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Classification and Reproduction of Time Sequences
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Classification and reproduction of time sequences

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Abstract

Many neural networks which deal with complex time sequences such as speech signals use preprocessing stages, e.g. Fourier transformations, and model the speech data as a time sequence of vectors which contain the intensity of ordered frequency components. This approach complicates the implementation, reduces the processing speed and is unsatisfactory both in the view of biological modelling and homogen VLSI-design technique.

In our approach we developed net structures and learning algorithms which show that artificial neural networks can recognize and reproduce the real-time data directly and avoid the preprocessing stage. We examine the capability of the two networks which can compute analog periodic time sequences directly.

1. INTRODUCTION

This paper gives an overview of our approach for networks which carry out the reproduction and recognition of analog periodic time sequences. Our networks seem to enable a quick signal processing with less implementation efforts compared to ordinary techniques.

The first net learns to reproduce a given time sequence. The second one has the task to recognize time sequences. Both nets receive the decorrelated input from an orthogonalization filter which is also realized by a prior network layer. All three functions reproduction, classification and decorrelation are learned by new algorithms which are applications of the gradient descent method (with some modifications).

We developed both nets on the basis of the mathematical description of time sequences by differential equations [BOS87]. One could show, that every periodic signal could be generated by a linear network and recognized by a nonlinear net.

2. INPUT PROCESSING

The input vectors for the recognition and reproduction nets are generated from the time sequence by a tapped delay line, which transforms the signal at descrete time steps in a sequence of vectors of appropriate width. At each time step the tapped delay line presents the last n values of the sequence to the nets as input. The minimal number of components (dimension) of the input vector depends on the complexity of the time sequences and is equal to the *order* of the differential equation of the time sequence.

Because the processed sequences are periodic, it suffice to give a whole period as input for test and correction during the learning phase.

We validated this model by computer simulations where it had to learn to reproduce an artificial sequence of low order. The error-correction procedure converged quickly.

5. CLASSIFICATION

The classification net should generate a discrete representation of the time sequence to which the actual input belongs. Different time sequences should be distinguishable by different representations. As our mathematical analysis shows, the classification problem is not linear separable. Thus, the net has to consist of a hidden unit layer besides the usual output layer and should contain neurons with non-linear activation functions and variable thresholds. For the case of simplicity and quick net operation we choose the sign function as activation function. We can show by mathematical considerations that a network with such an architecture can solve the classification problem.

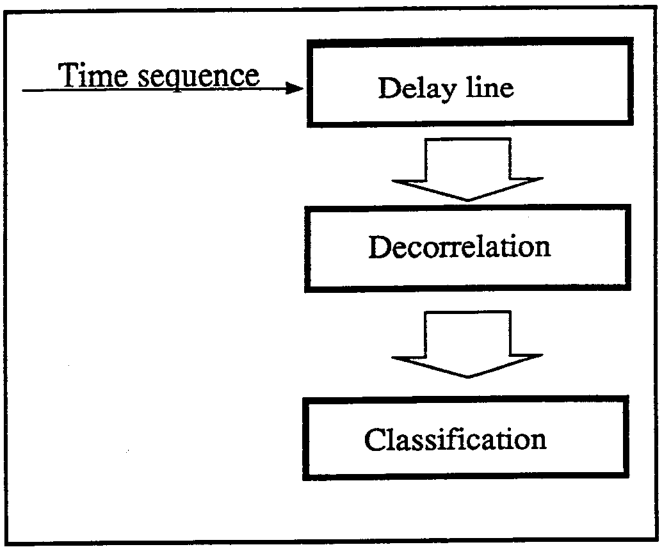

Fig.2 The classification system

The learning algorithm has to modify the weights such that for every input vector of every sequence the net outputs the right classification vector. This is done by an special error-correction procedure derived from the backpropagation algorithm [RUM86] and contains major modifications. The error signal for every weight was lowpass-filtered before weight updating. This enables symmetrie-braking and prevents that oscillations caused by the time sequence occure, it also smoothes the error landscape.

We tested this learning algorithm with two artificial sequences of low order. After tuning the lowpass-filer coefficients, it learned relativly quickly (about 100 learning steps) to classify correctly the two signals only by the input of parts of a period of them. Nevertheless, by testing the whole period the algorithm get stuck in local minima. Further investigations are nessecary to overcome this problem. Of cause, applying different coefficients for the lowpass-filters could help to avoid local minima.

If learning could be made successful, this approach promises a quick recognition of time sequences. Only a few time steps of a sequence are necessary as input to enable a correct classification.

3. DECORRELATION

The first layer consisting of linear neurons transforms these highly correlated signals into decorrelated sequences. For centered signals this becomes an orthogonalization and is learnt by a symmetric weight changing algorithm, described in detail in [SIM92]. It minimizes the correlation of the *n* output sequences by gradient descent and is related to a Gram-Schmidt vector orthogonalization. Computer simulations with artificial periodic signals showed that the symmetric learning algorithm converged, yet due to the high correlation of the sequences from the delay lines convergence times were long and oscillations in the remaining error occured. To speed up the learning process, we utilized the autocorrelation matrix of the input vectors [KRA56]. For further acceleration of the decorrelation procedure, it is also possible to implement an asymmetric learning, as presented in [SANG89].

The decorrelated sequences, which are transmitted to the reproduction net and also to the classification net as input, are an important precondition for successful learning in the following layers.

4. REPRODUCTION

The reproduction net, which consist of a linear neuron with *n* synapses, learns to reproduce a given time sequence z(t). For every time step *t* it should compute as output z(t) by summing up the actual *n* weighed input values from the decorrelation layer. The problem at hand is to find the weight vector, which enables the neuron to generate the correct sequence value at every moment of a period. This is done by a learning algorithm, which is a straightforward implementation of gradient descend. Mathematical analysis, showed us that this error correction procedure is only successful if the input sequences are decorrelated [SIM92].

If learning was successful, one needs only an arbitrary starting input vector (*n* consecutive values of the whole time sequence) and the trained network to generate the whole sequence. To do this, the reproduction neuron computes the actual value z(t) of the sequence. The input vector for the next time step is generated by feeding back z(t) to the input of the tapped delay line and shifting all previous inputs.

By mathematical transformations the linear decorrelation layer and the linear output neuron can be merged for the reproduction phase. Thus, a complex time sequence can be represented and stored only by two vectors, the starting vector and the weight vector.

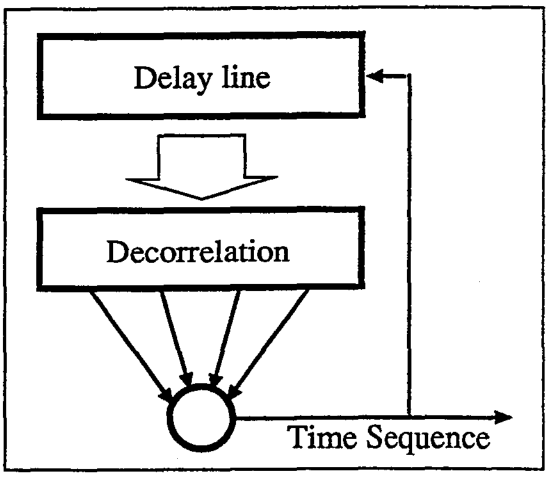

Fig. 1 The reproduction system

6. SUMMARY

This paper presents an pure neural network approach for the processing of time sequences. We presented nets for the direct reproduction and recognition of time signals. Computer simulation showed, that the presented learning algorithms are relatively successful in processing artificial periodic signals of low order. Furthermore, it seems also possible to process real-world-sequences with these nets. The higher complexity of these data would require greater layers with more neurons and will probably need longer learning times.

Our approach uses an decorrelation layer for the preprocessing of the signals and implements in fact a discrete Karhunen-Loeve transformation. In contrast to the often used Fourier transformation [KOH88] this approach gives decorrelated signals and is data dependent, thus yielding an optimal filter. The pure network approach reduces the implementation amount and enables quick signal processing. In both networks it is not necessary to present a complete period of signal, only a few input values suffice to enable a correct output generation.

In the area of speech processing analogue periodic signals correspond to sounds or vowels. Further investigation had to show if it is possible to deal with non-periodic signals like consonants.

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