A Soft Receiver Using Recurrent Networks

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ABSTRACT.

Two different neural network architectures have been used to realize a non-linear adaptive receiver for GSM signals. Using the well-established backpropagation technique we firstly built a recurrent network which has been trained considering different channels corrupted by ISI, fading and Doppler. The network has shown better performances than the a classic coherent receiver. A second recurrent architecture, based on a partially supervised Self Organizing Map, has been proposed in order to perform an effective real time learning .

1 PROBLEM DESCRIPTION

The principal causes of disturbances in mobile radio systems are due to gaussian noise, multiple reflections, fading and Doppler effect [1]. It is only thanks to highly sophisticated terminals and error correcting algorithms that it is possible to reconstruct a satisfactory signal. Most of these techniques employ maximum likelihood Viterbi equalizers trying to adaptively recover the inverse transfer function of the channel [2] . The first problem now is that the traditional approach uses linear filtering techniques, while the channel has non linear characteristics. A second problem is related to the variation in time of the channel characteristics.

The application of Artificial Neural Networks (ANN) to the equalization/demodulation process comes from recognizing this process as a classification one. Works have been carried out for example by I. Howitt and H. Reed in [3] considering a band limited communication system with a signal corrupted by co-channel interference and additive noise. The authors based their work on the results of a previous paper by Chen and Mulgrew [4], which show that a neural architecture can give an optimal bayesian solution for equalization. Their work is however limited to settle the optimal number of centres for a Radial Basis Function. Equalization is also the concern of the work of C. Pham and T. Ogunfunmi [5] showing that the equation of the decision statistics for an MPSK signal is homologous to that of the Hopfield energy function, which is minimized up to stability. Basically the same kind of approach has been presented in [6] by G. Pfeiffer. Another neural receiver based on Bayesian classification via maximum likelihood has been presented by J.W. Watterson in [7]. An MLP is trained to classify the patterns into two linearly separable classes and detect the presence/absence of a target signal corrupted by Gaussian noise. The Monte Carlo simulation with 2^M binary training patterns (M number of input nodes) shows performances identical to those of an optimum likelihood ratio receiver. Other aproaches have been proposed also by T. Petsche and B. W. Dickinson in [8], G. De Veciana and A. Zakhor [9], G. Kechriotis and E. Zervas in [10].

Following the approach in [11], this paper presents an equalizer/demodulator for QPSK signals based on a Recurrent BackPropagation (RBP) network. The basic structure of the receiver is described in section 2 of the paper, while results obtained by computer simulations are discussed in section 3. Some preliminary work on a Self Organizing Map (SOM) Kohonen network [15] is also introduced.

2 THE RBP RECEIVER

In a rapidly changing environment such as that of mobile radio communications, the capability of the receiver to track the channel variations is of paramount importance. For this reason , since the beginning our efforts have been aiming to determine a dynamic neural architecture [13] suitable for the application under consideration. Most of the networks above described are actually networks without memory: the architecture of strictly dynamical networks is characterized by a *state feedback* realized through suitable connections among nodes. In the state feedback the nodes receive as incoming signal both the network inputs and the output of the other nodes including its own (Fig. 1). The network presented in this work is derived from the work by Pineda [12] which is a generalization of the Multilayer Perceptron (MLP). by Rumelhart and Williams [14].

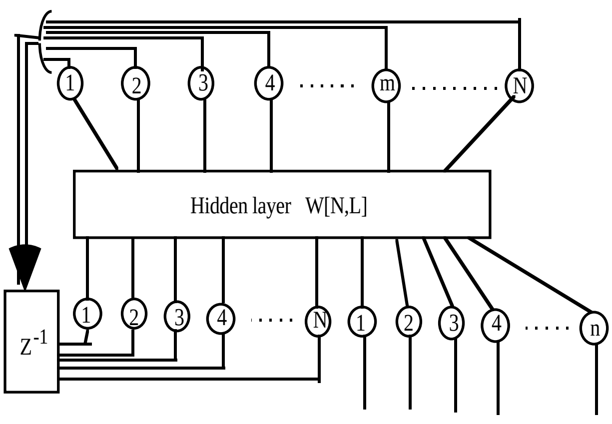

Figure 1. The generic architecture of a dynamic network

The input vectors $v_1,\ldots,v_n$, and output vectors $u'_1,\ldots,u'_N$ .are related to the output of the first layer z_j by

$$z_j = \begin{cases} u_j(k) & 0 \le j \le N \\ v_j(k) & N+1 \le j \le L \end{cases}$$

where z_0 is the possible bias node. The current output is

$$u'_i(k+1) = f(I_i(k))$$

where

$$I_i(k) = \sum_{j=1}^{L} w_{ij} z_j(k) + z_0$$

Thus the node equation [12] is

$$u(k+1)_i = f\left(\sum_j^n w_{ij} u_j(k) + v_j(k)\right)$$

where f is the sigmoid function .
To evaluate the performances of this architecture and to determine the best network topology, a series of recurrent backpropagation networks has been developed in ANSI C. After a series of simulations with different choices of input, hidden and output neurons, the best configuration turned out to be that with 74 input + 74 recurrent input nodes, 148 hidden nodes and 74 output nodes.
This result was in part expected since the discrete unit of information sent to the receiver was the GSM normal-burst (Fig. 2) which is composed of 148 bits. Such a network preserves the burst symmetry (148 samples), and has shown a good ability to converge during the training stage even with the growing of the sample size (148, 296,...,7104). Differently from the work in [11], the same network acts as an integrated equalizer/demodulator as this configuration allows to better exploit the correlations in the data stream and consequently increase the network convergence capabilities.
The training of the network has been performed feeding the network in different phases with both “pure” samples coming from the QPSK modulator and with noise corrupted samples. Given the recursive structure, the equalizer provides results which are dependent upon the present as well as the previous inputs.
This training phase provided very good results with almost perfect recovery of the input data whatever the length of the input stream although the number of epochs to achieve convergence was rapidly increasing (Fig. 3). Fig 3 also describes the behaviour of the Bit Error Rate (BER) obtained averaging the performances of the RBP network over the Signal to Noise Ratio (SNR) range 8÷20 dB.

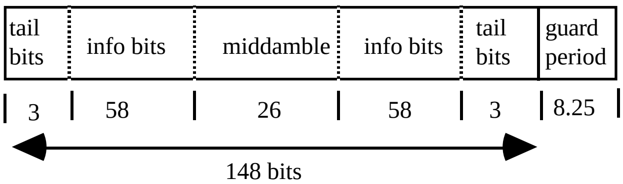

Figure 2. The GSM burst structure

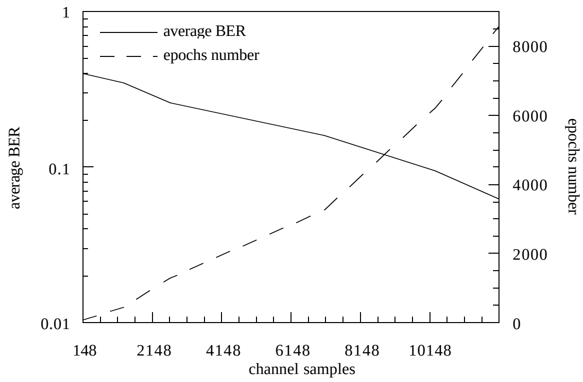

Figure 3. Network performances as a function of the number of samples used in the training phase.

During the testing phase, the network follows the channel variations tuning the weight matrix by matching the bits in the middamble of the burst. Convergence in this case was obtained in 20-30 epochs, i.e. the middamble was correctly recovered after this period: the weight obtained for the middamble are then used for the whole burst.

3 SIMULATION RESULTS

Computer simulations have been run considering a transmission environment composed of the following subsystems (see Fig. 4):

- a random sequence generator whose output is a sequence of +1/-1 bits coded with Not Return to Zero (NRZ) scheme;
- a QPSK modulator which maps couples of bits into an analog signal;
- a radiomobile channel in which the signal is corrupted by:
  - Rayleigh multipath fading
  - Doppler effect
  - bandwidth limitations;
- the neural receiver.

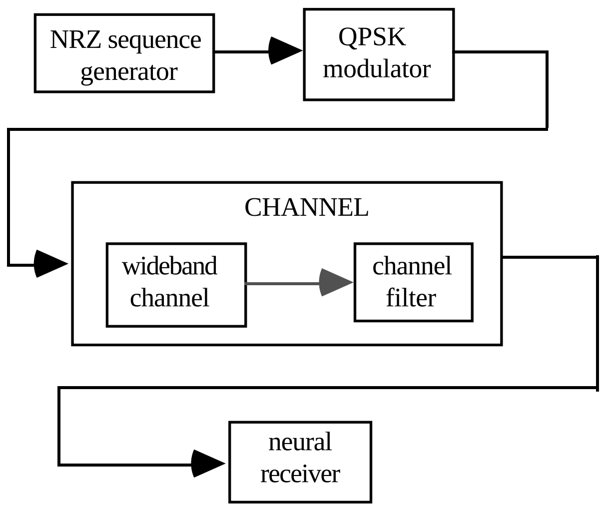

Figure 4. The simulated communication system.

The conditions on the radio channel may be determined according to the GSM testing environments setting the terrain type (urban area, rural area, hilly terrain), the mobile speed (10, 50, 100, 250 km/h) and the transmission SNR. Band limiting is achieved using a Butterworth filter with 8 poles and 1.75 normalized bandwidth.
It is important to underline that no error correction coding is performed on the input stream. Consequently the BER rate curves in figures 5, 6 and 7 for the tree types of terrain are those obtainable right after the demodulator without any coding gain. The receiver has also been compared with coherent (transversal equalizer + QPSK demodulator) and Viterbi receivers, but only in AWGN - bandwidth limited channel conditions.

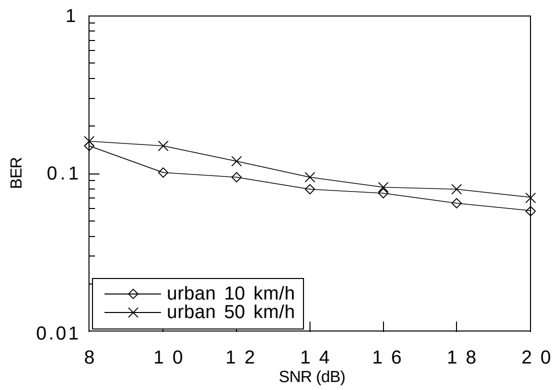

Figure 5. Performances in urban area conditions.

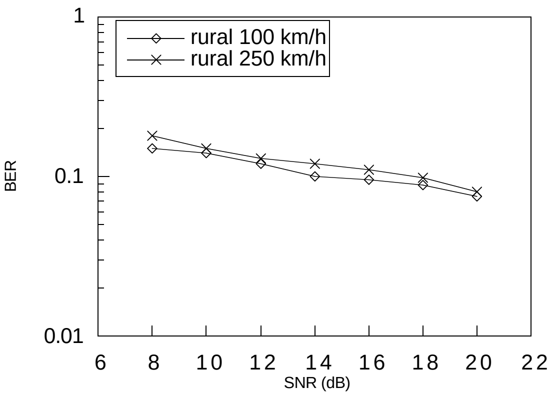

Figure 6. Performances in rural area conditions.

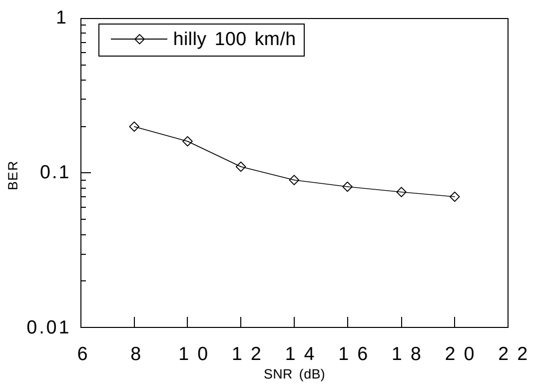

Figure 7. Performances in hilly terrain conditions.

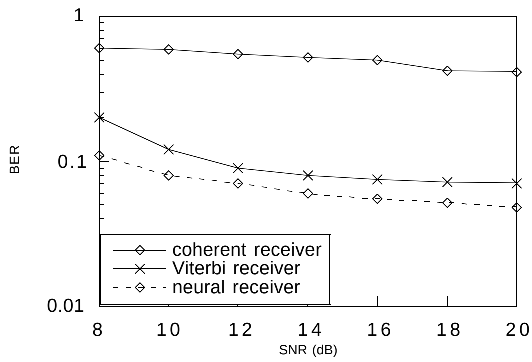

Figure 8. Performance comparison in bandwidth limited AWGN channel.

4. REAL TIME LEARNING AND UNSUPERVISED NETWORKS

The limits of the approach described in the previous part of the paper are twofold: on the one hand the extremely slow training stage (more than 24 hours on DECStation in batch mode, to be multiplied by the high number of the not converging trials), on the other hand the impossibility to obtain a weight vector univocally effective to any possible channel variation.
Therefrom our incentive to continue the search for an architecture actually able to follow the channel fluctuations in real time. Only in this case it is conceivable the idea of a neural processor operating in real time in the place of a standard receiver.
Therefore we directed our choice towards unsupervised neural architectures, i.e. networks able to obtain an input classification without knowing in advance the sample values to be transmitted.
One of the most reliable unsupervised learning models for its convincing neurophysiological bases and for its experimental successes is the Self-Organizing Map by T. Kohonen [15].
The structure of a Kohonen network consists of a layer of N elements. Each node receives n values $x_1,...,x_n$ that are coming from an input layer made by n elements. The intensity I_i of each Kohonen element is evaluated by

$$I_i = D(w_i, x)$$

where w_i is the weight vector which connects each input to the i-th Kohonen element, x is the input vector, and D is some distance, for instance the Euclidean one.
At this time a competition takes place, in order to evaluate which element has the minimum input intensity (i.e. which w_i is the nearest to x). The training is performed varying the weights related to the only neuron that won the competition (or possibly to a suitable neighbourhood) following the law

$$w_i^{new} = w_i^{old} + \alpha(x - w_i^{old})z_i$$

where $0<\alpha$Û1 and $z_i \neq 0$ just for the winning neuron.

The Kohonen algorithm acts as a vector quantizer for the input patterns, building a map of the input structure in such a way that similar inputs are related to similar outputs.
During the training, the network highlights a winning neuron, and inputs that highlight the same neuron are seen as belonging to the same cluster.
Our idea has been to adapt the SOM to our needs by endowing it with a tapped delay input line and a state feedback which could better its performances. Thus we built a recurrent SOM network with 74 input nodes, 74 memory nodes and a number of Kohonen neurons ranging from 10 to 35
The state feedback has been performed by alternating the position of the memory element with respect to the new input samples, in such a way as to maintain the known and steady sequence of 26 samples always fixed in the middle of the input vector while the stream runs on.
This device has improved the network symmetry speeding up the learning stage and has allowed to maintain the information on the position of the current known sequence. In this way, once each winning Kohonen element has been assigned to a cluster, it is possible to go up to the corresponding decision region by comparing it to the clusters formed by the elements of the known elements.
Seen that the processing time of the network, written in ANSI C, is particularly short (not more than two minutes for the longest stream), the simulations have been carried out on PC Pentium 75.
Though we have verified that the network performances tend to increase with the growing of the stream size, since the network model is unsupervised it is not needed to excessively increase the sample size: the idea is to submit the current stream to the network one burst at a time as an input vector, keeping the network steadily in the learning stage.
Preliminar simulations on show that the system, due to the nature of the Kohonen algorithm, exhibits a good metric discrimination, thus it is scarcely sensitive to the change of decision regions caused by the worsening of the channel conditions, while it is mostly disturbed by the ISI, that is present even in the case of a filtered gaussian channel: performances are around a 0.07 BER for the hilly terrain and slightly better in the case of gaussian channel. Moreover this result is obtained after only 50 epochs in hilly terrain conditions and in 30 epochs for the bandlimited gaussian channel. Actually, the quick convergence we have reached in order to obtain a real time learning does not allow the network to fully carry out its local adaptivity.

CONCLUSIONS

In this paper two different architectures for a neural network based adaptive receiver capable to cope with the channel constraints imposed by a mobile radio channel have been presented. The first approach is based on a recurrent network and provides good results at the expenses of a high complexity and long learning times. The second approach has been based on an unsupervised Kohonen network: although we do not have a complete set of results, it seems that this second receiver can exhibit interesting performances particularly in the real time learning phase corresponding to the normal system operation.

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