A SEMI-BLIND CHANNEL IDENTIFICATION METHOD FOR GSM RECEIVERS

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ABSTRACT

In this paper, we present a semi-blind channel identification scheme for GSM system. Even though the GMSK signal has almost zero excess bandwidth (oversample will give no more information), two diversity channels for each GMSK signal can be generated using a de-rotation scheme without additional antennas. Based on this single input and two output system, the semi-blind algorithm is applied to GSM signals under multipath distortions successfully. Simulation results are presented.

1. INTRODUCTION

The European GSM cellular wireless system has become a dominant wireless telephone standard today. Structured as a TDMA scheme within FDMA, GSM system use data burst as basic data unit for each user. The structure of a burst is shown in Figure 1. Due to the possibly fast time-variation of the wireless environment, the 26 bit training sequence, in the middle of each burst, is used to identify the combined channel impulse response (transmitter filter, physical channel, receiver filter). The estimated channel can then be used for receivers to recover the original data sequence through Viterbi algorithm. The complexity of the wireless environment can cause the channel length to vary. Sometime, 26 bit training sequence is not long enough to accurately estimate long channels. In [2], we presented a new method of blind channel equalization for GSM system without additional antenna unit. However, since the 26 bit training sequence is in standard GSM systems, a practical combination of the blind and training method to improve the overall GSM system performance is practically useful.

3	58 bits	26bits	58 bits	3	8.25
tail	data	training	data	tail	guard

Figure 1. GSM data frame for a single user.

Two obstacles must be overcome before blind/semi-blind algorithm can be used to GSM system. First, since GSM uses a nonlinear GMSK phase modulation techniques, we need a good linear approximation for GMSK modulation in order to comply with traditional blind equalization models. Second, even if GMSK signals can be approximated as QAM linear modulation system (as shown in the next section), the modulated signal has almost zero excess bandwidth [7]. Without using additional antenna, a de-rotation scheme [1] creates two diversity channels. Once these two obstacles are overcome, an explicit semi-blind algorithm can be applied to GSM system. In this paper, we shall show how these two obstacles are overcome and how semi-blind and blind equalizers can be developed for the nonlinear GMSK signal with zero-excess bandwidth.

2. LINEAR MULTI-CHANNEL MODELING OF GSM SYSTEM

2.1. Linear Approximation of GMSK Signals

GSM system uses nonlinear GMSK phase modulation which transmits a signal

$$s(t) = \exp\{j[\frac{\pi}{2}\sum_{n=-\infty}^{\infty}\alpha_n\phi(t-nT)]\} \tag{1}$$

where $\alpha_n \in \{\pm 1\}$ is the information bit. The pulse $\phi(t)$ is the integration of Gaussian pulse

$$\phi(t) = \int_{-\infty}^{t} g(\tau)d\tau \tag{2}$$

$$g(t) = B\sqrt{\frac{\pi}{2\ln 2}}exp(-\frac{\pi^2 B^2 (t-2T)^2}{2\ln 2}). \tag{3}$$

For GSM, $BT = 0.3$ is chosen and correspondingly we have

$$\phi(t) = \begin{cases} 0 & t \leq 0 \\ 1 & t \geq 4T \end{cases} \tag{4}$$

Following the linear approximation approach in [1] and [2], we can obtain an approximated linear model of GMSK as:

$$s(t) = \sum_{n=-\infty}^{\infty} a_n p_0(t-nT), \quad a_n = j\alpha_n a_{n-1}. \tag{5}$$

Unfortunately, the QAM pulse $p_0(t)$ has almost zero excess bandwidth, which means that oversampling will not generate multiple diversity channel outputs. Since channel diversity data is crucial for SOS blind algorithm as well as semi-blind algorithm based on SOS blind algorithm, we use a de-rotation method to induce channel diversity.

2.2. De-rotation for Channel Diversity

We observe that $a_n = j\alpha_n a_{n-1}$ at any given time can only take on two values. In other words, a_n is a pseudo-QPSK and is realized by rotating a BPSK signal. Hence, we can de-rotate the pseudo-QPSK signal by

$$\tilde{a}_{n-i} \triangleq j^{-(n-i)} a_{n-i} = \pm 1. \qquad (6)$$

For channel impulse response $c(t)$, the received signal is approximately

$$x(t) = \sum_{k=-\infty}^{\infty} s_k h(t - kT) + w(t), \qquad (7)$$

where $h(t) = p_0(t) * c(t)$ is the combined channel response and $w(t)$ is channel noise. The sampled discrete signals and responses are defined by

$$x_i \triangleq x(iT), \quad h_i \triangleq h(iT), \quad w_i \triangleq w(iT). \qquad (8)$$

The channel output samples are hence

$$x_n = \sum_{k=-\infty}^{\infty} h_k a_{n-k} + w_n.$$

As a result, we can obtain a new (de-rotated) sequence

$$\tilde{x}_n \triangleq x_n j^{-n} = \sum_{k=-\infty}^{\infty} [h_k j^{-k}] \tilde{a}_{n-k} + j^{-n} w_n. \qquad (9)$$

Since $\{\tilde{a}_n\}$ is a real sequence, we can induce two sub-channel outputs through:

$$\begin{aligned} x_{1,n} \triangleq Re\{\tilde{x}_n\} &= \sum_{k=-\infty}^{\infty} Re[h_k j^{-k}] \tilde{a}_{n-k} + Re[j^{-n} w_n] \\ x_{2,n} \triangleq Im\{\tilde{x}_n\} &= \sum_{k=-\infty}^{\infty} Im[h_k j^{-k}] \tilde{a}_{n-k} + Im[j^{-n} w_n] \end{aligned}$$

¿From the BPSK input data sequence, two sub-channel outputs can now be generated. We hence have shown that even without oversampling and extra antenna, existing method based on second order statistics can be applied if two sub-channel impulse responses

$$\{h_{1,i}\} = \{Re(h_i j^{-i})\} \quad \text{and} \quad \{h_{2,i}\} = \{Im(h_i j^{-i})\}$$

do not have common zeros.

Assume the channel order is L, sampled channel output signal vector of length M can be written as

$$\tilde{\mathbf{x}}[k] \triangleq \begin{bmatrix} \tilde{x}_k \\ \tilde{x}_{k-1} \\ \vdots \\ \tilde{x}_{k-M+1} \end{bmatrix} = \mathcal{H} \tilde{\mathbf{a}}[k] + \tilde{\mathbf{v}}[k]. \qquad (10)$$

where

$$\begin{aligned} \tilde{\mathbf{a}}[k] &\triangleq [\tilde{a}_k \ \ \tilde{a}_{k-1} \ \ \ldots \ \ \tilde{a}_{k-L-M+1}]' \\ \tilde{\mathbf{v}}[k] &\triangleq [j^{-k} w_k \ \ j^{-k+1} w_{k-1} \ \ \ldots \ \ j^{-k+M-1} w_{k-M+1}]' \end{aligned}$$

and the $M \times (L + M)$ channel Toeplitz matrix is defined by

$$\mathcal{H} = \begin{bmatrix} h_0 & h_1 j^{-1} & \ldots & h_L j^{-L} & 0 & \ldots & 0 \\ 0 & h_0 & h_1 j^{-1} & \ldots & h_L j^{-L} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & \ldots & 0 & h_0 & h_1 j^{-1} & \ldots & h_L j^{-L} \end{bmatrix}. \qquad (11)$$

Since $\tilde{\mathbf{a}}[k]$ is binary real, we arrive at the familiar equation

$$\mathbf{x}[k] = \mathbf{H} \tilde{\mathbf{a}}[k] + \mathbf{v}[k], \qquad (12)$$

where

$$\mathbf{x}[k] \triangleq \begin{bmatrix} Re\{\tilde{\mathbf{x}}[k]\} \\ Im\{\tilde{\mathbf{x}}[k]\} \end{bmatrix}, \qquad \mathbf{H} \triangleq \begin{bmatrix} Re\{\mathcal{H}\} \\ Im\{\mathcal{H}\} \end{bmatrix}, \qquad (13)$$

and $\mathbf{v}[k]$ approximates error and channel noise:

$$\mathbf{v}[k] \triangleq \begin{bmatrix} Re\{\tilde{\mathbf{v}}[k]\} \\ Im\{\tilde{\mathbf{v}}[k]\} \end{bmatrix}. \qquad (14)$$

$\mathbf{H}$ will have full column rank if $\{h_{1,i}\}$ and $\{h_{2,i}\}$ have no common zeros. For notational convenience, define subchannel vectors as

$$\begin{aligned} \mathbf{h}_1 &= [h_{1,0} \ \ h_{1,1} \ \ \cdots \ \ h_{1,L}]^T \\ \mathbf{h}_2 &= [h_{2,0} \ \ h_{2,1} \ \ \cdots \ \ h_{2,L}]^T \end{aligned}$$

3. A SEMI-BLIND ALGORITHM FOR GSM

SOS channel identification based on SIMO channel model was first addressed by Tong *et al.* [3]. A MUSIC-like subspace method (SSM) was later developed by Moulines and co-workers in [5]. A least-squares sub-channel matching (SCM) algorithm was also proposed by Xu *et al.* [4]. The SCM algorithm is simple but has a key drawback of being sensitive to channel length estimate. Given the 26 training bits in GSM, the channel length can be more accurately determined and a semi-blind approach can be described.

Define

$$\mathbf{X} = \begin{bmatrix} \tilde{\mathbf{x}}(L) & \cdots & \tilde{\mathbf{x}}(0) \\ \tilde{\mathbf{x}}(L+1) & \cdots & \tilde{\mathbf{x}}(1) \\ \vdots & \ldots & \vdots \\ \tilde{\mathbf{x}}(N) & \cdots & \tilde{\mathbf{x}}(N-L) \end{bmatrix}. \qquad (15)$$

Because both $Re\{\tilde{\mathbf{x}}[\mathbf{k}]\}$ and $Im\{\tilde{\mathbf{x}}[\mathbf{k}]\}$ are output with the same input, the following equality holds

$$[Im(\mathbf{X}) \quad -Re(\mathbf{X})] \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix} = \mathbf{0}. \qquad (16)$$

Concurrently, GSM provides a short training sequence of 26 bits for every frame. This training sequence can be used to assist the receiver in channel estimation. Since (12) also holds for the training sequence, we can rewrite the equation for training sequence as:

$$\begin{bmatrix} Re(\tilde{\mathbf{x}}[K : K+M]) \\ Im(\tilde{\mathbf{x}}[K : K+M]) \end{bmatrix} = \begin{bmatrix} A_t & \mathbf{0} \\ \mathbf{0} & A_t \end{bmatrix} \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix} \qquad (17)$$

where K is starting position of training sequence in data burst and $M+1$ is the length of training sequence.

Assume $M \geq L$. The de-rotated training sequence forms a Hankel data matrix

$$A_t = \begin{bmatrix} \tilde{a}_{K+M} & \tilde{a}_{K+M-1} & \dots & \tilde{a}_{K+M-L} \\ \tilde{a}_{K+M-1} & \tilde{a}_{K+M-2} & \dots & \tilde{a}_{K+M-L-1} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{K+L} & \tilde{a}_{K+L-1} & \dots & \tilde{a}_{K} \end{bmatrix}$$

Now combining equations (16) and (17), we obtain an augmented linear equation for channel estimation.

$$\begin{bmatrix} Im(\mathbf{X}) & -Re(\mathbf{X}) \\ \tilde{\mathbf{A}}_\mathbf{t} & 0 \\ 0 & \tilde{\mathbf{A}}_\mathbf{t} \end{bmatrix} \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ Re(\tilde{\mathbf{x}}[K:K+M]) \\ Im(\tilde{\mathbf{x}}[K:K+M]) \end{bmatrix} \quad (18)$$

The channel estimate can be solved from this least square equation.

In actual GSM receivers, maximum likelihood sequence estimation (MLSE) is implemented using the Viterbi Algorithm (VA). The de-rotated input data is only binary and VA can be easily implmented using our one-input-two-output system model without additional states or computations. Our simulation results are based on the VA algorithm.

4. PROPERTIES OF SEMI-BLIND METHOD

The sufficient and necessary condition for SOS blind channel identification is well established [3][5]. When a single input generates M outputs from M sub-channels $\{h_i(z)\}_{i=1}^{M}$, the channel can be blindly identified from second order statistics if and only if they are coprime (no common roots). If there is a common root shared by all subchannel, we can blindly identify all uncommon zeros except for a common factor.

For semi-blind identification, additional deterministic equation can assist channel identification. Here we characterize how semi-blind identification can relax the SOS identification conditions by virtue of its additional information. We need to consider identification of this common factor to determine if they are semi-blindly identifiable.

Denote $\hat{h}_i(z)$ as the $i-$th channel estimate. Let $\vec{\mathbf{h}}(z)$ be a vector polynomial with $i-$th entry $h_i(z)$ and $\hat{\mathbf{h}}(z)$ be a vector polynomial with $i-$th entry $\hat{h}_i(z)$. Recall that the order of channel $\vec{\mathbf{h}}$ is L. Let the order of channel estimate $\hat{\mathbf{h}}$ be L_e.

Lemma 5.1: *If there is a common factor $p(z)$ of order L_p shared by all sub-channels $\{h_i(z)\}_{i=1}^{M}$, then there exists common factor $c(z)$ such that for SCM channel estimates*

$$h_i(z)c(z) = \hat{h}_i(z)p(z)$$

and $c(z)$ is a common factor in all estimates $\{\hat{h}_i(z)\}_{i=1}^{M}$ with (ambiguity) order $Lc = (L_e - L) + L_p$.

Proof Let $Z\{\cdot\}$ denote the zeros for a polynomial. For subchannels sharing a common factor $p(z)$, $h_i(z) = p(z)h'_i(z)$ and polynomials $\{h'_i(z)\}_{i=1}^{M}$ are coprime. From SCM identification [4], we have:

$$h'_i(z)p(z)\hat{h}_j(z) = h'_j(z)p(z)\hat{h}_i(z), \forall j. \quad (19)$$

Because $h'_i(z)$ and $h'_j(z)$ are coprime, we have

$$Z\{h'_i(z)\} \subset Z\{\hat{h}_i(z)\}, \quad (20)$$

in other words,

$$\hat{h}_i(z) = h'_i(z)c_i(z).$$

Now, we can substitute it back into (19):

$$h'_i(z)p(z)c_j(z)h'_j(z) = h'_j(z)p(z)c_i(z)h'_i(z). \quad (21)$$

It is therefore simple to see that

$$c_j(z) = c_i(z) = c(z)$$

is a common factor to all channel estimate. Moreover since

$$\vec{\mathbf{h}}(z)c(z) = \hat{\mathbf{h}}(z)p(z),$$

We have $L_c = (L_e - L) + L_p$.

□

Lemma 5.2:
If channel estimates have a common factor with ambiguity order L_c, L_c indepent equations are needed from training data to resolve this ambiguity and identify the common factor except for a common gain.

Proof Let $\hat{h}(z)$ be one sub-channel estimate with common factor

$$c(z) = c_0 + c_1 z + \cdots + c_{L_c} z^{L_c},$$

such that

$$\hat{h}(z) = h'(z)c(z).$$

Since

$$h'(z) = h'_0 + h'_1 z + \cdots + h'_{L_e - L_c} z^{L_e - L_c}$$

has been identified, the overall unknown channel parameter vector is simply

$$\hat{\mathbf{h}} = T_h \mathbf{c},$$

in which

$$\hat{\mathbf{h}} \triangleq \begin{bmatrix} \hat{h}_0 \\ \hat{h}_1 \\ \vdots \\ \hat{h}_{L_e} \end{bmatrix} \qquad \mathbf{c} \triangleq \begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_{L_c} \end{bmatrix}, \quad (22)$$

and

$$T_h \triangleq \begin{bmatrix} h'_0 & & \\ \vdots & \ddots & \\ h'_{L_e - L_c} & \ddots & h'_0 \\ & \ddots & \vdots \\ & & h'_{L_e - L_c} \end{bmatrix} \quad (23)$$

If at least L_c independent equations are derived from training data, i.e., we have

$$\mathbf{x} = A\hat{\mathbf{h}}$$

in which A has row rank no less than L_c, then we have

$$\mathbf{x} = AT_h\mathbf{c}.$$

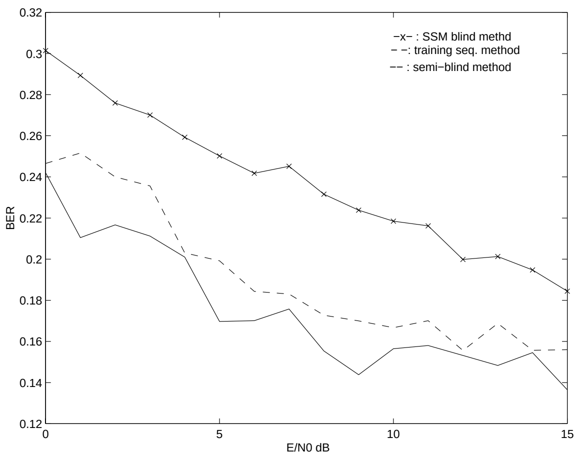

Figure 2. The simulation result for COST207 'BU' environment

Because the Toeplitz matrix T_h has full column rank $L_c + 1$ while A has row rank of at least L_c, the rank of AT_h is at least L_c and $\mathbf{c}$ can be determined with only a common gain ambiguity.

□

This lemma shows how training sequence in semi-blind identification can help resolve the ambiguity in blind equalization. This ambiguity of order L_c may be the result of an over-estimated channel order or the existence of common roots among subchannels. Even when this ambiguity is absent, joint estimation from semi-blind is expected to produce more accurate results.

5. SIMULATION RESULT

We now provide a typical simulation result of GSM system using the de-rotation scheme outlined earlier. The channel model is randomly generated 100 times from COST207[10] using BU environment. A root-raised cosine pulse with roll-off factor 0.1 was selected as the receiver anti-aliasing filter. True GMSK signal oversampled 16 times is generated for the simulation.

The channel order is estimated by using the MDL criterion[11] in all algorithms of comparison. Once channel estimates are obtained, the receiver use Viterbi algorithm to recover the binary data. The performance measure, BER, is averaged over 100 Monte Carlo runs, as shown in Figure 2.

We compared three different methods in simulations: the purely blind subspace method (SSM) by Moulines[5], the semi-blind method, and identification based on training only. The BER from VA demonstrates the advantage of semi-blind identification for GSM. For SNR ranging from 0 to 15dB, the semi-blind algorithm performs consistently better than training alone. It is also encouraging that for only 142 bits of data, the purely blind algorithm after de-rotation is not significantly worse than the result from training. Thus, blind algorithms after de-rotation appear to have great potential in GSM receivers and in designing future wirelss systems with similar characteristics.

6. CONCLUSIONS

We study the problem of blind equalization in GSM wireless systems. In order for many existing blind identification methods to be applicable without additional sensors, we use a de-rotation scheme to create two diversity channels from a single stream of GMSK signal sampled at the baud-rate. We present a semi-blind identification approach for GSM systems with 26 bits of training data. We show how additional training may help resolve ambiguities of blind identification. Effective simulation results were given for the proposed method in a comparative study.

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