# CO-CHANNEL INTERFERENCE SUPPRESSION USING A FUZZY FILTER

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**ABSTRACT**

This paper investigates the problem of channel equalisation in digital cellular radio (DCR) application. DCR systems are affected by cochannel interference (CCI), intersymbol interference (ISI) in presence of additive white Gaussian noise (AWGN). Here we propose a fuzzy equaliser to equaliser communication channels with these anamolies. This equaliser performs close to to the optimum Bayesian equaliser with a substantial reduction in computational complexity. The equaliser is trained with supervised and unsupervised scalar clustering techniques in sequence, and consist of a fuzzy equaliser with a preprocessor for CCI compensation. Simulation studies have demonstated the performance of the proposed technique.

## 1 INTRODUCTION

Digital cellular radio (DCR) communication systems encounter co-channel interference (CCI), adjacent ahannel interference (ACI), intersymbol interference (ISI) in the presence of additive white Gaussian noise (AWGN). The CCI is caused due to frequency reuse and the frequency spacing in different cells contribute to the ACI. While these effects affect the DCR in particular, the effects of ISI due to narrow band channel characteristics affect all digital communication systems in general. Adaptive equalisers [1] are used in communication receivers to mitigate one or more of these effects. In DCR applications CCI limits the performance of the equalisers. Generally linear fractionally spaced equalisers (FSE) have been used for equalisation of such channels [2, 3]. These equalisers treate CCI as a cyclostationary interference. The performance of these equalisers is limited due to the linear decision boundary provides by linear equalisers.

Nonlinear techniques have been used for equalisation of communication channels corrupted with CCI and AWGN [4, 5]. The nonlinear equalisers provide superior performance compared to linear equaliser due to their ability to form nonlinear decision boundaries. The upper performance bound of these equalisers is determined by the Bayesian equaliser [6]. Fuzzy filters [7] are nonlinear filters and they have been used for equalisation in a variety of communication systems [8, 9]. Recently the close relationship between Bayesian equalisers and fuzzy equalisers [10] has been demonstrated. Several nonlinear techniques have been proposed for the equalisation of channels with CCI [11–13]. The performance of these nonlinear equalisers id limited to low interference in high noise or low noise in high interference. Chen et. al. [14] proposed the Bayesian decision feedback equaliser (DFE) to mitigate the effects of CCI, ISI and noise. Although this equaliser provides good performance it suffers from a large computational requirement. This paper presents an extension of work reported in [15] and [10] for CCI suppression.

This paper is organised in 4 sections. Following the introduction, section 2 discusses the communication problem used here. Section 3 derives the Bayesian equaliser decision function for CCI suppression and also proposes the fuzzy implementation of this equaliser. Section 4 provides some simulation results and finally concluding remarks are provided.

## 2 SYSTEM MODEL

The discrete time communication system used in this problem is presented in Figure 1. The channel and the co channels are finite impulse response (FIR) filters represented by

$$H_i(z) = \sum_{j=0}^{p_i-1} a_{i,j} z^{-j} \qquad 0 \le i \le n \tag{1}$$

Here $p_i$ and $a_{i,j}$ are the length and tap weights of $i$th channel impulse response. $H_0(z)$ is the desired channel and $H_i(z), 1 \le i \le n$ are the interfering co-channels. Only the transmitted signal $s_0(k)$ of the desired channel is available at the receiver during training period. Without loss of generality it can be assumed that the communication system is binary. The transmitted sequences $s_i(k); 0 \le i \le n$ are mutually independent and are taken from independent identical distributed (iid) data set with values $+1$ or $-1$.

The input to the equaliser forms the observation vector from channel output. Each of the component of this vector can be presented as

$$r(k) = \hat{r}(k) + r_{co}(k) + \eta(k) \tag{2}$$

Here $\hat{r}(k)$ is the desired received signal, $r_{co}(k)$ is the interfering signal, $\eta(k)$ is the noise component and $k$ specifies

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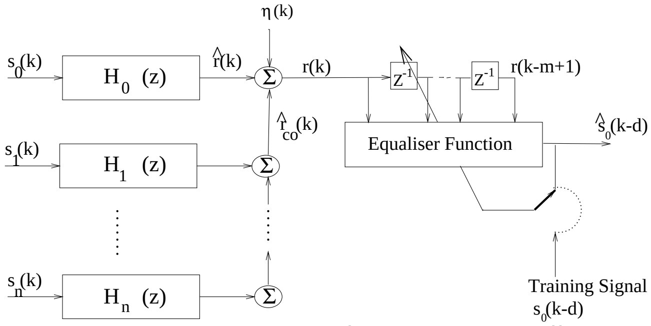

Figure 1: *Discrete time model of the DCR system affected by CCI, ISI and AWGN*

the time instant. The noise $\eta(k)$ is assumed to be Gaussian with variance $\sigma_\eta^2$ and is uncorrelated with the data. With this the signal to noise ratio (SNR), signal to interference ratio (SIR) and the signal to interference noise ratio (SINR) can be represented as

$$SNR = \sigma_s^2/\sigma_\eta^2 \tag{3}$$

$$SIR = \sigma_s^2/\sigma_{co}^2 \tag{4}$$

$$SINR = \sigma_s^2/(\sigma_\eta^2 + \sigma_{co}^2) \tag{5}$$

Here $\sigma_s^2$ and $\sigma_{co}^2$ represent the signal power and the co-channel signal powers respectively. The task of the equaliser is to estimate the delayed transmitted sequence $s_0(k-d)$ based on the channel observation vector $\mathbf{r}(k) = [r(k), r(k-1), ...r(k-m+1)]^T$. Here $m$ is the order of the equalizer.

## 3 BAYESIAN EQUALISER FOR CCI SUPRESSION AND ITS FUZZY IMPLEMENTATION

In this section we derive the Bayesian equaliser decision function for CCI (Bayesian_CCI) and propose its fuzzy implementation.

### 3.1 Bayesian equaliser for CCI suppression

The optimal decision function of a finite memory Bayesian equaliser in presence of ISI and AWGN can be expressed as [6]

$$f(\mathbf{r}(k)) = \sum_{i=1}^{n_s} w_i \exp\left(\frac{-\|\mathbf{r}(k) - \mathbf{c}_i\|^2}{2\sigma_\eta^2}\right) \tag{6}$$

Here $n_s$ is the number of channel states equal to $2^{p_o+m-1}$, $w_i$ are the weights associated with each of the centres. $w_i$ is +1 if $\mathbf{c}_i$ correspond to a positive channel state and -1 if it represents a negative channel state.

To derive the relationship for Bayesian_CCI we assume that there is only one co-channel. In the presence of CCI the interfering signal $\mathbf{r}_{co}(k) = [r_{co}(k), r_{co}(k-1), ..., r_{co}(k-m+1)]^T$ will have $n_{s,co} = 2^{p_1+m-1}$ co-channel states $\mathbf{c}_{co,l}$, where $1 \le l \le n_{s,co}$ corresponding to each of the channel states. The presence of the co-channel states will modify the decision function as

$$f_{CCI}(\mathbf{r}(k)) = \sum_{i=1}^{n_s}\sum_{l=1}^{n_{s,co}} w_i \exp\left(\frac{-\|\mathbf{r}(k) - \mathbf{c}_i - \mathbf{c}_{co,l}\|^2}{2\sigma_\eta^2}\right) \tag{7}$$

This forms the optimum solution for a symbol spaced equaliser decision function when the channel is corrupted with CCI, ISI and AWGN.

### 3.2 Fuzzy equaliser for CCI compensation

We proposed the fuzzy implementation of Bayesian equaliser in [10]. This equaliser can be represented as

$$f(\mathbf{r}(k)) = \frac{\sum_{i=1}^{n_s} w_i \left\{\prod_{l=0}^{m-1} \psi_{il}^{jo}\right\}}{\sum_{i=1}^{n_s} \left\{\prod_{l=0}^{m-1} \psi_{il}^{jo}\right\}} \tag{8}$$

where:

$$\psi_{il}^{jo} = \exp\left(-\frac{|r(k-l) - c_{il}^{jo}|^2}{2\sigma_\eta^2}\right) \tag{9}$$

Here (8) provides the normalised form of the decision function, in (6) and in (9) $j$ ranges $0 \le j \le M-1$ with $M = 2^{p_o}$ and is the number of scalar channel states. This equaliser presented by (8) represent a fuzzy system with Gaussian membership function (9), product inference, singletons fuzzifier and centre of gravity defuzzifier [7]. Modification of the membership function to

$$\psi_{il}^{jo} = \max_{\alpha=0}^{M_1-1}\left\{\exp\left(-\frac{|r(k-l) - c_{il}^{jo} - c_{co,\alpha}|^2}{2\sigma^2}\right)\right\} \tag{10}$$

can provide a powerful tool to compensate CCI. Here $\max$ refers to the maximum of the exponential function for different values of $\alpha$ ranging $0 \le \alpha \le M_1 - 1$ and $M_1 = 2^{p_1}$ constitute the scalar co-channel states. However in actual implementation, the membership function in (10) can be evaluated with following function, with substantial reduction in computational complexity.

$$\psi_{il}^{jo} = \exp\left(-\frac{\left\{\min_{\alpha=0}^{M_1-1} |r(k-l) - c_{il}^{jo} - c_{co,\alpha}|\right\}^2}{2\sigma^2}\right) \tag{11}$$

Here $\min$ performs minimum operation to find the closest scalar co-channel state corresponding to each of scalar channel states with respect to the input scalar. The schematic of the co-channel equaliser with fuzzy implementation is shown in Figure 2. Here the input scalar is fed to the membership function generator which are centred at the scalar channel states. The output of the membership function generator is delayed and this forms the membership function for previous received signal samples. The product block has $n_s$ sub blocks and each of these sub-blocks receive membership functions from one of the centres corresponding to each input scalar. These membership functions are suitably combined to provide the modified channel state output. The membership function generators consist of $M_0$ membership function sub-blocks. Each of the sub-blocks has $M_1$ centres. The closest centre to the corresponding input scalar provides the membership function to the product block. The product blocks corresponding to the positive and the negative channel states are suitably combined to provide the equaliser output.

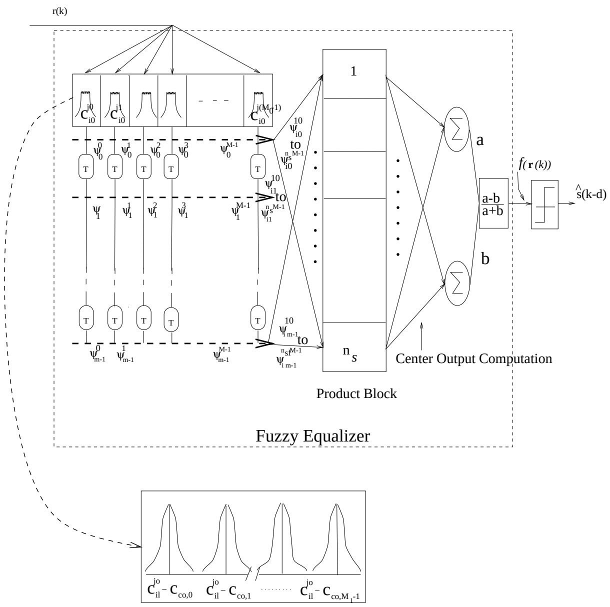


Figure 2: *Schematic of a fuzzy co-channel equaliser*

### 3.3 Fuzzy Equaliser training

The fuzzy CCI equaliser discussed above can be trained in 2 steps. The first step in training involves estimation of the scalar channel and scalar co-channel states and the second step involves learning weights of the output layer.

**Step-I: Determination of channel and co-channel states** The scalar channel and scalar co-channel states of the equalizer can be estimated by a clustering algorithm.

*Channel States:* Equalizer vector channel states can be estimated from scalar channel states, which can be determined from the noisy received scalars with a supervised clustering algorithm during the training period. The noise is zero mean and co-channel states occur in positive and negative pairs. Their effect will cancel in the process of channel state estimation. The SINR can be estimated from the supervised clustering during the scalar channel state estimates. The scalar channel states estimated, along with the training signal sequence producing them, can be arranged to form the vector channel states[14].

*Co-channel States:* Once the channel states have been determined the channel residue $r_{res}(k) = r(k) - c_s^j$ ($c_s^j$ is the scalar channel state) can be estimated. The channel residue arises from the CCI and AWGN. An unsupervised clustering algorithm such as k-means clustring or improved k-means clustering [14] algorithm can be used to estimate the scalar co-channel states and the noise variance ($\sigma_\eta$).

**Step-II Weight Training:** On completion of the channel and co-channel scalar state estimation, the equalizer can be constructed. The initial weights $(w_i)$ of the equalizer can be assigned as $+1$ if $\mathbf{c}_i$ correspond to positive channel state else they can be assigned as $-1$. The LMS algorithm can be used to fine tune the equalizer weights so as to reduce the error at the equalizer output due to the channel states estimation error.

## 4 SIMULATION RESULTS

To study the performance of a fuzzy equaliser in CCI compensation, consider a channel with impulse response $H_0(z) = 0.5 + z^{-1}$ corrupted with CCI from the channel $H_1(z) = \lambda(1 + 0.2z^{-1})$. The SIR can be varied by varying the factor $\lambda$. We observe the decision boundaries for the optimum Bayesian_CCI equaliser and the fuzzy equaliser proposed in this section for a SNR of 15dB and under SIR of 5dB and 10dB. The decision boundaries provided by the Bayesian_CCI equalisers and the Fuzzy equalisers are presented in Figure 3. From the decision boundaries it is observed, that the fuzzy equaliser provides near optimal decision boundary with only 8 channel states in comparison to Bayesian_CCI equaliser which uses 64 channel states.

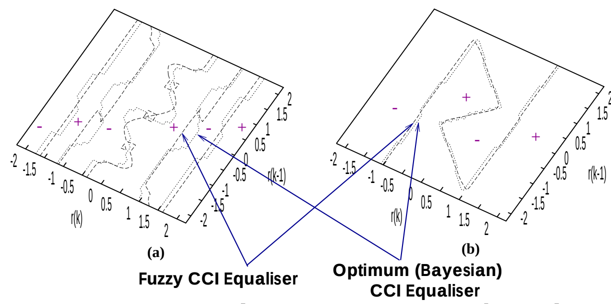


Figure 3: *Fuzzy and Bayesian_CCI equaliser decision boundary (a) SIR=5dB and (b) SIR=10dB*

In Figure 4 the decision boundary for the optimal equaliser without CCI is presented. Comparing the decision boundary of equalisers presented in Figure 3 with Figure 4, suggests that for this channel and cochannel combination and the particular SIR, CCI compensation is essential at SIR=5dB but is not very essential at SIR=10dB.

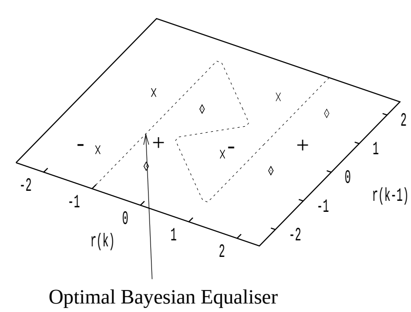


Figure 4: *Bayesian Equaliser decision boundary for SNR=10dB and SIR=$\infty$*

In the next part of the experiment we studied the bit error ratio (BER) performance of the equalisers in presence of one CCI. The channel and co-channel models considered are

$H_0(z) = 0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$ and $H_1(z) = \lambda(0.6 + 0.8z^{-1})$. The SIR was set to 5dB and 10dB and the equaliser order and decision delay were set to $m = 4$ and $d = 1$ respectively. Figure.5 presents the BER performance of the Bayesian_CCI equaliser, Bayesian equaliser treating CCI as noise and the fuzzy equaliser.

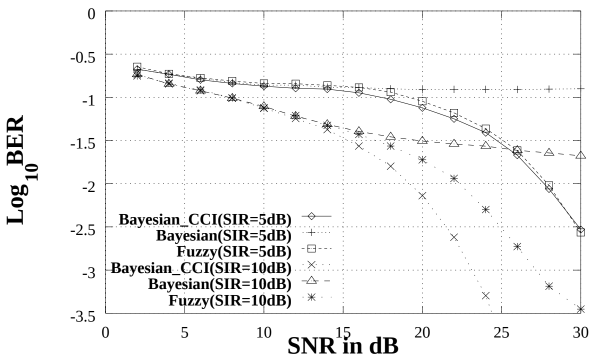


Figure 5: *BER performance of equalisers*

Here, the Bayesian_CCI equaliser uses 2048 channel states whereas, the fuzzy and the Bayesian equalisers use only 64 channel states for their decision function evaluation. From the performance curves its is seen that the fuzzy equaliser performs close to Bayesian_CCI equaliser but the performance of Bayesian equaliser treating CCI as noise is far from optimal. We have seen similar results for other channel and co-channel combinations as well.

## 5 CONCLUSION

In this paper we have demonstrated the capability of fuzzy equaliser to suppress co-channel interference. This equaliser is similar to the equaliser proposed in [10] with a different membership function generator at the equaliser input. This membership function generator can be used as a preprocessor under moderate to severe CCI and can be removed when CCI is very low, Providing a performance trade off with computational cost. The computational complexity of this equaliser can be further reduced by using different types of inference rules and defuzzification techniques [10].

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