Journal of Signal and Image Processing
ISSN: 0976-8882 & E-ISSN: 0976-8890, Vol. 2, Issue 2, 2011, pp-54-59
Available online at http://www.bioinfo.in/contents.php?id=48

A NEW FORECAST METHOD OF THE MOVING OPTICAL OBJECT POSITION BASED ON THE PARALLEL HIERARCHICAL NETWORK

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Received: December 08, 2011; Accepted: December 15, 2011

Abstract-This paper discusses principles necessary to develop a forecast method based on the parallel-hierarchical (PH) network and an idea of the hyperbolic smoothing of empiric data. Mathematic models for forecasting dynamic image series, as well as software for forecasting moving optical object positions on the example of energy centers of laser beam spot images are developed. The developed method is more efficient and less time consuming for real-time systems in realization of the forecasting operation of energy center positions of laser beam spots.
Key words - parallel-hierarchical (PH) network, laser beam spot images, statistical observations, dynamic series, forecasting.

Introduction

Rapidly growing requirements to modern computational media encourage development of new intelligent methods of information transfer and processing. Rigid requirements to real-time information processing systems force scientists to regularly create and upgrade data transfer systems. Today most internet channels cannot provide data exchange of the required quality between such systems, which, in turn, results in the congestion of those channels and formation of so-called digital bottlenecks. A possible solution of the problem of transfer of large volumes of information is to use a fiber-optic cable, but laying such cable is rather expensive, even on short distances. At the same time, this problem can be solved through application of the laser-based technologies [1-4], one of the most promising models of information transfer for the near future. In this case, for instance, tons of full-length films and virtual worlds could be transferred to any part of the globe in a blink of an eye.

Most satellites transmit information, such as TV programs, by means of microwave radiation, while laser-based information transmission could be hundreds of times faster, which, in turn, will considerably increase the carrying capacity of the channel.

The laser-based information transmission requires that both a satellite and a receiving unit (RU) were located in a certain position. A position of the RU lens, whose diameter is only several centimeters, must be adjusted to one thousandth degree, otherwise the information transmission will not happen.

One of the main problems in the process of satellite monitoring by the receiving unit, which occurs at all stages of the system operation, is the forecast of the laser beam spot image location, namely of its geometrical characteristics, which are being distorted by the turbulence and air masses.

Significantly noise-distorted images, in their turn, can both considerably worsen results of the spot location forecast, and set a system into the state when it will not be able to respond adequately to variations in the monitored object location.

To solve a problem of the efficient forecast, frames of the laser beam spot (LBS) image sequence should be classified with a goal to filter a laser route from images considerably distorted by noise, thus forming a tunnel of reference images.

Development of computerized real-time forecasting systems gained new momentum with the emergence of high-efficiency automated systems of information collection, processing and storage. Such systems consist of a complex of information collection and processing tools which are able, based on a system of specially developed algorithms, to solve a problem of the classification and forecasting of the characteristics of respective objects, phenomena or real time processes, in most cases using geometric characteristics of object boundaries. Fragments of laser beam routes used in the optical communication, navigation, ranging, and military equipment, are studied in this article. Development of the PH network-based forecasting system allows solving the following problems:

- Automatic object control;
- Laser-based data transfer;
- Forecasting of the moving optical object behavior.

Principles of the ph network organization

An image analysis consists of the consecutive transformation of the matched image components and determination (filtration) of the unmatched in time image components during neural network elements transfer from the current energetic state with certain coordinates into a state with lower energy and other space coordinates. A condition of the image transfer components to the next level is a presence of the mutual coincidence intermediate results dynamics of time processing in the corresponding low level channels. An analysis result is formed of image components isolated in the space-time domain [5].

Let us consider a mathematical model of the parallel decomposition of a set $\mu = \{a_i\},\ i = \overline{1,\ n}$ [4], used in each branch of the PH network.

$$\sum_{i=1}^{n} a_i = \sum_{j=1}^{R}\left(n - \sum_{k=0}^{j-1} n_k\right)\left(a^j - a^{j-1}\right), \quad (1)$$

Where $a_i \neq 0,\ R$ – dimension of this set, $a^k,\ k = \overline{1,\ R},$ – elements of subsets consisting of identical elements, n_k – a number of elements in the kth subset (i.e. the multiplicity of number a_i), a^j –an element of the set $\{a^k\}$ selected at the jth step, $j = \overline{1,\ R},\ a^0 = 0,\ n_0 = 0.$

Let us use an idea of the population coding [6] and construct a model of some end action performed by all current actions.

For the PH network, both a number of elements in the branch of each level, which are determined based on the model (1) and values of the element itself may be taken as averaged parameters. Obviously, at the neural network branch level, this end action corresponds to this network's averaged parameters when the population coding is implemented [6]. In this case the current image being recognized will be reflected by the current PH network and compared with the reference PH network with averaged parameters.

Having denoted an average value of the random element of the first level as $\overline{a}^{1}_{i.j}$, second level as $\overline{a}^{2}_{i.j}$, third level as $\overline{a}^{3}_{i.j}$, etc., the kth last level as $\overline{a}^{k}_{i.j}$, and an average number of elements of the first level as $N_{\overline{a}^{1}_{i.j}}$, second level as $N_{\overline{a}^{2}_{i.j}}$, third level as $N_{\overline{a}^{3}_{i.j}}$, etc., and the kth level as $N_{\overline{a}^{k}_{i.j}}$, one can form a PH network with averaged parameters.

A structure of the PH network with averaged parameters thus synthesized is shown at Fig. 1.

A current image or a tested image prepared by the PH network with current parameters $a^1_{i,j},\ a^2_{i,j},\ a^3_{i,j},\ \ldots,\ a^k_{i,j}$ and a respective number of elements in branches of each level $N_{a^1_{i,j}},\ N_{a^2_{i,j}},\ N_{a^3_{i,j}},\ \ldots,\ N_{a^k_{i,j}}$ is being compared with the reference image prepared by the PH network with averaged parameters $\overline{a}^{1}_{i.j},\ \overline{a}^{2}_{i.j},\ \overline{a}^{3}_{i.j},\ldots,\ \overline{a}^{k}_{i.j}$ and an average number of elements in branches of the respective level

$$N_{\overline{a}^{1}_{i.j}}\ ,\ N_{\overline{a}^{2}_{i.j}}\ ,\ N_{\overline{a}^{3}_{i.j}}\ ,\ldots,\ N_{\overline{a}^{k}_{i.j}}\ .$$

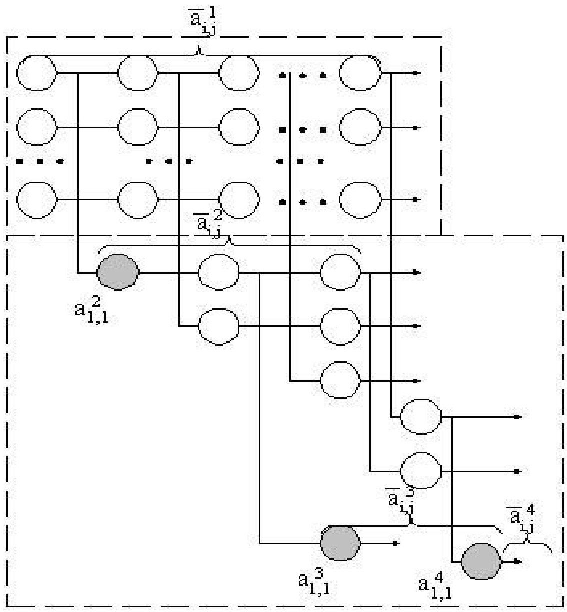

Fig.1 A structure of the PH network [4] with averaged parameters.

Using a preparation of elements of the PH network for each level [5], it is possible to proceed from averaged parameters $\overline{a}^{1}_{i.j},\ \overline{a}^{2}_{i.j},\ \overline{a}^{3}_{i.j},\ldots,\ \overline{a}^{k}_{i.j}$ to their representation with binarized preparations (-1, 0, +1) on the basis of the three-level coding. Then arrays of difference of the element with an average brightness value of decomposition elements of the image (or of its fragment where the image element is located) are determined.

For a random averaged parameter, a three-level transition may be presented by three types of preparations: zero - $a^0_{i,j}$, positive - $a^1_{i,j}$, and negative - $a^{-1}_{i,j}$. In this case

the PH network with the numerical count is transformed into the PH network with binarized counts $a^{0}_{i,j},\ a^{1}_{i,j},\ a^{-1}_{i,j}$ [7]. Then a procedure of correlation comparison of binarized counts of the current and reference PH networks becomes substantially simpler.
In order to form reference images, training within a sample should be conducted. For this purpose, it is necessary to perform averaging by branch elements of each level, i.e. to form averaged elements $\overline{a}^{1}_{i.j},\ \overline{a}^{2}_{i.j},\ \overline{a}^{3}_{i.j},\ldots,\overline{a}^{k}_{i.j}$, and then move to binarized preparations $a^{0}_{i,j},\ a^{1}_{i,j},\ a^{-1}_{i,j}$. Having completed manipulations described above, it is possible to form a PH network with reference parameters for current images. After that its correlation comparison with the PH network using current parameters can be performed. (Under the PH network with current parameters we understand a PH network with current values of its elements $a^{1}_{i,j},\ a^{2}_{i,j},\ a^{3}_{i,j},\ \ldots,\ a^{k}_{i,j}$ with a transfer to binarized preparations $a^{0}_{i,j},\ a^{1}_{i,j},\ a^{-1}_{i,j}$ and a current number of elements in the branch of each level $N_{a^{1}_{i,j}},\ N_{a^{2}_{i,j}},\ N_{a^{3}_{i,j}},\ \ldots,\ N_{a^{k}_{i,j}}$).
It is extremely important that a correlation coefficient can be calculated not only for each two levels, but also for two PH networks, thus increasing the reliability of a recognition result.

Description of the ph network-based forecasting method
The statistical information analysis makes it possible to reveal cause-and-effect relations of the phenomena under study, to identify impacts and interactions of various factors, thus permitting to evaluate efficiency of managerial decisions made. By comparing generalizing statistical indicators of phenomena understudy, it is possible to determine quantitative attributes of their space dissemination and temporal progress, to identify characteristics of their relation and interconnectedness, and formulate scientific and practical conclusions.
To analyze statistics understudy, it should be systemized by constructing the chronological series, also known as dynamic series. Every dynamic series consists of periods, or time moments *t*, to which series levels belong, and statistical indices which characterize time levels. Extended laser route data, namely, energy center coordinates of laser beam spots, are used as statistical indicators [8, 9].
An analysis of empirical data smoothing methods conducted in [8] shows that irrespective of a smoothing method or a method of trend line determination, a distribution of “peaks” and “wells” remains the same. It can be concluded therefore that in ducat or fluctuations for most phenomena may be determined by any empirical data smoothing method. That is why the least time consuming method should be used. A hyperbolic smoothing method described below will be used for the second stage of the statistical research, i.e. for the statistical aggregation and grouping of the initial data.

The hyperbolic smoothing method of statistical data
One of the key methods of the dynamic series analysis and generalization is the identification of a main trend of the series. A dynamic series trend line indicates a time change in the phenomenon under study without certain deviations caused by various factors. Atrend of temporal development of the phenomenon can be found according to the methods of increasing intervals, moving average and analytical smoothing methods.
The most efficient is the analytical smoothing method, a complex method of the main trend detection [10].
Let us consider the dynamic series levels as a time function (2):

$$\hat{Y}_{t} = f(t). \tag{2}$$

A problem of smoothing comes down to finding such form of the function that ordinates of its points are the closest to values of the actual dynamic series.
Most common regularities describing phenomenon development trends are: the straight line, power function, parable of the second and third order, hyperbola, logistic function, the exponent, Fourier series, etc. The analysis shows that the hyperbolic smoothing method using is most effective, because it is the hyperbola that most accurately describes the dynamic series increase or decrease; this smoothing method is also less time consuming compared to other methods [11, 12].
A hyperbola equation may be written as follows:

$$\hat{Y}_{t} = a_0 + \frac{a_1}{t}, \tag{3}$$

Where $a_0,\ a_1$ are hyperbola equation parameters. To find those parameters with the least-squared method, combined normal equations of the following type should be used:

$$\begin{aligned} &\sum Y = na_0 + \sum \frac{a_1}{t}; \\ &\sum Y\frac{1}{t} = a_0\sum\frac{1}{t} + a_1\sum\frac{1}{t^2}. \end{aligned} \tag{4}$$

If the equality $\sum t = 0$ is true, the set (4) will produce:

$$\begin{cases} \sum Y = na_0; \\ \sum Y\dfrac{1}{t} = a_1\sum\dfrac{1}{t^2}. \end{cases} \tag{5}$$

Having found the logarithm of combined equations (5), we obtain:

$$\begin{cases} \sum \lg Y = n\lg a_0; \\ \sum t\lg Y = \lg a_1 \sum t^2. \end{cases} \tag{6}$$

The system (6) gives us hyperbola equation parameters $a_0,\ a_1$ of the type:

$$\lg a_0 = \frac{\sum \lg Y}{n}. \qquad (7)$$

$$\lg a_1 = \frac{\sum t \lg Y}{\sum t^2}. \qquad (8)$$

Development of the forecasting method

Let us discuss an application of the hyperbolic smoothing method of empiric data as described above on a practical example. This example characterizes a fluctuation dynamics of the production costs of a business. Business data are shown in Table. 1 [10]

Table 1- Business production data

Year	Production Y unit cost, USD
2006	70
2007	50
2008	30
2009	20
2010	15

Having had the hyperbolic smoothing method (8) applied, and then having found the logarithm of the hyperbole equation, one can find hyperbole equation parameters a_0, a_1 by formulas (7) and (8):

$$\lg a_0 = \frac{\sum \lg Y}{n}. = \frac{7,5066}{5} = 1,50132 \Rightarrow a_0 = 31,72;$$

$$\lg a_1 = \frac{\sum t \lg Y}{\sum t^2} = \frac{-1,7356}{10} = -0,17356 \Rightarrow a_1 = -1,491.$$

Therefore, the hyperbole equation looks as follows:

$$\lg \hat{Y}_t = 1,50132 - 0,17356t \Rightarrow \hat{Y}_t = 31,72 - \frac{1,491}{t}.$$

The smoothing data are presented in Table. 2. *See Table 2.]*

Data from Table 2 are illustrated by the graph Fig. 2.

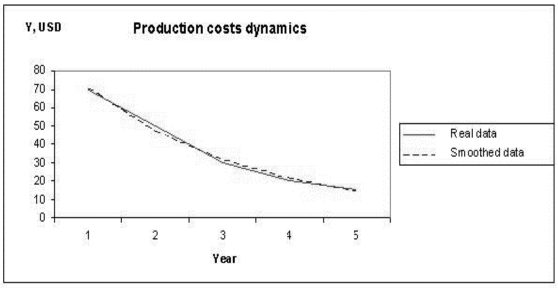

Fig. 2- Use of the hyperbolic smoothing for further forecasting

As Fig. 2 shows, the smoothed levels are very close to the empirical ones, therefore, this indicates that the hyperbola equation is appropriate for the trend representation.

Certain approximation of the smoothed series permits to forecast the trend for several steps. The qualitative indicators of the forecast can be found experimentally through determining an optimal discretization step and a number of forecasting steps, as well as the forecasting accuracy.

Consequently, input data – energy center coordinates of laser beam spot images – should be fed to the PH network. After that, a stage of PH network training with the developed combined method takes place.

The combined training method

An algorithm of the combined training method is based on the error correction and the PH network memory use in the image recognition:

1. Construction of the PH network structure of the selected image;
2. Application of a training method based on the memory usage. A number of PH network levels is used in this method as a classifier based on *k* closest neighbors.
3. Construction of the PH network structure of the reference image.
4. Application of a training method based on the error correction. A criterion used for verification in this method is a correlation coefficient at the zero level of the PH network.
5. Error correction for correlation coefficients is performed at the zero, first, middle, last but one, and third from the end PH network levels. The correction is conducted till network parameters come to an absolute equilibrium state (+1) or exceed it. If parameter values lead to (-1) state (or an absolutely non-equilibrium state), a conclusion is made that image couldn't classified to current class.

The network parameters are arrays of X and Y coordinated at certain period of time, as well as hyperbole equation parameters a_0, a_1 at the same period. A structure chart of the developed PH network-based forecasting method is shown at Fig. 3.

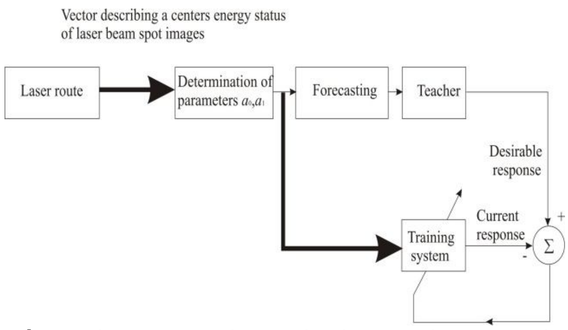

Fig. 3- The structure chart of the developed PH network-based forecasting method

Experimental Research Results

To test the developed method and determine its efficiency, experiments were conducted on forecasting positions of energy centers of laser beam images based on known neural networks [13-15]. The forecasting was performed for one step.

Experimental results of the dynamic series forecasting are shown in Table. 3.

Chart obtained for the dynamic series forecasting (for MP 5-5-4) is shown at Fig. 4, 5.

The conducted research indicate that average error is practically the same and amounts to 0,77%. The maximum error value of forecasting based on different neural networks varies in the range from 4,07- 4,24 % .

Let us perform a forecast with the developed PH network-based software. Fig. 6 and Fig. 7 demonstrate charts obtained by forecasting the dynamic series.

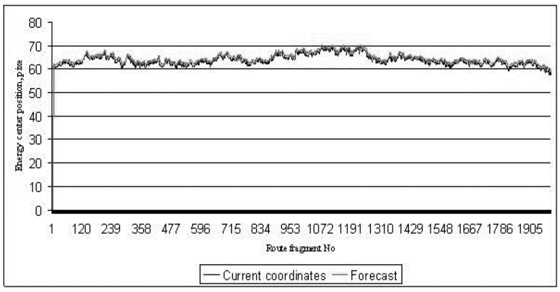

Fig. 4- Forecasting with the MP 5-5-4 neural network

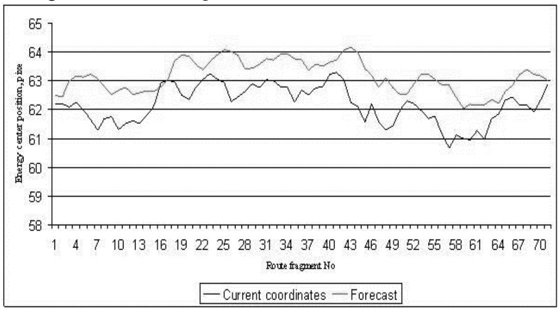

Fig. 5- Forecasting with the MP 5-5-4 neural network (enlarged fragment).

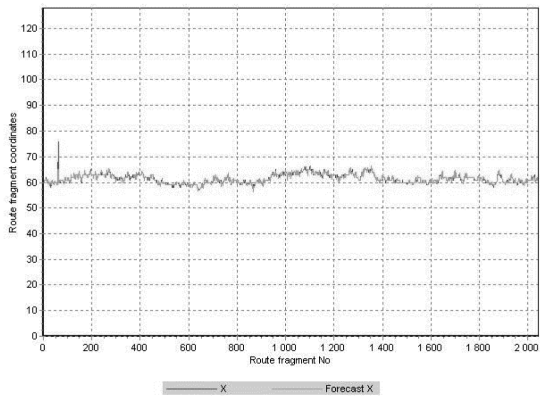

Fig. 6- Forecasting with the PH network

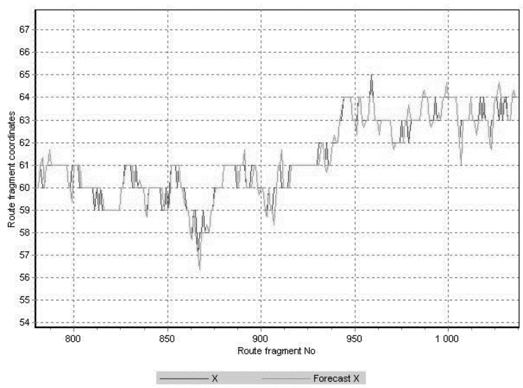

Fig. 7- Forecasting with the PH network (enlarged fragment

Respective parameters are:

- Average forecast error: 0.552%;
- Maximum value of the forecast error: 1.23%.

Conclusion

Principles necessary to design a PH network-based forecasting method are discussed in this article. An analysis of the statistical information permits to reveal cause-and-effect relations of phenomena under study, to determine an effect and interaction of various factors, therefore permitting to evaluate efficiency of the managerial decisions made. For the second stage of the statistical research, i.e. aggregation and grouping of initial data, the hyperbolic smoothing method is used. It was found out that the hyperbolic smoothing method is the most efficient, because it is the hyperbole that most accurately describes increase and decrease of the dynamic series. In addition, this method is less time-consuming in comparison with other methods. If certain approximation of the smoothed series is conducted, a trend forecast can be conducted for several steps. Qualitative parameters of the forecast are determined experimentally through calculation of the optimal discretization step and a number of forecasting steps, as well as of the forecast accuracy.

To automatize the forecasting process and to measure accurately coordinates of energy centers of laser beam spot images, special software was developed. This software contains a window reflecting a picture of a dynamics of laser beam spots by X- and Y-axes, and a prognostic chart of laser beam movement by X- and Y-axes. Fixation of the gravity center occurs dynamically in real-time with fixation of the following parameters:

- Position of the beam energy centers by X and Y axes respectively in pixel with accuracy to three decimal digits;
- Deviation of the beam energy center by X and Y axes from average values in pixels accurate within third decimal digit;
- Frame number.

Acknowledgment

Authors thank to General Constructor of the CJSC *KIA Systems* (Moscow, Russia) Yu.F. Kutayev for problem formulation at the initial stage of the research and for video data of fragments of laser rout images made available for the scientific research. Authors express their sheer gratitude to the team of the Chair of the Telecommunication Technologies and Automatics of the State Economy and Technology University of Transport (Kyiv, Ukraine) for their valuable comments and recommendations expressed in the course of experimental research. Authors also thank Professor M.V. Makarenko, Vice Rector on Scientific Work, Associate Professor V.I. Danilevskiy, and Dean of the Department of Infrastructure and Rolling Stock of Railway Transport Professor A.D. Voznenko for provided facilities and equipment for scientific studies of this problem in the framework of the state-financed scientific research topics.

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Table 2- Smoothing Data

Year	**Production Y unit cost, USD**	$\lg Y$	***T***	***T*²**	$t \lg Y$	$\lg \hat{Y}_t$	**Smoothing level** $\hat{Y}_t = a_0 + \frac{a_1}{t},$
2006	70	1,8451	-2	4	-3,6902	1,8484	70,53
2007	50	1,699	-1	1	-1,699	1,6749	47,31
2008	30	1,4914	0	0	0	1,5013	31,72
2009	20	1,301	1	1	1,301	1,3278	21,27
2010	15	1,1761	2	2	2,3522	1,1542	14,27
n = 5	185	$\sum \lg Y = 7{,}506$	$\sum t = 0.$	$\sum t^2 = 10$	$\sum t \lg Y = = -1{,}7356$	$\sum \lg \hat{Y}_t = = 7{,}5066$	185,1

Table 3- Experimental research results on dynamic series forecasting obtained with the known types of neural networks.

No	**Neural network [12]**	**Average forecast error, %**	**Maximum value of the forecast error, %**	**Number of forecast steps**
1.	Radial basis function S1[13]	0,78	4,23	1
2.	Linear S5 [14]	0,76	4,05	1
3.	Linear S3 [14]	0,77	4,04	1
4.	Multilayer perceptron (MP) 5-8-4 [8]	0,76	4,07	1
5.	Multilayer perceptron (MP) 5-5-4 [8]	0,76	4,08	1