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Volume II: Applications

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Modelling distributed time-delay neural network by a generalized net

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Abstract

The proposed GN model presents the work of the Time Delay Neural Networks (TDNN). Instead of other types neural networks, now we are describing the process during the time. We can teach this NN to fast changing processes, there behavior and environment. The TDNN can be used for prediction of the processes during there environment. Focused Time-Delay Neural Network FTDNN had the tapped delay line memory only at the input to the first layer of the static feedforward network.

Keywords: generalized nets, multi layer perceptron, time delay neural networks.

1 Introduction

In a series of papers the process of functioning and the results of the work of different types of neural networks are described by Generalized Nets [3, 4, 8-10]. This paper is based on [13].

Time Delay Neural Networks (TDNNs) are special artificial neural networks which receive input over several time steps. Time is represented in an explicit way. The architecture has a continuous input that is delayed and sent as an input to the neural network. The desired output of the network is the present state of the time series and inputs to the neural network are the delayed time series (past values). This type of the NN used delay block, which delayed input signal. The Figure 1 present TDNN. Practically the TDNN is a multilayer perceptrons (MLP's) NN [5, 6] whose inputs are formed from a time delay line. Neurons are organized into layers and the input signal propagates through the network layer by layer.

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In this paper, we design a Generalized Net model (GN) [1,2] that presents the work of the TDNN. All definitions related to the concept TDNN are taken from [11, 12].

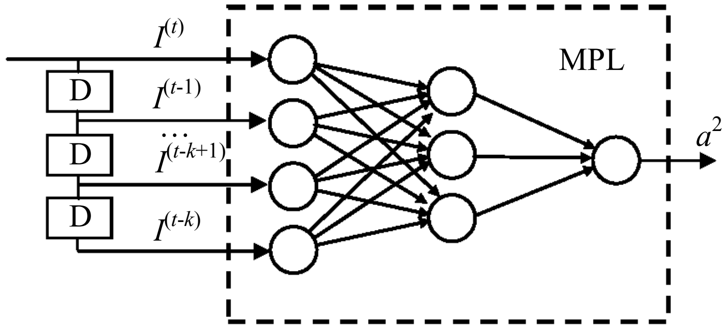

Figure 1

Let us have a NN with one input $I(t)$, where the signal $I(t)$ is a any signal during the time t. (Fig. 1), but first layer of the NN have k neurons. Each input of the neuron have input vector P.

According to [11], the Focused Time-Delay Neural Network (FTDNN) (Fig. 2) had the tapped delay line memory only at the input to the first layer of the static feedforward network. You can also distribute the tapped delay lines throughout the network. The distributed TDNN (DTDNN) was first introduced in [12] for phoneme recognition. The original architecture was very specialized for that particular problem. The figure below shows a general two-layer distributed TDNN.

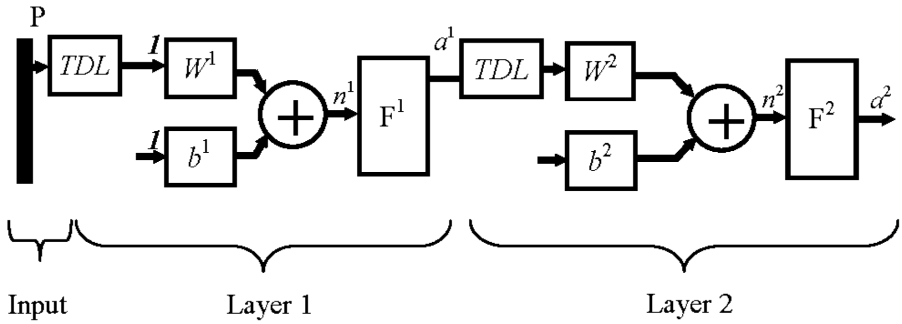

Figure 2: Distributed Time-Delay Neural Network

This network can be used for a simplified problem that is similar to phoneme recognition. The network will attempt to recognize the frequency content of an input signal. The Figure 2 shows a signal in which one of two frequencies is present at any given time.

2 A GN-model

All definitions related to the concept "GN" are taken from [1, 2]. The GN, describing the process of the work of the DTDNN, is shown on Fig. 3.
Initially the following tokens enter in the GN:

- in place I – α^1-token with initial characteristic $x_0^{\alpha^1} = I(t)$;
- in place S_{W1} – β^1-token with initial characteristic $x_0^{\beta^1} = w^1$ where w^1 is a matrix with weight coefficients for the first layer of the DTDNN;
- in place S_{b1} – γ^1-token with initial characteristic $x_0^{\gamma^1} = b^1$ where b^1 is a matrix with biases of the first layer of the DTDNN;
- in place S_{F1} – one δ^1-token with initial characteristic "transfer function";
- in place S_{W2} – β^2-token with initial characteristic

$$x_0^{\beta^2} = w^2 = \begin{vmatrix} W_{1,1} & W_{1,2} & \dots & W_{1,R} \\ W_{2,1} & W_{2,2} & \dots & W_{2,R} \\ \dots & \dots & \dots & \dots \\ W_{S,1} & W_{S,2} & & W_{S,R} \end{vmatrix}$$

  where w^2 is a matrix with weight coefficients for the second layer of the DTDNN;
- in place S_{b2} – γ^2-token with initial characteristic $x_0^{\gamma^2} = b^2$; where b^2 is a matrix with biases of the second layer of the DTDNN;
- in place S_{F2} – one δ^2-token with initial characteristic using "transfer function".

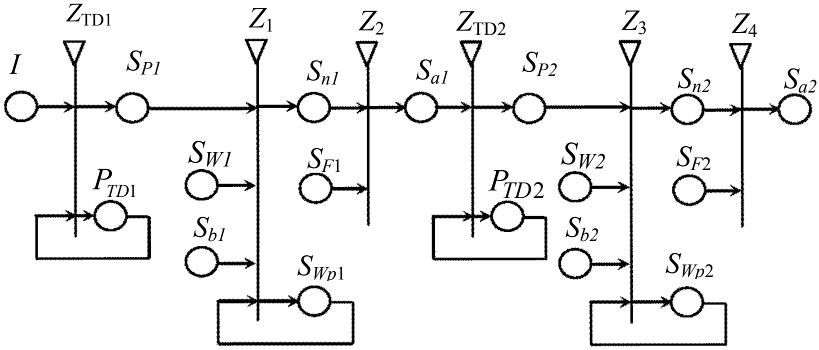

Figure 3: GN model of the Distributed Time Delay Neural Networks

The GN is presented by a set of transitions:

$$A = \{Z_{TD1,} Z_1, Z_2, Z_{TD2}, Z_3, Z_4\},$$

where transitions describe the following processes:

- Z_{TD1} – Preparing the input vector P^1 from the I(t);
- Z_1 – Calculating influence of the first layer of the MPL (n^1);
- Z_2 – Calculating the output of the first layer of the MPL (a^1);
- Z_{TD2} – Delayed the signal for the second layer ;
- Z_3 – Calculating influence of the second layer of the MPL (n^2);
- Z^4 – Calculating the output of the second layer of the MPL (a^2);

The transitions of the GN-model have the following forms.

$$Z_{TD1} = <\{I, P_{TD1}\}, \{S_{P^1}, P_{TD1}\}, R_{TD1}, \wedge(I,\ P_{TD1})>,$$

where:

$$R_{TD1} = \begin{array}{c|cc} & S_{P^1} & P_{TD1} \\ \hline I & False & True \\ P_{TD1} & W_{P_{TD},P^1} & True \end{array},$$

where

W_{P_{TD1},P^1} = “in position W_{TD1} exist x_k^{α} “.

The α-tokens obtain characteristic as follow:

$$x_0^{\alpha} = I(t);$$
$$x_1^{\alpha} = I(t), I(t-1);$$
$$\ldots\ldots$$
$$x_{k-1}^{\alpha} = I(t), I(t-1), \ldots, I(t-k+1);$$
$$x_k^{\alpha} = I(t), I(t-1), \ldots, I(t-k+1), I(t-k).$$

Z_1=<{ S_{P^1}, S_{W^1}, S_{b^1}, S_{Wp^1} }, { S_{n^1}, S_{Wp^1} }, R_1, $\wedge(\vee(S_{P^1}, S_{W^1}), \vee(S_{b^1}, S_{Wp^1}))$>,

where:

$$R_1 = \begin{array}{c|cc} & S_{n^1} & S_{Wp^1} \\ \hline S_{p^1} & False & True \\ S_{W^1} & False & True \\ S_{b^1} & True & False \\ S_{Wp^1} & True & False \end{array}.$$

Tokens α^1, β^1 and γ^1 union, into the χ^1-token according to [5].

Z_2=<{ S_{n^1}, S_{F^1} }, { S_{a^1} }, R_2, $\wedge(S_{n^1}, S_{F^1})$>,

where:

$$R_2 = \begin{array}{c|c} & S_{a^1} \\ \hline S_{n^1} & True \\ S_{F^1} & True \end{array},$$

Tokens δ^1 and χ^1 union into the σ^1-token according to [5].

Z_{TD2}=<{I, P_{TD2} }, { S_{P^2}, P_{TD2} }, R_{TD2}, $\wedge(I, P_{TD2})$>,

where:

$$R_{TD2} = \begin{array}{c|cc} & S_{P^2} & P_{TD2} \\ \hline I & False & True \\ P_{TD2} & W_{P_{TD2},P^2} & True \end{array},$$

where

W_{P_{TD2},P^2} = "in position W_{TD2} exist x_k^{α} ".

Z_3=<{ S_{P^2} , S_{W^2} , S_{b^2} ,S_{Wp^2} }, { S_{n^2} ,S_{Wp^2} }, R_3, ∧(∨(S_{P^2} , S_{W^2}),∨(S_{b^2} , S_{Wp^2})>,

where:

$$R_3 = \begin{array}{c|cc} & S_{n^2} & S_{Wp^2} \\ \hline S_{P^2} & False & True \\ S_{W^2} & False & True \\ S_{b^2} & True & False \\ S_{Wp^2} & True & False \end{array},$$

Tokens σ^1, β^2 and γ^2 union, into the χ^2-token according to [5].

Z_4=<{ S_{n^2} , S_{F^2} }, { S_{a^2} }, R_4, ∧(S_{n^2} , S_{F^2})>,

where:

$$R_4 = \begin{array}{c|c} & S_{a^2} \\ \hline S_{n^2} & True \\ S_{F^2} & True \end{array},$$

Tokens δ^2 and χ^2 union into the σ^2-token, using [5].

3 Conclusions

The proposed GN model present work of the Distributed Time Delay Neural Networks. It had the tapped delay line memory after the first layer and after the second layer of the static feedforward network The network is suitable to recognize the frequency content of an input signal.

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The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.
It may be viewed as a result of fruitful discussions held during the Ninth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2010) organized in Warsaw on October 8, 2010 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT - Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bystrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, and the University of Westminster, Harrow, UK:

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The consecutive International Workshops on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGNs) have been meant to provide a forum for the presentation of new results and for scientific discussion on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems have also been included. The Ninth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2010) is a continuation of this undertaking, and provides many new ideas and results in the areas concerned.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

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