A Review on Noise and Inter-Symbol Interference (ISI) Reduction Methods Using Advanced Signal Processing Techniques for Biomedical Communication and Healthcare IoT Systems

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ABSTRACT

In this paper various equalization techniques are introduced for improving the performance of signal passing through a communication channel. In digital communication system, the transmitted data get corrupted due to the dispersive nature of channel and these ISI and noise are removed by equalization techniques. Mostly blind equalization method is used, since it depends upon channel assumptions. Performance of the proposed detector is evaluated using computer simulations and its bit error rate is compared with a blind equalizer and a conventional particle filter-based method. Thus bit error rate is controlled.

KEYWORDS: Blind equalization, joint equalization and decoding, particle filtering, Markov Chain Monte Carlo.

1. INTRODUCTION

Digital communication systems must employ a form of channel equalization to mitigate the effects of intersymbol interference(ISI), which otherwise would render communication over such channels unfeasible. While classical equalization methods require the transmission of known signals (training sequences), untrained or blindequalization methods dispense with such need, being therefore preferable from an efficiency point of view. Since Sato's (1975) [1] original publication,a plethora of blind equalization methods have been developed. Most earlier methods implicitly estimate higher-order moments of the received signal, exhibiting consequently rather slow convergence properties. Later methods based on the estimation of second-order statistics [2], [3], overcome this problem, incurring nevertheless in severe performance issues due to the existence of non-identifiability conditions. Recently, advances in computer technology have made possible the development of numerical Bayesian inference techniques such as Markov Chain Monte Carlo (MCMC) [4] and particle filters (PFs) [5]. At the expense of high computational complexity of these techniques, approximate optimal Bayesian solutions to many estimation problems that, like blind equalization, could previously be solved only by *ad hoc* suboptimal methods. Blind equalizers based on MCMC [6] and PF [7] have been shown to perform near-optimally, closely approximating the performance of the maximum *a posteriori* (MAP) equalizer that has exact knowledge of the channel parameters. Blind detection methods are preferred to avoid bandwidth loss. Despite the good performance achieved by both MCMC and PF methods, PF-based techniques have attracted more interest, among other reasons, for being recursive and better suited for parallel processing [8]. Most practical digital communication systems employ, a form of coding to correct or detect transmission errors.For such systems, optimal detection requires that decoding and equalization are two essential operations at the receiver side which can be performed separately or jointly. For communication systems that *interleave* [9] the coded symbols prior to transmission, optimal joint equalization and decoding is in general impractical, even in the case that the channel parameters are perfectly known. However, heuristic methods based on the so-called *turbo-equalization* principle can be employed in this case, leading in general to good performances [10]. For communication systems transmitting non-interleaved convolutionally encoded [11] symbols, if the channel parameters are known, optimal joint equalization and decoding is practical, and can be performed via the algorithm by Bahl, Cocke, Jelinek and Raviv (BCJR) [12] operating on a super-trellis that regards the transmission channel as a second convolutional encoder. A review on various techniques used to mitigate the effects of intersymbol interference by employing a form of channel equalization. Thesetechniques include use of turbo equalization methods, different modulation techniques and by using particle filtering

2. MATERIALS AND METHODS

2.1 BLIND EQUALIZATION: Because of the desirable features and the challenges in the field of researchers,blind equalization has become an important problem in digital signal processing. In digital signal processing, blind equalization is a technique in which transmitted signal is equalized from the received signal, by only considering the transmitted signal statistics. The main aim is to recover the unknown input sequence to the unknown channel based on the probabilistic and statistical properties of the input sequence. If a BPSK signal is given as the input of below system, bit error rate have to be reduced.

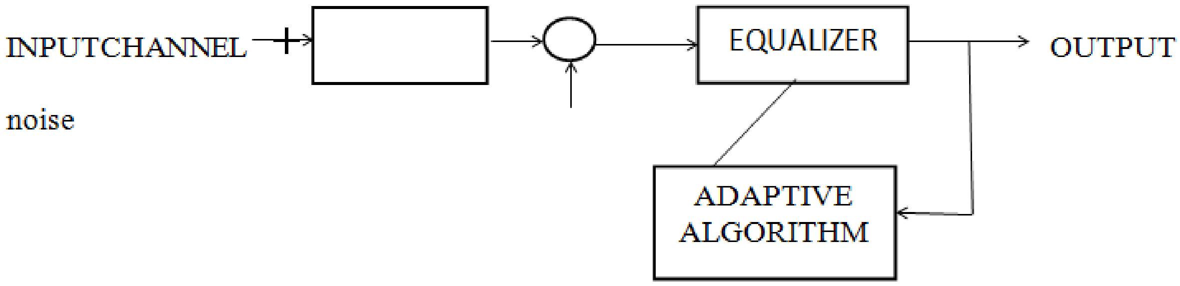

Fig1:Block diagram of Blind Equalization

2.1.1 Turbo Equalizer: Turbo equalizer is used to receive a message corrupted by a communication channel with ISI, hence it plays a role of receiver in digital communication system. It approaches the performance of a maximum a posteriori receiver through a iterative message passing between a soft-in soft-out(SISO)equalizer and its corresponding decoder. If the channel is viewed as a non-redundant convolutional code, this equalizer may be considered as a type of iterative decoder. The main difference between a turbo equalizer and a standard equalizer is the feedback loop of equalizer from the decoder. When a soft information is passed into turbo equalizer algorithm, such information is never formed based on information passed into algorithm concerning the same. Here equalizer and decoder tells new information to each other. This receiver mainly used for GSM radio access network using QAM modulation for overcoming dispersion of prior information. Also it helps in transmission over frequency selective fading channel.

2.2 BLIND EQUALIZATION AND IDENTIFICATION OF COMMUNICATION CHANNELS: Blind equalization finds different applications in data communication systems. In data communications, digital signals are generated and transmitted by the sender through an analog channel to the receiver. Analog media (such as telephone cables and radio channels) typically introduce distortion to the transmitted signal. Linear channel distortion as a result of limited channel bandwidth, multipath, and fading is often the most serious distortion in digital communication systems. The linear channel distortion, known as the inter-symbol interference (ISI), can severely corrupt the transmitted signal and make it difficult for the receiver to directly recover the transmitted data. Channel equalization has proven to be an effective means to compensate the linear channel distortion by removing much of the ISI.

2.2.1 Blind Single Channel Equalization: Although channel equalization has been the subject of intense research interest since the first adaptive implementation of channel equalizers by R. Lucky [12],[13], the concept of training-less blind equalization received its first wide coverage in 1975 when Y. Sato [1] presented a simple linear equalizer for pulse amplitude modulated (PAM) signals under the framework of single-input-single-output (SISO) discrete systems. Alternatively, iterative channel and symbol estimation approaches also appeared to estimate the unknown channel parameters. Given the knowledge on the input signal distribution (finite alphabet), an iterative channel and symbol estimation approach was presented by Seshadri [14] and Ghosh and Weber [15], a maximum likelihood (ML) algorithm was implemented through Expectation-Maximization (EM) by Kaleh and Vallet [16].

2.2.2 Blind Statistical Channel Identification: Parallel to the problem of blind channel equalization, an equivalent problem is the identification of the unknown channel impulse response from the output signal sequence.Given channel output statistics, second order statistics alone can only provide the amplitude information of the SISO channel frequency response. Specifically, the analytical relationship between the channel response and the higher order statistics (HOS) [17] can be exploited for channel identification from measured statistics. These explicit HOS algorithms select the channel response either by least square cumulant matching or by solving equations that the channel response must satisfy.

2.2.3 Multichannel Identification and Equalization: The research activities on blind channel identification and equalization received a strong boost from the well-known paper by Tong, Xu, and Kailath [18] which first presented the blind identifiability and, consequently, the equalizability of single input-multiple-output (SIMO) linear channels from only the second order statistics. In essence, this result allows the use of only second order statistics to identify linear discrete channels with the number of output signals exceeding the number of input signals. This important finding led to a number of statistical and deterministic algorithms for blind channel estimation and equalization. In practice, multiple antenna elements and/or oversampling of channel output with excess bandwidth can materialize the SIMO linear system model.

2.3 BAYESIAN ESTIMATION: In maximum likelihood(ML) estimation, parameters are assumed to be fixed but unknown. The parameters in the Bayesian estimation procedure, by its nature, utilizes whatever prior information is available about the unknown parameter. Bayesian methods considers these parameters as random variables having some known prior distribution. In estimation and decision theory, a Baye estimator or a Bayes action is an estimator or decision rule in which it minimizes the posterior expected value of a loss function and then it maximizes the posterior expectation of a utility function. Maximum a posteriori estimation is an alternative way of formulating an estimator within Bayesian statistics.

2.3.1 Maximum a posteriori(MAP): MAP probability estimate is an estimate of an unknown quantity, that equals the mode of the posterior distribution. On the basis of empirical data, it can be used to obtain a point estimate of an unobserved quantity and it is closely related to the method of estimation of maximum, but this employs an augmented optimization objective which incorporates a prior distribution over the quantity one wants to estimate. Therefore MAP estimation can be seen as a regularization of ML estimation. While only mild conditions are required for MAP estimation compared to Bayes estimation , it is not very representative of Bayesian methods in general. Because of this, MAP estimates are point estimates, whereas Bayesian methods summarize the data and draw inferences which is characterized by the use of distributions. Then, Bayesian methods tend to report the median or posterior mean instead, together with credible intervals. Because these estimators are optimal under squared and linear error loss respectively and they depends mainly on typical loss functions and because the posterior distribution may not have a simple analytic form. The optimization to find its modes may be difficult or impossible in this case and thus the distribution can be simulated using Markov chain Monte Carlo techniques.

2.4 MARKOV CHAIN MONTE CARLO: The main idea is to construct a Markov chain that allows one to sample from p $(x_n/ x_{0:n-1}, y_{1:n})$. However, it may take a lot of time to converge, particularly if the amount of system noise is small, and can generally be too computationally demanding for on-line analyses. The MCMC methods may help, however, with solution of other problem associated with particle filtering, in particular, samples depletion.The MCMC methods comprise a class of algorithms in statistics, which can be sampled from a probability distribution. By constructing a Markov chain that has the desired distribution as its equilibrium distribution, after a number of steps , one can obtain a sample of the desired distribution by observing the chain. There are more steps, the more closely the distribution of the sample matches the actual desired distribution. Practically, developed an ensemble of chains, starting from a set of points arbitrarily chosen and sufficiently distant from each other. The idea is to simulate N independent identically distributed (i.i.d.) samples $\{x^{(i)}_{0:n}\}^{N}_{i=1}$ from the distribution of interest, which is in our case the posterior p $(x_{0:n}/y_{1:n})$, and use them to obtain an empiricalestimate of the distribution.

2.5 STANDARD APPROACH TO FILTERING: The major breakthrough in the filter theory was due to Kalman and Bucy [Kalman & Bucy, 1961], who solved aequation to produce the Kalman filter for a linear Gaussian class of problems. The Kalman filter was then extended (EKF) to consider more general nonlinear non-Gaussian scenario. Later, with the increase in computer power, more computationally expensive filters were introduced approximating the posterior of interest by mixture distributions, with the Gaussian sum filter and Interacting Multiple Model algorithm among others. Finally, the grid based methods evaluating the required density as a set of nodes covering the state space appeared. All these methods are briefly described in this section, where we also mention some problems associated with their use.

2.5.1 Kalman filter: Kalman filtering is an algorithm in statistics and control theory, that make use of a series of measurements when it containing statistical noise and other interference observed over time . Then it produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe. It uses system model and sensor observation to estimate current state from previous states and usually used for linear system with Gaussian noise. Well normally Kalman filter is computationally easy to afford for working purpose. This filter has long been regarded as the optimal solution to many tracking and data prediction tasks. The Kalman filter has numerous applications such as for navigation, guidance, and control of vehicles, particularly aircraft and spacecraft. Furthermore, the Kalman filter is a widely used for the concept in time series, analysis used in fields such as signal processing and econometrics. In the field of robotic motion planning and control, Kalman filter is a major tool, and they are sometimes included in trajectory optimization. The Kalman filter also works for modeling the central nervous system for the control of movement.It is best for estimating linear systems with Gaussian noise. Kalman filter is less flexible and best for estimating linear systems with Gaussian noise. Thus Particle filter algorithm works for any arbitrary distribution and not just Gaussian.

2.5.2 Extended Kalman filter: Although the Kalman filter is extremely simple and optimal in the linear Gaussian scenario, new methods of filtering were required to consider more general case. Therefore, a number of approximate filters have been devised. Extended Kalman filter (EKF) is historically the first,and, probably, most used one.The filter works quite well for a weakly non-linear system. For a systems with higher degree of non-linearity, the accuracy of the linearization could be increased, for example, by using Iterated EKF.

2.5.3 Particle filter: Particle filter uses a random sampling to generate different system states and then assign high weight to those state that are supported by sensor data and it is used for non-linear system. The objective of PF is to use corresponding weight of the random sample to recursively approximate a desired probability distribution function.

2.5.3.1 Steps in the algorithm

The steps for the algorithm is simply illustrated through Fig2.

a. **Initialization:**Initialize the state of the filter and intialize our belief in the state.
b. **Prediction:**Use a system behavior to predict state at the next time step and adjust belief to account for the uncertainity in prediction.
c. **Update:**Get a measurement and associated belief about its accuracy. Compute residual between estimated state and measurement. New estimate is somewhere on the residual line.
d. **Resampling:**Particles with negligible weights are replaced by new particles in the proximity of the particles with higher weights. It is carried out only if it is less than a specified threshold.

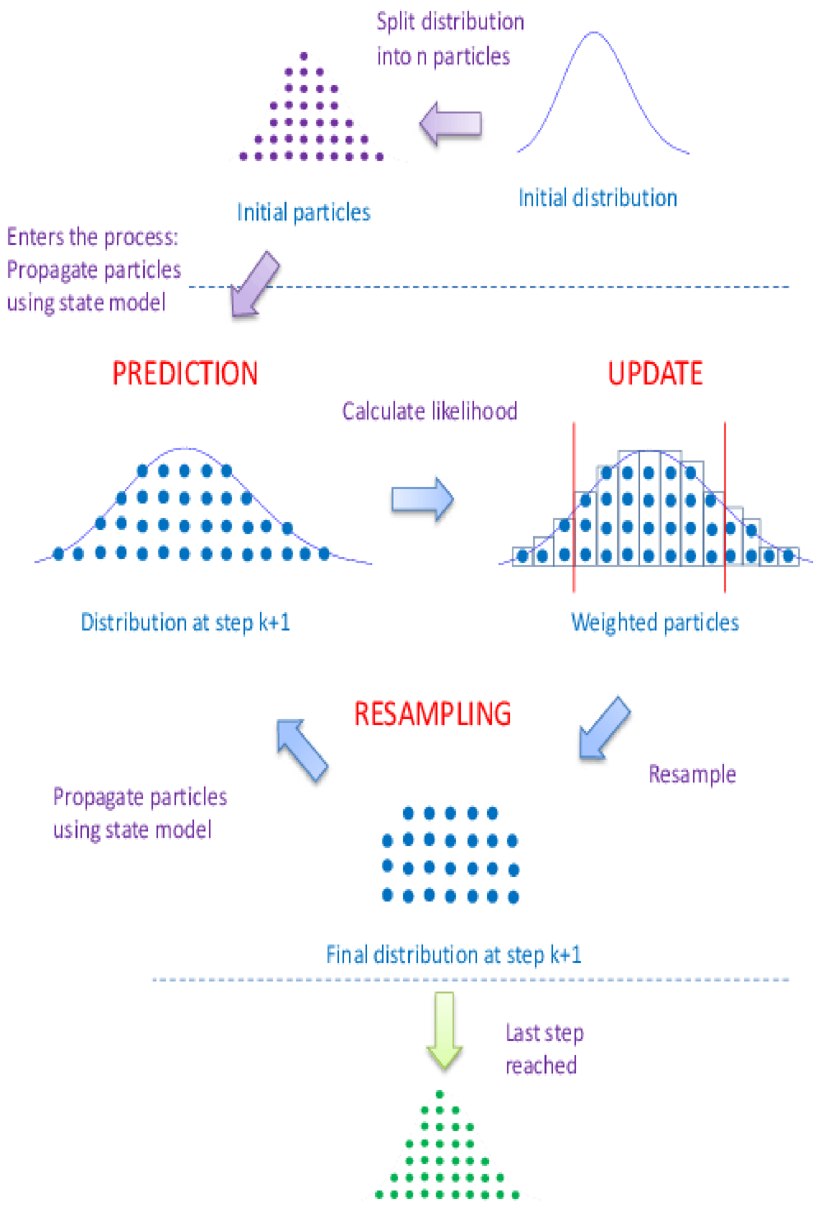

Fig2:Steps in the algorithm

Upto the step updation, the resulting algorithm is affected by a phenomenon called degeneracy and this results wasting of large computation effort. This can be controlled by providing resampling. In [6], [19] [20], alternative methods for obtaining smoothed estimates with PF were described, that results better performance than that of [21],incurring however in much higher computational efforts.

2.5.3.2 Applications of Particle Filtering:

- In digital communication
- To target tracking
- To speech and music

3. CONCLUSION

The revolution in global communications is leading to unprecedented access to information and knowledge. Affordability creates accessibility, and as the number of users and the demand for services grows, so does the need for efficient signal processing techniques capable of coping with the increasingly difficult communication environment. In this paper, we have provided an extensive review of different signal processing techniques to reduce ISI. Also this introduced novel algorithms for joint blind equalization and decoding of convolutionally coded communication systems. It should be noted that by separately applying channel equalization and decoding to the incoming signal, some of the information is ignored while when looked from the perspective of simultaneously equalization and decoding, the detection at the BPSK receiver may has a better performance. Python is very good library like numpy, matplotlib, scipy, which can help to save the time of engineerbut number of studies considering real-world datasets and number of features are still very limited. The sparse coding based approach and dictionary based approach are mainly used for Facial Expression recognition from images. Regression based approach and Deep Neural Networks based approaches can be used for both cases. Sparse coding based approaches and Deep Neural Networks based approaches give more effective results for Facial Image Recognition and Reconstruction.

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