# 行政院國家科學委員會專題研究計畫　成果報告

## 子計畫二：適用於高速移動擷取網路的等化碼技術與高階調變位元軟性決策解碼技術之研究(3/3)

計畫類別：整合型計畫
計畫編號：NSC94-2213-E-009-017-
執行期間：94年08月01日至95年07月31日
執行單位：國立交通大學電信工程學系(所)


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報告類型：完整報告

處理方式：本計畫可公開查詢

中　華　民　國 95年7月25日

1. 中、英文摘要及關鍵詞(keywords)

由於載具在高速移動時，傳輸通道會呈現極快速時變(time-varying)的特性，導致很難進行高速率傳輸。有別於其他相關研究是專注於設計更好的方法來更精準估計的時變通道參數，本計畫改採以通道編碼為導向的做法解決時變通道的傳輸效能。在計畫的第一年，我們建立了快速時變多路徑衰減通道解碼的設計理論；另外，也推導出以符元為傳送單位的高速率傳輸調變的最佳軟性解碼位元量度(soft bit metric)，此結果並已被 IEEE Trans. On Wireless Communications 接受為長篇期刊論文。在計畫第二年，我們嘗試並實驗一個新的想法：亦即在兩個連續的傳送區塊間，穿插傳送一串長度不短於通道記憶長度(channel memory)或記憶延展(channel spread)的隨機位元(random bits)，則通道原本的長程記憶特性可被削弱為近似區塊獨立特性(blockwise independent)。我們同時推想，或許可以使用經由交錯器(interleaver)打亂序列順序的訊息序列(information bit sequence)的同位檢查位元(parity check bits)，來作為上述的 " 隨機位元"，以使接收端可經由解交錯器(de-interleaver)得到額外的同位檢查訊息，來進一步提升系統效能。而一個最直接符合以上想法的範例架構，就是平行串接旋積碼(parallel concatenated convolutional code)。為了驗證這個想法，我們採用隨時間改變衰減的一階高斯-馬可夫通道為實驗平台。我們推導出疊代最大事後機率演算法(iterative MAP algorithm)在直接假設接收向量「因為以兩位元為單位，穿插一位元的交錯訊息序列的同位檢查碼」而具有 2 位元區塊為單位的區塊統計獨立的對應量度公式。此外，我們亦針對隨時間改變衰減的高斯-馬可夫傳輸通道，作通道傳輸極限(channel capacity)的探討。根據實際通訊系統的傳送端與接收端是否分別具有「通道狀態資訊」(channel state information)，定義出四種不同的通道傳輸極限公式。接著，我們推導高斯-馬可夫傳輸通道下的通道輸出與輸入信號間的通道轉換機率公式。由於，在傳送端與接收端均無「通道狀態資訊」的情況下，通道傳輸極限的計算相當困難，因此我們轉而探討其「獨立上界」(independent bound)。我們導出在不同的通道記憶級數下的一般獨立上界公式。在計畫第三年，我們延續前兩年的研究，並經由模擬確認我們提出的隨機位元系統與傳輸極限在 BER 為 $2\times10^{-4}$ 時僅差距 0.9dB。同時在第三年，我們亦將 2002 年史克蘭(Skoglund)，蓋斯(Giese)和巴克孚(Parkvall)所提出的結合通道估計(channel estimation)、等化(equalization)和錯誤保護碼(error protection code)的觀念，延伸到高斯-馬可夫通道(Gauss-Markov channels)下，亦即以成對錯誤發生率(pairwise error probability)作為電腦模擬鍛鍊演算法(simulated annealing algorithm)的判斷準則。相對於[15]的結果，當區塊錯誤機率(WER)為 0.01 且高斯-馬可夫通道記憶長度為 1 與 2 的情況下，我們的設計碼分別得到約 3.5dB 與 6dB 的改善。

關鍵詞：時變多路徑衰減通道、通道估量、通道等化、錯誤更正碼

The main difficulty for high-bit-rate transmission under high mobility is on the tracking of the fast time-varying channel characteristic due to movement. Different from other researches who mostly focus on enhancing the accuracy of the channel parameter estimation and equalization, this project aims at a pure channel-coding approach, i.e., to combine the channel estimation and equalization into channel code design. In the first year, we established the code design philosophy for resisting time-varying multipath interference. In addition, the derivation of a general soft bit-decomposed metric formula for symbol-based modulation scheme has been derived. The latter result has been accepted for publication as a full paper in the IEEE

Transaction on Wireless Communications. In the second year of the project, the idea that the *channel-with-memory* nature can be nearly weakened to *blockwise independence* by the insertive transmission of "random bits" between two consecutive blocks was experimented. Based on this idea, we further conjectured that these ``random bits'' can be another parity check bits generated due to interleaved information bits such that additional coding information can be provided to improve the system performance. A simplest exemplified structure that follows this idea is the parallel concatenated convolutional code (PCCC). We thus derived its respective iterative MAP algorithm for time-varying channel with *first-order* Gauss-Markov fading, and tested whether or not the receiver can treat the received vector as blockwise independence with 2-bit blocks periodically separated by *single* parity-check bit from the second component recursive systematic convolutional (RSC) code encoder. Also done in the second year was the derivation of the channel capacity of time-varying Gauss-Markov fading channels for comparison with the proposed system. Specifically, we first remarked on four different definitions of channel capacities according to whether the transmitter and the receiver have or do not have the channel state information (CSI). We then provided detailed derivations for the channel transition probability of the Gauss-Markov channels. As the true capacity formula for blind-CSI in both transmitter and receiver is hard to obtain, we derived its independent upper bound instead, and establish a close-form expression of the independent bound for any memory order $M$. Discussions are finally given by numerical evaluation of the independent bounds. In the last year, the project, we simulated and found by following our results in the previous two years that the performance of the insertive-random-bit system we proposed is at most 0.9 dB away from the Shannon limit at BER=$2\times10^{-4}$. Also completed in the last year of the project is the extension of the novel concept, combining channel estimation, equalization and error protecting coding technique, introduced by Skoglund, Giese and Parkvall in 2002, to the time-varying fast fading channel such as Gauss-Markov channels. By deriving the pairwise error probability as a code search criterion, our codes are shown to provide coding gains of about 3.5 dB and 6 dB, respectively, on the Gauss-Markov channels with channel memory orders 1 and 2 over those in [15] at WER= $10^{-2}$.

Keywords: Time-varying multipath fading channel, Channel estimation, Channel equalization, Error correcting coding

## 2.報告內容

### 2.1 Introduction and motivations:

The organization of present typical receivers for wireless communications mostly includes channel estimation and channel equalization devices in order to compensate the channel effect. A milestone research in 2002 by Skoglund, Giese and Parkvall [12] however demonstrated that a communication scheme which jointly considers error correcting code and multipath fading effect can achieve markedly better performance than a typical communication system even if perfect channel estimation and equalization are assumed. This exciting result provides a prospect that makes possible the achievement of a high data transmission rate for highly mobile users.

The main technology obstacle for high-bit-rate transmission under high mobility is the seemingly highly time-varying channel characteristic due to movement; such a characteristic enforces the dependence between consecutive symbols, and further enlarges the difficulty in compensating the intersymbol interference. In principle, the temporal channel memory can be eliminated by an intersymbol space longer than the channel memory spread. An example is the IEEE 802.11a standard, in which 0.8-μs "intersymbol space" is added between two consecutive 3.2-μs OFDM symbols to combat any delay spread less than 800 nano seconds. In order to take advantage of the circular convolution technique, the 0.8-μs "intersymbol space" is designed to be the leading 0.8-μ portion of the 3.2-μs OFDM symbol, which is often named the *cyclic prefix* [8][9]. Motivated by this, we experiment on a different view in the neutralization of channel memory, where the "intersymbol space" may be of use to enhance the system performance. Details will be introduced in subsequent sections.

In order to examine the performance of our proposed system, we tempted to establish the capacity [5] of the time-varying fading channel experimented. There have been several publications investigating the capacity of fading channels in the literatures. The capacity of the flat Rayleigh fading channel has been studied in [7] under the assumption that the state of channel fading is perfectly known to both the transmitter and the receiver. While neither the transmitter nor the receiver knows the channel state information (CSI), investigation of the capacity of memoryless Rayleigh fading channels can be found in [1].

For wireless communications, the main design challenge arises from the harsh propagation environment determined by channel fading parameters. It may be resulted from reflex and diffuse multipath loss, and cochannel interference, and then makes reliable transmission much more difficult to achieve. Multipath propagation and limited bandwidth are the two main causes of signal distortion that leads to intersymbol interference (ISI). ISI may lead to higher error rates in symbol detection at the receiver. Moreover, the more obstructions in the communication path, the faster the channel varies. The general methods to combat this problem are channel coding, channel estimation and equalization. Channel estimation scheme at the receiver estimates channel parameters at present by a known training sequence, and passes these parameters to equalizers to compensate the effect on the received signal induced by channel fading. Since the training sequence dose not carry any information data and is a waste of channel usage, an alternative approach, i.e., a blind method, which transmits no training data but only the channel output, is used for channel estimation. Another hybrid approach, called semiblind, utilizes both training data and input information to perform channel estimation. As aforementioned, in 2002, Skoglund, Giese and Parkvall introduced a novel concept of combining channel estimation, equalization and decoding, where they focused on the design of a coder that can improve the performance of parameter estimation [15]. To be specific, they tried to optimize the block error rate by designing a block code which can simultaneously provide channel estimation and error protection to the receiver. By comparing their designed code to a Hamming code with perfect estimation, equalization, they found that the designed code outperformed the above Hamming code significantly. The code designed in [15] has been proved to have excellent performance over the block Rayleigh-fading channel. However, it is not indicated how it will perform on a more critical channel which is not block fading. Usually the channel coefficients are changing during the period of transmission of codeword in practice. Thus, we are interested in finding a code suitable for a fast time-varying channel.

2.2 The research procedures in this project:

Based on the above motivation, there are two issues on which we concentrate in the first year of the project. The first issue is to establish the optimal criterion for decoding the equalizer codes. The second issue is to derivate the metric formulas of the bit-wise soft-decision decoding for the symbol-based modulation. We describe the details in the following subsections.

In the second year, there are two questions on which we concentrate. The first is to experiment on a different view in the neutralization of channel memory, where the "intersymbol space" may be of use to enhance the system performance. The second question that the research aims at is that what the *capacity* of a time-varying channel, like Gauss-Markov [3][4] is. Seldom publications have been emerged in the capacity study of Gauss-Markov channels. The understanding of this quantity helps the researchers understand the gap between a transmission scheme and the underlying limit.

In the last year of the project, we focused on the code design over the Gauss-Markov channel. The reason that we are enthusiastic about Gauss-Markov channels is that it can imitate any fast time-varying channels as long as the order of Markov factor is large enough. We design two kind of codes for this channels, i.e, PCCC code with iterative MAP decoder of Gauss-Markov channels and a nonlinear codes searched by simulated annealing. Details will be provided subsequently.

2.2.1 Equalizer code design:

In the first issue in the first year, our goal is to establish a framework of a systematic equalizer code in the time-varying environment. An important step in this phase is to find the optimal decoding metric. In addition, we also need to examine the properties of the derived metric in order to help the code construction and subsequent decoder design. The procedure of our research is separated into several parts. (1) The mathematical expression of the considered fading channels should be well-defined. (2) Based on the chosen channel model, what the maximum-likelihood (ML) criterion is under i.i.d. input information bit sequence. (3) Based on the derived ML criterion, how to construct a code, and design its feasible decoding algorithm for the code. (4) Finally, to derive the channel capacity of the channel, and to examine whether our code can achieve the capacity of the channel.

Two types of fast time-varying channel models are often adopted in the literature. The first type [11] such as Jakes' model, second-order Butterworth and rectangular spectrum…etc. is not analyzable. These models are widely accepted as realistic fading channel models and are usually utilized in simulations; however, they are mostly not analytically tractable. The second type of fast time-varying channel models includes autoregressive (AR) model, time-independent model, polynomial model [2] and quasi-static channel, which are basically analyzable. In this part of the research, we chose the first-order AR model as our research goal. This model is often named Gauss-Markov model, which is defined as:

$$r_k = \mathbf{a}_k^T \mathbf{h}_k + n_k \quad \text{and} \quad \mathbf{h}_k = \alpha \mathbf{h}_{k-1} + \mathbf{v}_k$$

where $k$=1,2,…,$N$, $\mathbf{v}_k$ is complex white Gaussian with mean $\mathbf{d}$ and covariance $\mathbf{C}$, $\mathbf{a}_k$ is the input, and $\alpha$ is a constant. The Gauss-Markov channel has been shown to be a good model to emulate a true fading channel [14]. The usual time-independent channel model and quasi-static channel model are its special cases.

By denoting $\mathbf{A} = [\mathbf{a}_1,\ldots,\mathbf{a}_N]^T$ and $\mathbf{H} = [\mathbf{h}_1,\ldots,\mathbf{h}_N]$ , we can derive the ML decoding criterion for the model through [10]:

$$\begin{aligned}\Pr(\mathbf{r}\mid\mathbf{A}) &= \int_H \Pr(\mathbf{r}\mid\mathbf{A},\mathbf{H})\Pr(\mathbf{H})d\mathbf{H}\\ &= \int_{h_N}\int_{h_{N-1}}\cdots\int_{h_1}\left(\prod_{k=1}^{N} e^{-\frac{|r_k-\mathbf{a}_k^T\mathbf{h}_k|^2}{\sigma^2}})\right)\prod_{k=1}^{N}\Pr(\mathbf{h}_k\mid\mathbf{h}_{k-1})d\mathbf{h}_1 d\mathbf{h}_2\cdots d\mathbf{h}_N\end{aligned}$$

The ML criterion for Gauss-Markov channel is

$$\Pr(\mathbf{r}\mid\mathbf{A}) \equiv e^{\mathbf{q}_N^H\mathbf{G}_N\mathbf{q}_N}\,|\mathbf{G}_N|\prod_{k=1}^{N-1} e^{(\mathbf{q}_k-\alpha^*\mathbf{C}^{-1}\mathbf{d})^H\mathbf{G}_k(\mathbf{q}_k-\alpha^*\mathbf{C}^{-1}\mathbf{d})}\,|\mathbf{G}_k| \tag{1}$$

where "$\equiv$" means "equal" except for a multiplicative constant, and for $1<k<N$

$$\begin{cases}\mathbf{G}_k = \left(\dfrac{\mathbf{a}_k^*\mathbf{a}_k^T}{\sigma^2}+(1+|\alpha|^2)\mathbf{C}^{-1}-|\alpha|^2\,\mathbf{C}^{-1}\mathbf{G}_{k-1}\mathbf{C}^{-1}\right)^{-1}\\ \mathbf{q}_k = \dfrac{r_k\mathbf{a}_k^*}{\sigma^2}+\mathbf{C}^{-1}\mathbf{d}+\alpha\mathbf{C}^{-1}\mathbf{G}_{k-1}\mathbf{q}_{k-1}-|\alpha|^2\,\mathbf{C}^{-1}\mathbf{G}_{k-1}\mathbf{C}^{-1}d\end{cases}$$

and

$$\begin{cases}\mathbf{G}_1 = \left(\dfrac{\mathbf{a}_1^*\mathbf{a}_1^T}{\sigma^2}+(1+|\alpha|^2)\mathbf{C}^{-1}\right)^{-1}\\ \mathbf{q}_1 = \dfrac{r_k\mathbf{a}_k^*}{\sigma^2}+\mathbf{C}^{-1}\mathbf{d}+\alpha\mathbf{C}^{-1}\mathbf{h}_0\end{cases}$$

$$\begin{cases}\mathbf{G}_N = \left(\dfrac{\mathbf{a}_N^*\mathbf{a}_N^T}{\sigma^2}+\mathbf{C}^{-1}-|\alpha|^2\,\mathbf{C}^{-1}\mathbf{G}_{N-1}\mathbf{C}^{-1}\right)^{-1}\\ \mathbf{q}_N = \dfrac{r_N\mathbf{a}_N^*}{\sigma^2}+\mathbf{C}^{-1}\mathbf{d}+\alpha\mathbf{C}^{-1}\mathbf{G}_{N-1}\mathbf{q}_{N-1}-|\alpha|^2\,\mathbf{C}^{-1}\mathbf{G}_{N-1}\mathbf{C}^{-1}\mathbf{d}\end{cases}$$

Notably, our criterion is an extension of that in [3], in which zero-mean for $\mathbf{H} = [\mathbf{h}_1,\ldots,\mathbf{h}_N]$ is assumed.

On the decoding algorithm, because $\mathbf{G}_k$ and $\mathbf{q}_k$ are functions of the entire information sequence, the standard Viterbi algorithm (VA) can not be applied. In [3], the authors employed the list Viterbi algorithm (LVA) to prune out some less likely data sequences, and showed that it is not beneficial to keep more than three survivor paths at each trellis node. In this project, we considered two alternative approaches: metric prediction and iterative decoding approach. On the metric prediction, we conjecture that the LVA (even with $L$ = 3) performance can be achieved by the standard VA ($L$ = 1) if a proper prediction metric can be added to the above derived metric. For example, in a flat fading environment, $\mathbf{G}_k$ and $\mathbf{q}_k$ in (1) are simply scalars. Also, $G_k$ remains almost the same for $k$ = 1…$N$. Let the mean $d$ = 0. Then a prediction metric can be set as:

$$h(r_j) = \mu_j C_j + q_j\cdot 2BD_j$$

where

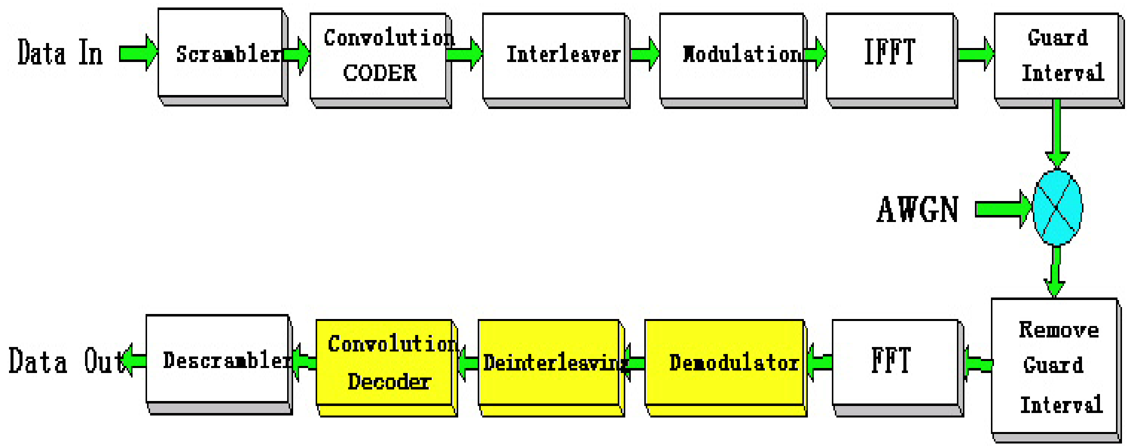
$$\mu_j = q_j^2,\ \ C_j = \frac{1}{A^2}C_{j-1},\ \ D_j = \frac{1}{A}D_{j-1} - |r_j|(1+C_j),\ \ A = \frac{\alpha G}{\sigma_v^2}\ \text{ and }\ B = \frac{1}{\sigma^2}.$$

This result can gradually migrate to frequency-selective fading channels. In addition, the recursive property of the ML criterion can be easy to use in an iterative decoding algorithm, such as Soft-Output Viterbi algorithm (SOVA).

Our next focus is on the code construction (possibly non-linear) for the chosen Gauss-Markov channel. The approach taken is basically to derive the pairwise error probability for two candidate codewords, and then uses simulated annealing algorithm to search for a good code. Subsequently, the mutual information of the Gauss-Markov channel is examined so that it can be applied to the evaluation of the channel capacity of the Gauss-Markov channel with unknown channel state information (CSI).

2.2.2 Bit-wise decomposition of $M$-ary maximum-likelihood symbol metric:

Another result that we obtained in the first year is a systematic recursive formula for bit-wise decomposition of $M$-ary symbol metric. The decomposed bit metrics can be applied to improve the performance of a system where the information sequence is binary-coded and interleaved before $M$-ary modulated. A straightforward receiver designed for certain system is to de-map the received $M$-ary symbol into its binary isomorphism so as to facilitate the subsequent bit-based manipulation, such as hard-decision decoding. With a bit-wise decomposition of $M$-ary symbol metric, a soft-decision decoder can be used to achieve a better system performance. The idea behind the systematic formula is to decompose the symbol-based maximum-likelihood (ML) metric by equating a number of specific equations that are drawn from squared-error criterion. It interestingly yields a systematic recursive formula that can be applied to some previous work derived from different standpoint. Simulation results based on IEEE 802.11a/g standards [8][9] show that at bit-error rate of $10^{-5}$, the proposed bit-wise decomposed metric can provide 3.0 dB, 3.9 dB and 5.1 dB improvement over the concatenation of binary-demapper, deinterleaver and hard-decision-decoder for 16QAM, 64QAM and 256QAM symbols, respectively. Also, only 0.13 dB performance degradation is resulted by introducing 32-level quantization for 16QAM signals. The quantization impact for 64QAM signals under 64-level uniform quantization can even be reduced to 0.07 dB. No further performance degradation, in addition to that due to quantization, can be observed, when mismatch of AGC gain is limited to be within $\pm 40\%$. The robustness of the proposed bit-decomposed metric against phase noise is also examined. When the phase drift increases up to $\pm 6^{o}$, the BER due to our bit-decomposed metric will increase from $10^{-5}$ to around $4\times10^{-5}$ at $E_b/N_0$ = 6.7 dB for 16QAM modulation. This phase drift tolerance reduces to $\pm 4^{o}$ at $E_b/N_0$ = 9.7 dB for 64QAM modulation, where $E_b/N_0$ is chosen such that the no-phase-drift BER is approximately $10^{-5}$. The system architecture considered is as follows.




Our goal is to find the functions $f_i\,(c_i\,,\,\mathrm{r})$ to approximate symbol-based Maximum-likelihood metric:

$$\sum_{i=1}^{N} f_i(c_i, r) \approx \min_{s\in S} \sum_{i=1}^{K} (r_i - s_i)^2$$

The criterion we adopt is the minimization of average square error, namely,

$$\min_{f_1, f_2} E[(f_1(c,r) + f_2(\bar{c},r) - [r - s(c,\bar{c})]^2)^2]$$

We can get these sub-optimum functions in $M^2$-QAM systems

$$\begin{cases} f_1^{16QAM}(c,r) = c\,|\,r\,| \bullet \mathrm{sgn}(-r) \\ f_2^{16QAM}(c,r) = c(|\,r\,|-2) \end{cases}$$

$$\begin{cases} f_1^{64QAM}(c,r) = c(|\,r-4\,|+|\,r\,|+|\,r+4\,|-8) \bullet \mathrm{sgn}(-r) \\ f_2^{64QAM}(c,r) = f_1^{16QAM}(c, 4-|\,r\,|) \\ f_3^{64QAM}(c,r) = f_2^{16QAM}(c, |\,r\,|-4) \end{cases}$$

$$\begin{cases} f_1^{(m)}(c,r) = c \bullet \mathrm{sgn}(-r)(\sum_{i=-(m-2)}^{m-2}(|\,r+2ui\,|-|\,2ui\,|)) \\ f_j^{(m)}(c,r) = f_{j-1}^{(m-1)}(c, (-1)^j[2^{m-2}u - |\,r\,|]), \text{for } 2 \le j \le m \end{cases}$$

2.2.3 Gauss-Markov channel models

The system model we consider in the later subsections is given by:

$$\boldsymbol{r}_k = \boldsymbol{a}_k^T \boldsymbol{h}_k + \boldsymbol{n}_k$$

where $a_k^T = [a_k, a_{k-1}, \cdots, a_{k-M+1}]$ and $M$ is the channel length indicating how serious the past transmitted bits affect the received bit in this time instance. Furthermore, $a_k^T$ is a complex row vector containing $M$ transmitted data from time $k$ to time $k$–$M$+1, $\boldsymbol{h}_k$ is a complex column vector with $M$ channel impulse response coefficients at time $k$, and $\boldsymbol{n}_k$ is the zero-mean Gaussian complex noise with variance $\sigma^2$. Let $\boldsymbol{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_N]$ be the matrix of channel coefficient vectors representing by columns, and let $\boldsymbol{A} = [\boldsymbol{a}_1, \cdots, \boldsymbol{a}_N]$ be the matrix of transmitted data representing by rows. Also let $\boldsymbol{r} = [\boldsymbol{r}_1, \cdots, \boldsymbol{r}_N]^T$ represent the received vector, while $\boldsymbol{n} = [\boldsymbol{n}_1, \cdots, \boldsymbol{n}_N]^T$ be the noise vector from time 1 to time $N$. If channel impulse response coefficients follow the Gauss-Markov distribution, then it is called a Gauss-Markov channel. Moreover, the channel impulse response $\boldsymbol{h}_k = \alpha \boldsymbol{h}_k + \boldsymbol{v}_k$ at time $k$, where $\boldsymbol{v}_k$ is a complex white Gaussian with mean $d$ and covariance $\boldsymbol{C}$, and $\alpha$ is a complex first-order Markov factor whose absolute value $|\alpha| = e^{-\omega T}$ with Doppler spread $\omega/\pi$ and sampling period $T$ [13]. As it can be seen, the Gauss-Markov channel is a channel whose time-varying behavior is constituted by Markovians and Gauss random variables.

2.2.4 A lower bound of the Shannon limit:

There are four kinds of capacities according to different assumptions on the knowledge that the transmitter and the receiver have. In notations, $C(S)$ corresponds to that both the transmitter and the receiver are unaware of the channel state, while $C^{'}(S)$ is the capacity under the assumption of perfect CSI knowledge to both the transmitter and the receiver. If only the receiver knows the channel state, the capacity is denoted by $C^{(R)}(S)$. If only the transmitter is aware of the CSI, the capacity is denoted by $C^{(T)}(S)$. Their formulas are listed below.

$$C(S) = \max_{P_X \in Pb(S)} \int_H p_H(h) \sum_{x \in X} P_X(x) \int_y p_{Y|X,H}(y|x,h) \log\left(\frac{p_{Y|X}(y|x)}{p_Y(y)}\right) dydh$$

$$C^{(T)}(S) = \int_H p_H(h) \max_{P_X \in Pb(S)} \sum_{x \in X} P_X(x) \int_y p_{Y|X,H}(y|x,h) \log\left(\frac{p_{Y|X}(y|x)}{p_Y(y)}\right) dydh$$

$$C^{(R)}(S) = \max_{P_X \in Pb(S)} \int_H p_H(h) \sum_{x \in X} P_X(x) \int_y p_{Y|X,H}(y|x,h) \log\left(\frac{p_{Y|X,H}(y|x,h)}{p_{Y|H}(y|h)}\right) dydh$$

$$C'(S) = \int_H p_H(h) \max_{P_X \in Pb(S)} \sum_{x \in X} P_X(x) \int_y p_{Y|X,H}(y|x,h) \log\left(\frac{p_{Y|X}(y|x)}{p_Y(y)}\right) dydh$$

After defining four definitions of channel capacity, we wish to evaluate the last one based on the Gauss-Markov fading channel model. Unfortunately, the problem of finding the channel input statistics that maximizes the channel input-output mutual information is beyond our management at this stage. Thus, we turn to the determination of good upper bounds for capacities.

**Theorem.** Assume that there exists a complex number $\mu_k$ such that $\mu_{k,i} = \rho_i\, \mu_k$ for some real number $\rho_i$ for every $1 \le i \le M$, where $\mu_k = [\mu_{k,1}, \mu_{k,2}, \ldots, \mu_{k,M}]$. Also, $\boldsymbol{C}$ is diagonal. Then, the capacity-cost function for blind-CSI system is upper-bounded by:

$$C(S) \le C_\infty(S) = \frac{2S}{\delta^2} - \int_R \frac{1}{\sqrt{2\pi}} e^{-t^2/2} \left[\log\left(\cosh\left(\frac{\sqrt{2S}}{|\delta|} t + \frac{2S}{\delta^2}\right)\right)\right] dt$$

where

$$\delta^2 = \frac{\sigma^2 + \dfrac{S}{1-|\alpha|^2} \sum_{i=1}^M C_{i,i}}{\left(\dfrac{1}{1-|\alpha|} \sum_{i=1}^M |\mu_i|\right)^2}.$$

With the availability of capacity upper bounds, performance lower bounds for bit error rates (BERs) can be obtained by means of the rate-distortion theorem and the joint source-channel coding theorem [15]. One can then evaluates the performance lower bound numerically in comparison with the simulations of his developed coding scheme.

2.2.5 Iterative MAP algorithm for Gauss-Markov channels

Referring to Fig. 1, the information bit sequence $\boldsymbol{u} = [u_1, u_2, \cdots, u_K]$ is comprised of $K$ independent and identically distributed (i.i.d.) bits with equal probable marginal, where each $u_j$ is either 0 or 1. This information bit sequence is fed into a parallel concatenated convolutional code (PCCC) encoder that consists of two (37; 21) recursive systematic convolutional (RSC) code encoders parallelly concatenated through an interleaver to generate the coded bit sequence. Antipodal modulation, i.e., $x_j = 2c_j - 1$, is then applied to the coded bit sequence before it is sent to the Gauss-Markov modeled time-varying channel. Finally, the received sequence $\boldsymbol{r} = [r_1, r_2, \cdots, r_N]$ is delivered to an iterative MAP decoder, and an estimate of the transmitted information bit sequence is outputted after sufficient number of iterations.

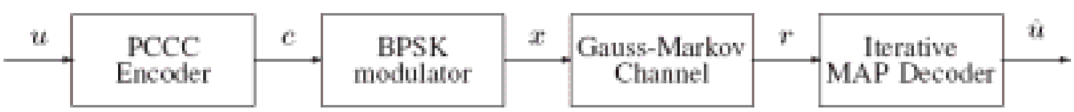



Figure 1: System model for coded transmission over Gauss-Markov channels.

We had derived the MAP metric of PCCC over Gauss-Markov channels last year. In this year, we verify the performance of the iterative MAP algorithm by simulations. The algorithm of the iterative MAP algorithm proposed is summarized below.

**Step 1**: Set $\Lambda_{2e}^{(0)} = 0$, and set $n$=1.

**Step 2**: Calculate $\boldsymbol{\Lambda}_1^{(n)}$ and $\boldsymbol{\Lambda}_{1e}^{(n)}$

1) *Initialization*:

- For $i$=1, $\cdots$, $K$, $\Pr\{u_i = 0\} = 1/(1 + e^{\Lambda_{2e}^{(n-1)}(i)})$ and $\Pr\{u_i = 1\} = 1 - \Pr\{u_i = 0\}$

- For $i$=1, $\cdots$, $K$, $s$=0, $\cdots$, 15 and $\bar{s} = 1, \cdots, 15$, compute $\gamma(T_s^{i-1}, T_{\bar{s}}^i)$ as

$$\gamma(T_s^{i-1}, T_{\bar{s}}^i) = \begin{cases} \Pr\{u_i = 0\} \prod_{k=1}^{2} e^{G_{3(i-1)+k}|q_{3(i-1)+k}|^2} & ,\text{if } (T_s^{i-1}, T_{\bar{s}}^i) \in \mathrm{B}_i^{(0)} \\ \Pr\{u_i = 1\} \prod_{k=1}^{2} e^{G_{3(i-1)+k}|q_{3(i-1)+k}|^2} & ,\text{if } (T_s^{i-1}, T_{\bar{s}}^i) \in \mathrm{B}_i^{(1)} \\ 0 & ,\text{if } (T_s^{i-1}, T_{\bar{s}}^i) \notin \mathrm{B}_i^{(0)} \cup \mathrm{B}_i^{(1)} \end{cases}$$

2) *Forward recursive*:

- Set $\alpha(T_0^0) = 1$ and for $s$=1, $\cdots$, 15, $\alpha(T_s^0) = 0$.

- For $i$=1, $\cdots$, $K$ and $s$=0, $\cdots$, 15, perform $\alpha(T_s^i) = \sum_{\bar{s}=0}^{15} \alpha(T_{\bar{s}}^{i-1}) \gamma(T_{\bar{s}}^{i-1}, T_s^i)$

3) *Backward recursive*:

- Set $\beta(T_s^{K+1}) = \alpha(T_s^K)$ for $s$=0, ⋯,15.

- For $i$=$K$, ⋯,1 and $\bar{s} = 0,\cdots,15$, perform $\beta(T_{\bar{s}}^i) = \sum_{s=0}^{15} \alpha(T_s^{i+1})\gamma(T_{\bar{s}}^i, T_s^{i+1})$

4) *Soft output*:

- For $i$=1, ⋯,$K$, update

$$\Lambda_1^{(n)}(i) = \log \frac{\sum\limits_{(T_s^{i-1}, T_{\bar{s}}^i) \in B_i^{(1)}} \alpha(T_s^{i-1})\beta(T_{\bar{s}}^i)\gamma(T_s^{i-1}, T_{\bar{s}}^i)}{\sum\limits_{(T_s^{i-1}, T_{\bar{s}}^i) \in B_i^{(0)}} \alpha(T_s^{i-1})\beta(T_{\bar{s}}^i)\gamma(T_s^{i-1}, T_{\bar{s}}^i)}$$

and

$$\Lambda_{1e}^{(n)}(i) = \Lambda_1^{(n)}(i) - \frac{2G_{3(i-1)+1}}{\sigma^2 \bar{\sigma}_{3(i-1)+1}^2}(r_{3(i-1)+1}\bar{h}_{3(i-1)+1}^* + r_{3(i-1)+1}^*\bar{h}_{3(i-1)+1}) - \Lambda_{2e}^{(n-1)}(i) - \Lambda_{2e}^{(n-1)}(i)$$

**Step 3**: Calculate $\boldsymbol{\Lambda}_2^{(n)}$ and $\boldsymbol{\Lambda}_{2e}^{(n)}$

1) *Initialization*:

- For $i$=1, ⋯,$K$, $\Pr\{u_i = 0\} = 1/(1 + e\Lambda_{1e}^{(n-1)}(i))$ and $\Pr\{u_i = 1\} = 1 - \Pr\{u_i = 0\}$

- For $i$=1, ⋯,$K$, $s$=0,⋯,15 and $\bar{s} = 1,\cdots,15$, compute $\gamma(T_s^{i-1}, T_{\bar{s}}^i)$ as

$$\gamma(T_s^{i-1}, T_{\ddot{s}}^i) = \begin{cases} \Pr\{u_{l(i)} = 0\}\prod_{k=1}^2 e^{\bar{G}_{3(l(i)-1)+k}|\bar{q}_{3(l(i)-1)+k}|^2} e^{\bar{G}_{3i}|\bar{q}_{3i}|^2} & ,\text{if } (T_s^{i\text{-}1}, T_{\ddot{s}}^i) \in \mathrm{B}_\mathrm{i}^{(0)} \\ \Pr\{u_{l(i)} = 1\}\prod_{k=1}^2 e^{\bar{G}_{3(l(i)-1)+k}|\bar{q}_{3(l(i)-1)+k}|^2} e^{\bar{G}_{3i}|\bar{q}_{3i}|^2} & ,\text{if } (T_s^{i\text{-}1}, T_{\ddot{s}}^i) \in \mathrm{B}_\mathrm{i}^{(1)} \\ 0 & ,\text{if } (T_s^{i\text{-}1}, T_{\ddot{s}}^i) \notin \mathrm{B}_\mathrm{i}^{(0)} \cup \mathrm{B}_\mathrm{i}^{(1)} \end{cases}$$

2) *Forward recursive*:

- Set $\alpha(T_0^0) = 1$ and for $s$=1, ⋯,15, $\alpha(T_s^0) = 0$.

- For $i$=1, ⋯,$K$ and $s$=0, ⋯,15, perform $\alpha(T_s^i) = \sum_{\bar{s}=0}^{15} \alpha(T_{\bar{s}}^{i-1})\gamma(T_{\bar{s}}^{i-1}, T_s^i)$

3) *Backward recursive*:

- Set $\beta(T_s^{K+1}) = \alpha(T_s^K)$ for $s$=0, ⋯,15.

- For $i$=$K$, ⋯,1 and $\bar{s} = 0,\cdots,15$, perform $\beta(T_{\bar{s}}^i) = \sum_{s=0}^{15} \alpha(T_s^{i+1})\gamma(T_{\bar{s}}^i, T_s^{i+1})$

4) *Soft output*:

- For $i$=1, ⋯,$K$, update

$$\Lambda_1^{(n)}(i) = \log \frac{\sum\limits_{(T_s^{i-1}, T_{\bar{s}}^i) \in B_i^{(1)}} \alpha(T_s^{i-1})\beta(T_{\bar{s}}^i)\gamma(T_s^{i-1}, T_{\bar{s}}^i)}{\sum\limits_{(T_s^{i-1}, T_{\bar{s}}^i) \in B_i^{(0)}} \alpha(T_s^{i-1})\beta(T_{\bar{s}}^i)\gamma(T_s^{i-1}, T_{\bar{s}}^i)}$$

and

$$\Lambda_{2e}^{(n)}(i) = \Lambda_{2}^{(n)}(i) - \frac{2\overline{G}_{3(l(i)-1)+1}}{\sigma^2 \overline{\sigma}_{3(l(i)-1)+1}^2}(r_{3(l(i)-1)+1}\overline{h}_{3(l(i)-1)+1}^{*} + r_{3(l(i)-1)+1}^{*}\overline{h}_{3(l(i)-1)+1}) - \Lambda_{1e}^{(n)}(l(i))$$

**Step 4**: Repeat Steps and 3 (by setting $n$=$n$+1) until the number of desired iterations is reached, and then make final hard-decision based on the last $\Lambda_2$.

2.2.6 Code construction for Gauss-Markov channels

On the second part of code design, we obtain the likelihood function as

$$f(\boldsymbol{r} \mid A) = \prod_{k=1}^{n} e^{\boldsymbol{q}_k^H \boldsymbol{G}_k \boldsymbol{q}_k} \mid \boldsymbol{G}_k \mid$$

where

$$\boldsymbol{G}_k^{-1} = \frac{\boldsymbol{a}_k^* \boldsymbol{a}_k^T}{\sigma^2} + \boldsymbol{C}^{-1} + |\alpha|^2 \left(\boldsymbol{C}^{-1} - \boldsymbol{C}^{-1}\boldsymbol{G}_{k-1}\boldsymbol{C}^{-1}\right)$$

$$\boldsymbol{q}_k = \frac{r_k \boldsymbol{a}_k^*}{\sigma^2} + \alpha \boldsymbol{C}^{-1}\boldsymbol{G}_{k-1}\boldsymbol{q}_{k-1}$$

Because the exact analysis of error probability $P_e$ is hard, we choose to derive an upper bound on $P_e$ as the criterion instead. Let the code be with length $N$ and rate $R = K/N$ (information bits per code bit). Then, the average block error rate can be upper-bounded by union bound as

$$\begin{aligned} P_e &= \Pr(\hat{\boldsymbol{x}} \neq \boldsymbol{x}) \\ &= 2^{-K}\sum_i \Pr(\hat{\boldsymbol{x}} \neq \boldsymbol{x} \mid \boldsymbol{x}(i) \text{ is transmitted}) \\ &\leq 2^{-K}\sum_i \sum_{j \neq i} p_{j|i} \end{aligned}$$

where $\boldsymbol{x}$ is the transmitted codeword, $\hat{x}$ is the decision at the receiver, and $p_{j|i}$ is the pairwise error probability of mistaken codeword $\boldsymbol{x}(j)$ when $\boldsymbol{x}(i)$ was transmitted. According to the maximum-likelihood decoding rule, we have

$$p_{j|i} = \Pr\left[\log\frac{\Pr[\boldsymbol{r} \mid \boldsymbol{x}(j)]}{\Pr[\boldsymbol{r} \mid \boldsymbol{x}(i)]} > 0\right] + \frac{1}{2}\Pr\left[\log\frac{\Pr[\boldsymbol{r} \mid \boldsymbol{x}(j)]}{\Pr[\boldsymbol{r} \mid \boldsymbol{x}(i)]} = 0\right]$$

Now we are able to derive the pairwise error probability on the condition that $\boldsymbol{x}(i)$ was transmitted and $\boldsymbol{x}(j)$ is received,

$$\begin{aligned} p_{j|i} &= \Pr\left[\log\frac{\prod_{k=1}^{N} e^{\boldsymbol{q}_{k(j)}^H \boldsymbol{G}_k(j)\boldsymbol{q}_k(j)} \mid \boldsymbol{G}_k(j) \mid}{\prod_{k=1}^{N} e^{\boldsymbol{q}_{k(i)}^H \boldsymbol{G}_k(i)\boldsymbol{q}_k(i)} \mid \boldsymbol{G}_k(i) \mid} > 0\right] + \frac{1}{2}\Pr\left[\log\frac{\prod_{k=1}^{N} e^{\boldsymbol{q}_{k(j)}^H \boldsymbol{G}_k(j)\boldsymbol{q}_k(j)} \mid \boldsymbol{G}_k(j) \mid}{\prod_{k=1}^{N} e^{\boldsymbol{q}_{k(i)}^H \boldsymbol{G}_k(i)\boldsymbol{q}_k(i)} \mid \boldsymbol{G}_k(i) \mid} = 0\right] \\ &= \Pr\left[\sum_{\mathrm{k}=1}^{\mathrm{N}}\left(\boldsymbol{q}_k(j)^H \boldsymbol{G}_k(j)\boldsymbol{q}_k(j) - \boldsymbol{q}_k(i)^H \boldsymbol{G}_k(i)\boldsymbol{q}_k(i)\right) > \sum_{\mathrm{k}=1}^{\mathrm{N}}\left(\log\frac{|\boldsymbol{G}_k(i)|}{|\boldsymbol{G}_k(j)|}\right)\right] \\ &= \frac{1}{2}\Pr\left[\sum_{\mathrm{k}=1}^{\mathrm{N}}\left(\boldsymbol{q}_k(j)^H \boldsymbol{G}_k(j)\boldsymbol{q}_k(j) - \boldsymbol{q}_k(i)^H \boldsymbol{G}_k(i)\boldsymbol{q}_k(i)\right) = \sum_{\mathrm{k}=1}^{\mathrm{N}}\left(\log\frac{|\boldsymbol{G}_k(i)|}{|\boldsymbol{G}_k(j)|}\right)\right] \end{aligned}$$

Here, we adopt the simulated annealing algorithm to search for good codes based on the above criterion. Researchers have shown great successes of using simulated annealing algorithms to construct good source codes, error-correcting codes, spherical codes [6], and also codes combining channel estimation and error protection [15] by optimizing the cost functions like distortion of source codes, minimum distance, minimum separating angle, and union bound of block error probability, respectively.

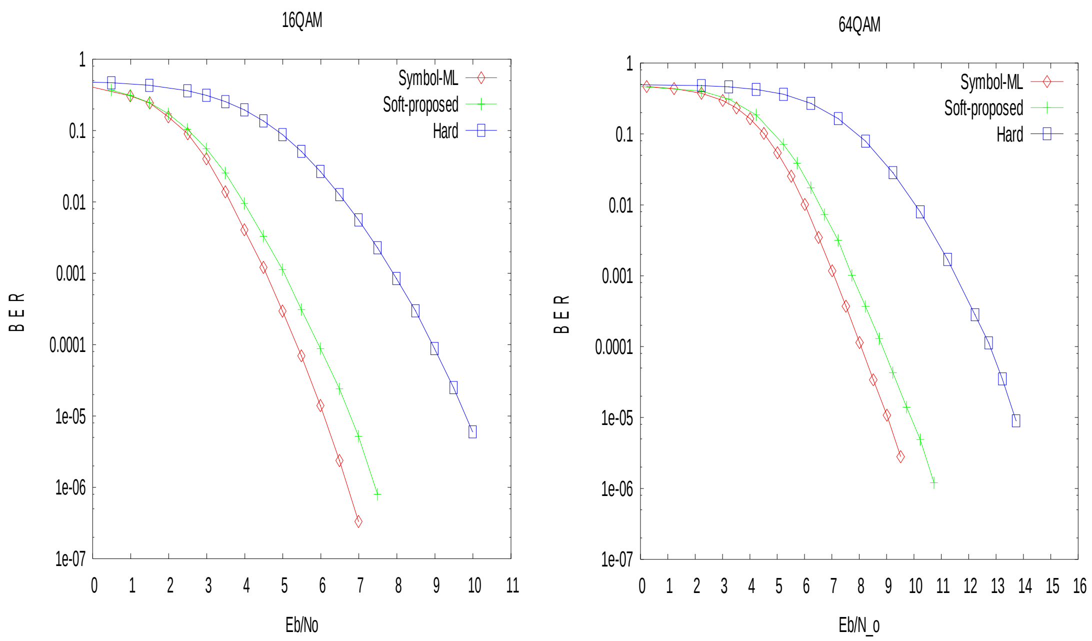
## 2.3 Achievements:

### 2.3.1 Equalizer codes technology:

We derived the ML metric for nonzero-mean-channel-response Gauss-Markov channel, and developed a suboptimum metric for off-line Viterbi algorithm, where the optimal heuristic function for the fast fading channels with Gauss-Markov model is showed. Our ongoing aim is on the design and performance evaluation of iterate decoding algorithm for time-varying Gauss-Markov channel.

### 2.3.2 Bit-wise decomposition of *M*-ary maximum-likelihood symbol metrics:

The two figures below reveal our Soft-proposed metric can further improve the performance of hard-decision, and approach to ideal symbol-ML performance. Further empirical study on system imperfection implies that the proposed bit-wise decomposed metric also improves the system robustness against gain-mismatch and phase-noise.




### 2.3.3 A lower bound of the Shannon limit:

Figure 2 shows the independent bounds for Gauss-Markov channels of different memory orders. By intuition, for fixed $C_{i,i}$ and $\mu_i$, the higher the channel memory order, the more involved in received vector $\boldsymbol{y}$ at the receiver end. Thus, it is reasonable to expect a lower capacity for larger

$M$. However, the independent bound shows that $C_\infty(S)$ grows as $M$ increases. This indicates that in the case we considered, the independent bound could be looser for higher $M$.

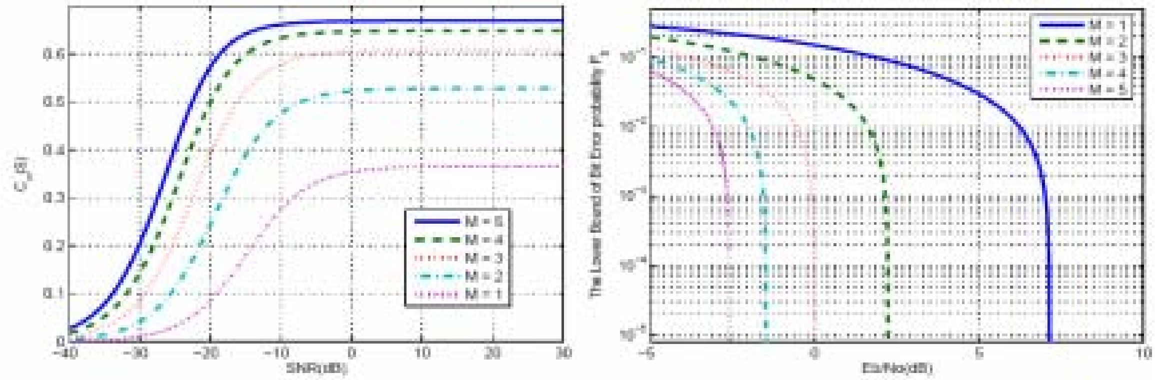



Figure 2: Illustration of $C_\infty(S)$. Parameters for Gauss-Markov channels are: (a) (left.) $C_{1,1} = C_{2,2} = C_{3,3} = C_{4,4} = C_{5,5} = 10$, $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = 1$, $\alpha = 0.7$ and $\sigma^2 = 1$. (b) (right.) $C_{1,1} = 10^{0.7}$, $C_{2,2} = 10^{1.5}$, $C_{3,3} = 10^2$, $C_{4,4} = 10^{2.5}$, $C_{5,5} = 10^3$, $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = 1$, $\alpha = 0.7$ and $\sigma^2 = 1$.

## 2.3.4 Iterative MAP algorithm for Gauss-Markov channels:

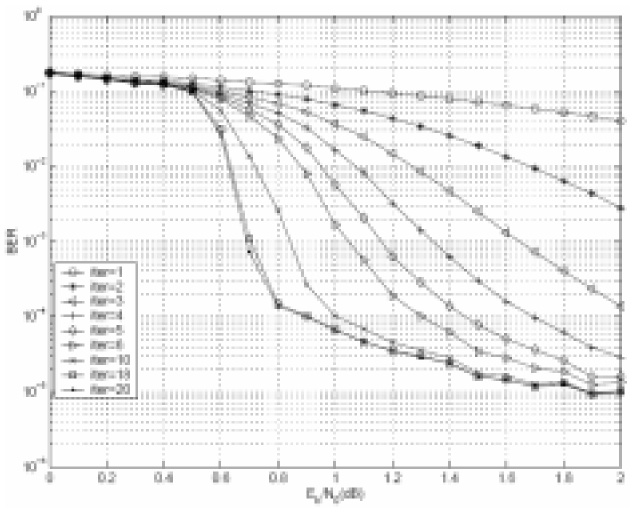



Figure 3: Performance curve of the proposed iterative MAP decoder. Parameters of Gauss-Markov channel are $\alpha$= 0:995, $\sigma_v^2$ = 0.001 and $h_0 = 1$.

Figure 3 shows the performance of the proposed iterative MAP decoder for channel parameters $h_0 = 1$ and $\sigma_v^2 = 0.001$. It indicates that the bit-error-rate (BER) decreases as the number of iterations increases from 1 to 20. Since the BER performance for 20 iterations is very close to that for 18 iterations, it is reasonable to anticipate that no further improvement can be obtained with more number of iterations. Besides, error floor can be observed in this figure. The performance curve for 20 iterations has apparently lower slope when Eb/N0 is beyond 0.8 dB. Figures 4(a) and 4(b) display how iterations improve the decoding performance when channel parameters are respectively $h_0 = 0.5$, $\sigma_v^2$ = 0.001 and $h_0 = 1$, $\sigma_v^2$ = 001. Notably, a smaller $h_0$ or a larger $\sigma_v^2$ in concept gives a noisier channel. Unlike the previous channel setting, the performances in the two figures saturate with much less number of iterations. When $h_0 = 0.5$ and $\sigma_v^2$ = 0.001, the iterative MAP algorithm with 13 iterations performs close to that with 20 iterations. When $h_0 = 1$ and $\sigma_v^2$ = 0.01, the sufficient number of iterations, which saturates the performance, reduces to seven.

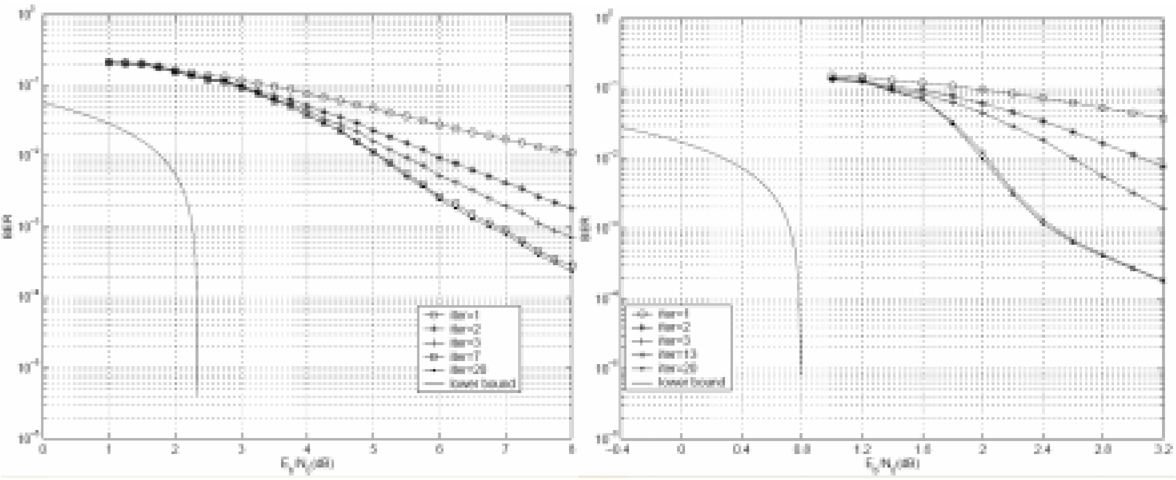



Figure 4: (a) (left) Performance comparison between the iterative MAP decoding and a lower bound of the Shannon limit. Parameters of Gauss-Markov channels are $\alpha$ = 0.995, $\sigma_v^2$ = 0:01 and $h_0$ = 1. (b) (right) Performance comparison between the iterative MAP decoding and a lower bound of the Shannon limit. Parameters of Gauss-Markov channel are $\alpha$ = 0:995, $\sigma_v^2$ = 0:001 and $h_0$ = 0:5.

### 2.3.5 Code construction:

We have simulated two designed codes for different channel lengths of the Gauss-Markov channel. One is for *M*=1, a singular path model, and the other for *M*=2, a channel with two fading paths. The codes were first encoded as BPSK signals, suffered fading through the Gauss-Markov channel, and then decoded according to the optimal rule. We compared the performance of our designed codes to the code presented in [15]. Figure 5(a) and 5(b) shows the word error rate (WER) for the designed (10, 5) code with *N*=10, *K*=5 when the channel length *M*=1 and *M*=2, respectively. Both codes use the optimal decoding rule. It can be observed that our designed code indeed outperforms the code given in [15] on Gauss-Markov channels. The coding gain is about 3.5 dB at WER = $10^{-2}$ when *M*=1 and is enlarged to 6 dB when *M*=2. Hence, when the channel becomes multipath, the performance gain of the designed code is almost double to that of the code given in [715] even though both codes perform worse than on the single path channel (*M*=1).

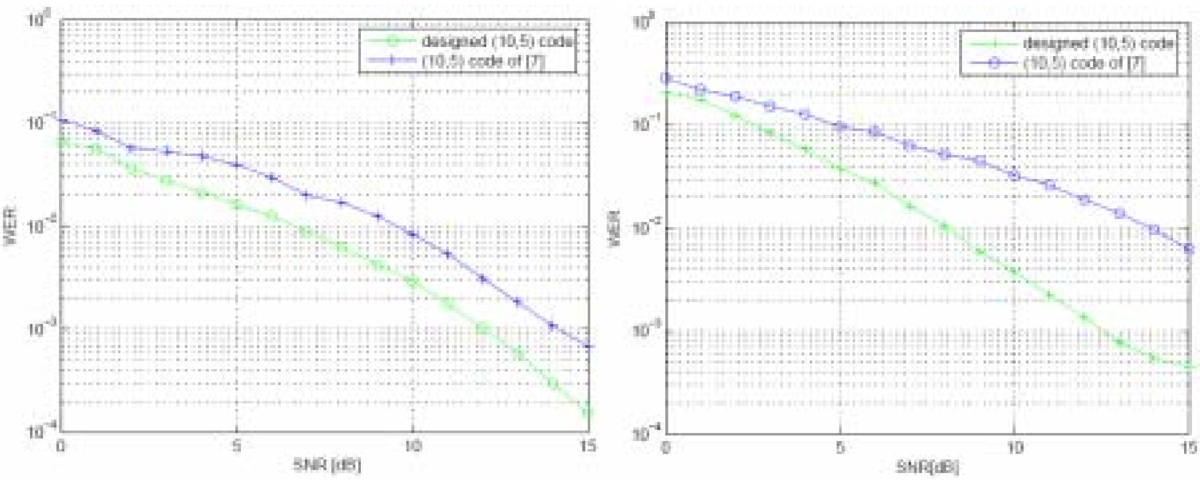



Figure 5: (a) (left) Word error rate for (10,5) code on the Gauss-Markov channel (M=1). (b) (right) Word error rate for (10,5) code on the Gauss-Markov channel (M=2).

The cost of the lower error rate is the price on higher algorithmic complexity in code search. In order to make the code be adapted to the fast-varying characteristic of channel, the code search algorithm is designed to deal with this characteristic so that the algorithm becomes more complicated. Table 1 lists the comparison of algorithmic complexities between the major computations of our criterion and that given in [15]. The complexity is counted by how many multiplications and additions are taken during the code search process. Table 1 records the computational complexity needed in once energy function calculation in simulation annealing algorithm for a code with length *N*. By taking an example of *N* = 10, the codes demonstrated in Figure 4, the total numbers of multiplications and additions are 68795 and 63124 respectively for our criterion, and 1961 and 1779 respectively for that given in [15].

Table 1: comparison of complexity

| Criterion for Gauss-Markov channel | | | Criterion of [7] | | |
|---|---|---|---|---|---|
| | number of multiplication | number of addition | | number of multiplication | number of addition |
| $\mathbf{Q}(j,i)$ | 24N-16 | 8N-6 | $\mathbf{P}_B(i)$ | $2N^2$+12N+13 | $N^2$+8N+4 |
| $\mathbf{G}(j,i)$ | 54N-40 | 18N-12 | $\mathbf{Q}(j,i)$ | 0 | $N^2$+2N+1 |
| $\mathbf{S}_q(j,i)$ | $\frac{4}{3}N^3 + \frac{187}{6}N^2 - \frac{241}{6}N + 23$ | $4N^2$+8N+2 | $\mathbf{S}_y(i)$ | $2N^2$+9N+7 | $2N^2$+6N+4 |
| $\mathbf{S}_q(j,i)\cdot\mathbf{G}(j,i)$ | $64N^3$ | $64N^3 - 16N^2$ | $\mathbf{S}_y(i)\cdot\mathbf{Q}(j,i)$ | $(N+1)^3$ | $N(N+1)^2$ |

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## 計畫相關學生論文

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2. 卓雅婷 [2005 June], 碩士論文: 高斯-馬可夫通道之疊代最大事後機率演算法 (*Iterative MAP algorithm for Gauss-Markov Channel*)
3. 蔣名駿 [2005 June], 碩士論文: 高斯-馬可夫衰減通道下雙極傳輸的管道傳輸極限上界 (*Upper Bounds of Channel Capacity for Bipolar Transmission Over Gauss-Markov Fading Channel*)
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7. Chia-Wei Chang, Po-Ning Chen and Yunghsiang S. Han, "Realization of a systematic bit-wise decomposition metric," *2004 IEEE Asia-Pacific Conference on Circuits and Systems (APCCAS'04)*, Tainan, Taiwan, ROC, December 6-9 (2004).
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## 4. 計畫成果自評

Accordingly to the project proposal, our aims in the first year are to develop and examine the design rule of equalizer codes in a time-varying multipath fading environment, and to derive the soft bit metric of symbol-oriented high-speed modulation. Both aims have been achieved in this year. In addition, we demonstrated a low-complex suboptimum metric prediction approach and verified the performance of our soft bit metric by simulation based on IEEE 802.11 a/g standard. The result of the second part has already been published in APCCS, 2003, and has been accepted for publications by the IEEE trans. on wireless communications.

Based on the result of the first year, the aims of this year are to design channel codes which have been considered the statistics properties of fading channels. In this work, we take the PCCC code and its respective iterative MAP decoder as a test vehicle to experiment on the idea that the *temporal channel memory* can be weakened to *nearly blockwise time-independence* by the insertive transmission of "random bits" of sufficient length between two consecutive blocks, for which these "random bits" are actually another parity check bits generated due to interleaved information bits. The simulation results show that the metrics derived based on blockwise independence with 2-bit blocks periodically separated by a *single* parity-check bit from the second component RSC encoder perform close to the CSI-aided decoding scheme, and is at most 0.9 dB away from the Shannon limit at $BER = 2 \times 10^{-4}$ when $h_0 = 1$ and $\sigma_v^2 = 0.001$. The result of the first part has been prepared for submission to IEEE communication letters. A natural future work is to extend the channel memory to higher order, and further examine whether the same idea can be applied to obtain well-acceptable system performance. In the second part of the second year's work, we have remarked on four different definitions of channel capacities according to the transmitter/receiver with/without channel state information. We then turn to the derivation of the independent bounds for the channel capacity without CSI in both transmitter and receiver. We then found that if there is no LOS signal existing, the capacity of the blind-CSI system will be reduced to zero.

On the last year, we demonstrate the well performance of PCCC code by considering the statistical properties of Gauss-Markov fading channels by simulations based on the MAP metric derived in last year. It proves the feasibility of our idea that the memory of channels can be weakened to blockwise independence by inserting "random bits" between two consecutive blocks. On the second part of this work, we derive the pairwise error probability as a function of the criterion for use of the simulated annealing algorithm. By the simulated annealing algorithm, we construct codes that have better WER performance than those obtained from [15]. Our designed codes provide a coding gain of about 3.5 dB and 6 dB on the Gauss-Markov channels with channel memory orders 1 and 2 respectively over those given in [15] at WER= $10^{-2}$. During the process to obtain this criterion, we found that the complicate characteristic of the channel increases the operations needed for code search drastically. Even though we have performed some reductions on the criterion to speed up the algorithm, it still takes a long time to search for good codes. A natural future work will be to further speed up the algorithm by simplifying the code search criterion.