NEURAL SEQUENCE DETECTOR FOR DIGITAL EQUALIZATION

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ABSTRACT

In this paper a new approach to the equalization of digital transmission channels is introduced and described. The proposed solution makes use of a fast neural architecture, coupled with a innovative error functional, and is able to perform the equalization task in a Viterbi-like fashion applied to a Decision Feedback architecture for the purpose of improving the resistance to imperfect knowledge of the channel and interference. Performance comparisons with standard techniques for different channels demonstrate the validity of the proposed approach, especially when the data model departs from assumptions and the computational cost is a critical issue.

1 INTRODUCTION

In recent years Neural Networks (NNs) have been often proposed as architectures for digital equalization of communication channels [1][2][3][4]. Due to their high degree of non-linearity, NNs can be effectively employed to decode symbols transmitted through difficult channels.

Current approaches to digital equalization typically use the Maximum Likelihood Sequence Estimation (MLSE) method, which is based on the popular Viterbi algorithm [5]. In this family of decoders, the channel identification plays a crucial role in determining the Bit Error Rate (BER) in the final decision stage. Identification of the channel has to be made on a few preamble symbols and can be impaired by channel non-stationarities and/or non-linearities. Traditional equalization does not require the perfect knowledge of the channel, but it is inadequate to cope with non-minimum phase channels, co-channel interference and wide delay spreads.

Digital equalization can be also regarded as a classification task [3]. NNs, like traditional Decision Feedback (DF) equalizers, can form decision regions in the space of received symbol sequences. In particular, due to their universal approximation capability, NNs can form arbitrarily shaped decision boundaries [6]. This property has fully justified the introduction of neural equalizers.

In addition, equalization through symbol classification is known to be intrinsically more robust than MLSE-based soft decoding in the cases of channel uncertainties or miss-modelling [2].

In this work we show how the concepts of Viterbi-like sequence estimation can be efficiently incorporated in neural architectures for the equalization task, leading to an innovative neural sequence detector. Feedforward and recurrent neural networks are trained with a novel discriminative error measure, that maximizes the distance among labelled symbols in the output space, coherently with the objective of BER minimization [3][7]. The training phase is accomplished by the fast Block Recursive Least Squares (BRLS) algorithm, that has been successfully used in several signal processing applications [3][8]. In terms of complexity, the new neural sequence detector is intermediate between linear decision-feedback equalizers and MLSE decoders.

2 PROPOSED ARCHITECTURE

The basic structure, depicted in Fig. 1, consists of a neural network, that can be either feedforward or recurrent [9], with multiple outputs. This scheme recalls the architecture of a traditional Decision Feedback equalizer. The input is taken from a tapped delay line (TDL), containing the sequence of received symbols at time \( k \). Training is performed on a preamble sequence \( s(k) \) (switch in position 1). During the decoding phase (switch in position 2), the decision on the output pattern is made by a soft Viterbi decoding and fed back to the input layer. In the following, we describe these two phases separately.

2.1 Training phase

Training is performed by minimizing a proper error functional, formed by comparing the network output with a local replica of the preamble sequence. In our approach, the error functional is built accordingly to the concepts of
**Discriminative Learning (DL)** [7], extended to the case of multidimensional output patterns. DL has been proven to be particularly effective in general classification tasks and also in the equalization problem [3]. Its strength stems from the direct connection with the objective of minimization of the classification error [7].

In the present application, DL is implemented by computing the error functional $E$ in the following fashion. At each time step, $E$ is computed as the difference of two contributions. The first contribution is the usual **Mean Square Error (MSE)** between the target and the detected outputs, which should be minimized; the second contribution is a measure of the Euclidean distance from the output sequence to all the possible wrong codewords, which in contrast should be maximized. The resulting global cost functional at time $t_i$ is:

$$E(t_i) = -MSE_i + \frac{1}{N-1} \sum_{j \neq i}^{N} MSE_j$$  \hspace{1cm} (1.1)

where $MSE_i$ and $MSE_j$ are respectively the output MSE with respect to the correct target sequence $i$ and the generic (wrong) sequence $j$. Note that, according to this formulation, $E(t_i)$ should be optimized. In order to keep the functional $E(t_i)$ bounded, non-linear activation functions placed at the outputs of the neural network must also be bounded (e.g. of sigmoidal type [6][9]).

Maximization of (1.1) can be performed by use of any non-linear optimization method. Anyway, in our approach the BRLS algorithm has been employed [8]. BRLS takes advantage of the typical structure of NNs, where each neuron is made of a linear combination of inputs followed by a nonlinearity. Optimization is performed in the space of the outputs of the linear combinations (called the **neuron space**); this operation reduces the computation of the optimal weights to a local quadratic problem (see [8] for more details). BRLS has been proven to give fast and robust neural learning procedures and is thus particularly effective in any application where speed and regularity of convergence is a requirement [8].

### 2.2 Decoding phase

Once the preamble sequence has been processed and training performed, the equalizer switches into the decision phase (see Fig. 1), where decoding of received symbols is realized. We propose a novel Viterbi-like decision criterion, based on the following considerations.

Ideally, at each time step the output pattern should be equal to the true (transmitted) sequence. In the decoding phase the actual network output is compared to a target which is dinamically formed and stored in the **feedback register** (see Fig.1). Namely, at each time step:

1. the oldest target symbol exits the register and constitutes the actual detected symbol, while the remaining components are time-shifted;
2. a new symbol is appended to the target; for all possible symbol choices, the output MSE is computed and ranked in a nonincreasing manner. The $P$ targets with the lowest MSE are the **survivors** that are retained for the subsequent step and generate a trellis [5].

In the steady state, with $P$ symbols, $L$ outputs and $S$ survivors, $P \times S L$-dimensional targets are formed at each time instant. In particular, the best matching target can be used for the optional weight tracking, performed by eqn. (1.1).

### 3 SIMULATION RESULTS

The proposed equalizer structure has been implemented using either a feedforward or a fully recurrent (Elman architecture [7][9]) neural network, and compared to the traditional Viterbi algorithm in different environments. It is important to remark that neural architectures are expected to exhibit some advantages when the noise is not Gaussian, the channel is non-linear, and/or co-channel interference is present.

Neural networks with five inputs, eight hidden (or recurrent) units and five output neurons were used. These architectures were empirically found to be optimal for the channels herein considered. This practice is consistent with the fact that receiver hardware and underlying channel model are usually validated and standardized before a widespread use. Modulation was BPSK [5]. In this paper results obtained in two typical cases are described.

**Test 1.** The input-output relationship of the first test channel was:

$$u(n) = -0.2052 \cdot x(n) - 0.5131 \cdot x(n-1) + 0.7183 \cdot x(n-2) + 0.3695 \cdot x(n-3) + 0.2052 \cdot x(n-4) + \eta(n)$$  \hspace{1cm} (1.2)

where $x(n)$ is the transmitted symbol sequence, $u(n)$ is the received sequence and $\eta(n)$ is white additive noise. This is a typical non-minimum phase channel, commonly used as a reference in experiments. Fig. 2 summarizes the BER obtained for this channel in the presence of Gaussian noise, while varying the Signal-to-Noise Ratio (SNR).

The capability of the proposed architecture to cope with non-Gaussian environments has been also experimented. Fig. 3 shows the results obtained when the noise belongs to a mixture of a Gaussian (60%) and a Laplacian (40%) distribution.

**Test 2.** The second channel was non-linear; its input-output relationships were:

$$w(n) = -0.2052 \cdot x(n) - 0.5131 \cdot x(n-1) + 0.7183 \cdot x(n-2) + 0.3695 \cdot x(n-3) + 0.2052 \cdot x(n-4)$$ \hspace{1cm} (1.3)

$$u(n) = w(n) \cdot [1 + 0.2w(n)] + \eta(n)$$

Fig. 4 shows the results obtained in this case.

It is important to remark that the proposed neural equalizers combine the two tasks of channel estimation and sequence detection in a single architecture. In
contrast, the simulated Viterbi decoder assumes the perfect knowledge of the channel, even in the non-linear case. Nevertheless, the performance of the Viterbi algorithm are only slightly better, in the SNR range typical of cellular telephony.

It is expected that the performance of classical Viterbi decoders gets worse in the case on-line channel estimation. Furthermore, if a consistent parametric model is not available, the Viterbi decoder can be completely ineffective. In contrast, it is stressed that NNs can still perform equalization in unknown environments, provided that the input-output channel mapping is not ambiguous and a sufficient number of state variables is used.

4 CONCLUSION

In this paper a new neural sequence detector for the equalization of digital communication channels has been introduced. The proposed approach is based on the combined use of a fast learning algorithm and an innovative error functional, tailored for the objective of sequence detection. The choice of a proper decision criterion allows to extend the capabilities of Viterbi algorithm to neural architectures. Results obtained in the simulation of typical channels have confirmed the efficacy of the proposed solution.

References


![Fig. 1: Proposed architecture](image)

![Fig. 2: BER curves of channel 1 in the presence of Gaussian noise.](image)
Fig. 3: BER curves of channel 1 in the presence of non-Gaussian noise. 
x: feedforward network, o: recurrent network, 
*: Viterbi algorithm.

Fig. 4: BER curves of channel 2. 
x: feedforward network, o: recurrent network, 
*: Viterbi algorithm.