MAP BASED SCHEMES FOR DETECTION OF ABRUPT CHANGES FOR FADING CHANNELS

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ABSTRACT

An algorithm for discrimination and detection of the two phenomena double talk and abrupt changes in the echo path is proposed for fading channels. Being able to discriminate and detect these two phenomena is crucial since the echo canceler must react differently. The suggested detection scheme is based on a sequential detection approach. The communication channel is modeled as a randomly time-varying linear system. An autoregressive model is used to describe the time evolution of the channel taps. The channel parameters are identified using a Kalman filter coupled with a recursive least squares algorithm, and, based on model assumptions, the maximum a posteriori probabilities corresponding to double talk and abrupt echo path changes are calculated. The proposed scheme is verified experimentally by way of computer simulations.

1 INTRODUCTION

In many communication channels, the signal to be transmitted is disturbed by ambient noise and acoustic echoes. It is necessary to consider the situation where echo is not negligible and echo control will be needed for the radio paths to all mobile terminals if these paths involve more than 40 milliseconds round trip delay [8]. So, a processing to reduce the disturbances must be performed before transmission. Typically, an acoustic echo canceler is used [1, 2]. When the near-end talker is silent, the adaptation of the echo canceler works well. During double talk, *i.e.* both subscribers talking simultaneously, though, the adaptation rate of the echo canceler should be reduced drastically in order to prevent the filter coefficients from diverging. When an abrupt change in the echo path occurs, the adaptation rate should, of course, instead be increased. Consequently, the echo canceler must react differently depending on whether double talk or an abrupt change in the echo path occurs, and by just studying the prediction error of the echo canceler, no conclusion can be made since both phenomena cause abruptly increased prediction errors. The problem is further complicated when the communication channel is subject to fading and scattering effects.

Here, the echo path is modeled as a finite impulse response (FIR) with randomly time-varying taps. Fitting a model to the variations of the channel taps is of course a challenging task because the tap coefficients are not observed directly. The first and simplest assumption on the time-variations of the taps is to use a random walk model. The design of the echo canceler is then a standard adaptive filtering problem. We will however use a more general approach by including a hypermodel in which the time variation is explicitely modeled as an autoregressive (AR) model. The channel taps are here described by general, multichannel AR processes. That is, both scattering and fading effects are included in the model. Frequency-selective fading is encountered in several communication applications and presents a major impeding factor [3, 4, 5]. Thus, our model is appropriate for the aforementioned channels, and the hypermodel, if known, is able to predict the time variations well. The problem here is that we are facing a non-linear filtering problem. We suggest a two-step method, where the hypermodel and FIR taps are estimated separately. The random walk model then becomes a special case.

The key point with this paper is to, based on model assumptions, compute the maximum a posteriori (MAP) test of the hypotheses normal mode, double talk and abrupt echo path change, respectively. The proposed method is based on running three parallel filters. The first one is a standard adaptive filter for estimating the FIR coefficients, and the other two are based on assumptions on double talk and echo path change, respectively. The first filter is applied to data over a long time horizon, while the latter ones are fed with data from a (rather short) sliding window in order to capture the fast time variations of the assumed events. The result of these three filters are compared in a MAP based hypothesis test. In [6], a similar approach to the same problem is proposed for the case when the communication system is a telephone channel.

2 MODELLING THE MULTIPATH FADING CHANNEL

In this paper, we consider a wireless communication channel which suffers from fading, scattering effects as well as abrupt changes in the channel characteristics due to double talk and abrupt changes in the echo path. The model used in this paper for describing fading effects is the same as in [7]. The output signal, y, consists of the echo signal, s, the background noise, n, and the double talk signal, d. We model the communication channel with an FIR filter of order P with stochastically time-varying taps that are assumed to be described with an AR process of order Q. The measurement noise consists of double talk and background noise and is modeled with a zero-mean Gaussian process. To sum up, the following model assumptions are made.

A0: $y(k) = s(k) + d(k) + n(k)$

A1: $s(k) = \sum_{j=0}^{P-1} h(k,j)u(k-j)$

A2: $h(k+1) = \sum_{j=0}^{Q-1} a_{j+1}h(k-j) + v(k)$

A3: $d(k) + n(k) = \sigma(k)e(k)$

where $\{u(k)\}$ denotes the known input signals, $\{e(k)\}$ and $\{v(k)\}$ are two uncorrelated zero mean Gaussian processes with variance 1 and covariance matrix σ_v^2, respectively, $h(k) = [h(k,0), h(k,1), \ldots, h(k,P-1)]^T$. The matrices $a_j, j = 1, \ldots Q$, have dimensions $P \times P$ and, in case they are not diagonal, model the scattering effect.

The communication system described by the model assumptions A0–A3, can be written in the following state-space form.

$$\begin{cases} x(k+1) &= Ax(k) + bv(k) \\ y(k) &= c^T(k)x(k) + \sigma(k)e(k) \end{cases} \quad (1)$$

where $c(k) = [u(k), u(k-1), \ldots, u(k-P+1), 0, \ldots, 0]^T, x(k) = [h^T(k), h^T(k-1), \ldots, h^T(k-Q+1)]^T$ and

$$A = \begin{bmatrix} a_1 & a_2 & \cdots & a_{Q-1} & a_Q \\ I & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{bmatrix} \quad (2)$$

is an unknown $PQ \times PQ$ matrix and $b = [I, 0, \ldots, 0]^T$. *Remark:* It has been shown in signal propagation studies, that the delay spread is a rather small number. In the North American Cellular Standard it has been shown that $P = 2$ [9].

3 OBJECTIVES

The objective of this paper is to study parameter tracking for fast time-varying communication channels, and, specifically, detect and discriminate between different kinds of abrupt changes in the channel characteristics. Using the state-space formulation in the previous section, we model an abrupt echo path change at time k as follows.

$$\begin{cases} x(t+1) &= Ax(t) + bv(t) + \xi\delta(k-t) \\ y(t) &= c^T(t)x(t) + \sigma(t)e(t) \end{cases} \quad (3)$$

If, on the other hand, the standard deviation, σ, of the measurement noise increases abruptly, we say, that double talk is present.

Assume that the following model holds for the communication system for $j < k$

$$\begin{cases} x(j+1) &= Ax(j) + bv(j) \\ y(j) &= c^T(j)x_0(j) + \sigma_0 e(j) \end{cases} \quad (4)$$

and that the following model holds for the system for $j > k$

$$\begin{cases} x(j+1) &= Ax(j) + bv(j) \\ y(j) &= c^T(j)x_1(j) + \sigma_1 e(j) \end{cases} \quad (5)$$

Assuming that hypothesis H_0 holds at time $k-1$, we define, based on the discussion above, the following hypotheses.

H_0 : $x_0(k) = x_1(k)$, $\sigma_0 = \sigma_1$ Nothing has happened at time k.

H_1 : $x_0(k) \neq x_1(k)$, $\sigma_0 = \sigma_1$ An abrupt echo path change occurs at time k.

H_2 : $x_0(k) = x_1(k)$, $\sigma_0 \neq \sigma_1$ Double talk occurs at time k.

Our proposed detection scheme is based on a sequential detection approach, *i.e* a global channel model is compared with a local one over a sliding window with a fixed length, L, and by calculating the MAP probabilities for the hypotheses above, we decide whether an abrupt echo path change or double talk has occurred or not. Finally, use a stopping rule to conclude which hypothesis holds.

4 DETECTION OF ABRUPT CHANGES IN THE CHANNEL CHARACTERISTICS

In order to detect and discriminate between abrupt changes in the echo path and double talk, we propose a sequential detection approach using a sliding window [10]. That is, we segment the output signal at time t into two segments, where the latter one consists of the last L samples, where L is a fixed number, and the first one is growing as time evolves. Based on model structure assumptions, the models connected to these two data sets are estimated by applying a channel identification method consisting of a Kalman filter coupled with an RLS algorithm. The RLS algorithm updates continuously the AR parameters over a sliding window of length N.

4.1 Tracking of the Channel Coefficients

The channel identificatfion method used in this paper is strongly influenced by the one proposed in [7]. The idea is, thus, to couple a Kalman filter with a RLS method and a system of Yule-Walker equations. The RLS algorithm and the system of Yule-Walker equations are used, based on known output and input signals and estimates of the channel taps, to estimate the AR parameters in the channel model, and the Kalman filter provides estimates of the channel taps based on known output and input signals and estimates of the AR parameters. Due to space limitations, these equations are not given here.

4.2 Derivation of the MAP Probabilities for Double Talk and Abrupt Echo Path Changes

In [6], the problem of detecting abrupt changes in the tap coefficients and in the variance of the measurement noise of an FIR channel with constant taps between the abrupt changes. Here, we consider the same problem but having randomly time-varying taps. Using results in [6, 11], the following result is achieved.

Result 4.1 Consider the signal model (1) and the hypotheses given in Section 3. The a posteriori probabilities are given by

$$l_i = -2\log p(H_i|y(1), y(2), ..., y(t)),\ i = 0, 1, 2. \quad (6)$$

Assume that $H_i, i = 0, 1, 2$, is Bernoulli distributed with probability q_i, *i.e.*

$$p(H_i) = \begin{cases} 0, & \text{with probability } 1 - q_i \\ 1, & \text{with probability } q_i \end{cases}, \quad (7)$$

For large t and L, $t \gg L$, the following approximations can, using Stirling's formula, be made

$$\begin{aligned} l_0 &\approx (n_0 + n_1 - 2)\log\left(\frac{V_0(x_0) + V_1(x_0)}{n_0 + n_1 - 4}\right) \\ &\quad + D_0(x_0) + D_1(x_0) - 2\log(q_0), && (8) \\ l_1 &\approx (n_0 + n_1 - 2)\log\left(\frac{V_0(x_0) + V_1(x_1)}{n_0 + n_1 - 4}\right) \\ &\quad + D_0(x_0) + D_1(x_1) - 2\log(q_1), && (9) \\ l_2 &\approx (n_0 - 2)\log\left(\frac{V_0(x_0)}{n_0 - 4}\right) + (n_1 - 2)\log\left(\frac{V_1(x_0)}{n_1 - 4}\right) \\ &\quad + D_0(x_0) + D_1(x_0) - 2\log(q_2). && (10) \end{aligned}$$

where q_i denotes the prior probability of H_i and where P_i denotes the covariance matrix of $h_i, i = 0, 1$ and where the loss function, V_i, is the sum of squared prediction errors, *i.e.*,

$$\begin{aligned} V_0(x_0) &= \sum_{k=1}^{t-L} \left(y(k) - c^T(k)x_0(k)\right)^T \sigma_w^{-2} \\ &\quad \times \left(y(k) - c^T(k)x_0(k)\right) \quad (11) \end{aligned}$$

and

$$\begin{aligned} V_1(x_1) &= \sum_{k=t-L+1}^{t} \left(y(k) - c^T(k)x_1(k)\right)^T \sigma_w^{-2} \\ &\quad \times \left(y(k) - c^T(k)x_1(k)\right) \quad (12) \end{aligned}$$

and where S_i denotes the prediction error covariance matrix

$$\begin{aligned} S_0(k) &= c^T(k)P_0(k)c(k) + \sigma^2(k), \\ &\quad k \in \{1, 2, \ldots, t - L\} \quad (13) \end{aligned}$$

and

$$\begin{aligned} S_1(k) &= c^T(k)P_1(k)c(k) + \sigma^2(k), \\ &\quad k \in \{t - L + 1, \ldots, t\}. \end{aligned}$$

and

$$D_0(x_0) = \sum_{k=1}^{t-L} \log\det S_0(k, x_0), \quad (15)$$

$$D_1(x_j) = \sum_{k=t-L+1}^{t} \log\det S_1(k, x_j),\ j = 0, 1. \quad (16)$$

$$\begin{aligned} V_1(x_0) &= \sum_{k=t-L+1}^{t} \left(y(k) - c^T(k)x_0(k)\right)^T \sigma_w^{-2} \\ &\quad \times \left(y(k) - c^T(k)x_0(k)\right), \quad (17) \end{aligned}$$

where

$$x_0(k) = \left(\prod_{j=t-L+1}^{k} A(j)\right) x_0(t-L),\ k \in \{t-L+1, \ldots t\} \quad (18)$$

To sum up, the involved quantities are defined below.

$$\begin{array}{rcc} \text{Data}: & \multicolumn{2}{c}{\underbrace{y_{t-N+1}, .., y_t}} \\ \text{RLS est.combined with} & & \\ \text{sol. from Yule} - \text{Walker eq.}: & \multicolumn{2}{c}{A(t)} \\ \text{Data}: & \underbrace{y_1, .., y_{t-L}}, & \underbrace{y_{t-L+1}, .., y_t} \\ \text{Model}: & M_0 & M_1 \\ \text{Kalman est.}: & x_0, P_0 & x_1, P_1 \\ \text{Pred. error cov. matrices}: & S_0 & S_1 \\ \text{Loss functions}: & V_0(x_0) & V_1(x_1) \\ \text{Number of data}: & n_0 = t - L & n_1 = L \\ \text{MAP function}: & \multicolumn{2}{c}{l_i, i = 1, 2, 3} \end{array}$$

□

Remark: In order to reduce the sensitivity when the input signal u is close to zero, *i.e.* during silence, an inverse Wishart prior [11, 12] can been used on the variance. The likelihood functions are then modified according to [6].

4.3 Detection Scheme

A segmentation approach is used since we want to detect frequent abrupt changes. Furthermore, we want the alarm time to be estimated as accurately as possible rather than as fast as possible. The last statement holds since the abrupt change will, if it is observed, be detected within a window length, L.

Detection algoritm:

- Step 0. Choose the model structure, *i.e.* P and Q, the length, L, of the sliding window. Let $t := 0$.
- Step 1. If $t < L$, let $t := t + 1$.
- Step 2. Estimate the AR-parameters, *i.e.* estimate $a_l(t), l = 1, \ldots Q$, based on the data with time indices in the set $\mathcal{N} = \{t - N + 1, t - N + 2, \ldots t\}$.
- Step 3. Estimate h_0, h_1, P_0, P_1 by applying Kalman filters to (1) using the estimates of $a_l,\ l = 1, \ldots Q$ from Step 2.
- Step 4. Compute S_0, S_1, V_0, V_1 using (11)-(14).
- Step 5. Compute by using Result 4.1, the maximum a posteriori probabilities, $l_i,\ i = 1, 2, 3$, for the hypotheses $H_i,\ i = 1, 2, 3$.
- Step 6. Use a stopping rule to conclude which hypothesis is valid.
- Step 7. If H_0 is rejected, restart the algorithm by letting $t := t + 1$ and going to Step 0.
- Step 8. Let $t := t + 1$ and goto Step 2.

5 SIMULATION STUDIES

In this section, the proposed detection scheme is evaluated by way of computer simulations. The AR parameters are not estimated and chosen as in [13], *i.e.*,

$$A = \begin{bmatrix} 1.9958 & 1.0000 \\ -0.9960 & 0 \end{bmatrix}.$$

That is, we fix the dimensions P, Q to be equal to 2 and 1, respectively, Furthermore, the standard deviations of the noise processes are chosen as $\sigma_v = 0.005, \sigma_0 = 0.0015, \sigma_1 = 1$. The length of the used sliding window was 50. A change in the echo path was simulated during the time interval $[275, 350]$ and double talk during the time interval $[200, 275]$. In Fig. 1, the results of 100 different noise realizations are presented. We can conclude that, in these simulation studies, our proposed detection scheme succeeds in detecting the simulated hypotheses with probability higher than 90%.

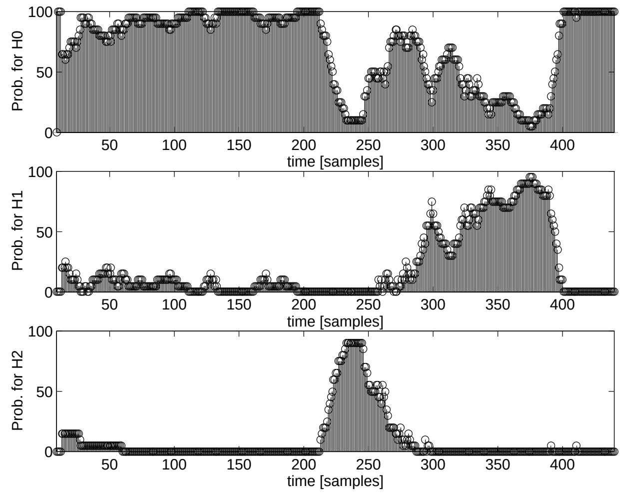

Figure 1: Probablity for alarm for the different hypotheses

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