment were plotted on the image and labelled as ‘expected Doppler’ (red circles).

Both the FM and FMCF signals had maximum correlation values that were close to the expected Doppler ratio for objects further away from the sensor. However, for the closest object (at 11.66 ms, 2 m away from the sensor), the FM signal maximum correlation coefficient values were closer to the expected Doppler ratio compared to the FMCF signal. The objects closest to the sensor were spatially (and thus temporally) closer to the consequent objects, causing the echoes of these objects to coalesce more than for objects further away from the sensor. This blending of echoes from the objects, along with the narrower frequency band of the FMCF signal and the subsequent wider distribution of correlation power across the time axis, potentially led to inaccuracies of the correlation values.

However, when there is a heading component in the sensor (dense and angled 45° from the Yg axis), this effect was not seen in the FMCF WAF\textsubscript{CORR} image, and the maximum correlation values appeared to match the expected Doppler ratio (Figure 4.14, Dense + Angled) better than the FM signal. In this angled case, objects that were at the same radial distance to the sensor returned different Doppler shifts (due to different relative angles) at the same time. This meant that the WAF\textsubscript{CORR} image would return two peaks at a single time, and for the wide distribution of correlation peaks with the FM signal, the separation of these could not be extracted, giving false-peaks along the time axis. Since the FMCF signal returned more separated correlation peaks in the Doppler axis, the different Doppler ratios from the two objects can be easily separated and extracted.

![Figure 4.15 Example WAF\textsubscript{CORR} image result used to illustrate the spread of correlation coefficients due to the signal frequency sweep. A more wideband (FM) signal will spread the correlation coefficients in the Doppler ratio axis (red arrows), and compress the correlation coefficients in the time axis (black arrows), since more of the signal has correlated with the match filter signals. A more narrowband signal will spread the correlation coefficients in the time axis (black arrows) and compress the spread of correlation coefficient in the Doppler axis (red) since less of the signal only correlated the match filter signals.](image-url)
STFT images

Figure 4.16 Short time Fourier transform STFT result of the echo trains for all signals and environments. The images present frequency vs. time data as a colour-scaled image, where the colourmap represents the Power/Frequency (dB/Hz) of the data at
a specific frequency and time of the signal. The theoretical Doppler shifts were plotted on the image, and the time for these were time-corrected to where the peak power frequency of the signals was.

For the STFT images (Figure 4.16), the sparse environment test showed the temporally separated objects in the echo train for both the FM and FMCF signal. The CF signal however, due to its long duration, returned a long, connected echo train. However, in both dense environments, the echo train for all signal types were closely overlapped. Compared to the WAF\textsubscript{CORR} image, the object echoes in the dense environment were not temporally separated.

**Peak Finding**

![Peak Finding Diagram](image)

Figure 4.17 Peaks extracted from the WAF\textsubscript{CORR} and STFT images from Figure 4.14 and Figure 4.16, for the sparse and dense environments with no heading component to the sensor. Peaks from the STFT were time-corrected, i.e. the time-to-object considered the time at which the maximum frequencies (of both signal and echo) were located at.

The properties of these different signals and the subsequent WAF\textsubscript{CORR} and STFT images affected the resulting estimation of Doppler ratios in the two different frequency extraction methods. The peak finding algorithm finds the peaks firstly along the time axis of the image, and then across the Doppler ratio axis. Thus, intuitively, to return accurate peaks, a clear separation between the high correlation values in the images both in the time and Doppler axis would be essential. For FM and FMCF signals that were well separated in time in the both the WAF\textsubscript{CORR} and STFT images, there were lower errors in the temporal positions of the peaks (Figure 4.17) whilst the long CF signal that overlapped with the
echoes did not return distinguishable temporal peaks in this instance. This was the case for all the tested environments.

For the sparse environment, the peaks were correct both in Doppler ratio value and temporal position for the FM and FMCF signals extracted from the WAF\textsubscript{CORR} images. In the STFT images, the peaks aligned with the expected ratios temporally (with a slight offset, likely due to small temporal offset in the frequency peaks of the returned signal), there was a clear overestimation of Doppler ratios for the FMCF signal, and underestimated ratios for the FM signal. One possible contribution to this is the binning effect of STFT, where some of the power of the frequencies in the signal has been distributed into another frequency bin of the STFT. For example, in the FM signal, the peak power frequency was calculated at 43800 Hz. Since the resolution of the STFTs were around 50Hz, a doppler shift of 1% (or 1.01 ratio) would return a peak of 44238 Hz, which is a 438 Hz increase. As the binning resolution of frequencies were around 54 Hz, the maximum frequency will be between bins 819 and 820, which will then instead be distributed between these two bins. Therefore, for the small range of Doppler shift in these environments, (between 1% and 3%) the binning disadvantage of the STFT affects the peak extraction accuracy and thus Doppler ratio of the objects. For the FM signal, power is more evenly distributed across a range of frequencies (see Figure 3.9, Section 3.4), whereas for the FMCF signal, the maximum power is highly concentrated at the same frequency. The maximum frequencies were, 43.84 kHz for the FM signal, and 40.75 kHz for the FMCF. It was likely that because higher frequencies were absorbed more in air at further distances (see Figure 4.6, C), only the lower frequencies were in the reflected echo signal, potentially removing the higher, maximum expected frequency from the echo signal. This, combined with the evenly distributed power across frequencies in the FM signal, likely led to the underestimation of the Doppler ratios. The FMCF signal, however, returned overestimated Doppler ratios. It was possible that the lower maximum frequency of the emitted signal was not affected by atmospheric absorption as much as the FM signal.

For the sparsely populated environment and the WAF\textsubscript{CORR} images, both the FM and FMCF signals returned accurate peaks for all objects whilst the long CF signal only returned accurate but faint peaks that were present later in the echo train, and the highest peaks at the Doppler ratio of 1 (which was the Doppler ratio of the closest object, next to the sensor). The CF signal did not return any accurate correlation peaks at the intermediate ranges of the Doppler shift. This was likely because the long CF signal resulted in the largely-overlapped echoes from the objects, resulting in only accurate peaks at the beginning and end of the echo train. Since the Doppler ratio of the further objects in the echo train converges to a single value (~1.03, see Figure 4.2, A), it was likely that the CF signal were able to return accurate Doppler shift peaks for these objects, as the echoes returned similar Doppler ratios. This was the case for all environments tested with the long CF signals, as the signal tended to extract peaks at single Doppler values, either close to Doppler ratio of 1 at the beginning of the signal, or the maximum expected Doppler ratio at the end of the echo train.
In the dense environments, the WAF\textsubscript{CORR} images returned accurate peaks only for the FM signal (Figure 4.17, left and bottom image). However, in the angled case (heading angle 45°) for the same FM signal, peaks were also found around the Doppler ratio of 1, although the powers for these peaks were low (Figure 4.18). From the WAF\textsubscript{CORR} images, the effect of the coalescing of echoes from multiple objects that were closely spaced were seen for the signals with a CF component. The FMCF signal, likely due to its short duration and a narrow FM component, could be seen with correlation values that were close to the Doppler ratio and were well separated in time. Which resulted in accurate temporal separation of the peaks, even if the Doppler ratios were inaccurate. For the STFT images, the densely populated environments conjoined echo train for all signals did not lead to accurate finding of peaks, and in turn, Doppler ratios.

In all cases, the returned peaks were noisy, as they were dependent on the threshold value for the peaks. Since a single threshold value was used for each environment, false peaks can be obtained and the amount of peaks differ between the signals used. For the dense environment with a 45° sensor heading component, this effect can be clearly seen for the mouse-eared and pipistrelle bat signals, where a cluster of peaks were found at the Doppler ratio of 1.
Template Matching Via Image Masking

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*Figure 4.19* Results from template matching and image masking of the WAF$_{CORR}$ and STFT images to obtain accurate angles (A) and lateral displacements (D). Accurate measurements are indicated as green boxes, and inaccurate measurements in red. The errors are shown as discrete absolute errors of multiples of ± 5deg or ±1 m from the expected values.

Since the template matching technique was confined to the design (i.e. resolution and range) of the templates, the errors were discrete angle (±5º) or distance errors (±1 m). In the three environments studied, both the FM and FMCF signals had comparable performances using this technique with both the STFT and WAF$_{CORR}$ images. The FM signal had a lower angle error compared to the FMCF signal in the WAF$_{CORR}$ images for the dense environment with the sensor at 45º heading to the wall. This was expected, WAF$_{CORR}$ image for the FM signal showed a clearer temporal separation than the FMCF with this heading angle.

However, the FMCF (or pipistrelle) signal performed slightly better by successfully obtaining the right angle and distance using the STFT image in the dense, 0º heading environment. This was surprising, as the signal had a slightly lower angle error than the FM signal in the sparse environment. However, since the STFT Doppler ratios were calculated from the frequency peak of the signal and the frequency peaks of the echo train, the ratios vary depending on the accuracy of the obtained peaks. A slight overestimation or underestimation of the Doppler ratio can be expected (as shown in Figure 4.17 for the sparse environment peaks), likely resulting from errors in the resolution of the STFT (binning errors). Due to the FMCF having more power distributed evenly at a single frequency (50 kHz tail end), there was likely a better estimation of the peak frequencies compared to the FM signal with power distributed over a range of frequencies.

Reviewing the WAF$_{CORR}$ images (*Figure 4.14*) for both FM and FMCF signals in all environments, it was expected for these signals to perform well using the template matching technique, as the maximum correlation values followed the expected Doppler ratios considerably better than the CF signal. Separation in time between the objects can be clearly seen, and the maximum correlation values for each object follows the expected Doppler ratio distribution over time especially well with the FM signal.
The CF signal only managed to obtain accurate angles for the sparse and dense environment (both at 0°) using the WAF\textsubscript{CORR} image with this technique. This was expected as the WAF\textsubscript{CORR} image for this signal did not return a clear image with separated values of Doppler ratios (see WAF\textsubscript{CORR} images, Figure 4.14). However, this signal managed to obtain accurate lateral distances in the single sparse environment instance. This was most likely due to the lesser overlap of the echo signals in the sparse environment.

It is important to note that the environment here (Figure 4.2, C) is different from the next section (Part B, see Figure 4.3 for the environment for Part B), where the sensor starts in the middle of the corridor. This section uses the same template library, but the reflected objects behind the sensor (\(Y_g<0\)) were not present in this environment. This meant that the first few Doppler ratios in the templates, where the heading angle significantly defines the ‘curve’, was not present in this environment and was likely why the template matching algorithm did not return accurate angles in this case.

As both the FM and FMCF signals performed similarly using the WAF\textsubscript{CORR} image, another test was required to determine whether this was an isolated instance for the case of a single combination of heading angle and lateral displacement, or they both indeed perform similarly for different environments. Therefore, the extended test (used later in part B) of multiple combinations of lateral displacements and heading angles was performed on these signals. Note that in this case, the sensor started from the middle of the ‘wall’, compared to the previous analysis. The test showed that the FMCF signals did not accurately detect the angles for more cases than the FM signal, and in some cases with higher errors of absolute angle (up to 15°, Figure 4.20). The well-separated correlation values in the WAF\textsubscript{CORR} image of the FM signal may have contributed to its overall performance. The test, however, is a single instance for a perfect environment, not subjected to any noise, object properties or some form of randomization to make an objective decision as to which of the two bat signals performed better in extracting heading angles and lateral distances.
Figure 4.20 Multiple heading angle and lateral displacement tests for two real bat signals (FM and FMCF) using the template matching and image masking method with the WAF\textsubscript{CORR} images.
4.4.2 Part B: Artificial Signals and Realistic Environments

Heading Angle and Lateral Displacement Template Matching

Figure 4.21 Results for all artificial signals tested at multiple heading angle and lateral distance combinations. Top three rows were results from different frequency sweeps (FM) and durations. Bottom row: results from the artificial FMCF (5.5 ms) signal and the FM-CF-FM signal (65 ms)
In this section, the method of template matching for the WAF\textsubscript{CORR} images to extract accurate heading angles and lateral displacements were tested with artificial signals. The objective of which, was to determine what properties of the different signals contributed to its success of extracting heading angles and distances with the proposed method.

As expected, a shorter signal with a frequency sweep (similar to the mouse-eared bat, FM signal) returned more accurate angles (Figure 4.21, top left) compared to a longer, constant frequency signal (like the horseshoe bat, CF signal; Figure 4.21, bottom right of the FM signals, and the FM-CF-FM signal) due to the overlapped object echoes, similar to the test between the real bat signals in part A. For the same signal duration, a decrease in frequency sweep returned more accurate angles. As mentioned in part A, a broader frequency sweep of a signal resulted in high correlation values across a wider range of Doppler ratios in the WAF\textsubscript{CORR} image. In the template matching method, the template images vary in small increments of Doppler ratio across different heading angles. A broad frequency sweep with the wider power distribution of correlation across the Doppler axis is not favourable in this case, as high correlation values may be present in the masked image of multiple templates. This was why the narrower range (100-40 kHz) of frequencies for the short 5 ms signals returned more accurate angles. For the 5 ms CF signal, the angles returned were of comparable accuracy with the other signals in the 5 ms duration range, which implied that a CF signal would perform well if the duration were shorter than the object separation, avoiding most of the echo overlap between the objects. This was also seen for the FMCF signal, where the signal performed similarly with the other signals in its duration range (5 ms signals).

Interestingly, the signal did not necessarily perform worse when the duration is increased for the same frequency sweep. For both the 100-20 kHz and 100-40 kHz sweep, the 25 ms and 45 ms durations obtained more accurate angles than the shorter 5 ms signals, with the latter performing slightly better. This was likely due to the decreased frequency sweep rate as the signal duration increased, as frequencies in the signal was spread over a longer time. This resulted in the high correlation values across a wider portion of the WAF\textsubscript{CORR} time axis. This effect essentially created a separation in the Doppler axis of the WAF\textsubscript{CORR} image, which, like the increase in frequency sweep effect, prevented the detection of high correlation values in other image templates.

For long CF signals, as expected, the overlapping of object echoes most likely contributed to their poor performance in obtaining accurate angles. This was especially true for higher angles, where two object echoes at the same radial distance from the sensor produced different Doppler shifts (due to different relative angles) but arrived the sensor at the same time. However, for the horseshoe inspired FM-CF-FM signal, the presence of the short FM tails seemed to improve the performance at higher heading angles, although not enough to overcome the effects of overlapping echoes due to its long duration (65
ms). In these tests, the signal-echo overlap has not been considered yet, and thus some accurate angles were still obtained at closer distances.

When the method accounted for the overlapping of emitted signal and echo train, the longer signals as expected, did not manage to obtain accurate angle for shorter distances. Most of the early part of the echo train had been filtered (or silenced) out of the received signal, returning only the latter part of the echo train to process, leading to the inaccuracy of the detected angles. This can be seen clearly for the 1-2m lateral distances for the 25ms signal and for the 45ms signal, at distances between 1-3m (Figure 4.22).

![Diagram showing heading errors for longer signals (25 and 45 ms) that had the signal-echo overlap removed. Previous analysis disregarded the overlap completely, whilst this analysis removed the signal-echo overlap in the echo train, returning only the latter half of the echo train.](image)

**Figure 4.22** Heading errors for longer signals (25 and 45 ms) that had the signal-echo overlap removed. Previous analysis disregarded the overlap completely, whilst this analysis removed the signal-echo overlap in the echo train, returning only the latter half of the echo train.

From this point onwards, only five signals were advanced to the subsequent analyses, which were the signals that returned the best performances (i.e. low angle errors). For the FM signals, these were the 100-40 kHz signals for all durations, even with the effects of removing the signal-echo overlap for the longer signals (25 ms and 45 ms). The other two were the short (5 ms) CF signal and the FMCF (5.5 ms) signal.

**Template Mismatch**

When the same tests were made for perfect reflectors (no dispersion or noise effects) at distances and angles that were not exactly at the template resolution, it was clear that the distance mismatch affected the results more severely than the angle mismatch (Figure 4.23). This was the case for the FM artificial
signals for every duration. However, the angle errors decreased as the signal duration increased for the same frequency sweep, a performance pattern seen in the previous analyses and likely due to the same reasons. Since this analysis removed any signal-echo overlap in the echo train, the longer FM signals returned inaccurate angles for the heading angle mismatch, as well as inaccurate distances for the distance mismatch at closer lateral distances (between 1-3 m).

For signals with the CF components (pure CF and FMCF signals), however, the template mismatch (for both distance and angle) did not affect the angle accuracy as severely as the FM signals. There were generally lower angle errors, with the highest errors (up to 30º for FMCF and up to 10º for CF) for larger angles and shorter lateral distances cases. Between the two (FMCF, CF) signals however, the purely CF signal was most robust to the template mismatches. This was not surprising, as the template matching in the perfectly aligned templates were already sensitive to the decrease in sweep rate, that had reduced the spread of maximum correlation coefficients across the Doppler axis of the $WAF_{CORR}$ templates.
Figure 4.23 Results for heading angle (+1.25 deg) and distance (+0.25 m) mismatch. Results for both ‘no mismatch’ and heading angle mismatch did not return any distance error and was thus omitted in the figure. Signal-echo overlap of the echo train was removed in the long FM signals (25 ms and 45 ms) of this analysis (as seen in the angle and distance errors at closer distances, between 1-3m).
Echo Dispersion and Noise Effects

For some of the signals, it was difficult to obtain a clear pattern of the performance in obtaining the angles for the different test cases, especially when the distance and angle tests were aligned with the templates. Errors in the perfect reflector environments showed that the template matching was dependent on frequency sweep, however the differences between short duration signals were not clearly observed (Figure 4.21). Adding dispersion (through randomization of reflected object echo angles) and noise to the echo train signal gave a better indication on how these signals would perform in more realistic environments. The results (Figure 4.24) showed that adding dispersion barely affected the performance for signals with pure FM components (FM signals for 5 ms, 25 ms and 45 ms) compared to the environment with perfect reflectors, but decreased the performance of the FMCF and CF signals more than the other signals, especially when attempting to match higher angles. The pure CF signal however, decreased in performance more than the FMCF signal from the perfect reflector case. This meant that the CF signal was not robust when the objects become more realistic. However, it is important to note that the dispersion of objects did not return angle errors in the CF and FMCF signals that were as high as the errors obtained by the FM signals in the template mismatch studies (Figure 4.23).

The effect of adding noise (pink) to the echo train can be seen on the farther lateral displacement tests (Figure 4.25). The angles obtained for these distances were inaccurate, as the further distances would return weaker echoes, which would be dominated by the higher power spectral content of the noise. This effect was likely intensified as most of the high frequencies in the echo train was absorbed in air at further distances, leaving more of the lower frequency content of the echo train returned that would have intermingled with the noise. The FMCF signal was more robust to noise, returning lower angle errors for lesser heading and lateral distance tests compared to the CF signal. This suggested that a more FM signal was more tolerant to noise, which is seen in some bats increasing their bandwidth to distinguish prey from background clutter [99].
Figure 4.24 Dispersion of sound from randomising the reflected angles from objects. The test was repeated 10 times with different randomisation each time, to produce the averaged results of mean and standard deviation of the errors. The number of repetitions was determined to be sufficient as the standard deviation of the errors were low.
### 4.4.3 Part C: Speed Template Matching Analysis

For the test of finding accurate speeds using template matching (dense, perfect reflector environment with 0° heading), the signals performed similarly to the tests of finding heading angles and lateral displacements. For all signals, the templates managed to obtain accurate speeds within a maximum absolute error of 0.7 ms\(^{-1}\) (Figure 4.26). For FM signals, the increase in duration improved the template matching performance, especially when tested at higher speeds. This was likely due to the increase in separation of maximum correlation values along the Doppler axis with decrease in frequency sweep rate in the WAF\(_{CORR}\) images, as seen in the heading angle studies. Comparing the short signals, the performance improved as the influence of CF components increased, that is, the pure CF signal performed the best, followed by the FMCF and FM signals, respectively. Again, the separation of Doppler ratios due to the reduction in frequency sweep proved to be imperative in obtaining accurate template matches.

For speed templates, the most sensitive area to match accurate speeds occur at the later Doppler ratios, contrary to the heading angle templates sensitivity to the earlier portion of Doppler ratios, where the

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**Figure 4.25** Noise effect (N) on some of the signals. The FM signals (100-40 kHz) were only affected by noise at further distances, whilst the CF signal was greatly affected by the presence of pink noise. The FMCF signal however, returned low angle errors compared to other signals.
different angles were clearly defined. This is because the latter portion of the Doppler ratios correspond to the maximum Doppler ratios, and thus the actual relative speed. Since the speed templates were confined to a single heading angle and lateral distance, the variations in the templates only depend on speed changes and vice versa for the heading angle (and lateral distance) test, where the speed of the sensor was constant at 5 m/s⁻¹.

When including effects of template mismatch (Figure 4.27), the signals again performed similarly to the heading and lateral distance template mismatch tests. The signals returned the highest speed errors when there was a mismatch in lateral distance, compared to other types of mismatches (speed and angle). The signals with CF components (FMCF and CF) were robust in the distance mismatches whereas the purely FM (for all durations) signals’ performance drastically reduced, returning high speed errors. For the FM signals, the 45 ms signal returned the lowest speed errors (around 2-3 ms⁻¹), followed by the 25 ms signal (errors ~ 4-5 ms⁻¹) and the short 5 ms signal (errors up to 8 ms⁻¹ for some speeds). This was a similar pattern observed in the previous analyses of extracting heading angles, where increasing frequency sweep (or decreasing sweep rate in this case, i.e. increasing signal duration for the same sweep range) of the signal improved the performance.

The effect of noise and dispersion of echoes from the objects reduced the performance of all the signals, except for the FMCF signal. This observation was similar to that of the heading angle and lateral distance test, in that although both the CF and FMCF signals were robust to template mismatches, the FM component in the FMCF signal made it more robust to noise and echo dispersion. Therefore in a
more realistic environment, the FMCF signal was the most robust signal to use with this template matching algorithm for heading angles, lateral distances and speeds.
Figure 4.27 Speed template results of the artificial signals for the same analyses in the heading angle and lateral distances, which were to mismatch templates by 25% (speeds at +0.025 ms\(^{-1}\), angles at +1.25\(^\circ\), and distances at +0.25 m) and to add noise (pink noise, N) and echo dispersion (through randomisation of reflected angles, R) effects.
4.5 Discussion

From the analyses, it was clear that processing echoes from a complex acoustic environment (with multiple objects, object properties and noise) required an equally complex signal processing method. The coalescing of echoes makes it difficult for the standard Fourier Transform methods to obtain accurate Doppler shifts, even when improving the resolution of the transform. This was simply because the addition of echoes affected the power addition and subtraction of frequencies in the signal unpredictably (due to the stochastic nature of the echo coalescing), and therefore required a different approach of obtaining frequency changes from the resulting echo train. The cross-correlation between the signal and the match filter in the WAF method essentially provided a compressed representation of the Doppler shifts for every object echo in the echo train, which, even for objects close together, were still temporally separated in the resulting WAF image. This made it a more robust analysis compared to the FFT when object echoes coalesce. This was why the ambiguity function is commonly used to obtain Doppler shifts, since the Doppler shift estimates are reliable, accurate and faster to process than some FFT methods [88, 100, 101].

The template matching proved to return more accurate estimations of Doppler compared to peak finding. A library of templates can be applied for a range of signals without fine-tuning the templates, whereas the peak finding threshold values ('minpeakdistance' and 'minpeakprominence') required knowledge of the environment (object spacing) and need to be tuned for different signals. The tuning of the peak thresholding also determined the amount of noise in the Doppler ratios obtained, in that reducing the threshold would return false peaks, whereas the template matching only returned values within the template Doppler ratios.

The template matching technique combined with the WAF images was able to extract both lateral distance and heading angle information from a single echo train. In perfect conditions, the error returned from this method was low (up to 15deg error for real bat signals). In the presence of noise, object properties, and template mismatches however, the analyses showed that the shorter the signal and the lower the frequency sweep, the more robust the signal was to these effects. These were determined to be the short signals (5 – 5.5 ms) with CF components (i.e., pure CF and FMCF signal). It was observed, however, that the FMCF signal was more robust and did not degrade in performance as much as the short CF signal when introduced to noise and echo dispersion. This suggested that an FM component in the signal used was still necessary to improve the sonar acuity in extracting Doppler ratios.

The robustness of the short signals with CF components in obtaining Doppler shift in the echoes may add to why some bats emit FMCF signals for the same foraging habitat as purely FM bats [102], as well as why some bats have even evolved their FM calls to include this CF component in the signal [103]. The analysis also showed that pure FM signals were still Doppler tolerant, and in some cases in the analysis, even better at obtaining accurate Doppler ratios in the echo train.
4.6 Conclusion

The study showed that it is possible to obtain position, heading and speed information through self-motion cues in the Doppler shifts of object echoes within a single echo train. Using the proposed signal processing module, and for the range of artificial signals studied, the bat inspired FMCF (or pipistrelle) signal proved to be most robust in obtaining speed, lateral distances and heading angles in the specific environments and conditions tested. The environments tested in the analyses were still simplistic, in that only 2D environments were considered and only a subset of conditions were tested for robustness. Other signals may perform better in different environments, or if the signal processing method was changed or improved. For example, since the purely FM signals were very sensitive to the template mismatch in distance, perhaps increasing the resolution or redefining the templates may improve their performance in obtaining the angles.

Most optic and acoustic flow methods have used information from two subsequent responses to obtain the flow velocity. This method has potential for fast signal processing, due to the fast processing of cross-correlation and the analysis only used a small template library. However, further testing is necessary to determine whether the combined processing method and template library would be robust for real-world navigation. A large template library would be necessary to be robust in different navigation scenarios, although this can be handled with proper template definitions or even extending the methods to incorporate machine learning techniques that can benefit from the large template dataset.

The analysis proved that for any bat signal, the information of motion from Doppler shift is present, at the very least in the simple ‘hedgerow’ environment presented here, with varying accuracies. Although the use of Doppler shift for navigation in echolocating bats have yet to be observed extensively, the analysis presented a method of processing Doppler information in an echo train, that is useful not only in determining speed, but heading angles as well. Thus, the use of this information, as well as how bats can process them for navigation needs to be studied in future behavioural and neural processing experiments. Since the analysis showed that certain signal types were more robust in obtaining Doppler shift, the focus of these experiments should be on bats that emit these signals.
Chapter 5

Doppler-Acoustic Flow Navigation Simulation of Heading, Position and Speed Control

5.1 Chapter Abstract

This chapter investigated the possibility of using the Wideband Ambiguity Function (WAF) and image template matching signal processing method introduced in Chapter 4 to perform simple autonomous navigation tasks. The two most robust signals determined in the previous chapter for the proposed signal processing method were emitted by a moving sensor in a 2D environment with a ‘wall’ structure made of densely spaced objects. These signals were (a) a short 5ms constant frequency (CF) signal of 80 kHz, and (b) a short 5.5ms signal with a combined frequency modulated component (FM, 100-40 kHz) and constant frequency (40 kHz) component, mimicking a pipistrelle bat (FMCF) signal. The returned echoes of the signal from the environment were processed to estimate self-motion navigation information of the sensor (i.e., speed, lateral position, and heading angle) relative to the ‘wall’. Two tests were performed in this experiment. The first was a series of open loop tests. The sensor speed was estimated, first from the stationary reflectors (‘wall’), and then with a portion of the wall having a motion component which was designed to emulate the physical experiment environment of the FMCF bats in Chapter 2. Heading angles and lateral positions were also estimated in an open loop test of moving the sensor towards the wall at an angle with a fixed turning rate (5 deg/pulse), starting from different lateral positions to the wall. The errors between the measured data using the signal processing method and the expected data were reviewed for both the CF and FMCF signals. The FMCF signal was found to be more robust to noise and the dispersion of echoes from randomised object surfaces in these tests. In the second test, the FMCF signal was used to perform a closed-loop navigation of heading control. The sensor goal was to either turn away from the wall completely, or to adjust its heading angle to fly parallel (or at a specific small heading angle) to the wall. A proportional controller of different gains was tested for multiple starting distances and heading angles to investigate the performance of the controller in carrying out the task. The FMCF signal, processing method and navigation control used proved to be able to perform these tasks at any given proportional gain well within the margins of a safe distance to the wall (< 0.4 m). The results showed that a bat inspired FMCF signal could be used combined with the new method of single pulse-echo processing in the dense environment proposed as a successful self-motion estimator. This could shed light as to how FMCF signals may be used for bats in cluttered environments as well as how an autonomous Doppler-Acoustic flow system could be developed for robotic navigation.


5.2 Introduction

In flow-based navigation, where motion is perceived through the relative motion between the moving platform and its surroundings, the perceived motion is usually measured as the differences between one scene, and the next. Specific parameters of the scene, that is optically or acoustically described, are extracted for the algorithm to track and measure flow velocities from. In optical flow, the change in pixel brightness in the image is usually the parameter of interest. In acoustics, although multiple parameters are available in a sound signal, it was found that frequency changes (or Doppler shift) due to the relative motion between the signal source and the object the signal reflects off, is the only parameter that can reliably return estimates of flow velocity (Chapter 3).

Acoustic flow navigation experiments, have so far, attempted to extract flow from the different sound parameters such as amplitude, Time-of-Flight (TOF) and frequency of the sound signal, with varied results. All of these, however, either measured the flow from one scene to the next (or between two pulse-echoes) [49] or extracted flow from single objects, or simple cases where the objects were distinctly separated [67, 68]. These methods work well, as distance to objects can be consistently tracked, without the influence of echoes from other objects affecting the results. However, more complex environments (like the environments faced by bats) for acoustic flow navigation have not been thoroughly investigated, especially in the context of bat echolocation. Recent experiments have shown that self-motion estimation from Doppler can be determined [104], although none have demonstrated the practical uses of Doppler-Acoustic autonomous navigation in cluttered environments.

In Doppler navigation, robots equipped with Doppler-radar were shown to estimate its robot pose (position and heading) from the measured Doppler shifts due to static landmarks at known locations [50] generated from the robots’ own motion. Although proven to be able to self-localise, these techniques required the positional information of known, largely spaced landmarks. Similar to most acoustic flow (and optic flow) experiments, flow change is usually determined between at least two consecutive pulse-echoes.

Therefore, the following simulation experiment proposes an acoustic flow navigation study, in which Doppler ratios were extracted from a moving sensor’s (constant speed of 5ms⁻¹) single pulse-echo response of the emitted signal. The tracking of Doppler for acoustic flow is referred to as Doppler-Acoustic flow in this case. The two signal types used in the experiment were a 5ms CF signal, and a 5.5ms FMCF signal that mimicked a pipistrelle call. The signal processing module in this study consisted of a new cross-correlation method using the Wideband Ambiguity Function (WAF) complemented by an image template matching algorithm, that was introduced in Chapter 4. The signals used in this experiment were the two most robust signals used with the processing module to obtain speed, position and heading angles in the study. The navigation environment mimicked a ‘hedgerow’-like structure that the bats encountered in their environment in Chapter 2. The simulation environment
consisted of a lateral structure, with a dense population of objects (0.1m spaced) aligned in a straight line like a ‘wall’ of reflectors in two-dimensional (2D) space. The objects were also given target properties measured from ivy leaves and randomized (up to ±45°) in orientation to provide a dispersion effect for the reflected echoes. The effects of background noise (pink noise) were also considered in the experiments.

The objectives of the experiment, were to determine if, (a) the signals tested were able to extract speed, position and heading angle of the sensor, and if so, which performed better at these; and if (b) a closed loop navigation algorithm can be determined to successfully use the signals and processing module to turn away or keep parallel to the ‘wall’ of reflectors. The first objective (a) was investigated via a series of open loop navigation tests, comparing the root mean squared error (RMSE) of the obtained speeds or heading angles for the CF and FMCF signals. This result could also help in the understanding of how the bats in the Chapter 2 experiment perceived the speed changes in the manipulated environment. The signal determined to have lower RMSE or that was more robust to noise and object properties was then used in the closed loop experiments in (b). The results of which were used to infer the potential uses of the combined FMCF signal and processing module of Doppler-Acoustic flow, for both bat and autonomous navigation.
5.3 Methods and Materials

5.3.1 Simulation Environment

The entire simulation analysis was conducted within MATLAB v.2020. A similar 2D environment (Figure 4.3) and coordinate system (Figure 4.1) as in Chapter 4 (Section 4.3.1) was used, where a global coordinate space \((X_g, Y_g)\) encompassed the sensor \((x_{bg}, y_{bg})\) and objects \((x_{og}, y_{og})\) aligned in a line along the \(Y_g\) axis to mimic a ‘wall’. These objects were densely spaced between each other (0.1m) and were placed along the \(Y_g\) axis from \(y_{og} = 0\)m to 100m and at different lateral \(x_{og}\) positions depending on the individual tests. The sensor was given a heading angle component \(\varphi\), relative to the \(Y_g\) axis of the global coordinates. The sensor also had a local coordinate system \((X_b, Y_b)\) in which the relative positions between the objects and the sensor \((x_{ob}, y_{ob})\) were defined from. This study, as in Chapter 4, also assumed that the direction of the emitted signal is the same as the direction of motion of the sensor, and therefore the relative angles \((\theta_{ei})\) of the object to the sensor were calculated in the same way (Eqn. 4.2 to Eqn. 4.4).

The objects in this environment were not always assumed to be perfect reflectors, i.e. target strength and echo dispersion properties were present for each object in some tests. The objects’ target strength properties were taken from tomography measurements of ivy leaves (from Figure 4.6, D) and the dispersion effect was created by randomizing the reflected echo from the object up to ±45°. Pink noise (SNR = 3.84 dB) was also added to the echoes, similar to Section 4.3.5 in Chapter 4.

5.3.2 Signal Design and Processing

Two artificial bat-inspired signals were used in the analysis, which were the most robust signals in the analysis with the signal processing module (Wideband Ambiguity Function (WAF) and template matching via image masking) designed in Chapter 4. These were the signals that was least affected by noise, echo dispersion, and the misalignment of the defined templates (Section 4.4.2). The first, was a short 5ms constant frequency signal of 80 kHz, much like a short horseshoe bat signal (~60 ms, 80kHz). The signal had a power distribution that was normally distributed, with a mean of half the length of the signal \((\mu = T/2)\) and standard deviation of 20% of the signal length \((\sigma = T/5)\). The second was an artificial signal that mimicked a pipistrelle call, that was created by combining a short logarithmic chirp (80-40 kHz frequency sweep, 1.5 ms) with a longer (4.0 ms) constant frequency tail of 40 kHz. The pulse repetition rate (PRR) of the emitted signals in the navigation simulations were both 10 Hz (or 10 signals per second).

The echoes from the environment (produced in the same way as Chapter 4, 4.3.3) were processed via the Wideband Ambiguity Function (WAF) method of cross correlating the echo signal with artificially Doppler shifted versions of the emitted signal. The result of which, was compared with the pre-defined templates of heading angles and lateral positions. The heading angle analysis used the heading angle
templates with a fine lateral displacement (X-resolution of 10 cm, and \( \varphi \) resolution of 5\(^\circ\)). For speed templates, a template database of speeds varying between 2 ms\(^{-1}\) and 10 ms\(^{-1}\) (speed resolution 0.1ms\(^{-1}\)) with a fixed x-lateral position of 2 m and heading angle of 0\(^\circ\), was used (as depicted in Figure 4.11 Template image creation.).

### 5.3.3 Open-Loop Navigation Tests

The study first tested an open loop navigation of the sensor to observe the general behaviour of the signal processing algorithm in obtaining heading angles, speed, and lateral distances. This was created to derive a control algorithm in which the system could successfully apply in an autonomous closed-loop controlled navigation. The open loop tests simply tested the ability of the algorithm to estimate approach angles, speed, and lateral displacements for pre-defined navigation simulations. Two navigation simulations were tested, the first was to emulate a bat flying parallel to the wall and adjusting its velocity to a preferred speed, and the second mimicked a bat approaching a wall at an angle and correcting the heading angle to fly parallel to the wall.

**Speed Analysis**

Two tests were made in the speed analysis to investigate the accuracy of measuring speed for the chosen signals. For both tests, the sensor was placed at a constant lateral displacement, starting at \((x_{bo}, y_{bo}) = (2, 0)\) m to the wall with a heading angle of 0\(^\circ\). First, a moving sensor \((V_s = 5\text{ms}^{-1}\) was accelerated and decelerated by \(a = \pm 2\text{ms}^{-2}\) starting from \(t = 0.5\) s to \(t = 1\) s (Figure 5.1, a). This test was performed on three object (or environment) scenarios. The first, was to determine the response of the signals in a perfect scenario, where the objects were perfect reflectors (denoted as \(P\) scenario). The second was performed for a more realistic scenario, where the objects were given target strength properties and an echo-dispersion effect, which essentially randomises the reflected echo angle returning to the sensor (up to \(\pm 45\text{deg}\), denoted as \(R\) scenario). Finally, the third test scenario was an extension of second test case that included naturalistic background noise, modelled as pink noise of SNR = 3.84 dB (\(R+N\) scenario). For the second and third test cases, the tests were repeated 50 times (\(N = 50\)), with a different echo-dispersion (or randomization) effect every time. The mean and standard deviation of the values were calculated for the 50 trials, and a root mean squared error (RMSE) was calculated between the mean values and the expected speeds.

The acceleration (or deceleration) was applied between the pulses at \(t = 0.5\) s to \(t = 1\) s in the simulation. Starting from the sensor velocity of \(V_s = 5\text{ms}^{-1}\), the subsequent expected speed at every pulse \((V_{t=0.5...1})\) during the applied acceleration or deceleration can then be calculated from the equations of linear motion as
Chapter 5. Doppler-Acoustic Flow Navigation Simulation of Heading, Position and Speed Control

\[ V_t = V + at \]  

Eqn. 5.1

where \( a \) is the acceleration (positive value) or deceleration (negative value). Using the relative velocity component of the sensor to the bat, and since the heading (\( \varphi \)) was calculated clockwise from the \( Y_g \) axis (refer to Figure 4.1), the sensor positions at every pulse can be calculated as

\[ x_t = x_{t-1} + V_t \sin \varphi t \]  

\[ y_t = y_{t-1} + V_t \cos \varphi t \]  

Eqn. 5.2

Thus, for the speed test where there was no heading component (\( \varphi = 0^\circ \)), the x position remains constant whilst the y position increases proportionally with acceleration (or deceleration).

The second test measured the speed when the objects were given speed components. This was to mimic the scenario for the experiment where pipistrelle bats managed to regulate their speed relative to the manipulated speed of artificial foliage in their flight path (Chapter 3). A section of objects in the ‘wall’ of 5m in length (10m to 15m, Figure 5.1 (b)) were given a speed component of -2ms\(^{-1}\) (i.e., opposite to sensor flight direction). The objective of these cases was to observe if the changes in velocities could be detected for both cases, or whether the small section of objects with velocity components could not be detected by the sensor.

The same environment scenarios (perfect, with randomisation, and with noise; \( N = 50 \) trials) were used in this second test, although error (RMSE) values for the small section test of the wall were not calculated as the object speed’s influence in the measured signal could not be accurately determined in the time of the simulation.

**Heading Angle Analysis**

The second, open-loop analysis studied the extraction of heading angles and lateral displacements of a sensor approaching from \( X = 2m, 4m, 6m \) and \( 10m \) to the wall at \( \varphi = 45^\circ \) heading and turning away from the wall at \( 5^\circ \) per pulse rate (PRR = 10Hz). As the heading changed for each pulse, and the speed remained the same in the heading direction (\( v = 5ms^{-1} \)), the location of the bat was also calculated as in Eqn. 5.2, with \( \varphi_n = 45, 40, 35 \ldots 0 \) degrees.
5.3.4 Closed-Loop Navigation

This section of the analysis tested a closed loop navigation control of heading using the signal determined to be robust with noise and randomization effect from the open loop analyses. The same environment conditions were kept from the open loop heading angle analysis including noise and object dispersion effects. The goal of the navigation was to simply turn away from the 2D ‘wall’ and maintain the input heading angle (tested at 0deg or 5deg) to the wall. The navigation control was modelled after a proportional (P) controller, that uses proportional gains of the errors to control the system. To investigate whether the proportional controller with an appropriate gain can return successful results, the proportional gain ($K_P$) was varied ($K_P = 0.2, 0.4 \ldots 1$) for different test combinations. The first was to investigate the effect of heading inputs of the system, by testing desired heading inputs of 0deg and 5deg. The sensor was position at fixed start conditions of 3 m lateral start position (X) from the wall and 30deg heading to the wall. The desired heading input that allowed the sensor to correct its heading and move parallel to the wall was then used for the second test. The second test was to determine whether the system could successfully turn the sensor away from the wall and maintain the desired heading input, starting at different lateral (X) positions (X = 2 m, 4 m, 6 m). The final test was like the second but varying starting heading angles instead ($\phi_{\text{start}} = 10, 20, 30, \text{and} 40$) for a constant X start position of 3 m.
Closed-Loop Control

Figure 5.2 Closed loop control block diagram of the heading proportional control system. For a desired heading input ($\phi_{desired}$) the difference or error between the input and the measured heading angle, $\phi_{error}$, was fed into the proportional controller, in which the output (or input for the plant), $\phi_{input}$ was then fed as a command to the plant (or sensor system).

Proportional Control Law

The control law for heading correction was simple, and the system corrected the error in a linear, closed loop proportional control system (Figure 5.2), immediately from the beginning of the simulation ($t = 0$). The heading error $\phi_{error}$ was the difference between the measured angle, $\phi_{measured}$, and the desired angle $\phi_{desired}$. This was then multiplied by the proportional $K_P$ gain as the command from the proportional controller, $\phi_{input}$:

$$\phi_{input} = \phi_{error}K_P$$  \hspace{1cm} \text{Eqn. 5.3}

For example, given a desired heading angle of $\phi_{desired} = 0^\circ$, if the measured angle from the sensor system was $\phi_{measured} = 30^\circ$, controller command would be $\phi_{input} = K_P (0 - 30)^\circ$. That is, the system would command the plant to turn by -30° if the gain, $K_P = 1$. From the conventions, a positive heading angle indicated the system was angled toward the wall, and thus $\phi_{input} = -30^\circ$ would then be a command to turn anti-clockwise, away from the wall.
5.4 Results

5.4.1 Open-Loop Navigation

Speed Analysis

For both signals used, in the scenario where the objects were perfect reflectors (P) and no noise was added to the echo train signal, the measured speeds followed the expected speeds well, with a maximum RMSE no more than 0.52 ms\(^{-1}\) (Figure 5.3). In the acceleration test (Figure 5.3, A), the short CF signal performed better than the FMCF signal, although the opposite was true in the deceleration. This contradictory result, however, was likely due to the single outlier in the CF deceleration test at 1s in the simulation. This outlier could be caused by random artefacts in the WAF\(_{\text{CORR}}\) image, since the template matching algorithm can be sensitive to various factors (signal sweep, duration and coalescing of object echoes, Chapter 4). Therefore, the true responses of these signals could be better explained in the repeated trials with randomization (or echo dispersion) and noise effects.

Overall, the CF signal had lower RMSE values in every environment scenario compared to the FMCF signal (with the largest RMSE\(_{\text{MV}}\) = 0.61 ms\(^{-1}\) in the third environment with randomization and noise, R+N). However, the FMCF signal returned similar RMSE values in all environments, whereas the CF signal increased the most in RMSE value (from perfect scenario) for the most realistic environment scenario (R+N). Additionally, the standard deviation of the measured values for the R+N scenario of the CF signal were larger than the FMCF signal, especially at highest the expected speed (7 ms\(^{-1}\)). This suggested that the FMCF signal, although inherently returning larger errors than the CF signal, was more resilient to randomization and noise effects.

In the second test of including object speeds for a small portion of the ‘wall’, considering the sensor range was up to 17 m (limited by the sensor PRR of 10 Hz), the area of objects with speed components should theoretically already be detected in the beginning of the simulation (10m away from the first object with speed component). However, it was not till the sensor reached around 1.5 seconds (i.e., when the sensor was positioned at 7.5 m in the simulation or ~2.5 m before being positioned exactly next to the moving objects) in the simulation that changes started to be noticeable (Figure 5.4). This suggested that the coalescing of the non-moving objects and the moving objects could only be detected by the signal processing module if the more than half of the echo train contained the echoes from the moving objects. This also explains why the measured relative speed of the sensor started to decrease halfway through passing the area of moving objects. In the perfect conditions, P, the CF signals, although they had low RMSE values at the beginning of the area, abruptly decreased to the 5 ms\(^{-1}\) value, whilst the FMCF signal gradually decreased. This indicated that the FMCF signal, although underestimating the values by a small fraction, could still detect the frequency changes even if the echoes from non-moving objects start to dominate the echo train. Like the speed analyses, the FMCF
signals did not vary much when noise and randomization effects were added to the simulation compared to the CF signal, which had higher standard deviation when detecting the change in relative motion.

**Figure 5.3** Speed analysis extraction between the CF and FMCF signals. (A) Acceleration analysis with the corresponding environment conditions: P = Perfect reflector, R = randomised (or with echo dispersion), tested for 50 trials and R+N = randomised with pink noise effects. (B) Deceleration analysis of the same conditions for the two signals. RMSE\(_{mv}\) is the RMSE value of the mean speeds with the 50 trials.
Heading Analysis

For the heading analyses, the results were slightly different compared to the speed analysis, as the angle RMSE for FMCF signal in the perfect environment (P) was generally lower (maximum FMCF RMSE\(_{p}\) =13.6\(^\circ\), 7.91\(^\circ\) at 2 m and 4 m lateral start positions) than the CF signal (max. CF RMSE\(_{p}\) = 17.89\(^\circ\), 13.04\(^\circ\) at 2 m and 4 m lateral start positions), especially at closer distances (Figure 5.5, Table 5.1). For both signals, however, the angle RMSE values were lower at further lateral start positions. The CF signal returned slightly lower RMSE values for lateral distances, although not very different to the FMCF, and overall, both RMSEs were relatively low (< 0.6 m). Both the CF and FMCF signals returned the highest distance RMSE at the closest lateral start position of 2 m. This showed that for both signals, the errors for both heading angle and lateral distance were generally higher when the sensor was closer to the ‘wall’.
**Figure 5.5** Heading and lateral distance measurement analysis for perfect conditions, P, at different lateral (X) start positions. The left-hand side plots were the measured data, plotted against the expected (black dashed line) data. Right-hand side plots are the RMSE values for the different lateral (X) start positions.

This was expected, as in the analysis studying the effects of lateral distance template mismatch (Chapter 4) on the template matching algorithm, the highest corresponding angle errors were at closer lateral distances. This was likely due to more object echoes overlapping at the same time with different Doppler ratios at closer lateral distances (especially for larger heading angles).

<table>
<thead>
<tr>
<th>Start Pos. (m)</th>
<th>CF</th>
<th>FMCF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P</td>
<td>R</td>
</tr>
<tr>
<td>2</td>
<td>17.89</td>
<td>17.35</td>
</tr>
<tr>
<td>4</td>
<td>13.04</td>
<td>12.57</td>
</tr>
<tr>
<td>6</td>
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*Table 5.1* Angle RMSE for heading analyses for the two signals for all conditions
Lateral (X) Distance RMSE (m)

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</table>

Table 5.2 Lateral (X) distance RMSE for heading analyses for the two signals for all conditions

When introduced to randomization effects (R, echo dispersion), both signals performed similarly, returning comparable values of angle RMSE ($\text{RMSE}_R \leq 17.35^\circ$ for both signals) with the same trend of decreasing RMSE with further lateral start positions (Figure 5.6). The lateral distances RMSE both increased from the perfect reflectors condition but were still lower than 0.6m. The effect of adding noise and randomization of reflected object echoes, however, increased the angle RMSE for the CF signal more than the FMCF signal, similar to the effect of noise on the speed analyses. This confirmed that the FMCF signal was indeed more robust than the CF signal when combined with this signal processing module, in obtaining all navigation information.

Since the FM component in the FMCF signal spreads the maximum correlation coefficients in the WAF$_{CORR}$ image over a wider range in the Doppler ratio axis of the image, a purely CF signal that has a lower spread of maximum correlation coefficients in the Doppler axis would return more accurate estimations of heading. The perfect case in the analysis could have been a single instance where the FMCF obtained more accurate angles than the CF signal. The lateral distance RMSE for the FMCF signal was slightly higher than the CF signal for the furthest start position at 10m, though the difference was very small ~0.18 m. However, for both signals, the RMSE of heading angles for the realistic conditions (R, R+N) were comparable, and the better signal for this case cannot be completely determined.
Figure 5.6 Heading analyses results for more realistic environment conditions. The top half, (R) only introduced randomisation (or echo dispersion) effects to the echo signal, and the bottom half introduced both noise and randomisation effects (R+N). The tests were repeated for 50 trials and averaged, similar to the previous tests with noise and randomisation.

5.4.2 Closed-Loop Navigation

Varying heading inputs

Since the template angle range did not account for negative angles (i.e., angled away from the wall), the sensor could never return angles that were less than 0°. Thus, for the 0° desired angle test, if the heading angle of the sensor is negative (or pointed away from wall), the sensor returns 0° error and continued the negative heading moving away from the wall (Figure 5.7). When given a 5° desired angle, the sensor should then turn towards the wall whenever a 0° heading was measured, to maintain the 5° heading. The results indicated that the system measured the negative angles mostly as 0°, as the sensor
turned back to the wall whenever negative angles were measured, which caused the sensor to oscillate around the 5° input as the system tries to mitigate the errors.

![Graphs showing heading and position]  

**Figure 5.7** Proportional controlled navigation test of heading angle with different heading inputs, 0° and 5°, showing the heading of the sensor throughout the simulation (left) and the position of the sensor to the wall in the environment (right).

### Varying Lateral Start Positions

For the same starting angle of $\varphi_{start} = 30^\circ$, the moving sensor managed to turn away from the wall and keep the desired input of 5° heading to the wall for the higher lateral start positions (4 m and 6 m) tested (Figure 5.8), at least for the duration of the simulation. For the closer start position at 2 m, the higher gains ($K_p = 0.6, 0.8, 1$) made the sensor turn away from the wall faster than the lower gains, and took a longer time to correct for the negative angles and turn back to the wall. This could be because when the sensor is closer to the wall, the heading angle errors were higher (refer to RMSE results at 2 m, Table 5.1).

The higher proportional gain on the errors led the system to overshoot quickly, and combined with the high angle errors, exactly when the system corrects itself can vary between the gains used. In all lateral position start cases, however, the system managed to ensure the sensor stayed more than 0.4 m from the wall.
Varying Start Heading Angles

When approaching the wall at different starting angles, the system managed to correct the angles to the desired angle ($\phi_{desired} = 5^\circ$) with a closest lateral displacement ($X$) to the wall of $> 0.4$ m, Figure 5.9. The higher start angles ($30^\circ$ and $40^\circ$) both reached the desired angle at similar times for all the gains. The lower gains ($K_P = 0.2, 0.4$) intersected the desired heading angle line between 1 to 1.25 s in the simulation, whilst the higher gains intersected the desired input at slightly earlier times (between 0.4 to 0.7 s for both angles with $K_P = 0.6, 0.8, 1.0$; except for $K_P = 0.8$ for $40^\circ$ heading start, intersecting at $\sim 1.25$ s). This was expected as the higher gains would correct for the error faster than the lower gains. However, for the lower start angles, the higher gains resulted in the system continuously turning away

**Figure 5.8** Proportional controlled navigation test of heading angle control with different start lateral (x) positions for a sensor heading start of $30^\circ$.
from the wall (for $K_P = 0.6$ for 10° start, and $K_P = 0.6, 1.0$ for the 20° start). This meant that the measured angle $\varphi_{\text{measured}}$ was consistently at the desired heading angle, and the error term $\varphi_{\text{error}} = 0$, since the system did not command the sensor to turn back to the wall as it did for the other cases. This could be due to the high errors of the measured angles at these positions. Since the system limits the control input (or turning angle) to $-45^\circ$, if the system erroneously measured $-45^\circ$, the system would continue turning away from the wall at that angle, until a positive error (or the system measured $\varphi_{\text{measured}} = 0^\circ$) was obtained. However, if the sensor was faced away from the wall but was still receiving echoes from the wall, the system may yet command the sensor to turn back to the wall, had the simulation continued for a longer time.
Figure 5.9 Proportional controlled navigation test of heading angle control with different sensor heading start angles with a lateral (x) start position of 3m from the ‘wall’.
Chapter 5. Doppler-Acoustic Flow Navigation Simulation of Heading, Position and Speed Control

5.5 Discussion

The analysis showed that the two signals used could estimate the sensor’s speed, position and heading angle relative to its motion and the environment (or ‘wall’ of reflectors) using the proposed signal processing method. In the open loop tests, the FMCF signal generally performed better than the CF signal, as the signal was less affected by the addition of noise and object properties (target strengths and echo dispersion). In perfect conditions however, the CF signal had lower RMSE errors than the FMCF signal in obtaining speed, although the opposite was observed in obtaining heading angles, as the FMCF performed better at closer lateral distances. This was attributed to both the type of templates used in the processing and the type of frequency modulation in the signal. The signal with FM components tended to give more distinct temporal separation (or acuity) of the object echoes than signals with only CF components (Chapter 4, Sections 4.4.1 to 4.4.2), and for obtaining heading angles, the angle differences were defined at Doppler ratios of objects closer to the sensor (i.e. where temporal spacing between the objects is small, and so temporal acuity in the signal is important). For the speed templates, the defining speed differences are from objects further away with a constant maximum Doppler ratio, which CF signals can obtain, as the Doppler ratio (spectral) acuity is clearer than signals with an FM component.

The open loop speed experiment also showed that relative speed changes can be detected by both the CF and FMCF signals, even if only a small portion of the ‘wall’ was moving. The change in speed was also obtained at distances before the sensor passed the first moving object and the effect gradually reduced even before the sensor completely left the area, because the sensor range was large enough to cover both the stationary and moving objects ahead of it. This can shed light as to why the pipistrelle bats in the experiment in Chapter 2 responded and changed their speed before entering the moving panels and corrected their speeds halfway through entering the moving panels (Section 2.4.4).

The closed loop experiment using the FMCF signal successfully showed that a navigation system using Doppler-Acoustic flow can be designed to turn away or follow a parallel path alongside the linear structure (or ‘wall’). This, however, was only when the system was given the lowest desired heading of 5º, which made the system oscillate around that angle in a zig-zag parallel motion along the ‘wall’. This was due to the limits of the template angle range, which meant that the system cannot return angles less than 0º, or when the sensor was pointed away from the ‘wall’. Although the heading templates only covered a small range of positive angles (angled towards the ‘wall’), the system was able to correct the sensor heading no closer than 0.4 m to the wall in the time of the simulation. This was the case for all the proportional gains used in this analysis. The analysis showed the efficacy of the acoustic flow basis for control, even though some gains led to overshoot and steady state errors. However, these errors are usual for a proportional only control of the gains and can be mitigated using a combination of integral or derivatives of the errors (or PID control). Further tests would be necessary to determine the limits of the template ranges for more navigation tasks, as this may require larger templates of finer template
resolutions. Despite the limitations, the algorithm shows potential, as flow-based navigation usually measures changes in two subsequent signals [49, 53], and no known acoustic navigation experiments has used FMCF type signals. Using a single signal to measure flow velocity can potentially reduce processing time and may be robust to noise. For example, the flow velocity estimates can be noisy if there was a sudden jump between the parameters of two consecutive signals (an effect seen in the experiment in Chapter 3, of estimating flow velocity from time of flight, TOF).

5.6 Conclusion

The analysis successfully showed that the proposed signal processing module of using the WAF and image processing (template matching via image masking) can process single pulse-echo signals reflected off a dense modelled ‘hedgerow’, to obtain self-motion estimates of speed, distance, and heading angle to the objects. The results showed that an FMCF bat-inspired signal returned reliable estimates of the motion parameters compared to a short constant frequency (CF) signal, as it was more robust to effects of background noise. The method of processing the Doppler ratios vs. time of a single pulse echo, combined with a bat inspired FMCF signal, is unique, as most flow-based navigation is dependent on measuring changes between two signals, and Doppler-based navigation usually uses CF signals. The successful demonstration of the simple navigation tasks shows promise in the development of this type of Doppler-Acoustic flow for autonomous navigation.

Future work will have to expand on the limitations of this study, like increasing template ranges for multiple speeds, positions and heading angles. The simulation was modelled in simple a 2D environment, and thus for a realistic 3D environment, the effect of the ground or other objects will need to be considered. The proposed algorithm could also be used for other autonomous navigation tasks, like automated landing and self-centring. These will need a larger library of the templates, as the system will have to extract more than one navigation parameter. For artificial sensors, other effects like electronic noise, processing time, etc. will need to be considered for future work with physical experiments and measurements. In the biological side, to mimic a complete bat acoustic flow navigation, one would have to consider the fact that bats are binaural. This means that bats will have to balance the dynamic echo information coming from either side of their ears. Thus, the complete simulation should consider having two receivers, and process the echoes of objects on either side of the receivers.
Chapter 6

Summary and Future Work

6.1 Chapter Summary

This chapter summarizes the main conclusions of each chapter, highlighting the significance and implications of each study, as well as reiterating the problems and future work suggested within them. The overarching contribution from the chapters towards the general objectives of the thesis will be underlined here as well, which shows how the specific studies in each chapter contributed to answering the main research questions of the thesis described in Section 1.3.

6.1.1 Chapter 2: Acoustic Flow Velocity Perception in Pipistrelle Bats

The chapter showed that free-flying wild pipistrelle (FMCF) bats perceived the acoustic flow velocity changes induced in the experiment. As far as we know, this was the first experiment to show changes in bat velocities in response to acoustic flow. The study also suggested that, since it was unlikely that the bats could perceive amplitude or time of flight changes from the stimuli, due to the difficulty in separating individual objects that were moving in the manipulated flow section, frequency changes might be what the bats were responding to. This would also be the first behavioural experiment to show a navigational response from bats due to Doppler shift. The only other known response to Doppler shift in bats, is that some bats adjust their echolocation frequency to optimize neural processing of the echoes, as the bats have sections in their brains tuned to the specific frequency (Doppler shift compensation in CF bats [105]). This helps them discriminate their prey (and their acoustic properties) in dense environments [42, 106], as they can detect changes in velocities as small as 0.1ms⁻¹[89].

The bats, however, did not change their velocities to regulate the full relative velocity induced by the panels. As mentioned in Section 2.5.1, to obtain more prominent speed responses, the effect of the surrounding background will need to be mitigated or considered. In that future experiments will require a longer test section that is separated from the natural environment (an enclosed chamber, for example). These experiments, however, would suffer from the usual implications of indoor experiments, like the ambiguity for the motivations of trained bats. The results in this experiment were significant, and the bats adjusted their flow velocities according to induced flow velocity changes (i.e., sped up or slowed down), indicating that the response to flow velocity is present in wild bats, which would give confidence that this was an inherent and genuine response.
Future work on the neural processing of Doppler changes for FMCF bats would be a necessary investigation to follow, as this may also give insight as to how the Doppler changes can be processed for future work in navigation systems.

6.1.2 Chapter 3: Theory of Acoustic Flow and the Acoustic Flow Parameter

The chapter reviewed all the different acoustic parameters of the bat call echoes in a dynamic scenario, and suggested that frequency (or frequency changes, i.e., Doppler shift) was the most robust parameter in extracting acoustic flow velocities, especially when the influence of distance to objects on the parameters were removed.

The implications of the result were twofold. Firstly, this analysis gave a clearer understanding as to why speed changes were not observed in previous acoustic flow experiments, as most of these did not separate distance information from relative velocity. This made it difficult to determine whether the bats were simply integrating the distance to the echoes, rather than perceiving the change of flow from the motion. The second implication was that, since frequency may be the only reliable parameter to track in realistic scenarios, the acoustic flow parameter to focus on in future studies is frequency. This was contrary to the previous suggestions of using amplitude, time of flight or bearing changes as the acoustic flow parameter. This was also contrary to optic flow, as the parameter used to track flow is usually brightness, which is analogous to intensity (or amplitude) of sound.

The results also highlighted the behaviour of the different bat signals (mouse-eared-FM, pipistrelle-FMCF and horseshoe-CF bat call types) in these dynamic environments. The study suggested how certain bat calls could be used in self-motion estimation, and why some signals may be better at this than others. The study showed that, whilst the popular belief that signals with constant frequency components would result in more accurate Doppler shift estimations was true for simple, single object cases, the contrary was true when dealing with multiple objects. The fully FM signal obtained a more accurate estimation of Doppler shift, indicating that the Doppler tolerance (i.e., more of the signal is Doppler shifted, and can be extracted with high SNR values) of the FM signal was more tolerant to the coalescing of echoes. This combined with the short duration of the signal provided a clearer separation of objects both temporally and spectrally. The FMCF signal still managed to obtain better estimates than the CF signal in this case, as well as more accurate estimates than the pure FM signal when tracking single objects, which implied the combination of both FM and CF components in a signal may be beneficial in estimating Doppler in all scenarios. However, since the study only considered specific two-dimensional, perfect reflector environments, further experiments in more realistic environments will be necessary to fully understand why the signals behaved in this manner.
This study also suggested a different approach to extracting ‘flow’, in that a single pulse-echo can be analysed to obtain spatial information. This was presented as the Doppler ratio vs. time (or ‘Doppler evolution’) of each object in the single echo train. This was because Doppler shifts of individual objects were dependent on the position and bearing of the object to the sensor. This revealed a novel way of motion estimation or position mapping using Doppler-Acoustic flow that takes advantage of the rich information available in the echoes. Since the coalescing of echoes from the objects affected the accuracy of the combined object echo frequency shift, future experiments using the proposed ‘Doppler evolution’ presented a possible approach of analysis that may be robust to this effect. This was proven to be the case in the following chapters of the thesis.

6.1.3 Chapter 4: Computational Simulation of Doppler-Acoustic Flow in Bats and Artificial Systems

Following the results in Chapter 3, this chapter expanded on the idea of Doppler-Acoustic flow, and how to successfully process the information to obtain self-motion navigational cues (speed, position and heading). Using the idea of processing single pulse-echoes (or extracting ‘Doppler evolution’) proposed, the signal design and processing methods for this were explored in this chapter. This resulted in the creation of a novel signal processing module, that used both the wideband ambiguity function (WAF, in radar theory) and image processing (or image template matching and masking) to process the combined echo train. The study compared signal processing methods of the Short Time Fourier Transform, STFT accompanied by the peak finding algorithm to obtain Doppler ratios, as well as the WAF method combined with the peak algorithm. It was clear that (a) STFT techniques succumbed to effects of echo overlap, and (b) the accompanying peak finding algorithm returned noisy data.

The study successfully showed that one can determine speed, position and heading angles relative to a 2D ‘wall’ within an acceptable error margin (see Section 4.4, Part B and C), using the proposed signal processing module. This was achievable even in the case of adding target properties (i.e., randomization of reflected angles or dispersion) and noise. The signal processing module is novel, and showed that rich, acoustic flow information can be extracted within a single pulse-echo signal, contrary to the use of two subsequent signals in optic flow. This may lead to benefits of lower processing time and complexity in flow-based navigation. The processing module, however, used a library of templates for specific combinations of speed, position, and angles, which can limit the processing time and power of the module, especially when considering a wider range of templates to encompass different scenarios. However, future experiments could attempt different sets of templates that may be applicable to multiple scenarios. Other options would be to benefit from the large template dataset to train a machine learning algorithm to automatically detect the desired navigation input. For example, in a simple supervised learning algorithm, the corresponding expected echoes (or WAF\textsubscript{CORR}) from the templates
could be used as an input to map to the expected heading angle, speed or position. The algorithm then analyses the input-output training data to produce a function that can be used to map new scenarios [107]. Machine learning techniques have already proven to be successful in autonomous navigation [108-110] and therefore it is highly possible that the dataset presented in this chapter can be used with the techniques for acoustic flow autonomous navigation.

The analyses also investigated the impact of different signal design parameters, like signal duration and frequency sweep, in obtaining accurate estimations of Doppler ratios and accurate motion estimates of heading angles, position, and speed. It was found that FM signals returned object echoes that were temporally separate from each other and spectrally separate, in that the Doppler ratios in the WAF result were more widely spread in the signal. This was consistent with the known fact that short FM signals in bats are used to provide better target acuity [36, 111, 112]. In this analysis, however, the spectral separation allowed the longer FM signals (25 and 45 ms) to return accurate estimations of heading angles, distance, and speed using the proposed processing module, compared to the unsuccessful long CF signals. However, short duration signals could still return low error estimations, even without the FM components (i.e., pure 5 ms CF signal). This implied that the spectral overlap of CF signals did not necessarily affect the signal performance in extracting Doppler ratios in the dense environment, as much as the signal having longer signal durations (i.e., temporal overlap of echoes). Which was why the short, FM signal also managed to obtain accurate Doppler ratio estimates, and in turn, accurate heading angles, position, and speed from the template matching. However, it was clear that signals with both CF and long durations performed poorly in the analyses. Between the two short FM and FMCF signals, it was shown that the FMCF signal was more tolerant to the addition of pink noise (or background noise, i.e., the rustling of leaves). Prior to the study, it was not clear why some bats use one or the other in the same foraging habitat. Most studies address the importance of the FM signal in separating clutter, but this does not explain why some bats still have the CF component in the same cluttered environments. The robustness in obtaining Doppler shift information for FMCF bat signals could give insight on this matter, as well as why some bats adapt signal plasticity (FM to CF, or CF to FM) [37, 113].

6.1.4 Chapter 5: Doppler-Acoustic Flow Navigation Simulation of Heading, Position and Speed Control

The final chapter explored the question on how effective the novel processing module (and the successful signal designs used with it: CF, 5 ms, FMCF, 5.5 ms) was for Doppler-Acoustic flow navigation. The chapter simulated a navigating sensor that emitted the two most robust bat calls in the previous chapter, to perform simple tasks of autonomous navigation. Two topics were addressed here; whether speed can be accurately estimated (especially in the realistic acoustic flow induced scenario faced by the bats in Chapter 2), and whether heading angles of the sensor to the wall can be accurately...
estimated. The proposed processing module and signals were successful in both areas, although the FMCF signal showed more tolerance to noise effects, as seen in the previous chapter.

The experiment showed that speed (including acceleration or deceleration) can be estimated with low errors in both signals. More importantly, the experiment showed that the changes in speed for a portion of the objects in the ‘wall’ could be perceived using the signals. This was determined at a lower proportion than the expected speed. It was also shown that the speed in this case could be detected ahead of the sensor passing through the area with moving objects. These findings were consistent with the results in the Chapter 2 experiment, in that the bats adjusted their speeds ahead of passing through the moving section, at a smaller proportion of the relative velocity induced than expected. This further supported the theory that the bats were attuned to frequency changes when estimating relative motion.

The navigating system was then tested for autonomous control of heading for two navigation scenarios. They were to turn away from the 2D ‘wall’, or to follow a parallel path to the wall. The results showed that using a simple proportional controller was enough for the system to successfully turn away from the wall, within a safe distance. The system also managed to keep a parallel path to the wall, by oscillating around the lowest, non-zero heading input (5°). This was because the measurement of heading angles was limited to the templates used. The implications of this are numerous. The algorithm proposed showed that a simple navigation control of heading can be applied for a moving system using only Doppler shift estimates. Since the templates also gave estimates in lateral position, ranging (or time-to-object, time-of-flight) estimations were not necessary to ensure collision avoidance if the sensor was headed towards the ‘wall’. Although the templates were only for a specific speed (5 m s⁻¹), it was proven, from the previous analyses, that speed estimates could also be obtained. This meant that if the template library covered a wide range of speed, position, and angles, the algorithm may have the potential to be fully self-sufficient in navigating. This, however, may be subjected to memory, signal processing power and time limitations.

The study (and the studies in previous chapters) only simulated a two-dimensional environment. Future work will have to consider the effects of multiple objects in the height axis of 3D space. This may reduce the chances of accurately obtaining the ‘Doppler evolution’ from the environment, although the maximum Doppler shifts in a 3D space would still correspond to the objects with the highest relative velocity, which would be the objects at the same height as the sensor (i.e., in the 2D plane). Therefore, there is some confidence that the algorithm may still work, especially if the influence of the lower Doppler shift from objects that were not in the same 2D plane as the sensor is small. A physical experiment should also follow this analysis, to determine whether there are limitations in the available sensors (e.g., sampling rate, power, range, and field-of-view limitations) or any other physical limitations. In these experiments, different speeds, environments, and navigation paths should be considered to successfully transfer the algorithm into real-world scenarios.
6.2 Conclusion Summary

The thesis set out to answer three main questions. The first question of whether bats can perceive acoustic flow velocity was addressed in chapter 2, in that pipistrelle bats did perceive the induced acoustic flow velocity as they responded by changing their flight speeds. The chapter also introduced the question of which acoustic cue or parameter the bats were likely attuned to. Although it was suggested that frequency was likely the parameter, since the experiment set-up might make it difficult for bats to focus on a single, moving object, this was not conclusive as there was no evidence to confirm this was the case. Therefore, further studies were made in the following chapters, to try to determine how the bats may perceive this, which was the second main question of the thesis. This was partly answered in Chapter 3, where the three acoustic parameters (amplitude, time-of-flight, and frequency) were analysed against each other in order to determine which parameters can return accurate estimates of flow velocity. The study proved that, in absence of distance estimation to the objects (like the environment in Chapter 2), frequency returned relative velocity information and was thus the likely parameter that the bats were attuned to in estimating flow velocity. This motivated the analyses in the following chapter, Chapter 4, which was to determine how to successfully extract the frequency changes for estimating accurate flow velocities. It was in this analysis that a new method of processing Doppler from a single pulse-echo was presented, alongside the proposed signals that were successful with this method. The combination of the analyses in Chapter 4, and the following autonomous navigation analysis in chapter 5, answered the final question of how to successfully use Doppler-Acoustic flow for navigation. The analysis in both Chapter 4 and Chapter 5 showed that not only changes in speed can be determined but heading angles and distances as well. Chapter 5 successfully showed how the proposed processing module and signal could be used for autonomous navigation control of heading and opened new avenues for investigation of acoustic flow navigation using these methods.
References


### Figure A.1
Type II normality test results, tested at every distance bin (m) of the bats’ trajectory.

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<td>0.9900</td>
<td>0.6436</td>
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</tr>
</tbody>
</table>
APPENDIX B

B.1 Calculations for maximum range for bat call from simple sound attenuation

From the data in the chapter, i.e., assuming the bats emitted a call at a source level (SL) of 130 dB SPL (at 10 cm reference) facing the object directly (no directionality effects), the minimum hearing threshold of the bats at 0 dB SPL, the calculated atmospheric absorption coefficient of -1.84 dB SPL/m, the target strength (TS) for the leaf of -10 dB SPL, and ignoring the noise level (NL) term; the maximum range (m) for sound to travel to and from the bat can be estimated from the sonar equation Eqn. 3.6 from Section 3.2.1

\[ 0 = SL + TS - 2TL \]

\[ 0 = 130 - 10 - 2 \left( 1.84m + 20 \log_{10} \frac{m}{0.1} \right) \]

The maximum range (m) can be estimated as the distance where the sound pressure level (SPL) value is 0 dB SPL from the graphical plot below, which is around 10.5 m.

The above plot is generated via MATLAB to depict the sound pressure level of a reflected echo returned to a bat emitting a call at 130 dB SPL (at 10 cm reference) at various distances.
B.2 Calculations for proportional factor k of Time of Flight

If the sensor was approaching the object head on, the distance to the object at the first echo pulse is $s_1$, at $t_1$, and the distance to the object at the second echo pulse is $s_2$, at $t_2$, where $s_2 < s_1$, the time of flight (TOF) of the sensor to the object can be calculated as

$$\text{ToF}_n = \frac{2s_n}{c}$$

Where $n = 1$ and 2 for the first and second pulse, and $c$ is the speed of sound. If the sensor was emitting a pulse with a repetition rate PRR, the flow velocity, $\bar{V_F}$ is then

$$\bar{V_F} = (\text{ToF}_2 - \text{ToF}_1)/\text{PRR}$$

Substituting TOF will then give

$$\bar{V_F} = \left(\frac{2s_2}{c} - \frac{2s_1}{c}\right)/\text{PRR}$$

$$\bar{V_F} = \frac{2}{c}(s_2 - s_1)/\text{PRR}$$

And since the sensor speed can be determined as $V_s = (s_1 - s_2)/\text{PRR}$, equating $\bar{V_F}$ with $V_s$ returns the proportional factor $k$

$$k = -\frac{2}{c}$$