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ON APPLICATION OF THE NEURAL NETWORK MODELLING TO PROBLEMS OF APPLIED ECOLOGY AND HYDROMETEOROLOGY

On the basis of previously developed models of neural network modelling it is studying a dynamics of neural networks with different types of input patterns and a problem of forecasting the spatial and temporal structure of the dusty concentration fields for the industrial city's atmosphere as well as the rainfall intensity fields.
Keywords: *neural network modelling, complex patterns*

I. Introduction

Development of new effective methods and schemes for the theoretical and experimental modeling and measuring the characteristics of air pollution, for example, in an atmosphere of industrial cities, modeling different structures temporal and spatial distribution in the various classes of problems in modern hydrometeorology, applied ecology etc. With the development of new technologies and the development of experimental methods have received research involving the use of radar, laser systems, etc. In the theoretical developments, in addition to the classical physical-chemical analysis models in recent years been used successfully and relatively new methods of mathematical modeling, and, above all, the methods of chaos theory, neural network (NN) modeling and artificial intelligence (see., for example, [1-5]). In this context, of particular interest is the use of the NN modeling and pattern recognition. It is important to emphasize that, although some progress in the study and construction of various NN schemes is achieved, however, many of the key issues related to their basic dynamic parameters, models of operation are still far from being solved. Moreover, the specific application of the NN modeling in the applied ecology and hydrometeorology are actually at the initial stage [1-10].

Among the extremely urgent problems here, first of all, one should include the adaptation of simulation NN models to specific environmental systems. Among the unsolved problems it is extremely important the feed problem of so-called noisy patterns into the system during modeling the NN system dynamics. This paper continues our studies [4-10] on the study and modeling of the dynamics of multi-layer NN and illustrative adaptation of the our photon echo NN set to modeling spatial and temporal structure of the air pollutants concentration fields in the atmosphere of industrial city and also similar to the problem of simulating the intensity of rainfall fields (objects). Note that earlier [7-12] using object-orientation programming we did a software implementation of new numerical models of 3-layer systems on the basis of the National Assembly of the photon echo and conducted computer experiments to determine their optimal information capabilities in pattern recognition problems and complex signals.

II. Neural networks modeling scheme

The main aspects of the neural networks modeling scheme, based on the photon echo are earlier presented, in particular, in [5-9]. Therefore, we limit ourselves to a summary of the fundamental aspects of the implementation of the modeling scheme. The model, based on neural network [4], has been worked out to forecast the air pollution fields in the industrial city's atmosphere in space and time. The model has been tested on the measured and compilated data on the dusty concentration (2000-2002 years), obtained and described in ref. [19]. This product provides maps of maximum values of the dusty concentration projection upon the horizontal surface in the range of about 40km^2 with spatial resolution 0,2x0,2km. The input data applied to the model has consisted of sequences of N consecutive images with 15 min. time step. The forecast has been calculated for the next 15 minutes. The neural network (NN) is a feed-forward non-linear five-layer training network, consisting of input, hidden and output layers (see Ref. [4]). In Refs. [5-10] the same neural networks scheme has been tested with different input patterns. Each layer is composed of n_k nodes and consecutive layers (k-1 and k) are interconnected by arrays of weights ($w_{i,j}^{k}$). At first the neural network is trained on a large sample of representative data. Training is to optimise weights on the basis of the error between the expected and calculated outputs. It is conducted with back propagation algorithm on N+1-element sequences of radar images. The rainfall values in all n0 pixels of the whole radar maps sequence constitute the input vector y_i^0 .

Table 1 - Data vectors applied in the model

Layers	Denitation	Range	Size
1st input layer	y_i^0	$i=1,\ldots,n_0$	$n_0=n\times100$
2nd hidden layer	y_i^1	$i=1,\ldots,n_1$	$n_1=300$
3rd output layer	y_i^2	$i=1,\ldots,n_2$	$n_2=1\times100$
Expected output	y_i^3	$i=1,\ldots,n_3$	$n_3=1\times100$

The vector y_i^0 is transformed into the vector y_i^1 (hidden layer), which in turn is transformed into the output vector y_i^2 . Both transformations are performed using arrays of weights $w_{i,j}^{k}$ according to the following formula

$$y_i^k = f\{\sum_{j=1}^{n_k-1} w_{i,j}^k y_j^{k-1} + w_{i,0}^k\} \quad i=1,\ldots,n_k;\ k=1,\ldots,2;$$

In the above formula the function f is so-called transfer function; we use sigmoid function:

$$F=1/[1+x^{b(D)}]$$

Here b(D) is sigmoid transfer function parameter, which requires optimisation; D is a fractal dimension (c.f.[18]). In figure 2 it is presented the qualitative shape of response function for direct propagation (curve 1) of the patterns chain (massive of values of the air pollution concentration) and for reverse propagation (curve 2). They are close to function, which is corresponding to derivative of the response function. Such a choice provides an optimal realization of the NN training process. From mathematical point of view the neural network leaning process is multi-parameter task of the non-linear optimization. The referent process is in choice of optimized values of matrix elements for given topology of links between neurons. A regular output vector is formed on output for introduction of input vector from training pattern chain to neural network (i.e. output vector practically coincides with expected sample vector and further process of leaning is finished). It should be noted that a method of reverse mistake propagation is in fact a generalization of the non-linear squares approach to multi-layers neural network (see detailed description in ref.[4]).

The output vector y_i^2 constitutes the result of model process. It is compared with the expected real values from the time the forecast is prepared for. Thus it is possible to calculate the error:

$$e_i^2 = y_i^3 - y_i^2, \qquad i=1,\ldots,n_2;$$

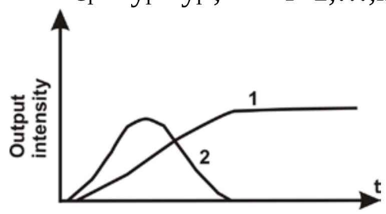

Figure 1 - The response function of neuron in the neural network: 1- response for direct propagation of the patterns chain (massive of values of the air pollution concentration); 2- for reverse propagation ; I—output intensity of data

On the basis of these errors the corrections for all weights between hidden and output layers are calculated as follows:

$$\Delta w_{i,j}^2 = \alpha^2 e_i^2 (1 - y_i^2) y_i^2 y_j^1, \qquad i=1,\ldots,n_2;\ j=1,\ldots,n_1;$$

where α^2 is the layer learning factor. Next the errors e_i^2 and corrected weights $w_{i,j}^k$ are propagated backwards in order to calculate errors of previous layer:

$$e_i^1 = (1/n_2) \sum_{j=1}^{n_2} e_j^2 w_{j,i}^2 \quad i=1,\ldots,n_1;$$

Finally by analogy the corrections for all weights between input and hidden layers are computed. The training is conducted until either the defined number of iterations is performed or desired accuracy is reached. When the training is finished, the forecasts for 15 minutes ahead (N+1 st elements) are carried out on the basis of N-element sequences applying the known weights. The quality of neural network is checked on both dependent (included in training sample) and independent (not included in training sample) data.

III. Modelling results and conclusions

As usually [5,11], at first stage of modelling some attempts of model training with different inputs were carried out. In the first attempt 25 sequences of N=2 images (the dusty concentration level) with spatial resolution 0,2 x 0,2 km were applied as input [12,13]. After training was complete, model quality was checked on independent data. As a result the forecast, which was carried out, was not extrapolation of images, but in fact resembled the sum of all images used as training sample. Further there were the attempts consisted in radical limitation on amount of the data in the input with simultaneous increase in values of other parameters (number of iterations, size of hidden layer, stochasticity level, training sample etc). Next tests, aiming at checking recognition of movements, were carried out. Training sample consisted of 64 sequences of N=5 artificially generated images with 40x40 pixels. Neural network parameters: size of hidden layer and number of iteration was increased to 1,000 and 5,000 respectively. Tests resulted in quite acceptable forecasting in terms of extrapolation of the spot position in N+1 st image (fig.2).

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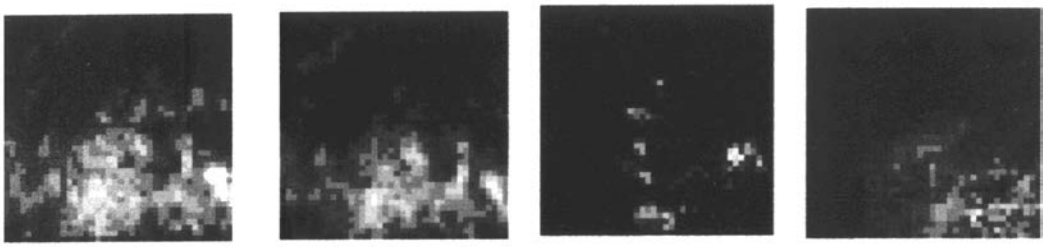

(a) (b) (c) (d)

Figure 2 – NN modeling data: (a), (b) - calibration data (time series of real images with 20 sec interval; (c), (d) – predicting images (correspondingly, poorly trained and well-trained).

It indicated that in this case model was capable of learning spot movement. Taking the previous results into account, the attempts of applying simplified real images as input were made. After training, the model quality was checked on both dependent and independent data. The forecasting, calculated on events included in the training process, seemed to be quite acceptable. However in the case of independent data model did not perform well in terms of movement recognition and changes in shape and intensity of spots. The training process was repeated. Model was tested on a series of events not included in the training sample to check the model quality.

The whole conclusion is that the preliminary NN modeling of the structure of the air pollutants, as well as parallel of the precipitation field intensities showed that the predicted and the expected distribution of the desired patterns are correlated with the match data (especially taking into account the further increasing the size of the layer and the number of iterations). In conclusion let us note that the analysis of results of the NN modeling dynamics for different input sequences of images, including, in the case of a noisy input sequence, as well as preliminary results of forecasting the space-time structure of the air polluting substances fields and intensities of the rainfall fields clearly points to the prospects of using the NN simulation in studying dynamics of different environmental systems.

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До питання про застосування апарату нейромережевого моделювання в задачах прикладної екології та гідрометеорології

Препелица Г.П., Грушевський О.М., Лобода А.В., Сухарев Д.Є., Буяджи В.В.

На основі раніше розвинутих моделей нейромережевого моделювання розглянуті задачі моделювання динаміки нейромереж з різними видами вхідних паттернів та прогнозування просторово-часової структури полів концентрацій забруднюючих атмосферу промислового міста пилових речовин, а також полів інтенсивності опадів.

***Ключові слова**: нейромережеве моделювання, складні паттерни*

К вопросу о применении аппарата нейросетевого моделирования в задачах прикладной экологии и гидрометеорологии

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На основе ранее развитых моделей нейросетевого моделирования рассмотрена задача моделирования динамики нейросети с различными видами входных паттернов и прогнозирования пространственно-временной структуры полей концентраций загрязняющих атмосферу промышленного города пылевых веществ, а также полей интенсивности осадков.

***Ключевые слова**: нейросетевое моделирование, сложные паттерны*