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JOINT BLIND AND SEMI-BLIND DETECTION AND CHANNEL ESTIMATION FOR SPACE-TIME TRELLIS CODED SYSTEMS

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ABSTRACT
This paper considers a Multiple-Input Multiple-Output (MIMO) communication system, which uses Space-Time Trellis Coding (STTC). A novel method of decoding STTC without a need to transmit training sequences is developed. The technique uses only a single channel estimate to acquire a complete set of the channels’ estimates while performing STTC detection. The method is akin to blind trellis search techniques (per-survivor processing - PSP) and adaptive Viterbi. Our solution consists of the deployment of a bank of Kalman Filters. The bank of Kalman Filters is coupled with Viterbi type decoders, which produce tentative decisions based on Kalman channel predictions. In return, the Kalman filters use the tentative decisions to update and track the MIMO channels corresponding to a number of tracked hypotheses. The proposed technique is particularly applicable to space-time systems operating in rapidly fading environments, where STTC can be decoded and MIMO channels efficiently tracked without relying on periodic pilot sequences.

1. INTRODUCTION
Until recently considerable effort was put into designing systems so as to mitigate the perceived detrimental effects of multipath propagation. However, recent work [1] has shown that by utilising multiple antenna architectures at both the transmitter and receiver, so-called multiple-input multiple-output (MIMO) architectures, vastly increased channel capacities are possible. The ideas behind space-time trellis coded modulation (STTCM) were first presented in [2]. The maximum likelihood detection of STTC requires provision of the channel state information (CSI). Typically the CSI is acquired via training sequences. The resulting CSI estimates are then fed to a space-frequency Viterbi decoder, which performs an MLSE search. Kalman filter tracking of Space-time block coded system has been first reported in [3]. An attempt has also been made to jointly estimate and decode space-time trellis codes [4]. In [4] the authors propagate posterior distribution for the decoded symbols. This results in a complex nonlinear problem that can only be tackled by particle filters (sequential importance sampling). However, this also introduces a phase ambiguity in this application. Our approach is computationally less demanding and avoids the phase ambiguity problems even in blind version. The approach is based on per-survivor processing (PSP) (blind trellis search techniques) proposed in [5] and [6], to cope with the problem of unknown or fast changing channels. The PSP techniques are based on adaptive Viterbi and LMS detection, and were developed in the context of blind MLSE equalisation. However, PSP is unsuitable in MIMO case.

2. SPACE-TIME CODING
To describe STTC we assume a MIMO system with \( N_T \) transmit and \( N_R \) receive antennas. The information symbols \( \{ s_t ; 1 \leq t \leq T \} \) are encoded to a codeword \( (N_T \times T) \text{ matrix} \): \( \{ c_1, c_2, \ldots, c_T \} \). Each element in \( c_t \) is transmitted from a separate antenna simultaneously. Signals arriving at the receive antennas undergo independent fading. The received signal \( \{ y_t ; 1 \leq t \leq T \} \) is a linear mixture with the coefficients given by the channel \( H_t \), embedded in additive noise:

\[ y_t = H_t c_t + n_t \]  

(1)

In an AWGN channel, the maximum likelihood decoder can be realised using the Viterbi algorithm with the Euclidean metric:

\[ \hat{c}_t = \arg\min_{\tilde{c}_t} \sum_{t=1}^{T} \| y_t - \tilde{H}_t \tilde{c}_t \| ^2 \]  

(2)

In Equation (2) it is assumed that some form of channel estimation resulting in \( \{ \hat{H}_{1:T} \} \) has been performed prior to detection.

3. RECURSIVE CHANNEL ESTIMATION IN SPACE-FREQUENCY TRELLIS CODED SYSTEMS
Is this section the novel technique is developed. It is assumed that only \( \{ H_0 \} \) is available and that this knowledge suffices to estimate \( \{ \hat{H}_{1:T} \} \) and decode the SFTC code. Since the concept rests on the developments from recursive Bayesian estimation theory, we start with a brief recap on recursive Bayesian estimation.

3.1. Recursive Bayesian estimation
The hidden states (unobserved signal) of interest \( \{ h_t; t \in \mathbb{N} \} \) are modelled as a Markov process:

\[ f ( h_t | h_{0:t-1}, y_1, \ldots, y_t ) = f ( h_t | h_{t-1} ) \]  

(3)

The observations \( \{ y_{1:t} \} \) are independently and identically distributed (iid) conditioned on the current state:

\[ f ( y_t | h_0, \ldots, h_{t-1}, y_1, \ldots, y_{t-1} ) = f ( y_t | h_t ) \]  

At time \( t \) the joint posterior distribution is given by Bayes’ theorem:

\[ f ( h_{0:t} | y_{1:t} ) = \frac{ f ( y_{1:t} | h_{0:t} ) f ( h_{0:t} )}{ f ( y_{1:t} | h_{0:t} ) f ( h_{0:t} ) \text{d} h_{0:t} } \]  

(4)
The problem amounts to finding a transform \( f (b_{0:t+1} | y_{0:t+1}) = \Phi \{ f (b_{0:t} | y_{0:t}) \} \) To find out the required transform \( \Phi \) we invoke Bayes’ theorem:\n\[
\begin{align*}
f (b_{0:t+1} | y_{0:t+1}) &= f (b_{0:t+1} | y_{t+1}, y_{0:t}) = \\
&= \frac{f (y_{t+1} | b_{0:t+1}, y_{0:t}) f (b_{0:t+1} | y_{0:t})}{f (y_{t+1} | y_{0:t})}
\end{align*}
\]
However, the observations are conditionally independent:
\[
f (y_{t+1} | b_{0:t+1}, y_{0:t}) = f (y_{t+1} | b_{0:t+1})
\]
This leads to the required recursive formula:
\[
f (b_{0:t+1} | y_{0:t+1}) = \frac{f (y_{t+1} | b_{0:t+1}) f (b_{0:t+1} | y_{0:t})}{f (y_{t+1} | y_{0:t})}
\]
The above step updates the prior density \( f (b_{0:t+1} | y_{0:t}) \) once the measurements \( y_{t+1} \) become available. To complete the recursions the prior density has to be specified. This is known as a prediction step:
\[
f (b_{0:t+1} | y_{0:t}) = \int f (b_{0:t+1} | b_{0:t}) f (b_{0:t} | y_{0:t}) \, db_{0:t}
\]
Equations (6) and (7) constitute a basis for Bayesian recursive estimation. Deceptively, the above recursions are straightforward to perform. However, the integrals involved are, in general, too difficult to compute. An exception is the case, where the states evolve according to some linear function and both the state and the observation noise are Gaussian.

### 3.2. Application of channel estimation in STTC

It is well known that the Kalman filter is an optimum Bayesian recursive estimator when both the state transitions and observation systems are linear and both the state and the observation noise are Gaussian. The Kalman filter performs the recursions from previous section, when the underlying problem has a form:

The estimated state \( \hat{b}_{t} \) evolves according to:
\[
\hat{b}_{t+1} = A_{t} \hat{b}_{t} + w_{t+1}
\]
And the observed signal is given by:
\[
y_{t+1} = C_{t} \hat{b}_{t+1} + v_{t+1}
\]
The state noise \( w_{t} \) and the observation noise \( v_{t} \) are distributed according to:
\[
f (w_{t}) = N (0, Q)
\]
\[
f (v_{t}) = N (0, R)
\]
Equations (8,9,10,11) imply that the estimated process evolves sequentially and constitutes what is known as Gauss-Markov random process.

We can now cast our problem of channel estimation in STTC onto the above framework. In order to apply the Kalman filter framework we need to redefine equation (1) to the equivalent form as in (9), which is achieved by defining \( C_{t} \) and \( b_{t} \) as:
\[
C_{t} = \begin{bmatrix} e_{t}^{T} & 0^{T} & \cdots & 0^{T} \\ 0^{T} & e_{t}^{T} & \cdots & 0^{T} \\ \vdots & \vdots & \ddots & \vdots \\ 0^{T} & 0^{T} & \cdots & e_{t}^{T} \end{bmatrix}
\]
\[
b_{t} = \text{vec} \left\{ \hat{b}_{t}^{T} \right\}
\]

As mentioned in the previous section, sequential estimation amounts to repeated calculations of two alternating steps: prediction and update.

#### 3.2.1. Prediction

Suppose that the random variable \( b_{t+1} \) conditioned on the observations \( y_{1:t} \), is Gaussian:
\[
f (b_{t+1} | y_{1:t}) = N (\mu_{t}, P_{t})
\]
From equation (8) it can be deduced that \( f (b_{t+1} | b_{t}) = N (A_{t} b_{t}, Q) \) \( (A \) is a constant matrix here: \( A_{t} = A \). Then from equation (7) the predictive marginal distribution is given by:
\[
f (b_{t+1} | y_{1:t}) = \int N (A_{t} b_{t}, Q) N (\mu_{t}, P_{t}) \, db_{t}
\]
After some tedious but straightforward manipulations this becomes:
\[
f (b_{t+1} | y_{1:t}) = N \left( A_{t} \mu_{t}, Q + A_{t} P_{t} A^{T} \right)
\]
Following definitions are made: \( \mu_{t+1} = A_{t} \mu_{t} \) and \( P_{t+1} = Q + A_{t} P_{t} A^{T} \). Then the predictive density is fully defined by:
\[
f (b_{t+1} | y_{1:t}) = N \left( \mu_{t+1} , P_{t+1} \right)
\]

#### 3.2.2. Update

Using (17) and (11), the update formula of (6) can be specified as:
\[
f (b_{t+1} | y_{1:t+1}) = \frac{N (C_{t+1} b_{t+1}, R) N (\mu_{t+1}, P_{t+1})}{f (y_{t+1} | y_{1:t})}
\]
After some tedious algebraic manipulations the posterior marginal density is expressed as:
\[
f (b_{t+1} | y_{1:t+1}) = N \left( \mu_{t+1}, P_{t+1} \right)
\]
with the following notation:
\[
P_{t+1} = [I - K_{t+1} C_{t+1}] P_{t+1} \quad K_{t+1} = P_{t+1} C_{t+1} R^{-1} \quad \mu_{t+1} = \mu_{t+1} + K_{t+1} [y_{t+1} - C_{t+1} \mu_{t+1}]
\]
Since both the predictive density \( f (b_{t+1} | y_{1:t}) \) and the updated posterior density \( f (b_{t+1} | y_{1:t+1}) \) are Gaussian, the mean and covariance describes them completely.

#### 3.3. Description of the proposed algorithm

The initial training results in an estimate \( \hat{b}_{0} \). This estimate, together with the corresponding covariance matrix, is propagated to the next time instant using eq (16). The prior channel estimate \( \hat{b}_{t+1} \) and thus \( \hat{b}_{t+1} \) via eq. (13) is simply the mean \( \mu_{t+1} \) of the predictive density in (16). It is important for this method that the SFTC trellis always starts from a known state. This is depicted in figure 1, where it is assumed that the trellis starts from a zero state. For simplicity, of presentation figure 1 depicts a 4 state BPSK space-time code. In this case the two possible input symbols (‘0’ and ‘1’) would result in two transitions (to state 0 and state 1 respectively). Corresponding to the two transitions there are two codewords: \( c^{(0,0)} \) and \( c^{(0,1)} \) (and thus \( C^{(0,0)} \) and \( C^{(0,1)} \)) via eq. (12). The superscript \( (i,j) \) denotes a transition from an \( i^{th} \) state to the \( j^{th} \). Subsequently, the update of the channel estimates is performed. Using set of equations (20) the process (channels), the channels covariance matrices and the Kalman gain matrices all get updated. Since the \( C^{(i,j)} \) are in general different, the update
A novel joint detection and channel estimation technique has been developed for Space-Time Trellis Coded systems. The technique uses only a single initial estimate in the semi-blind and none in the
Fig. 3. Phase tracking versus consecutive data symbols (4-PSK) over 1 frame @ FDoppler = 500Hz (635kph) of our technique. The MIMO system uses 16 state 4-PSK code with 2 Tx and 2 Rx antennas.

Fig. 4. FER of space-time coding enhanced D-AMPS (IS-136) versus SNR @ FDoppler = 120Hz (carrier fc = 850MHz).

blind mode. In both cases the entire channel estimate is fully recovered and SFTC is decoded even in fast faded channels. The technique allows space-time coded systems operate at much higher Doppler spreads. It does not require determination of the expected Doppler spread before transmission.

6. REFERENCES


