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Summary

In the past decade, the requirement for speed and reliability of information transmission increases very quickly, and certainly it will keep growing in the coming future. High speed data transmission usually suffers from the disturbance in the communication channel. During the transmission, the channel brings additive noise and its frequency selective nature, due to limited bandwidth or multipath fading, introduces InterSymbol interference (ISI). As a consequence, the transmitted signal waveform may be severely disturbed, which will cause the loss of information at the receiver end. Reliable transmission can not be achieved without the compensation for these disturbances. The equalization in digital communication systems is a compensation process, which combats the ISI and additive noise to reconstruct the transmitted signal, and the compensator in this process is called equalizer.

Traditionally, the equalization is treated as an inverse filtering problem, where the transversal structure based linear equalizer (LE) tries to form an approximation to the inverse of the distorting channel. However, due to the noise enhancement, the accurate approximation and good equalization performance can not be achieved by this low computationally demanding equalizer. From the estimation theory, it is known that the best performance is obtained by detecting the entire transmitted sequence using the Maximum Likelihood Sequence Estimation (MLSE). High complexity and deferring decisions associated with the MLSE are however often unacceptable in many practical communications systems. Recent researches focus on Neural Network (NN) based equalizers, which consider the equalization as a geometric classification problem and provide alternative compromises between performance and complexity, Compared with the LE, NN based equalizers have the same architecture of making decisions symbol by

symbol, but can handle a hypersurface decision boundary rather than the hyperplane decision boundary of the LE, thus achieve superior performance. In particular, Bayesian Equalizer (BE), a.k.a. Radial Basis Function (RBF) equalizer because of the perfect implementation by RBF networks, is the error probability optimized solution for symbol-decision equalization. The BE presents slightly poorer performance then MLSE but has significantly lower complexity and shorter delay. Therefore, it is regarded as a very promising equalization technique.

The conventional equalization is purchased with the assistance of pilot sequence, which is known at the receiver and sent before the information-bearing signal sequence being sent. In contrast to pilot-aided equalization, the equalizer without the benefit of a pilot sequence is said to be self-recovering or blind equalizer. In blind equalization, the Bussgang statistics approaches are based on a LE, thus they inherit the noise enhancement characteristic; the Second Order Statistics (SOS) and Higher Order Statistics (HOS) based approaches are essentially channel identification solutions, which do not directly give equalization solution. Furthermore, these three classes of blind equalization approaches are not suitable for nonlinear channel. For blind MLSE, although theoretically it can be applied on nonlinear channel, it suffers from not only the difficulty of nonlinear channel identification but also the high complexity and long decision delay like the MLSE. On the other hand, since BE is designed in accordance with the channel output states (COSs), the channel identification and the noise enhancement can be avoided. Due to these attractive characteristics, naturally , it is desirable to develop the blind equalization techniques based on BE.

So far the Bayesian family equalizers are developed for single channel, while that for multi-

channel case has not been discussed yet. Aiming at performance improvement and wide-range application, this thesis focuses on two topics, one is Bayesian Decision Feedback Equalizer (BDFE) with receiver diversity combining and another one is blind equalization using BE. The major contributions of this thesis lie on two proposed combining schemes for BDFE with receiver diversity and the proposal of three kinds of Blind Bayesian Equalizers (BBEs) . The main components of this thesis and the major results of the presented work can be summarized as follows:

Chapter 1 introduces the history of the equalization research and gives an overview of this thesis.

Chapter 2 describes the mathematical model of baseband communication system, explains the reason of ISI and derives the BE and the BDFE.

Chapter 3 investigates the problem of BEFE with receiver diversity combining and proposes two combining schemes. In the first combining scheme, Bayesian Decision Variable Combining (BDVC), we employ several BDFEs corresponding to the same numbers of receivers, and the decision variable is defined as the product of the Bayesian Decision Variables (BDVs) in the corresponding BDFE of each sub-channel. Since the BDVC exploits the maximum diversity at BDV level, we give the optimal solution for multichannel. However, this optimal solution is computationally expensive. To make a compromise between performance and complexity, a complexity reduced linear combining is proposed, where a linear combiner is used to combine the received signals of each subchannel before being fed to a BDFE. This eigenvector based Maximal Delay span channel energy Combining (MDC) maximizes the desired part energy of the combined channel, which the performance of the followed BDFE mainly depends on. Consequently , the significant complexity reduction is achieved, at a price of light performance loss. Although the MDC based BDFE shows somewhat worse performance than that based on BDVC, it is more practical due to its simplicity . The validity and performance superiority of these two combining schemes are demonstrated by the simulations.

Chapter 4 focuses on the proposed first approach to blind equalization using BE, blind BDFE with channel estimators. For the challenging blind equalization problem, due to the lack of channel information, a straightforward idea is to employ a cannel estimator. Chen et al. have proposed a blind BDFE (BBDFE) , where the channel and the signal are estimated in a joint sense. However, this decision-directed based approach suffers from the incorrect convergence, without the suitable initialization corresponding to the small ISI. How to find a suitable initialization becomes a key problem. Chen et al. have suggested an initialization according to the partial information of the channel. In contrast, with no any knowledge of the channel, a "start" vector that has several states is used to obtain several channel estimates, which are the initial channel estimates in the proposed method. Then the decision-directed algorithm is individually purchased from these initializations with the corresponding BDFEs. By evaluating the Bayesian likelihood which is defined as the accumulation of the natural logarithm of the maximum BDV decision variable at each instant, the optimal channel estimates corresponding to the maximum Bayesian likelihood can be found, as well as the optimal BDFE. Compared with Chen's BBDFE, the proposed one not only presents better convergence performance with less computational complexity, but also is able to deal with the channel having severe ISI and in-band spectral null satisfactorily.

Chapter 5 develops the received signal constellation (RSC) estimation based BBE, the proposed second approach to BE based blind equalization. Since BE is based on the classification viewpoint, it essentially depends on the COSs, rather than the channel itself. In other words, only the RSC, which composes the COSs, is important. Based on this property, we develop a BBE and highlight its application in nonlinear channel. Usually, most of the algorithms for blind equalization are developed on linear channel models because of the simplicity. The difficulty in nonlinear case is that not only the channel parameters but also the channel model is not known exactly. Fortunately, a BE cares about the RSC only, so it is very suitable for nonlinear channel. Using the Bayesian likelihood cost function which has been defined in the last chapter, the problem becomes to maximize the Bayesian likelihood cost function with respect to the RSC, and the complex channel modeling is avoided. For this high dimensional complex optimal problem, a hybrid simplex genetic algorithm, in which the simplex operator is incorporated with genetic algorithm, is proposed. Furthermore, this RSC estimation based BBE is extended to couple with adaptive array antenna, and by employing the above mentioned BDVC, we propose a Blind Spatial and Temporal Bayesian Equalizer (BSTBE). Also simulation results are given to evidence the validity of the proposed BBEs.

Chapter 6 discusses the last kind of the proposed BBEs, Cluster Map based Blind RBF Equalizer (CM-BRE), which highlights a new cluster matching consideration of blind equalization problem. Without channel estimator, the desired numbers of COSs (RBF centers) can be obtained by an unsupervised clustering algorithm, Neural Gas Algorithm (NGA). Based on the cluster matching viewpoint, which comes from the classification nature of the BE, a cluster map generated from the known RBF equalizer structure is used to partition the unlabeled RBF centers into appropriate subsets merely by several simple sorting operations, which corresponds to the weight initialization. Finally, the weights are adjusted iteratively by an unsupervised Least Mean Squares (LMS) algorithm. Since the weights are initialized according to the underlying structure of RBF equalizer, the proposed CM-BRE can achieve almost identical performance with the optimal BE and avoid the calculation of the complex cost function, for example, the above mentioned Bayesian likelihood. Moreover, by further exploration on the COSs, CM-BRE is extended to a Cluster Map based Blind RBF Decision Feedback Equalizer (CM-BRDFE), in which not only the determination method of the feedback vector is given, but also the high computational load mainly caused by NGA is reduced by a downsizing method that employs the inter-relation among RBF centers. The proposed CM-BRDFE also has the close performance to the optimal RBF decision feedback equalizer, which is demonstrated by the simulations.

Chapter 7 concludes this thesis and gives some topics for future research.

List of Publications

No.	Article's Title	Author(s)	Journal's Name, Vol., Pages (Year).	Corresponding Chapter
1	Blind Equalization Using Parallel Bayesian Decision Feedback Equalizer	H. Lin K. Yamashita	Mathematics and Computers in Simulation, Vol. 56, pp.247-257 (2001).	Chapter 4
2	Fractionally Spaced Bayesian Equalizer	H. Lin K. Yamashita	Proc. of Int. Conf. On Neural Information Processing, pp.81-84 (Shanghai, China, 2001).	Chapter 3
3	Hybrid Simplex Genetic Algorithm for Blind Equalization Using RBF Networks	H. Lin K. Yamashita	Mathematics and Computers in Simulation, Vol. 59, pp.293-304 (2002).	Chapter 5
4	Blind RBF Equalizer for Received Signal Constellation Independent Channel	H. Lin K. Yamashita	Proc. of IEEE Int. Conf. on Communication Systems, pp.82-86 (Singapore, 2002).	Chapter 6
5	Fractionally Spaced Bayesian Decision Feedback Equalizer	K. Yamashita H. Lin	IEICE Trans. on Fundamentals, Vol. E86-A, pp.215-220 (2003).	Chapter 3
6	Cluster Map Based Blind RBF Equalizer	H. Lin K. Yamashita	IEICE Trans. on Fundamentals, Vol. E86-A, pp.2822-2829 (2003).	Chapter 6
7	A Design Method of Blind Spatial and Temporal RBF Equalizer Using Genetic Algorithm	K. Watanabe H. Lin K. Yamashita	IEEJ Trans. on Electronics, Information and Systems, Vol. 124-C, pp.941-946 (2004).	Chapter 5
8	Blind RBF Equalizer with Decision	H. Lin K. Yamashita	Proc. of IASTED Int. Conf. on Artificial	Chapter 6

	Feedback		Intelligence and Application, pp.645-650 (Innsbruck, Austria, 2004).	
No.	Article's Title	Author(s)	Journal's Name, Vol., Pages (Year).	Corresponding Chapter
9	A Cluster Map Based Blind RBF Decision Feedback Equalizer with Reduced Computational Complexity	H. Lin K. Yamashita	IEICE Trans. on Fundamentals, Vol. E87-A, pp.2755-2760 (2004).	Chapter 6
10	Bayesian Decision Feedback Equalizer with Receiver Diversity Combining	H. Lin K. Yamashita	IEICE Trans. on Fundamentals, Vol. E88-A, (2005) (in press).	Chapter 3

審査結果の要旨

本論文は、デジタル通信システムにおけるチャネル等化の Bayesian 手法に関する一連の研究をまとめたものであり、以下の成果を得ている。

(1) 受信機ダイバーシチ技術を Bayesian 等化器の設計に導入し、各受信機で設計した Bayesian 等化器の判定変数を合成する方法を提案している。提案手法の特徴は、各 Bayesian 等化器で判定するよりも、合成した等化結果の誤差確率が低減化し得る点にあり、このことを数学的および実験的に明らかにしている。

(2) 上記の Bayesian 等化器における、判定変数決定の計算負荷を軽減化するため、各受信機の信号を重み付け合成した信号を用いる Bayesian 帰還型等化器を提案している。この重み付け係数の決定アルゴリズムは、Bayesian 帰還型等化器の性能を向上することに目的を置いている。

(3) 線形チャネルのブラインド等化問題に対して、チャネル推定アルゴリズムと Bayesian 等化技術を結合した、パラレル型ブラインド Bayesian 帰還型等化器を提案している。提案した等化器は、従来のブラインド Bayesian 帰還型等化器に比較して、良い初期条件が得られることと Bayesian 尤度関数を評価関数に用いていることから、ヌル特性をもつ取扱いが非常に困難なチャネルに対しても、優れた特性をもつことを明らかにしている。

(4) 非線形チャネルのブラインド等化問題は、非線形チャネルの推定が困難であることから非常に難しい問題とされてきた。Bayesian 等化器は基本的に、チャネル特性を直接利用せず、送信信号と Bayesian 等化器において重要な役割を担うセンタ要素間の関係より構築することができる。ここでは、最尤法に基づいた評価関数を定義し、センタ要素を大域的探索法である遺伝的アルゴリズムを用いて決定している。

(5) 教師なしクラスター学習方法は、受信信号からラベルなしクラスターを抽出できる。この点に注目し、受信信号から抽出したクラスターと Bayesian 等化器固有の構造から得たクラスターマップをマッチさせることにより、送信信号を復元し得る新たなブラインド Bayesian 等化器を提案している。提案した等化器は、簡単な並び替えの操作で、線形と非線形チャネルにおいて、最適 Bayesian 等化器に近い性能を得ている。

以上の諸成果は、デジタル通信システムでの Bayesian 等化技術の実用化のための基礎的な知見や基盤を与えるものであり、この分野の技術の発展に貢献するところ大である。また、申請者が自立して研究活動を行うに十分な能力と学識を有することを証したものである。

3．審査委員会の所見

本委員会は、本論文の審査ならびに学力確認試験の結果から、博士（工学）の学位を授与することを適当と認める。