Cochannel Interference in Wireless LANS and Fuzzy Clustering

P. Golding*, Alan E. Jones
Home Communications Department
HP Laboratories Bristol
HPL-97-95
August, 1997

cochannel interference,
hiperlan,
fuzzy clustering

In this paper a technique is described that permits increased receiver tolerance to uncoordinated CCI in a wireless LAN environment. The technique uses supervised clustering to determine the signal states due to ISI and a form of unsupervised Fuzzy clustering for finding the signal states due to CCI. Using a decision feedback approach, it is shown that the receiver is capable of operating in high levels of CCI, providing usable error rates.

*Magic E Company Ltd, Swindon, Wiltshire, England

COCHANNEL INTERFERENCE IN WIRELESS LANS AND FUZZY CLUSTERING

P. Golding[1] A.E.Jones[2] (Author for correspondence)
1 Magic E Company Ltd, 7 Cloche Way, Swindon, Wiltshire SN2 6JN, England
Tel:++44 (0)1793 513001, Fax:++44(0)1793 821553
2 Hewlett Packard Laboratories, Filton Road, Stoke Gifford, Bristol BS12 6QZ, England
Tel:++44(0)117 922 8767, Fax:++44(0)117 922 8924
Technical Area (B9)

Abstract: *In this paper a technique is described that permits increased receiver tolerance to uncoordinated CCI in a wireless LAN environment. The technique uses supervised clustering to determine the signal states due to ISI and a form of unsupervised Fuzzy clustering for finding the signal states due to CCI. Using a decision feedback approach, it is shown that the receiver is capable of operating in high levels of CCI, providing usable error rates.*

I Introduction

There are particular applications where communication in a wireless LAN is confined to relatively short distances, such that time dispersion from the propagation channel tends to be low, and the received signal strength is generally high. In such applications, the system error rate performance is generally limited by Cochannel Interference (CCI), which arises due to uncoordinated users occupying the same bandwidth within, or near the local vicinity. Since conventional demodulation and signal detection is based on the interference being Gaussian distributed its performance in this scenario is sub-optimum.

There are two approaches for reducing the effect of CCI. The first is based on additional processing in the Medium Access Control (MAC) to determine the level of CCI and select an appropriate channel based on some metric, usually the received signal strength of the CCI, or request that other users in the immediate vicinity stop transmitting while information is transferred between nodes. This technique essentially employs conventional demodulation and relies on the MAC to perform all processing and decision making. The second approach, is to move the responsibility further down the protocol stack to the physical layer, where the receiver is expected to perform CCI rejection. The benefit of the second approach is two fold. Firstly, there is less overhead in terms of measuring and reporting channel quality between layers, and secondly, since the receiver can withstand higher degrees of CCI there is a net increase in capacity since more users can be accommodated in a given area.

In this paper we consider the second approach and propose a receiver architecture based around the physical layer of the recently standardised HIPERLAN (High PERformance Radio LAN). The receiver is similar to that described in [1] [2] and [3], where a decision feedback structure is used to select a subset of signal states for performing minimum distance detection. The signal states are obtained using a three stage clustering algorithm. The first stage uses supervised clustering on the 450 bit HIPERLAN training sequence to partition the modulation ISI states. The number of states is minimised by exploiting the geometrical symmetries in the signal space. In the second stage, each ISI state is partitioned into two clusters using unsupervised fuzzy clustering, which assigns a degree of membership to each of the training vectors. Finally the third stage of clustering determines the CCI states by first defuzzifying the fuzzy partition matrix and then performing fuzzy clustering on each row independently. The CCI states are then obtained from the final set of fuzzy partition matrices.

The performance of the proposed receiver is demonstrated by means of computer simulation. A typical environment is described, and it is shown that the proposed receiver is capable of operating with a high degree of robustness, providing usable error rates when compared to a conventional approach.

II Background

Consider the system block diagram shown in Fig.1, included in the diagram is the standard HIPERLAN packet structure for transmission of one data block [4]. The output of the data source corresponds to a block encoded and interleaved data frame vector of 496 bits. This is subsequently applied to the packet precoder which takes the data frame vector and applies selective bit inversion and differential precoding. This pre-processing is necessary in order to ensure a linear data mapping onto the modulated carrier. The output vector from the precoder is applied to the packet assembler which takes the 496 bit precoded vector and places it at the end of a 450 bit training sequence[1]. The output of the packet assembler is a vector which is converted into a serial bit stream with a composite packet length of $450+47\times496$ bits at a transmission rate of 23.5294Mb/s.

[1] Note, the low bit rate (LBR) part of the HIPERLAN data burst is not included in the system model.

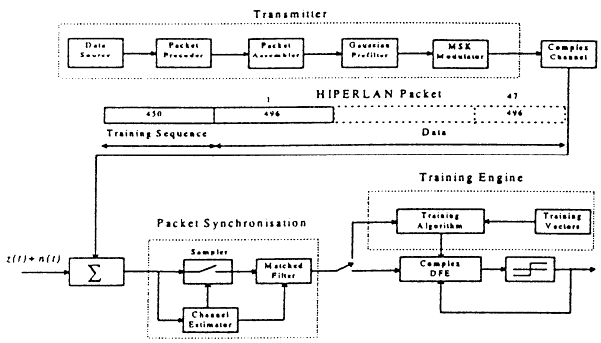

Fig.1 System Block Diagram

This data stream is prefiltered with a three tap finite impulse response Gaussian filter with a normalised bandwidth of 0.3. The output of the prefilter is applied to an MSK modulator which produces a phase trellis with a modulation index of 0.5 and an envelope of constant magnitude. Due to the linear mapping of the data by the precoding, the output of the MSK modulator can be mathematically approximated by its linear baseband equivalent, which is given by

$$r(t) = \sum_i \alpha_i g(t - iT) \qquad (1)$$

where α_i can be either $\pm j$ or ± 1, T is the signaling interval, $g(t)$ represents the impulse response of the modulation and i takes on all possible integer values. When there is no ISI from the modulation prefiltering, the GMSK signal can be considered as equivalent to Offset Quadrature Phase Shift Keying (OQPSK), having four distinct points in space ($\pm$j,$\pm$1; $j = \sqrt{-1}$). After transmission through the channel, the signal is corrupted by CCI and noise, such that

$$y(t) = a(t)r(t) + b(t)\sum_i \alpha_i h(t - iT) + n(t) \qquad (2)$$

where the first term is the wanted, the second term is CCI, the third term, $n(t)$, is complex Additive White Gaussian Noise with zero mean and variance σ^2, and $h(t)$ is the impulse response of the CCI The terms $a(t)$ and $b(t)$ are complex valued with a Rayleigh distributed envelope and uniformly distributed phase. It is assumed that the response of the analogue receive filtering introduces no distortion into the modulation and the noise at the input to the receiver is uncorrelated. After synchronisation, the sampled received signal is given by[2]

$$y(k) = r(k) + z(k) + n(k) \qquad (3)$$

[2] Synchronisation is performed by channel estimation, symbol spaced sampling, and matched filtering, where the matched filter is a single complex tap, removing the composite channel phase offset.

where $z(k)$ is the CCI. The inputs to the DFE are the vector $[y(k)\ y(k\text{-}1)]$ and the vector of fed-back symbols, $[x(k)\ x(k\text{-}1)\ x(k\text{-}2)\ x(k\text{-}3)]$, where $x(k\text{-}2)$ and $x(k\text{-}3)$ are previous decisions, and $x(k)$ and $x(k\text{-}1)$ take on all possible values. As described in [3], the purpose of the feedback vector is to select a subset of ISI states in an attempt to increase the minimum Euclidean distance between nearest neighbours. The equalizer performs distance calculations between the input vector and the selected subsets, such that the decision on the transmitted symbol is given by

$$\bar{\alpha} = \mathrm{sgn}\left[\left(d^-_{min,k} + d^-_{min,k-1}\right) - \left(d^+_{min,k} + d^+_{min,k-1}\right)\right] \qquad (4)$$

where d^-_{min} and d^+_{min} are the minimum Euclidean distance of the negative and positive subset respectively. When the channel is noisy it is necessary to determine the mean of the ISI states, since the distribution of training vectors exhibit distinct clusters in the signal space. The training sequence length in HIPERLAN permits this operation since a sufficient number of states are probed due to the finite length of the modulation prefiltering.

III Supervised Training

To illustrate the method, we first consider the non-CCI case. The received packet, $y(t)$ is defined as

$$\mathbf{Y} = [\mathbf{Y_T} \vdots \mathbf{Y_D}] \qquad (5)$$

where $\mathbf{Y_T}$ is the set of received training vectors and $\mathbf{Y_D}$ is the set of received data vectors. Secondly, we define the set of locally stored training vectors, $\mathbf{P}$, be the same length as $\mathbf{Y_T}$ ($p_1,p_2,p_3,\ldots,p_{450}$) and each vector is complex valued ($\pm$j,$\pm$1) defining a complex point in one dimensional Euclidean space.

In GMSK with BT=0.3, the number of phase states in T spaced sampling instants corresponds to 16 where 4 states are duplicated on the real and imaginary axis. Due to the geometrical symmetry of the ISI we note the following relationship [5] :

$$\mathbf{Q}^-_{re} = -1\times\mathbf{Q}^+_{re}\,;\ \mathbf{Q}^+_{im} = +j\times\mathbf{Q}^+_{re}\,;\ \mathbf{Q}^-_{im} = -j\times\mathbf{Q}^+_{re} \qquad (6)$$

where $\mathbf{Q}^+_{re} = \{\, q^+_{1,re} q^+_{2,re} q^+_{3,re} q^+_{4,re} \,\}$ and

$$q^+_{i,re} = \{\pm j\times h(-T) + h(0) \pm j\times h(+T)\} \qquad (7)$$

By performing the modification

$$\mathbf{Y_T}' = \mathbf{Y_T}\mathbf{P}^* \qquad (8)$$

the received training vectors are sorted into four sets which correspond to the ISI states of $\mathbf{Q}^+_{re}$, where '*' denotes complex conjugate, and each element of $\mathbf{P}$ has an associated label defining the associated state. The state labels are described by a three bit binary sequence and are ordered, such that each received training vector in the set of training vectors $\{\mathbf{Y_T}\}$ has a corresponding state label that defines an associated state. During training each received training vector is sent to its associated state by means of the state label. At the end of the training sequence there are four sets each one containing the associated ISI state perturbed by Gaussian noise. The cluster centres are determined by performing averaging within the four sets. Reproducing the remaining three sets is a simple task, as defined by the relationships of eqn.6.

This is illustrated below in Fig.2, where Eb/No=20dB, the channel is narrowband fading and the number of training vectors is 400. In this example, the reproduced rotated versions of the cluster means are also included.

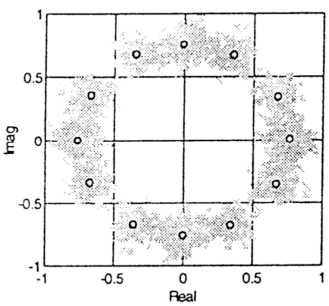

Fig.2 Cluster Centres Produced by Supervised Training

By mapping the training vectors into the real ISI states not only reduces the complexity, but also permits co-location in the signal space . This enables an increase in the size of the training set, which is particularly important when there is an imbalance in the distribution of CCI states. If we assume that CCI is present and the channel is noiseless, then the modified received training vector is given by

$$y'_T(k) = aq^{+}_{i,re} + p^{*}_k z(k)\,;\ i=1\ldots4;\ k=1\ldots450 \qquad (9)$$

where the CCI, $z(k)$, increases the number of cluster centres per ISI state, and the ISI from the wanted can be considered as a complex valued offset in the signal space of the CCI. The modification by the locally stored training vector produces additional states from the CCI that are either purely real or purely imaginary. This results in a reduced number of clusters per ISI state of 8, giving 32 CCI states in total. In fact, since certain states are co-located producing duplication, the actual number of differing states corresponds to 18.

Since the CCI is uncoordinated, the location of its associated training sequence is unavailable to the receiver. Consequently, it is necessary to consider alternative clustering algorithms which do not rely on labeled data.

IV Unsupervised Fuzzy Clustering

The usual approach adopted for unsupervised clustering of complex valued data is to use the c-means clustering algorithm, which arbitrarily partitions the signal space into c clusters and then attempts to find the optimum partitioning. This is achieved by initially calculating the mean of each cluster and then determining the Euclidean distance of each data sample from each cluster mean. The clusters centres are then updated by assigning the data element to the cluster that produced the minimum distance [6]. A problem with this technique however, is its dependency on the finite cardinality of the partition due to the crisp membership of classes. That is, a training vector can only be a member of one class, and consequently, an accurate partitioning of the signal space is initially required for optimal convergence [7]. This is extremely difficult due to the uncertainty associated with the choice of cluster centres in the signal space. However, the fuzzy-c-means algorithm overcomes this problem by assigning a degree of membership to a training vector for each cluster. Consequently, the algorithm tends to be forgiving if the initial partition is a bad choice [7].

The fuzzy clustering algorithm partitions each data set into clusters with a degree of object data similarity, $\{\mathbf{A}_i, i=1,2,\ldots c\}$, where the number of clusters is related to the amount of channel ISI in the CCI. The membership value that the kth training vector has in the ith cluster is indicated with the following notation

$$\mu_{ik} = \mu_{A_i}(y_{T,k}) \in [0,1] \qquad (10)$$

where the sum of all membership values for a single vector in all the c clusters has to be unity, such that

$$\sum_{i=1}^{c} \mu_{ik} = 1; \forall k \qquad (11)$$

where there can be no empty clusters and no clusters that contain all of the training vectors, as shown by the following condition

$$0 < \sum_{k=1}^{n} \mu_{ik} < n \qquad (12)$$

where n is equal to the number of training vectors. Defining a set of fuzzy partition matrices, M_{fp} , for the clustering involving c clusters and n vectors, yields the following set of matrix partitions

$$M_{fp} = \left\{ U \left| \mu_{ik} \in [0,1] : \sum_{i=1}^{c} \mu_{ik} = 1; 0 < \sum_{k=1}^{n} \mu_{ik} < n \right. \right\} \qquad (13)$$

where U is a $[c,n]$ matrix, and satisfies the conditions defined by eqn.10 through to eqn.12. Since there exists an infinite number of membership values, there is also an infinite number of partitions. The choice of optimum partition is resolved by defining an objective function

$$J(\mathbf{U},\mathbf{s}) = \sum_{k=1}^{n} \sum_{i=1}^{c} (\mu_{ik})^{m'} (d_{ik})^2 \quad (14)$$

where the Euclidean distance is given by

$$d_{ik} = \left\| \mathbf{y}_{T,k} - \mathbf{s}_i \right\| \quad (15)$$

The cluster centre is given by **s**, and m′ is a weighting parameter which defines the degree of fuzziness. The optimum fuzzy partition is the one that minimises eqn.14, yielding

$$J^{o}(U^{o},\mathbf{s}^{o}) = \min_{M_{fp}} J(U,\mathbf{s}) \quad (16)$$

In order to arrive at the minimum value of eqn.16, the fuzzy clustering occurs in two stages. The first stage partitions the CCI into two fuzzy classes, the positive and negative class. This improves the convergence to an optimal partition by exploiting the property that any ISI state in the positive class of the CCI cannot belong to an ISI state in the negative class. The second stage takes each cluster of training vectors defined by the fuzzy partition and partitions them again in an attempt to determine the ISI states in the positive and negative fuzzy classes. This is achieved by first defuzzifying the fuzzy partition matrix by using the maximum membership approach, and then performing fuzzy-c-means clustering on the clusters resulting from the defuzzification process. Once the clustering algorithm has converged to a suitable value, the cluster centres are given by

$$\mathbf{s}_i = \frac{\sum_{k=1}^{n} \mu_{ik}^{m'} y_{T,k}}{\sum_{k=1}^{n} \mu_{ik}^{m'}} \quad (17)$$

where μ_{ik} are the membership values of the final fuzzy partition matrix. The performance of the fuzzy clustering algorithm described above is illustrated in Fig.3, where C/I=10dB, Eb/No=20dB, m' =2, and the number of training vectors, n=400. In this example, the gaussian clusters correspond to the real set of training vectors and the 'o' and '+' correspond to the cluster centres for the negative and positive classes respectively.

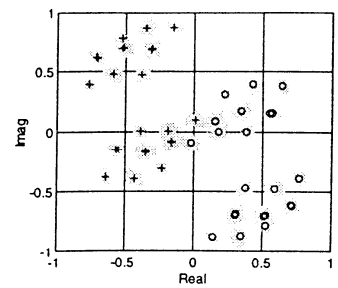

Fig.3 Cluster Centres from Fuzzy clustering ({+} Positive Class, {o} Negative Class)

In order to incorporate the additional cluster centres from the CCI, the decision feedback is modified, such that the fed back vector selects a subset of ISI states that includes the associated CCI states. Note, in order to arrive at the correct state, the fed-back vector has to be remodulated and modified by conjugating all values with the central value of the ISI span producing a vector which is {Im Re Im...Re Im Re}. The set of values and associated states for $y(k)$ and $y(k\text{-}1)$ are shown in Table I.

$x(k)$ $x(k\text{-}1)$	$x(k\text{-}1)$ $x(k\text{-}2)$	$x(k\text{-}2)$ $x(k\text{-}3)$	$y(k)$ $y(k\text{-}1)$
-1	+1	-1	I_1
-1	+1	+1	I_2
+1	+1	-1	I_3
+1	+1	+1	I_4

Table I Modified Decision Feedback Labels

The labels I_1, I_2, I_3 and I_4 correspond to the four associated states or clusters. The detection process in the DFE is performed in the same manner as before except the data samples from the data set $\{\mathbf{Y_D}\}$ are rotated in the signal space rather than the set of cluster centres. This can be considered as a reciprocal process, but in terms of implementation rotating a single complex data sample is much simpler than rotating the entire set (or alternatively, creating three additional subsets).

V Simulation Results

The simulation is based on the system model described in Section.2. The oversampling rate used in the simulation is equal to one and the HIPERLAN channel is modeled as a narrowband Rayleigh fading channel, where the wanted and CCI are statistically independent. In addition, we assume that the channel is static during the transmission of a packet. The distance calculations used in the detector process are based on d^2_{min} for reasons of reduced complexity. The number of packets transmitted during the simulation was set at 10000, and the size of the training set is 400. Uncoded error rates below 10^{-3} are considered acceptable, since in HIPERLAN the BCH(31,26) SEC code is capable of correcting sufficient errors to produce the required packet failure rate of 0.01 [8].

The error rate performance of the DFE with Fuzzy Clustering is shown in Fig.4, where for comparison, a coherent GMSK receiver is included for the situation when Eb/No=40dB. The three labeled curves correspond to a Eb/No of (i) 20dB, (ii) 30dB and (iii) 40dB. Firstly, we compare the coherent GMSK receiver with curve (iii). It is apparent, that the DFE with Fuzzy Clustering significantly outperforms the coherent receiver, particularly, when the CCI is significantly greater than the wanted. This is understandable, since increasing the level of interference effectively raises the wanted signal from the noise floor. This can be considered as a corresponding increase in d_{min} between nearest neighbours of opposing classes. The result, being an improvement in the error rate performance.

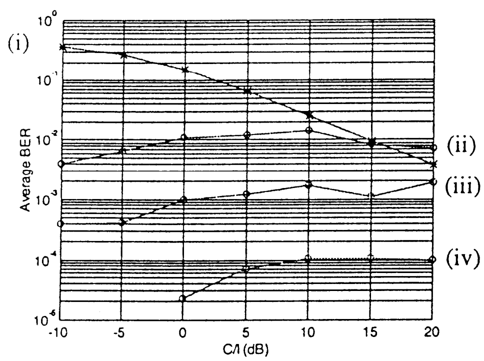

Fig.4 Performance of DFE with Fuzzy Clustering
(i) Coherent, (ii) 20dB, (iii) 30dB, (iv)40dB

For cases (i) and (ii), the effect of increasing the noise variance (which corresponds to a decrease in the received signal strength) is to increase the error floor of the receiver. However, the improvement at higher levels of CCI is still clearly evident, again, due to the mechansim described previously. If we consider the system model described in Section.II, the anticipated range is expected to be <10m. Consider a simple free space path loss model and a standard HIPERLAN RF receive architecture, the expected signal-to-noise ratio at a range of <10m will be >40dB. Clearly, the DFE with Fuzzy Clustering would comfortably achieve this figure with significant margin across a broad variation in CCI.

Next we consider the effect of shortening the HIPERLAN training sequence for the situation when the signal to noise ratio is maintained at 40dB. The error rate performance is shown in Fig.5. It is apparent that a reduction from 400 to 200 has negligible impact when C/I>5dB. However, when the interferer is greater then the wanted there is a marked difference. For a training sequence length of 100 acceptable error rates are possible for C/I>7dB, beyond this value the degradation in performance is significant.

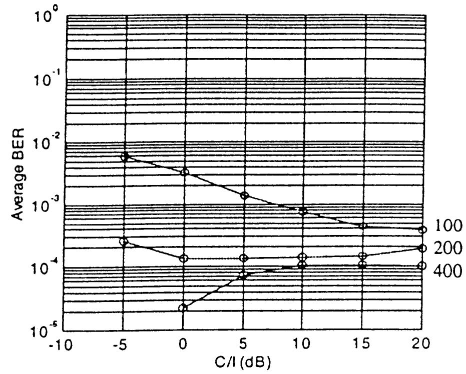

Fig.5 Effect of Shortening Training Sequence

VI Conclusion

In this paper a technique has been presented for improving the performance of a receiver in a controlled ISI channel when the receiver is limited by CCI. The technique uses both supervised and unsupervised clustering for finding the cluster centres, and decision feedback for maximising the Eulcidean distance. Using the HIPERLAN physical layer as an example, simulation results have demonstrated the high robustness of the technique, and its capability of providing usable error rates particularly at high levels of CCI.

References

[1] B.Mulgrew;'Applying Radial Basis Functions', IEEE Signal. Processing. Magazine., March 1996, pp.50-65.
[2] S.Y.Lee, *et al*:' Complex LMS Fuzzy Adaptive Equalizer with Decision Feedback', GLOBECOM 96, Lond., pp.191-195.
[3] S.Chen *et al*:'Bayesian Decision Feedback Equaliser for Overcoming Cochannel Interference', IEE Proceedings, Vol.143, No.4, Aug. 1996, pp.219-225.
[4] HIgh PErformance Radio Local Area Network (HIPERLAN) Type I, ETSI F.D., REF:DE/RES-10-01.
[5] A.P.CLARK;'Techniques for Simplifying some Near Maximum Likelihood Detectors, IEE Proceedings, Vol.137, Pt.I, no.5, Oct 1990, pp.281-289.
[6] J.C.Bezdek:'A Convergence Theorem for the Fuzzy ISODATA Clustering Algorithms', IEEE Trans. Pattern Anal. Mach. Intell., Vol.PAM1-2, No.1, Jan. 1980, pp1-8.
[7] T.Ross:'Fuzzy Logic with Engineering Applications', McGraw-Hill, 1st.ed, 1995.
[8] D.Wedge;'Theoretical Evaluation of Range Limitations in HIPERLAN Receivers', IEE Electronics Letters,Vol.32, no.8, April 1996, pp.717-718.