Addition of a Biomimetic Fingerprint on an Artificial Fingertip Enhances Tactile Spatial Acuity

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Abstract—**The fingerprint is a morphological aspect of the human fingertip that has interesting implications for our sense of touch. Previous studies focused on how the fingerprint affects the perception of stimuli that excite high temporal frequencies, such as for texture perception. These studies also only add papillary ridges to their sensors. Here, we endow a biomimetic sensor with both papillary ridges (fingerprint) and a dermal stiffness contrast (stiffer intermediate ridges), and assess the impact on localization perception accuracy. The sensor is based on a novel modular version of a three-dimensional printed tactile sensor (TacTip). Tactile data were collected with these tips on nine stimuli with varying curvature. The location perception acuity of three tips [smooth, fingerprint, and fingerprint (cores)] were compared with a probabilistic classification method, finding that both fingerprinted tips increase the perceptual acuity of small spatial scales. Interestingly, the fingerprint variant had poorer accuracy than the smooth tip for larger spatial scales; however, adding cores to enhance the dermal stiffness counteracted the degradation of accuracy. This supports the theories that the fingerprint aids the classification of edges and smaller spatial scales, and demonstrates that the addition of a fingerprint to an artificial tactile sensors improves its acuity.**

Index Terms—**Force and tactile sensing, siomimetics.**

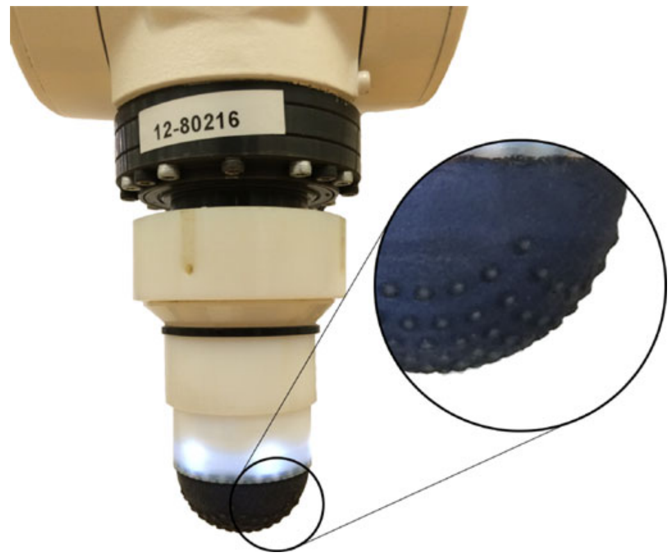

Fig. 1. Biomimetic fingertip (TacTip) with a tip endowed with an artificial fingerprint. This sensor is used in this experiment, with variations in tip design, to demonstrate the improvements in location perception acuity on smaller spatial scales due to a fingerprint.

I. Introduction

The human fingertip is an extremely complex and efficient sensing device that provides us with the key information for manipulating objects and tools. It has evolved multiple morphological aspects that aid its perceptive performance. One of these aspects that is particularly interesting is the fingerprint. The fingerprint has multiple aspects that can be linked to the sense of touch, including but not limited to an intricate interaction between the two layers of skin and concentrations of sensory cells located under the ridges that make up the fingerprint. Utilising these features in biomimetic systems may make it possible to enhance the functionality and performance of existing tactile sensors, which will in turn improve the abilities of systems to perform more complex tactile tasks such as in-hand manipulation where shape detection and object reconnection are crucial [1].

In this letter, we explore the effects of a novel combination of a simple papillary ridge structure and an enhanced stiffness contrast on biomimetic intermediate ridges upon the accuracy of location perception on stimuli with varied curvature. Thus we aim to identify if a fingerprint is beneficial feature for a tactile sensor in spatial perception tasks. The use of fingerprints on tactile sensors is not a new idea and research into the effect of fingerprints has shown some interesting tactile enhancements. Multiple studies support the finding that textural perception and classification (temporal features of tactile contact) are improved by the presence of a fingerprint [2]–[4]. Artificial papillary ridges have been used to enhance the local shape classification of stimuli [5] to show that the inclusion of these ridges may enhance the detection of curvature. Also FEM studies [6], [7] on the effect of intermediate ridges in the human fingertip have pointed towards a lensing affect that focuses the stress of a contact to allow finer detection and localisation of edges.

There is limited coverage, in literature, on the effect of an artificial fingerprint for localization perception on small spatial scales. Also, endowing a biomimetic fingertip with both

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epidermal and dermal enhancements based on the human fingertip is completely unexplored. To examine this, we use multi-material printing methods to produce three tips for a modified TacTip optical tactile sensor [8] (Fig. 1). These tips are the same in volume, diameter, and pin layout but differ in their morphology. Firstly, there are papillary ridges made from nodules on the exterior skin that mirror the pin layout on the interior, in the same way that papillary ridges mirror the intermediate ridges in the human fingertip. Secondly, there is an increase in the contrast of stiffness between the skin (epidermis) and flesh (dermis). The latter is achieved by adding a solid core that runs through the pin body to the pin tip. We expect to see improvements in the localisation accuracy of the tips on smaller spatial scales by including the artificial papillary ridges, as well as a further improvement at these scales due to the inclusion of the enhanced dermal stiffness contrast.

The acuity of location perception of these tips is calculated from an off-line probabilistic classifier and compared for 9 stimuli of varying curvature. We show that the addition of papillary ridges improves the sensor sensitivity (lower ambiguity between sensory readings) which in turn improves accuracy of our tactile sensor to localisation tasks on features that are smaller spatially (lower curvature). Interestingly the enhancement of dermal stiffness contrast does not further improve the detection at these ranges as expected. Although the enhanced stiffness does appear to negate negative effects due to the presence of fingerprint on larger spatial scales, possibly due to supporting the structure of the pins creating a more consistent deformation. Hence we demonstrate that the inclusion of the papillary ridges and stiff intermediate ridges of the human fingertip in a biomimetic fingertip improves the sensor's locational perception acuity to smaller spatial scales without impairing sensing on larger scales.

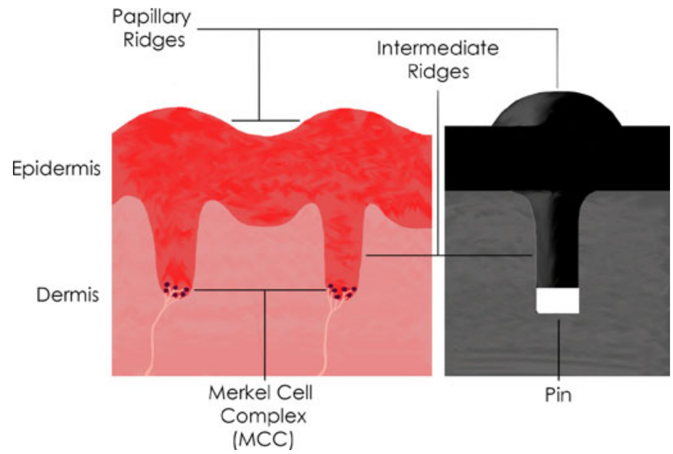

Fig. 2. Structure of the fingerprint. The top layer of the skin is the epidermis, which has protrusions on the surface called papillary ridges (fingerprint). These ridges overlay epidermal protrusions into the dermis (inner layer of skin) called intermediate ridges. At the tip of these ridges are touch receptor cells (Merkel cells). The right image depicts the biomimetic principles of our sensor, with an epidermis and dermis, as well as papillary ridges and intermediate ridges.

II. Background and Related Work

The fingerprint is believed to have a purpose in tactile sensing. It is made up of parallel whorls of ridges on the outer layer of skin (epidermis) known as papillary ridges. The epidermis protrudes into the dermis (a deeper layer of skin) creating a junction of interlocking sections of tissue [9], [10]. This interlock creates ridges of epidermal tissue known as intermediate ridges, that mirror the papillary ridges. Limiting ridges follow the grooves between the papillary ridges and act to limit movement between the two layers. The tips of the intermediate ridges have a cluster of 5–10 mechanoreceptors known as Merkel cells, that adapt slowly (SA) throughout contact with stimuli [10], [11]. This is known as the Merkel cell complex (MCC). This structure produces a sophisticated interaction between stimulus and sensor (Fig. 2).

There have been many theories on the function of the human fingerprint, many of which may not be mutually exclusive; thus, the fingerprint would appear to aid the human sense of touch in many ways. One hypothesis is that the fingerprint assists grasping by acting as a high friction surface between the fingertip and the contacted object [12], or as an aid for slip detection [13]. Another suggestion presented in *The Anatomical Record* in 1954 by Cauna [9] suggests that the fingerprint aids tactile perception by allowing the intermediate ridges to follow the motion of the papillary ridges acting as a small mechanical lever which magnifies the response to tactile contact. Although recent publications by Gerling and Thomas, 2005 [6] and Gerling, 2010 [7] have shown that the 'mechanical lever explanation' may not be adequate, by producing FEM models of a human fingertip that explore the effect of intermediate ridges on the transference of stresses from a contact to the sensory cells. Their findings have shown that the intermediate ridges focus the stress of contact and increase the signal over background noise to allow finer edge detection. It is important to note that this model focuses on the intermediate ridges and does not include papillary ridges. It was also found that the stress distribution through the tip is not altered by the ridges and thus does not aid classification between the edge and gap probes that they explored.

Many tactile sensors have been developed and each has properties motivated by convenience of fabrication, durability, biomimesis and intended use [10], [14], [15]. Some applications of tactile sensors include object identification, control, and manipulation (combination of identification and control). A desirable property of tactile sensors is that they are soft and compliant, for example to allow the sensor to conform to the stimulus as well as to exhibit hyper-acuity/superresolution properties. A sensor with superresolution utilises the compliance of the surface to spread the contact over multiple nodes (taxels, pins, or mechanoreceptors) thus enabling a triangulation to contact localisation on a scale smaller than the resolution of the sensor [16].

There is some existing work on integrating fingerprints into tactile sensors. One such integration was shown in *Science* by Scheibert *et al.* [2] where an artificial fingerprint improved fine texture perception (spatial scale $<200\ \mu$m) possibly due to spectral selection and amplification of the features. Similarly, other work has considered improving texture identification [3], [4]. In both cases the fingerprint is used as an amplifier of the temporal frequency features of the textured surfaces, with results demonstrating that use of an artificial fingerprint improves perception of texture. Another study using a fingerprint on a tactile sensor was performed in 2011 by Salehi *et al.* [5], in which they used 3 stimuli (flat, curved, and edged) to show that shape detection is improved with the presence of a pair of papillary ridges. The curved stimulus was chosen to be the same spatial scale as the sensor to avoid confusion between flat and curved surfaces.

A TacTip sensor has previously been endowed with a fingerprint in a study by Winstone *et al.* [4]; however, there are important differences with the present study. The previous study used a miniaturised TacTip with rings of embossed material, on the exterior, lying above the rings of pins on the inside of the sensing surface, and as discussed above focused on the temporal aspects of tactile perception (using a high frequency 1 kHz camera and considering texture perception). In contrast, here we use local additions (nodules) of material on the surface of the skin to identify more local spatial effects of tactile features; we have also added a rigid core to enhance the stiffness contrast between the skin and the flesh. Since we are concerned here with spatial features, it is sufficient to use a low frame rate (30 Hz) camera. In addition, the present study utilizes probabilistic methods for biomimetic tactile perception that have been demonstrated to be robust and accurate over many different stimuli and tasks with similarities to biological sensory encoding [17], enabling comparison with other work in tactile perception such as super-resolution [16], [18].

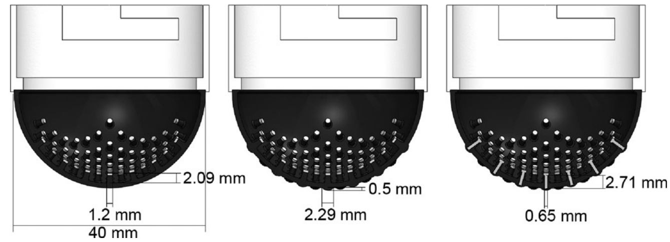

Fig. 3. Cross sectional comparison of the TacTip tactile sensor tested in this letter. The left tip is the basic TacTip sensor with a smooth surface. In the middle is the tip with artificial papillary ridges. Finally the tip on the right has the fingerprint and the further addition of an enhanced dermal/epidermal stiffness contrast

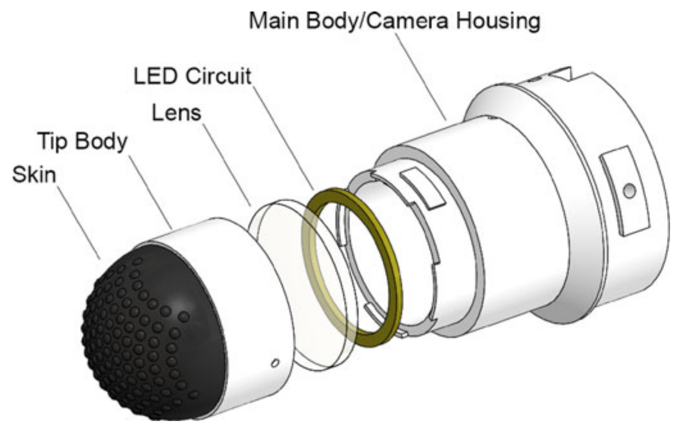

Fig. 4. Exploded view of the modular TacTip; the tactile skin, modular body (with bayonet fitting), and a clear acrylic lens make up the interchangeable tip module. The main body of the sensor acts a focal length spacer for the camera, houses the LED circuit, and is the part connected to the robotic arm. Finally, the camera mount fits to the top of the main body, and securely fits a modified Microsoft Lifecam.

III. Methods

A. Experimental Procedure

1) The Tactile Fingertip: The TacTip is an optical tactile sensor developed at Bristol Robotics Laboratory [4], [8], [16], [18]–[21]. The TacTip sensor was designed to be primarily 3D printed. This makes the sensor relativity cheap and easy to modify. The sensor uses an off-the-shelf CCD (LifeCam Cinema HD) to track an array of pins on the internal side of a silicone skin. It is important to note that previous work on the sensor has utilised incorrect terminology to describe the biomimesis of the sensor. The pins were claimed to be inspired by the dermal papillae, although this feature of the fingertip is the part of the dermis created by the protrusion of the epidermis. Upon closer inspection the pins are more akin to the intermediate ridges that protrude from the stiffer epidermis into the softer dermis tissue.

The TacTip has multiple beneficial aspects. The ready availability, low cost, and plug'n'play properties of modern webcams mean that this sensor benefits from only having a single cable, being easy to install, as well as remaining low cost. The silicone skin (Vytaflex (Shore A 60)) is filled with an optically clear gel that gives the sensor compliance. There is a difference in the hardness of this flesh material and the skin, similarly to the difference in stiffness between the stiffer epidermis and more compliant dermis in the human finger. The skin has a relatively low cost and keeps any contact far from any delicate electronics, meaning the sensor is robust and easily replaceable if damaged.

2) TacTip Modifications: In recent work, Ward-Cherrier *et al.* modified a TacTip so that the sensor could be integrated into a thumb on a modified openhand model M2 gripper (TacThumb) [20]. In this case the skin and pins are printed as part of the body of the sensor, rather than molded separately and attached later. High material and time costs for setting up manufacture of the original tips has limited the past optimization of the TacTip, but as the 3D printed tips can be cheaply and easily produced in different configurations, many different versions can be tested for optimization.

To test the different tips the TacTip was redesigned to be modular. This allows the tips to be interchangeable, which in turn speeds up the test process and lowers cost (as otherwise an entire sensor would be needed for each new tip). The modules are a tip module that has the Tactile tip (3D printed Tango Black + (Shore A 26-28)), gel (RTV27905, Techsil UK (∼Shore 00 10)), lens, and a body (Vero White). The base holds the LED ring, and is the bulk of the 3D printing (Vero White), as well as being the connection to the Robot arm. These modules are connected together by a secure bayonet fitting (Fig. 4).

The original TacTip was designed with a high density (∼1.5 mm between pin centres on the surface) of small pins in a

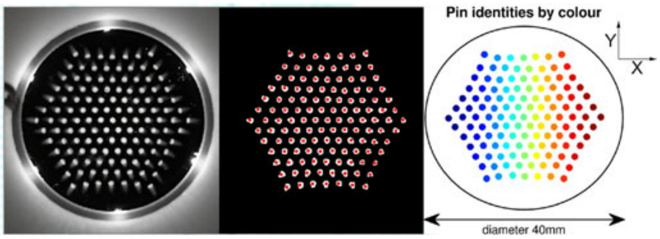

Fig. 5. The tip modules used in this study use a hexagonal projection for the pin layout, which creates evenly spaced pins on the 2D CCD image (~3.0 mm between pin centres on the CCD image). This new layout helps support robust pin tracking without sacrificing resolution due to the superresolved properties of the system. On the left is raw image and right is processed image

TABLE I
TABLE OF THE STIMULI CURVATURES

Stimuli (ncs)	Radius (mm)	Curvature (mm^{-1})
1 (Edge)	0	∞
2	1.25	0.8000
3	2.5	0.4000
4	5	0.2000
5	10	0.1000
6	20	0.0500
7	40	0.0250
8	80	0.0125
9 (Surface)	∞	0

geodesic pattern to produce an evenly spaced pin layout [8]. The geodesic pattern on the hemispherical surface leads to greater pin density towards the edges of the CCD image. Therefore a hexagonal projection is used to create even visual spacing in the CCD image (~3 mm between pin centres on the CCD image). The resulting pin layout is far more suitable for robust pin tracking (Fig. 5).

The biomimetic fingerprint design was inspired by the human fingertip by considering the mirroring of the papillary ridges and the intermediate ridges. This was done by adding domes (diameter 2.29 mm, height 0.5 mm) on the exterior of the skin in a concentric alignment to the pins, to mimic the role of the papillary ridges. The second adaptation of the tip is to include an enhanced stiffness contrast achieved with a plastic core (Vero White 3D printed material (Shore A 85)) that starts in the interior of the dome/skin and connects directly to the pin tip (2.71 mm from base of tip to base of dome). These cores are only possible by utilising dual material 3D printing (Fig. 3). The publication by Gerling [7] shows that the location of the mechanoreceptors on the tip of the intermediate ridges is adventitious due to the fact that the epidermis is stiffer than the dermis. Thus the idea is that increasing this stiffness contrast will improve the perception of edges, as suggested by the FEM models.

3) Experiment: To test effects of the enhancements, a set of stimuli are developed for the sensor to examine. These stimuli have varying curvatures, as curvature can be conveniently linked to spatial scale. The curvatures chosen range from 0.8000 mm^{-1} to 0.0125 mm^{-1}; the set is completed with an edge (as close to ∞ curvature as possible) and a flat surface (0 curvature) (Fig. 6).

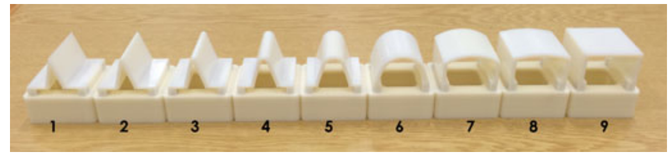

Fig. 6. The 9 stimuli used in this experiment, ranging in spatial scale from an edge (1) to flat surface (9) with intermediate curvatures ranging from 0.8 (2) to 0.0125 (8). The sensor travels (y) from right to left on each stimulus, covering 30 mm symmetrically about the apex of the stimulus.

Curvature is calculated as $(\text{radius})^{-1}$. It is important to note that stimuli 9 should be completely ambiguous to all sensor tips due to its lack of changing features across the range. Stimuli 6 mirrors the curvature of the sensor itself, and 3 is approximately the same scale as the spacing between the artificial papillary ridges. Hence we describe spatial scales of ≤ 2.5 mm as small and ≥ 20 mm as large, with the middle range bridging the gap between them. Note that these definitions of spatial scale may change for other fingertips, as the interpretation of spatial scale depends on tip morphology.

4) Data Collection: The platform for the system was a six degree-of-freedom robot arm (IRB 120, ABB Robotics), which precisely positions the attached end effector with an absolute repeatability of 0.01 mm. The TacTip sensor is used as the end effector on this arm for this study.

The system is trained with supervised learning, by tapping the stimuli and recording the tactile information. This is done for every class (0.1 mm) along the y direction, up to the full range (30 mm) for each of the stimuli. Each of the taps is a 5 mm press from 1 mm above the stimuli apex (maximum tap indentation of 4 mm, corresponding to a maximum force of 0.3 N on the tip) and records approximately 1.5 seconds of data, with ~35 recorded frames per tap. By tapping the stimuli, aspects of the material such as texture, caused by surface roughness, will be minimised and are thus not considered here. The data acquired for the results in this letter were collected in two distinct sets for each stimuli, ensuring that the training and test sets are different, and that the validation of the results is based on sampling from an independent data set to that used to train the classifier.

5) Data Preprocessing: The data from the TacTip sensor is extracted from the recorded frames of each tap. Time series are constructed from ~35 frames with a resolution of 640 $\times$ 480 pixels. These frames are subsequently filtered in opencv (http://opencv.org/) using a Gaussian spatial filter with adaptive threshold, which accommodates varying luminosity in the tip, and a mask is applied to the edge of the image to remove glare caused by LEDs.

Each pin is tracked from frame to frame by linking that pin's new location to the nearest location in the prior frame. A limitation of the original TacTip was that it was difficult to track pins due to a non-uniform pattern and high spatial density; this has been improved with the new design by adopting a more regular pattern with slightly larger spacing (but still sufficient for fine spatial perception). By having a reduced density of pins (127 pins) this issue is avoidable and creates a method of pin tracking that is robust.

The training data is collected for a range of distinct locations $x_l, 1 \leq l \leq N_{\text{loc}}$ where $N_{\text{loc}} = 300$ over a 30 mm of stimulus. This is stored as a multi-dimensional time series of taxel values z:

$$z = \{s_k(j) : 1 \leq j \leq N_{\text{samples}}, 1 \leq k \leq N_{\text{dims}}\} \qquad (1)$$

where the x and y components of the pin deflections are treated as distinct data dimension $s_k(j)$, and thus the number of dimensions is equal to the number of pins multiplied by the number of spatial dimensions, $N_{\text{dims}} = 127 \times 2 = 254$. Each time series is zeroed before analysis, meaning that only deflections are considered, irrespective of the pin's starting position. This effectively resets the sensor before each tap in the data, and acts to reduce long term hysteresis of the sensor tip. The time series are also truncated to 15 frames, $N_{\text{samples}} = 15$, for each tap. Thus the overall data dimension is $(300 \times \{254 \times 15\})$.

B. Classification and Validation

The collected training data set is used in a standard 'histogram' likelihood model. The histogram model has been indicated as analogous to spatial and temporal summation in neurons [17], but those aspects will not be central here. This classifier has been used in past work by the group for similar work with posterior estimation [16]–[18]. Hence, for constancy with past work we continue its use here. The histogram model is constructed by encoding the training to determine the increment of evidence for each perceptual hypothesis based on the logarithm of a likelihood model of the contact data.

$$\log P(z|y_l) = \sum_{k=1}^{N_{\text{dims}}} \sum_{j=1}^{N_{\text{samples}}} \frac{\log P_k(s_k(j)|(y_l)}{N_{\text{samples}} N_{\text{dims}}} \qquad (2)$$

assuming statistical independence between all data dimensions k and time samples j. A histogram method is then applied to the training data, where sensor values s_k are binned into equal intervals $I_b, 1 \leq b \leq N_{\text{bins}}$ for the entire range of the training data.

$$P_k(s_k|y_l) = P_k(b|y_l) = \frac{n_{kl}(b) + \epsilon}{\sum_{b=1}^{N_{\text{bins}}} n_{kl}(b)} \qquad (3)$$

The sample count in each bin b for dimension k over all training data in class y_l is $n_{kl}(b)$ ($\epsilon \ll 1$ a small constant that regularizes the logarithm).

A Monte Carlo procedure is used to randomly sample data from the test set. The sampled data is used in the above method to classify locations, returning the training class with the maximum likelihood to the sampled data. This is repeated with 10000 iterations of a Monte Carlo procedure to sample all the data classes in the test set. The difference in perceived and actual class location is the error in the perception.

IV. Results

A. Inspection of Data

The effect of varying sensor location (y) over the stimulating feature changes the extent to which the pins displace, both in magnitude and direction. Each time-series is a distinct set of displacements for that particular surface structure. As the data contains a large amount of information about specific locations, it permits location perception. As with any classification, the lower the ambiguity is over the stimulus/data, the greater the accuracy of perception. The data sets are shown in Fig. 7 (for stimuli 1, 4, and 8) to demonstrate the effects of varying the spatial scale.

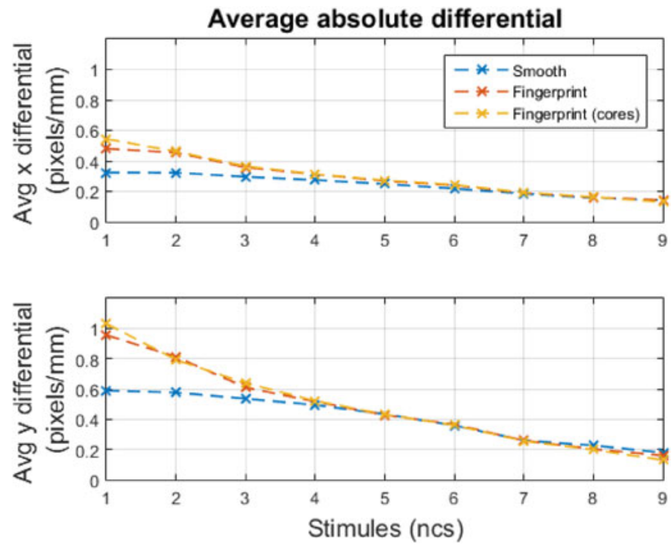

Fig. 7. The graphs above represent the pin deflections collected by the smooth tip (left), fingerprint (middle column), and fingerprint with cores (right), for stimulus 1 (top), 4 (middle row), and 8 (bottom) over a 30 mm range. It can be seen that the rate of change of pin deflection over the length of the recording, becomes lower on higher spatial scale stimuli. It is important to note that this rate is improved for the fingerprint tips, over the smooth, on the smaller spatial scales.

Data from the tips contacting smaller spatial features show a high rate (deflection/class location) of change in pin deflection (e.g. stimulus 1 shown in Fig. 7(a), (b), and (c)) when compared to that of the high spatial scales (e.g. stimulus 8 shown in Fig. 7(g), (h), and (i)).

When comparing the data sets for the smaller spatial scales between the tips, there is a visible change in the structure of the data. This is an increase in the rate of pin deflection per unit length (Fig. 7(b), and (c)). This increase in rate of deflection at smaller scales is highlighted by the values of the average absolute differential of the data. These values are obtained by calculating the differentials at every class for each taxel, after noise is reduced via a 5 point moving average. The differentials are taken as absolute and averaged across taxels, between the contact range of 5 mm and 25 mm, then for the set. The average absolute differential shows that, in the direction of travel (y), the value is up from 0.59 pixels mm^{-1} for the smooth to 0.96 pixels mm^{-1} and 1.03 pixels mm^{-1} for the fingerprint and fingerprint with cores respectively, on stimuli 1 (Fig. 8). The direction of travel is relevant here as it appears that the fingerprint has the greatest influence in that dimension for these stimulus. This means that the data for the fingerprint tips is inherently less ambiguous (sharper) in the direction of sensor travel (y), and thus more conducive to perception of location and classification.

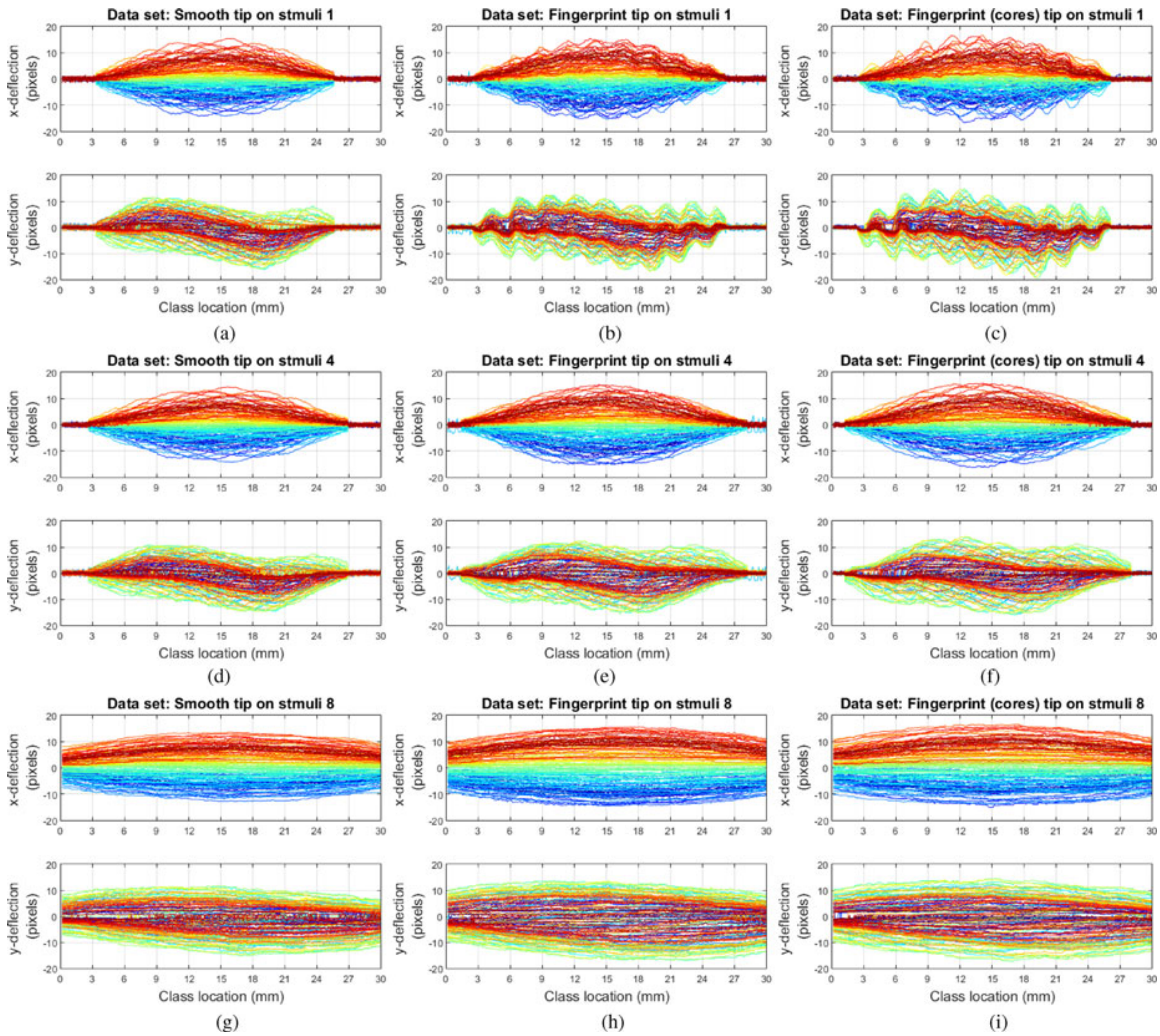

Fig. 8. Plotting the average absolute differential for each tip on each stimulus shows that the rate of change of pin deflection for the fingerprinted tips is improved over that of the smooth tip, for small spatial scales. This is most notable in the direction of travel (y). This difference in rate of change of pin deflection quickly dissipates as you increase the spatial scale of the stimulus and may help make the data for the fingerprinted tips less ambiguous at lower spatial scales.

B. Error Analysis of Classification

Using the Monte-Carlo analysis described in Section III-B, the data is processed off-line to determine the perceived location class of samples from a test set. The distance from the real location is taken as the error in localization $e_{\mathrm{loc}}(y)$. These errors can be plotted to highlight regions of high and low ambiguity (Fig. 9). The graphs (using the same stimulus sample as in Fig. 7) show the regions of no contact for stimulus 1 and 4, these are below 5 mm and above 25 mm. These no contact regions inherently detect no changes in the sensor and thus are totally ambiguous. The contact region of stimulus 1 is the smallest and it is chosen to be the comparison range for all the stimuli (5 mm–25 mm). In this range it is clear that error increases in size, for all tips, as you move up in stimulus scale. This is consistent with the visual increases in ambiguity mentioned about Fig. 7.

To compare the tips themselves the mean error of the contact range (5 mm–25 mm) is taken. The mean localization error provides a single value for the overall performance of the tip on that stimulus. When plotted together it can clearly be seen that the error increases with the spatial scale (Fig. 10 Top). The errors become extremely large for stimulus 9; this was expected as a flat surface has no discernible features.

To draw out the changes in sensor accuracy, due to the presence of the added features, the relative errors are calculated using the smooth tip as the base (Fig. 10 Bottom). The results show that the presence of the papillary ridges, irrespective of the enhanced dermal stiffness contrast, improves the accuracy of the sensor to 140–170% of the accuracy of the smooth tip, for spatial scales of 2.5 mm and less. For stimulus 4 and 5 the accuracy of the fingerprint tip is similar to that of the smooth tip, before dropping of to 80% of the accuracy of the smooth tip for the reaming stimuli (spatial scales 20 mm and greater). Interestingly the fingerprint (cores) tip remains more accurate for stimulus 4 and 5 and tends towards a similar accuracy to the smooth tip for the larger spatial scales, in contrast to fingerprint tip. This suggests that the enhanced dermal stiffness contrast contracts negative effects of the artificial papillary ridges on

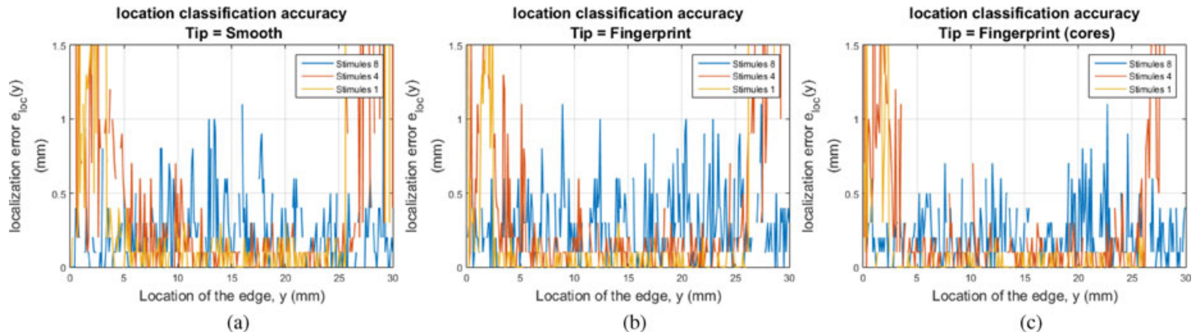

Fig. 9. For the same three stimuli as show in Fig. 7 the graphs represent the error in perception over the stimulus. The range of 0–5 mm and 25–30 mm show poor errors for stimulus 1 and 4, this is expected as the sensor is not in contact at these locations. Through the considered range (5–25 mm) it is clear that the errors are lower for stimulus 1, and higher for stimulus 8 (consistent for all tips). It can be seen from the graphs that the fingerprint (cores) is better over all shown stimuli, whereas the fingerprint appears to be the least accurate for 8, and the smooth has the highest errors for 1 and 4.

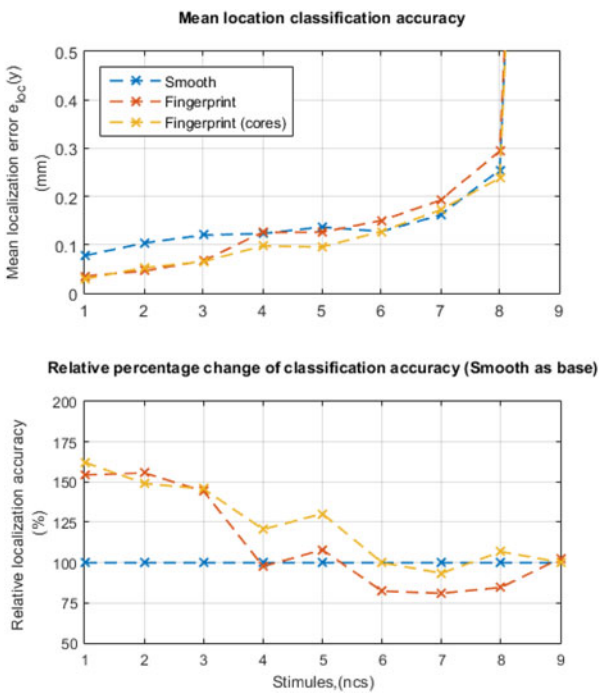

Fig. 10. By taking the mean error for each tip and stimulus, over the contact range (Top), it can be seen that the errors increase with the size of the spatial scale, as expected from the data sets. Stimulus 9 is a flat surface with 0 curvature and thus is totally ambiguous, hence the sharp rise in error. To fully identify the effect of the modifications, the errors are calculated relative to the smooth tip (Bottom). This demonstrates the increase in location perception, due to the fingerprint, on smaller spatial scales. It also highlights the negative impact of the fingerprint on large spatial scales, and that this is negated by the fingerprint (cores) tip. (a) Mean location classification accuracy. (b) Relative percentage change of classification accuracy (smooth as base).

larger spatial scale stimuli. By the looking at the average root mean square difference of taps between data sets, where the values are 0.303, 0.316, and 0.286 pixels for smooth, fingerprint, and fingerprint (cores) respectively, it can be said there is an improvement in the repeatability of the sensor.

V. Discussion

In this study we set out to show that the addition of biomimetic aspects of the human fingerprint to a biomimetic fingertip would improve the localisation perception accuracy of small spatial scales in much the same way as they are believed to in the human fingertip.

We found that the inclusion of papillary ridges on our tactile sensor improves the accuracy of location perception on small spatial scale ($\leq$2.5 mm) to 140–170% of the accuracy of the sensor without this feature. This confirms our prediction that including papillary ridges on a biomimetic tactile sensor enhances the focusing of the stress induced by contact down the pins (intermediate ridges), increasing the rate of change in deflection directionality (from 0.59 pixels mm^{-1} in smooth to 1.03 pixels mm^{-1} in the fingerprint (cores), thus sharpening the sensory recordings. This result also supports the belief that these ridges are linked to edge encoding in human tactile sensing. As mentioned, the definitions of spatial scale used here may change for other fingertips, as the interpretation of spatial scale depends on tip morphology.

There was an expectation that enhancing the dermal stiffness contrast would aid edge encoding and sensing on the smaller spatial scales. However, the results did not support this expectation: the tip with this enhancement was no better nor worse than the fingerprint tip without it. At first sight this would appearer to contradict the FEM model from Gerling [7], which claims that the stiffness contrast at the tip of the intermediate ridges enhances edge encoding. On close examination however, the TacTip already has a contrast between skin and flesh, thus the enhancement used may not have been a necessary addition for enhancing edge encoding.

There was a clear impact on the perceptual accuracy of the tip with the papillary ridges on the larger spatial scale of 20 mm up. The reason for this impact is unknown but may be due to noise in the deflection of the pins, instigated by the interaction between the ridges and the more gradual surfaces at this scale. Interestingly this same effect seems to be absent in the fingerprint (cores) tip. This suggest that the fingerprint tip could be noisy due to the compression of the ridges into the pins causing inconsistent deflections, as the cores would resist compression and thus reflect the surface of more gradual surfaces as if it was a single plainer surface like the smooth tip. This is supported by the average root mean square differences that show that the fingerprint (cores) tip has better repeatability across sets (0.286) when compared to the fingerprint (0.316) and the smooth tip (0.303).

To date, research has shown that the fingerprint aids high temporal frequencies perception [2]–[4] and lightly touched on its influence on local shape detection [5]. The present research provides strong evidence for advantageous influences of the fingerprint on the perception of small spatial scales for both robotics and biology. In addition to this, our findings have shown that having very stiff intermediate ridges may support the papillary ridges and prevent them from impairing tactile sense on large spatial scales.

The inclusion of the fingerprint on the tactile sensor requires minimal extra material, yet provides a strong increases in the versatility of the sensor. Thus papillary ridges could be used to improve other compliant tactile sensors. We expect that the inclusion of the artificial fingerprint in biomimetic fingertips will improve their ability to perform tactile tasks such as edge perception/exploration following and fine feature classification, with potential implications for object perception and manipulation with robotic hands.

VI. Conclusion

This study demonstrates that the location perception of a biomimetic tactile sensor can be improved on small spatial scales by the inclusion of papillary ridges (by up to 140–170% when compared with the smooth tip). It was also found that an enhanced dermal stiffness contrast negates the negative effects of papillary ridges on larger spatial scales in our tip. Therefore, the inclusion of these biomimetic features on other tactile sensors with biomimetic properties should improve the tactile acuity and versatility of the sensors also this study supports the concept that the fingerprint is an amplifier of small spatial scale stimulus, and is thus an extremely versatile adaptation of the human fingertip.

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