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PROBABILISTIC NEURAL NETWORKS IN THE PROBLEMS OF TIME SERIES IDENTIFICATION

The given paper considers the possibility of time series identification on the basis of probabilistic neural networks and their modified versions. The influence of kernel function width on adequate restoration of density and classification quality is investigated. Modified versions of probabilistic neural networks and peculiarities of their application are considered. Advantages and disadvantages of probabilistic neural networks are shown.

Key words: *probabilistic neural networks (PNN), identification, patterns identification, analysis of time series.*

Introduction

The problem of identification (of processes, systems) or construction of mathematical model by the results of observations occupies important position in modern control theory and for decision-making in various spheres: engineering, economy, biology, etc. The most efficient mathematical models, which can be used for forecasting of processes development, are those models for construction of which time series are used [1].

Conventional approaches, used for identification, become less suitable for modeling of complex nonlinear systems. Greater part of the processes cannot by described by means of convectional statistic models, since they are mainly nonlinear and have either random or quasiperiodic or mixed (stochastic, random-dynamic, determined) base. Adequate apparatus for construction of models of practically any non-linear structures may serve methods, based on artificial intelligence, namely artificial neural networks, which enable to simulate non-linear processes, adapt them, and allow to operate with noise data. Most promising are radical-basis structures. These structures are characterized by high learning speed and universal approximating abilities [2, 3].

Probabilistic Neural Networks (PNN) can be referred to such tools, since they, as compared with other intelligent facilities, that can be used in identification systems, have several considerable advantages, which will be listed in the given paper. Probabilistic neural networks are referred to neural networks of radial-basis type, which, due to their reliability, nowadays are used in various problems of pattern classification [5-16]. It is natural that in [17] the author states that PNN is the most efficient neural network. Probabilistic neural networks are suggested by Specht D. F [18-20] as perfection of statistic methods of pattern recognition.

The aim of the given research is to improve the efficiency of probabilistic networks and their modifications in the problems of identification of time series in real time mode.

Problem set-up

For forecasting of processes development, the application pattern recognition methods, the aim of which is classification of objects by several classes is very promising. Such approach helps to solve the complex pf problems that are very important for forecasting [2, 21].

The considered set of neural networks can be used for study of the following processes, presented by time series;

forecast of electric loads;

forecast of quotations change;

forecast of sate and quality of surface waters;

distribution of network load among information flows.

For realization of this purpose the method of sliding window can be applied. Let identified non-linear dependence be presented as the sample «input-output»:

$$\left(X_i, y_i\right).\ i = \overline{1, M}, \qquad (1)$$

where $X_i = \left(x_{i,1}, x_{i,2}, \ldots, x_{i,p}\right)$ – is the vector of inputs, y_i – is the output i-th pair, M – is the volume of the sample.

The task of identification is to find model F, which provides minimum value of model output value deviation at values of inputs, set by X_r vector, from output y_r.

In probabilistic neural networks patterns are classified on the basis of evaluation of their similarity with neighboring samples. Formal rule for classification is that the class with higher density of probabilities distribution in the area of unknown sample will have the advantages as compared with other classes. For evaluation of the function of probabilities distribution density non-parametric methods of evaluation are used. The review of research dealing with this problem, showed, that, as a rule, method of Partsen is applied, according to this method, for each sample certain weight is considered, this function is called function of potential or core.

As a rule, simplified Gauss function is taken as core function:

$$K(X) = e^{\left(-\frac{\|X - X_i\|^2}{2\sigma^2}\right)}, \qquad (2)$$

where X_i – i-th sample of X vector , $i = \overline{1, L}$, X – is unknown sample, σ – is the parameter, that sets the width of Gaussian core function and determines its influence. But the form of function of K core practically does not influence the accuracy of density restoration and the quality of classification.

Structure of probabilistic neural network

The example of probabilistic neural network, intended for solution of the problem of classification of p-x component input vectors x by M classes, is shown in Fig 1.

Input layer of the network does not perform calculations and serves for receiving and division of input vector signs x. The number of neurons of input layer is defined by the number of vector x signs. Pattern layer contains one neuron for each pattern of input vector from teaching sample. That is, at total volume of teaching sample, that contains L patterns, pattern layer must contain L neurons. Input layer and pattern layer form connected structure.

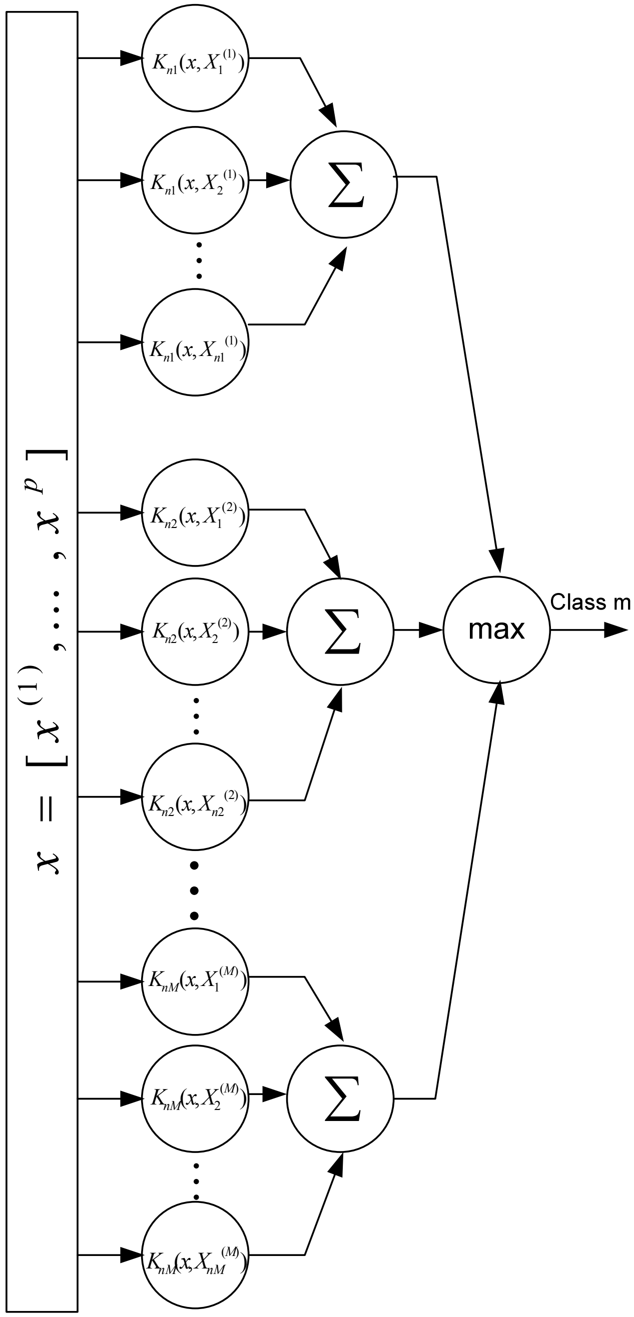


Fig. 1Architecture of probabilistic neural network

Addition layer contains the number of neurons equal to the number of classes, into which input patterns are divided. Each neuron of addition layer has connections only with neurons of patterns layer, which refer to corresponding class. All weights of connections of addition layer in convectional probabilistic neural network equal one.

Basic neuron performs functions of discriminator of threshold value. It indicates which neuron of addition layer has maximum output signal. In such a manner class, the given input pattern belongs to, is determined. Connections weights of the neuron of outcome layer are determined in such a way, that the neuron of addition layer with highest value of activity is identified at its output.

In the process of teaching the structure of probabilistic neural network is formed. Dimension N of teaching sample vectors X_i, $i=\overline{1,L}$ determines the number of neurons and the structure of input layer. Total dimension L of teaching sample X_i, $i=\overline{1,L}$ corresponds to the total number of neurons of samples layer.

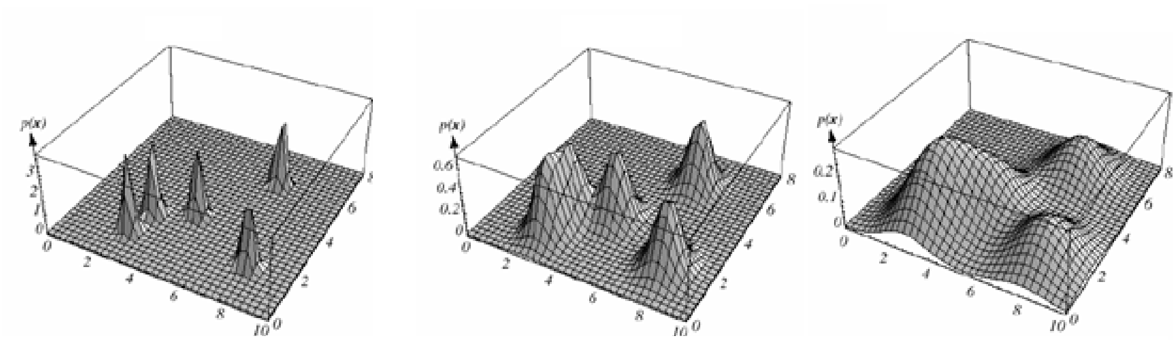
Presentation of the network of each of L samples is accompanied by the teacher's indication of the number of k-th class, to which sample belongs. Presentation of teaching samples can be performed in any sequence. After presentation of all L vectors of teaching samples the structure of network is formed and certain parameters of the network are defined in the form of matrix. The process of probabilistic neural network teaching is accomplished and the network is ready for classification of unknown samples.

In operation mode, input pattern X of unknown class is presented, this pattern is normalized and then multiplied by weights matrix and activates neuron of samples layer. Each neuron of samples layer shows at its output certain level of activity $y_i(X)$. Each k-th neuron of addition layer adds equal activities $y_i(X)$ of all neurons of samples layer of its k-th class and shows, at its output total level of activity of the given k-th class $y^k(X), k=\overline{1,M}$, determines which neuron of addition layer has maximum output signal $y^k(X)$. Thus, by the number of k-th neuron the number k class, to which with greater probability pattern X belongs, is determined.

Hence, probabilistic neural networks, belong to the class of neural networks with a teacher, who automatically puts forward one more very important problem of formation of efficient teaching sample. Applying the above-described tool, we may predict relative change of future values of time series; identify the trend (ascending, descending, lateral); construct the indicator for identification of the points of trend turn.

Correct choice of the value of smoothing parameter σ is critical for the efficiency of probabilistic neural network.

It should be noted, that the value of σ influences the quality of density restoration. The results of modeling of the influence of core function width value on density restoration is shown in Fig 2.



a) b) c)

Fig. 2. Influence of control parameter σ on the form of Partsen evaluation:
a) small σ ; b) middle σ ; c) large σ

It follows from Fig 2 that if the value of σ is smaller then the density is concentrated near training samples and the function of probabilities density will undergo sudden changes. However, if the value of σ is great, then, the details of density will be blurring. Hence, there must be optimum value of window width σ, at which restored density will be most adequate. Optimum width of the window σ is a compromise between the accuracy of data description and smoothness of empirical function.

Activity function of k- th summation neuron defines the value of probabilities distribution density for the whole k- th class. In general form it is calculated by the formula:

$$Y^k(X) = \frac{1}{N(2\pi)^{\frac{p}{2}}\sigma^p} \sum_{j=1}^{L_k} e^{\left(-\frac{(x-x_{kj})^T (x-x_{kj})}{2\sigma^2} \right)}, k = \overline{1,M}, \tag{3}$$

Weighted probabilistic neural network (WPNN) is the improved version of conventional probabilistic neural network (PNN). Such a network provides higher recognition factor and keeps the advantages of PNN. Separation of classes is used as one of basic criteria of selection for samples classification. Unlike WPNN, convectional probabilistic neural network establishes equal weights for all samples without calculation of classes separation. That is, WPNN includes weight coefficients between samples layer and addition layer. The structure of WPNN is similar to PNN, the only difference is the presence of weight coefficients. Activity function of k- th summation neuron is calculated by the formula:

$$Y^k(X) = \frac{1}{N(2\pi)^{\frac{p}{2}}\sigma^p} \sum_{j=1}^{L_k} V_{k\,j} e^{\left(-\frac{(x-x_{kj})^T (x-x_{kj})}{2\sigma^2} \right)}, k = \overline{1,M}, \tag{4}$$

where $V_{k\,j}$ – is weight coefficient, that is high for the sample with high degree of classes separation and small for the sample with small degree of classes separation. Convectional probabilistic neural network, suggested by Specht D. F., is realized by means of algorithm, that provides training of the network while a single passage. Application of another modification of probabilistic neural network (MPNN) is very expedient for analysis of non-linear time series. This is achieved as a result of introduction of the connection between the structure of PNN and radial basic Gaussian functions like PNN, training of MPNN is memory-oriented and requires only one passage. While training, neural network saves training input vectors as centers of neural network. These centers are connected with the values of desired outputs. During classification the closest relatively each of the centers, classified input vector is defined by means of core function. Output is associated with the centre, that is the nearest to the input vector as the most suitable output. The model of such network:

$$\hat{y}(x)=\frac{\sum_{i=1}^{N} Z_i y_i e^{\left(-\frac{(x-c_i)^T(x-c_i)}{2\sigma^2}\right)}}{\sum_{i=1}^{N} Z_i e^{\left(-\frac{(x-c_i)^T(x-c_i)}{2\sigma^2}\right)}}, \qquad (5)$$

where c_i – is the center of vector for class in the input space, Z_i – is the number of input vectors, associated with the centre c_i [5].

Conclusions

The given paper analyzes the possibilities of application of probabilistic neural networks for analysis and forecast of time series. These networks are characterized by high training rate, that allows to use them for identification of time series in real time mode and by the possibility of obtaining useful results at small training samples even of inaccurate data are available.

The survey of sate-of-art the problem showed, that nowadays probabilistic neural networks are efficiency used for the solution of classification problems for investigation of various objects. It was proved, that the efficiency of the given method of identification is determined by the quality of preparation of input data: Provide their statistic independence and normalization that maximally increases their entropy. Methods of efficiency enhancement based on regulation of basic parameters of neural networks are investigated.

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