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EXTRAPOLATION OF OBJECT TRAJECTORY: METHODOLOGICAL APPROACHES OF PROBLEM SOLVING ON THE BASE OF PARALLEL-HIERARCHICAL TRANSFORMATION

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Abstract. Authors have worked out a nonstationary signal analysis method on the example of research of laser lines. This method disclosed relationship between signal approximation coefficients and geometry signal characterizations (for instance, energy center, moment of inertia). The example, which is demonstrating an application of this method for exact coordinate determination problem in laser line at displacement compensation in laser imaging are present. Various extrapolation approaches of laser beam location in real time are considered.
Keywords: parallel-hierarchical network, laser path, real-time image sequences, dynamic tunnelling system, fractal.

1. INTRODUCTION

Nowadays the necessity of wider application of optoelectronic systems with automatic adjustment of formed light radiation distortions is felt, especially, in laser processing of materials, location, optical communication and other areas of engineering. These distortions might be caused by destabilizing effect of the mechanical or climatic factors, instability of light source performances, optical tract perturbations, maladjustment of optical elements etc. The providing of an acceptable correction quality demands continuous runtime check of light radiation performances, for example, of space intensity distribution, including estimation of deviation of the indicated distribution from the initial or pattern one.

The given work offers new approach to the creation of computing medium - of parallel -hierarchical (PH) networks, being investigated in the form of model of neurolike scheme of data processing. The approach has a number of advantages as compared with other methods of formation of neurolike media (for example, already known methods of formation of artificial neural networks). The main advantage of the approach is the usage of dynamics of multilevel parallel interaction of information signals at different hierarchy levels of computer networks, that enables to use such known natural features of organization of computations in cortex as: topographic nature of mapping, simultaneity (parallelism) of signals operation, inlaid cortex, structure, rough hierarchy of the cortex, spatially correlated in time mechanism of perception and training. The formation of multi-stage PH networks assumes the process of sequential transformation of correlated and formation of decorrelated in time elements of neural networks at its transition from one stable state into another. The key feature of the offered approach is analysis of dynamics of spatially correlated mechanism of transformation of current and formation of resultant elements of neural networks. Such mechanism allows to present in a new way the processing in neural networks as the process of parallel-sequential transformation of various components of image and ac count of time responses of transformation. Physical contents of input elements of neural networks, that participate in correlation - decorrelation, such as, for example, the amplitude or frequency, phase or energy of signals, cohesion or texture of images, is determined by the type of transformation being used, the selection of which depends on the class of problems being solved. In general view the multistage concept regarding image processing can be formulated in the following way. The image analysis presents sequential transformation of concurrent and detection of discrepant in time image components at transition of neural network elements from current energy state with certain space coordinates into states with less energy with other space coordinates. Such process of image analysis occurs at many stages, each of which includes realization of above-stated procedure. The condition for transition of image components at higher level is availability of dynamics of mutual coincidence of intermediate results of processing in time in parallel channels of lower layer. The output image proceeding from analysis of image components distributed in time-space area.

Recently, we have suggested a method of estimate of the geometry characterizations of laser beams, distorted by atmosphere. The aim of our approach may be generalized as follow. Let ***g(t)*** – original vector, and ***Y(t)=X(g(t))=g(t)–D(g(t))*** – analysed distorted vector. To make analysis, making it possible to restore of vector ***Y(t),*** the geometry signal characterizations should be claimed. A key idea include that: 1) for non-displaced distorted vector for each given signal value a optimum non-linear stable specific density is pointed out; 2) a displacement ***D***(*t*) for a displaced distorted vector by its approximation coefficients relationship is defined; 3) the errors that is depended of discretization and statistical parameters are eliminated. In this paper we show that it is a row of correspondences between ***X(g(t))*** and factors of approximating, and also fluctuations of geometric signal characterizations, which are predict by approximation functions.

The work consists from description of point of reference determining method, learning algorithm and experimental results. We shall consider the initial signals on example of sequence of laser images series [1] in our experiments.

In our research certain restoring of geometry signal characterizations is exceeding other methods, be based on traditional way of approximation [2]. The present methods may be spreading on multivariate event.

2. REFERENCE POINT COORDINATE ESTIMATION

By reference point coordinates *(x,y)* (further a reference point) of frame we mean the energy center coordinates of image *X(g(t))*. Components of this image have be depended on direction of laser beam stream propagation only and will be invariant to ***X(t)***. (*x*,*y*) coordinate of energy center coordinate (*x*,*y*) with non-linear specific density *w*(*g(t)*)=(*w(f(x,y)) (t=const)*), corresponding given brightness *f*(*x*,*y*) value (further density). Its moment value is expressed as follow:

$$x=\frac{1}{M}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} w\,(f\,(x,y))\;\cdot x,\qquad y=\frac{1}{M}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} w\,(f\,(x,y))\;\cdot y,\qquad M=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} w\,(f\,(x,y)).\tag{1}$$

Reference point estimation learning algorithm is optimal density *w*(*f(x,y)*) determination method combined with image classification and segment partitioning by edge line approximation coefficients, which will consensus with multiple valued to be approximated defects.

For our method description, first assume that for considered image a centers of limited by various signal edges Fig. 1 (further - partial centers) do not vary significantly. In this case, to find reference point it is necessary to find the density that corresponds to given value (brightness) of signal.

To find reference point we determine non-linear densities of regions of given brightness from equation systems:

$$\sum_{i=0}^{n-1} w_i \sum x_i^{(j)} \cong x_e;\ \sum_{i=0}^{n-1} w'_i \sum y_i^{(j)} \cong y_e; \qquad (w_i>\lambda_x;\ w_i'>\lambda_y),\tag{2}$$

where w_i – densities to be found, corresponding to i-th given brightness (w_i – for x-parameters, w'_i – for y) $\Sigma x^{(i)}$, $\Sigma y^{(i)}$– points coordinate (x, y) sum corresponding to j-th image, x_e, y_e –etalon parameters; λ_x, λ_y – small negative edges used to numerical stability making. (2) Differently expressed:

$$\sum_{i=0}^{n-1} w_i x_i^{(j)} \cong x_e.\ \sum_{i=0}^{n-1} w_i' y_i^{(j)} \cong y_e; \qquad (w_i>\lambda_x;\ w_i'>\lambda_y),\tag{3}$$

x_i, y_i — partial centers for regions of unit non-linear weights of prescribed brightness *i,* respectively. At this as x_e and y_e assumpt averaged partial centers value of images which have least scatter of partial centers values.

Then, more commonly, with account of scattering of partial centers, reference point coordinates express as follow:

$$x=\frac{1}{M}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} w(f(x,y))\cdot(x+\delta_x); \qquad y=\frac{1}{M}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} w(f(x,y))\cdot(y+\delta_y), \quad (4)$$

where δ_x and δ_y – point coordinate displacements from distortion, are corresponded to given image for the signal relatively to initial.

Thus, a non-linear weights we discover from equations:

$$\sum_{i=0}^{n-1} w_i \sum (x^{(i)}+\Delta x)=x_e, \quad w_i>\lambda_x, \quad \sum_{i=0}^{n-1} w'_i \sum (y^{(i)}+\Delta y)=y_e. \quad w_i>\lambda_y, \quad (5)$$

over image sample bellow considered image line classification particularities and also close partial center displacements *(Δx, Δy)* between actual and distorted signal.

A formalization of the reference points determination is possible by performing partial differentiate system. In case of the large dimensionality using of multilevel network, proposed in [3] also possible.

Let us to return to image line classification. In the geometrical characteristics for image behaviour evaluating, we will use edge lines of image in treating photo. Theirs fragments at polar coordinate system segment will be considered. At image selecting an edge lines approximation by a method of least squares used. Was made [4], that for natural origin image at scanned edge line approximation, possible to utilize the ratio of square to cubic approximation coefficients. At that, monotonous components have a appreciable this coefficients correlation, and it being known that given ratio depends on monotonous phases.

Were noticed that similar behaviour images may had a close square and cubic coefficient ratio (further approximation parameter) (see sec. 4 and Fig. 1), particularly for image partition fragments. For the high quality images may be supplementary other coefficient quotients used to detection of small displaces and at reconciliation of ratio comparison precision.

To increase information content, approximation of tunnelling during image parameters partition is carried out according to algorithm in Fig. 3.

At the multivariate event segments the expert result discrimination was used. Generalizing above-stated, the main learning method for reference point coordinate estimation is contained in Fig. 2. After learning cancel, a non-training sample of the images is partitioned over values of correspond approximation parameter, and through calculated densities and displacements the reference points (energy centers) is found.

Here a set of possible values within tunnel with etalon E of the $w^*=c_2^*/c_3^*$ coefficients is selected under Fig.3 and so that was carry out the conditions:

$$x_e\text{--}x^*<E_{max},$$

$$y_e\text{--}y^*<E_{max}, \quad (6)$$

$$w_e - w^* < min(E(w^*)>=E_{max}),$$

where E_{max} – maximal error coordinate, $E(w)$ – error corresponded to w.

At calculation of reference points for elimination discretization error and effects influential in particular statistical parameters, the edge lines points sequence should be passed through the differentiating filter or through bank of filters [5].

3. POPULATION CODING WITH PARALLEL-HIERARCHICAL NETWORK APPLICATION

From recent neurobiological research it has been known that in order to code sensor information the human brain applies the approach referred to as population coding. Within its frame the information is represented by the whole population of active neurons [7].

This important property was demonstrated by the experiments carried out by D. Sparks. Analyzing the way the ape's brain controls the motion of the eyes, the conclusion was reached, that the needed motion is being coded by the population of cells, each of them represents motion, that slightly differs from others. The motion, performed by the eye, corresponds to averaged motion, coded by active cells. As the experiments carried out by M. Young and S. Yamane with temporal cortex of monkey's brain, population coding proves to be valid not only for the motion of eyes but also for features of the face. According to the idea of population coding, the current image, being recognized, must be compared. Taking into account certain averaging, whys representation of reference image – average by all current images otherwise along the whole learning sample on the base of averaging of parallel – hierarchical (PH) networks parameters [8].

The aim of the given researches is application of suggested hypothetic module of information structuring in cortex of cerebrum based of PH network, represented in details in [8], for its teaching while images recognition.

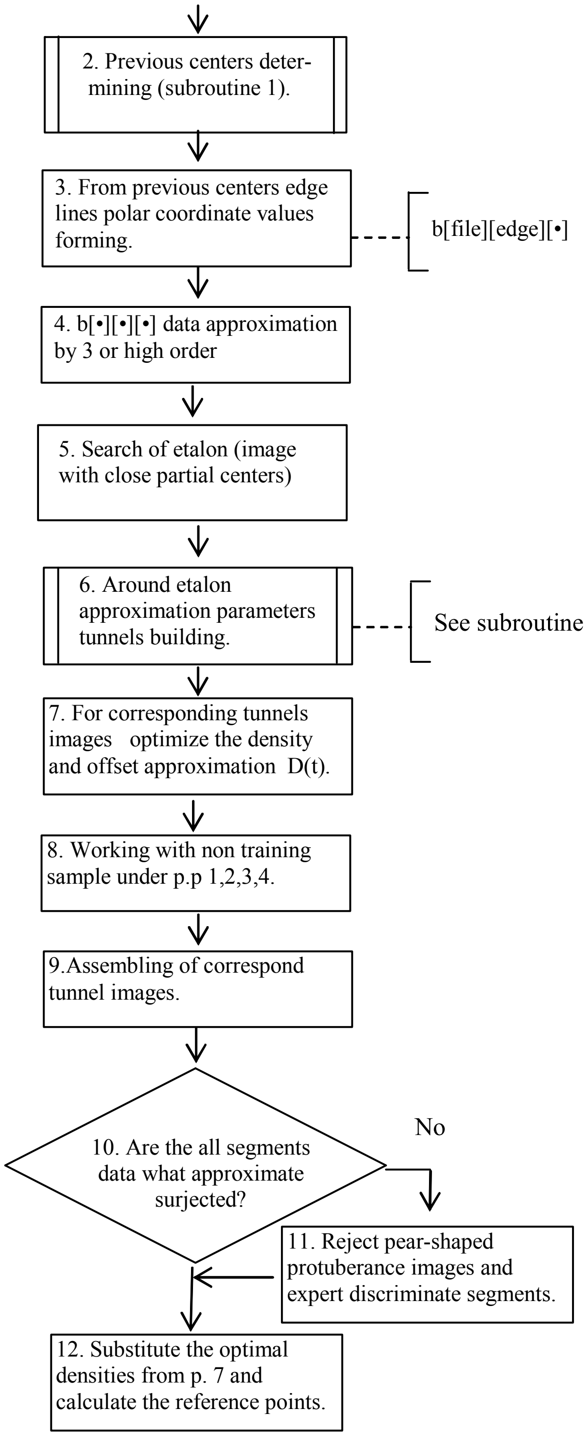


Fig.2. Learning algorithm for reference point estimation.

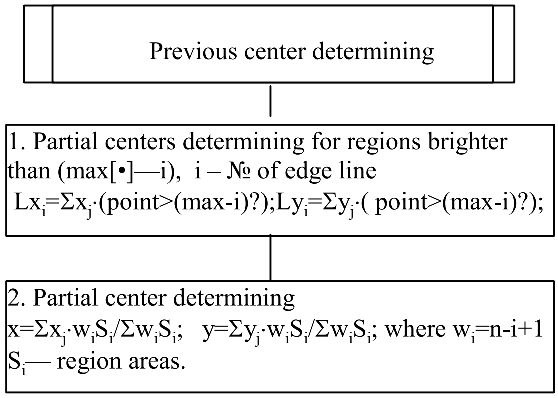
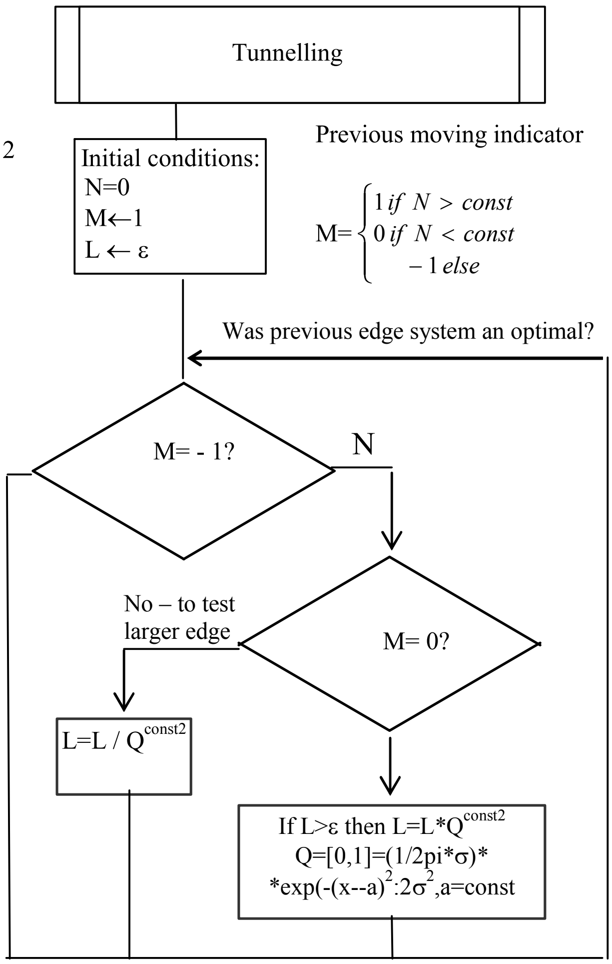


Fig. 3. Subroutine 1.



N - resolved parameter intervals quantity,
L - reference point coordinates error/error of approximation of D(t) polynom, which is ordered to tunnel what give.

Fig. 3. Subroutine 2.

Formation of multistage PH network assumes the process of sequential conversion of correlated spare regions and creation of decorrelated in time elements of neural network while transition from one stable state into another.

Lets apply the idea of population coding [7], having constructed the model of any final action, being performed by all current actions. It is obvious, that on the level of neural network branches given final action corresponds to averaged parameters of this network. For PH network the number of elements in the branch of each level determined on the base of the module [11] and values of the element itself can be such averaged parameters. In this case current image, being recognized will be presented by current PH network and will be compared with reference PH network with averaged parameters.

In order to form references it is necessary to teach them within the frame work of teaching sample. For this purpose while each teaching it is necessary to make averaging by elements of the branch of each level, that is, form averaged elements $\overline{a}^1_{i,j}$, $\overline{a}^2_{i,j}$, $\overline{a}^3_{i,j}$,..., $\overline{a}^k_{i,j}$, further passing to binary preparations $a^o_{i,j}$, $a^1_{i,j}$, $a^{-1}_{i,j}$. Hawing completed above-mentioned actions we can form PH network with reference parameters for reference and current images.

Having formed PH networks with reference parameters for current and reference images we can compare it with PH network, that uses current parameters. PH network with current parameters we refer to PH network with current values of its elements $a^1_{i,j}$, $a^2_{i,j}$, $a^3_{i,j}$,..., $a^k_{i,j}$ with transition to binary preparations $a^o_{i,j}$, $a^1_{i,j}$, $a^{-1}_{i,j}$, and current number of elements in the branches of each level $N_{a^1_{i,j}}$, $N_{a^2_{i,j}}$, $N_{a^3_{i,j}}$,..., $N_{a^k_{i,j}}$ ... . Procedure of comparison of PH network with reference parameters and PH networks with current parameters comprises its topographic overlapping of one on another and calculation of the number of coincidences of the same binary elements.

Two binary PH network coincide; if by pair all countings of each of preparations located in the network are equal. In case of can coincidence of dimensionality of PH networks being compared, it is necessary to introduce in its branches additional nodes with coding of the fourths state. In order to evaluate the result of binary PH networks comparison let's introduce quantitative index, that characterizes the degree of their coincidence.

$$R(c_э,c_m)=\sum(a^{1(\cdots)}_{i,j})_э\cap(a^{1(\cdots)}_{i,j})_m+\cdots+\sum(a^{k(\cdots)}_{i,j})_э\cap(a^{k(\cdots)}_{i,j})_m, \quad (7)$$

where $c_э=f_э(a^1_{i,j},a^2_{i,j},\cdots,a^k_{i,j})$ - network function of reference image, $c_m=f_m(a^1_{i,j},a^2_{i,j},\cdots,a^k_{i,j})$ - network function of current image, and $a^{k(\cdots)}_{i,j}\in\{a^{k(0)}_{i,j},a^{k(1)}_{i,j},a^{k(-1)}_{i,j}\}$, $\cap$ - sign of coincidence of the same binary preparations in case of their comparison. Components (7) are equal to unit only when the same preparations coincide. That is,

$$(a^{k(\cdots)}_{i,j})_э\cap(a^{k(\cdots)}_{i,j})_m=\begin{cases}1, \text{ if } (\cdots)=(\cdots)\\ 0, \text{ in other case}\end{cases}.$$

Total number of elements in reference PH network is calculated in the following way:

$$N_э=N_{a^1_{i,j}}+N_{a^2_{i,j}}+\cdots+N_{a^3_{i,j}}+N_{a^k_{i,j}}$$

Normalized measure of comparison is calculated as

$$\Re=\frac{R(c_э,c_m)}{N_э}$$

Let's consider the example of comparison of binary preparations on the second level for two PH networks (Fig.4).

Lets calculate for this example (Fig.4) the degree of coincidence $R(c_э,c_m)$ and normalized degree of comparison $\Re$ for the second level of current and reference PH networks.

$$R(c_э,c_m)=(1)+(1+1)+(1+1)+(1+1+1)+(1+1+1+1)+(1+1+1+1)=16.$$

Total number of elements in PH network on its second level $N_э$=21.

Then normalized degree comparison $\Re$. While networks for there second level will be the following.

$$\Re = \frac{R(c_э, c_m)}{N_э} = \frac{16}{21} \approx 0{,}762$$

It is obvious that normalized degree of comparison of two PH networks is determined within the following limits

$$0 \le \Re \le 1 \, .$$

Very important factor is that normalized degree of comparison can be calculated not only separately for each of two levels, but also common for both PH networks, this improves the probability of formation of recognition result.

The paper suggests for teaching of the network, using the idea of population coding in artificial neural network, and its approaching to natural neural networks to represent current image by current PH network with current parameters and convert them on the base of generalized contour preparation in binary preparations with further comparison on the base of normalized degree of comparison with reference PH network of reference image with averaged parameters, the elements of which are binary preparations parameters, the elements of which are binary preparations.

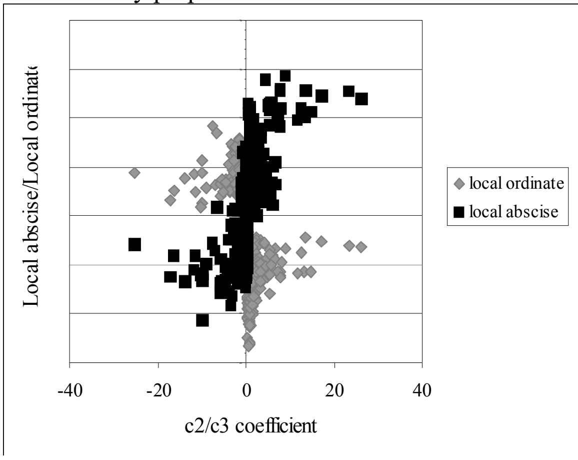


Fig. 1. Function of coordinate from c_2/c_3 quotient.

a)	b)
1	1
0 -1	0 -1
-1 0 1	0 0 1
0 1 0 1	0 1 0 -1
1 -1 0 0 -1	1 -1 1 0 -1
0 1 0 1 -1 1	0 1 0 0 -1 0

Fig. 4. The example of comparison of binary preparations on the second level for two PH networks

Unlike known structures of artificial neural networks [10], where non-normalized (absolute) similarity criteria are used, the given teaching method uses normalized criterion. In this case, normalized degree of comparison is suggested to be calculated not only separately for each of two levels, but also calculate common for both PH networks; it will improve the accuracy of recognition results formation.

The stage of PH network learning consists in formation of reference PH network structure for the reference image. Is formed reference PH network for those images, which form the certain tunnel borders till the left part and till the right part from the central tunnel.

4. VARIATION OF LEARNING METHODS REALIZATION

VARIATION 1

We tested the performance of our model on five data sets. Let us show that x_e and y_e templates should be determined as respective to best in sense of coincidence of local centers to the map. From experiments was showed that those images have close c_2, c_3 approximation coefficients. From [5] follows, that these images have close displacement. Obviously, that in case of high displacement nonuniform distribution of energy appears, that result in dispersion of local centers coordinates.

A distribution of the cubic coefficients and the square coefficients with respect to brightness edges is showing on Fig. 1. The vertical axis denotes the cubic coefficients and the horizontal axis shows the square coefficients. In Fig. 1, a) global image sample observes; the correlation between the cubic and square coefficients is approximately 35-40 %. It is more than between other coefficients. In the case of selective sample that correlation is increasing.

The computational complexity of algorithm allows to perform processing of hundred images per second on the usual computer.

As a result of offered learning the inaccuracy of definition of reference points does not exceed 1,5 pixels. It consists of inaccuracy of definition of the determined template, inaccuracy inside ranges of displacement, not absolute correlation of square and cubical factors of approximating for fixed displacement and from inaccuracy from discretization effects and effects influence on statistical parameters.

On the Fig. 5 showed edge line of used example template image, and correspond image on Fig. 6. Fig. 1 shows a graph of the distribution of the quotient of square on qubic coefficients from local centers. Table 1 shows results of determining reference point of laser paths of 140 used images. 70 images used for training and the rest used for center dynamic locating.

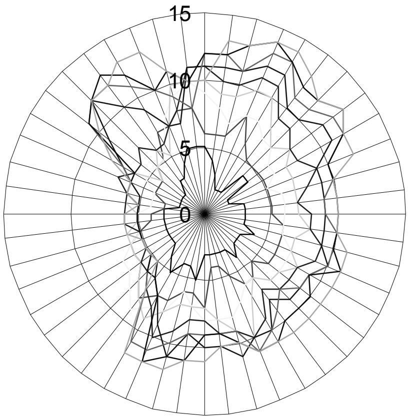


Fig. 5. Etalon image edge lines

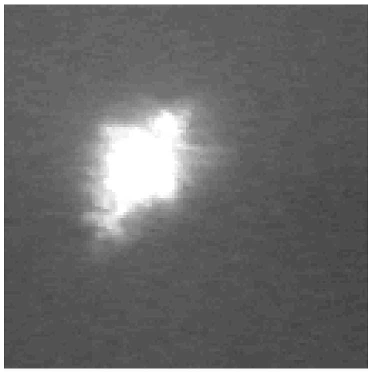


Fig. 6. Determined etalon image (128×128)

There is a special interest represented by the problem of a forehead laser spot position prediction on the basis of the already known part of the path. Considering the fact that the trajectory of power centre of a laser spot is represented given next parametric a curve

$$\begin{cases} x = x(t) \\ y = y(t) \end{cases},$$

where x, y are coordinates of centre, t is time. Given problem represents a task of extrapolation of a function, given discrete values (x_i, y_i) in discrete time series t_i, $(i = 1,2,...,n)$. Because of the actual physical nature of this function it is possible to suppose presence its continuity and smoothness. It allows to fulfil extrapolation using formulas of numerical differentiation. Considering, $\Delta t = 1$, first and second coordinate derivatives are computed using time points of already known piece of the path.

$$x'(t_n) = x(t_n) - x(t_{n-1}),$$

$$y'(t_n) = y(t_n) - y(t_{n-1}),$$

$$x''(t_n) = x(t_n) - 2x(t_{n-1}) + x(t_{n-2}),$$

$$y''(t_n) = y(t_n) - 2y(t_{n-1}) + y(t_{n-2}).$$

Then the coordinates of centre of a spot at time point are evaluated under the formulas.

$$x(t_{n+1}) = x(t_n) + 2\frac{x(t_n) - x(t_{n-1})}{t_n - t_{n-1}}\Delta t + \left(\frac{x(t_n) - x(t_{n-1})}{t_n - t_{n-1}} - \frac{x(t_{n-1}) - x(t_{n-2})}{t_{n-1} - t_{n-2}}\right)\Delta t^2,$$

$$y(t_{n+1}) = y(t_n) + 2\frac{y(t_n) - y(t_{n-1})}{t_n - t_{n-1}}\Delta t + \left(\frac{y(t_n) - y(t_{n-1})}{t_n - t_{n-1}} - \frac{y(t_{n-1}) - y(t_{n-2})}{t_{n-1} - t_{n-2}}\right)\Delta t^2,$$

$$x(t_{n+2}) = x(t_{n+1}) + 2\frac{x(t_{n+1}) - x(t_n)}{t_{n+1} - t_n}\Delta t + \left(\frac{x(t_{n+1}) - x(t_n)}{t_{n+1} - t_n} - \frac{x(t_n) - x(t_{n-1})}{t_n - t_{n-1}}\right)\Delta t^2,$$

$$y(t_{n+2}) = y(t_{n+1}) + 2\frac{y(t_{n+1}) - y(t_n)}{t_{n+1} - t_n}\Delta t + \left(\frac{y(t_{n+1}) - y(t_n)}{t_{n+1} - t_n} - \frac{y(t_n) - y(t_{n-1})}{t_n - t_{n-1}}\right)\Delta t^2.$$

Due to a laser path discretization and errors of power centre definition, the evaluation of values of derivatives has major number of errors, that does not allow to receive satisfying extrapolation of a path more than on one step forward (i.e. at a moment $t_{n+1} = t_n + \Delta t$).

The preliminary cubic spline-interpolation of an available trajectory of power centre with consequent extrapolation under the formulas was applied to improve the quality of extrapolation

$$x(t) = x_n + \left(\frac{(t_n - t_{n-1}) m_{n-1}}{6} + \frac{x_n - x_{n-1}}{t_n - t_{n-1}} \right)(t - t_n) ,$$

$$y(t) = y_n + \left(\frac{(t_n - t_{n-1}) m_{n-1}}{6} + \frac{y_n - y_{n-1}}{t_n - t_{n-1}} \right)(t - t_n) ,$$

where x_n, y_n is the final point of the path, *t* is a time point, for which prediction is made, *m* is a coefficient of a normal cubic spline. The example of an extrapolation is presented in the table 2.

The approach based on spline - interpolation gives essentially better quality of extrapolation, however does not allow to extrapolate a path more than for three steps forward. The reason for that, apparently is, that the "dot" approach to a laser path as to a trajectory of spot power centre, coordinates of which heavily fluctuating, is ill conditioned from an extrapolation problem point of view. For this purpose, possible perspective approach can be to use "area" performances of the parameters of a spot or its preparats, which are free from fluctuations. Besides that, the opportunity of extrapolation of paths with the help of a self-learning neural network is researched.

VARIATION 2

Application of method for the rise of exactness of foresight for the points of realization is considered, that after the led signs get in the digit of extrapolation. A question of realization of prognoses for the sentinel rows for the case of short-term prognoses is considered possibly to use single-step methods of prognostication. For implementation of prognoses of middle and large duration a known method of "sentinel windows" is used, but a task is substantially complicated for the cases of polyvalent prognostication, when estimation of future values of parameters for a few interconnection processes is carried out. In this case it is necessary not only to sort out all possible parameters, that determine essence of process, but also optimum sizes of entrance and initial sentinel windows, that swims out from necessity to take into account the different sentinel delays (time after action) of influence of one parameters on other. As a result the necessary sizes of sentinel windows can turn out enough large, and measurable of neural networks, that are used for prognoses - considerable. In such situation of application of neural networks on the basis of model "Functional on the great number of tabular functions - FTF", that secure high speed of teaching for the tasks of large measurable, turns out more effective [12].

The example of method realization on the basis of FTF model for forecasting location of the power centres of laser beam images is shown in Fig. 7.

Fig. 7. The example of method realization on the basis of FTF model

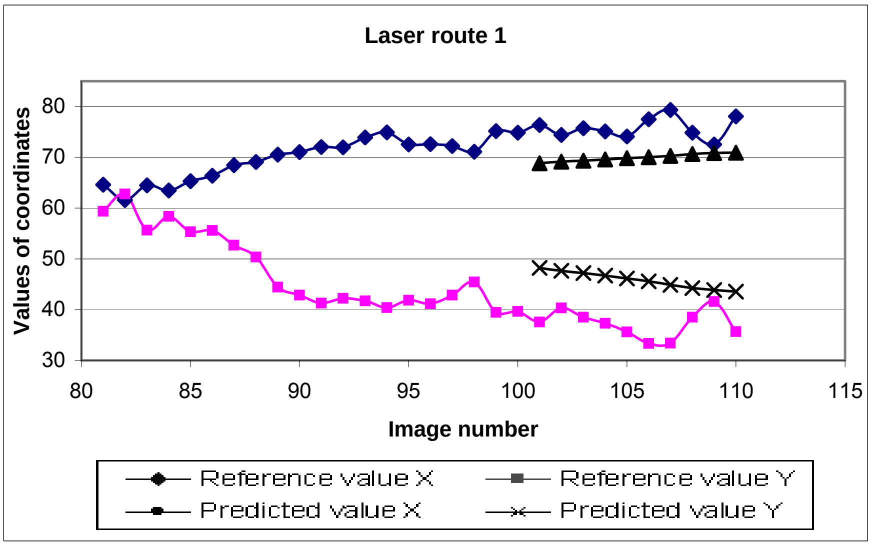
VARIATION 3

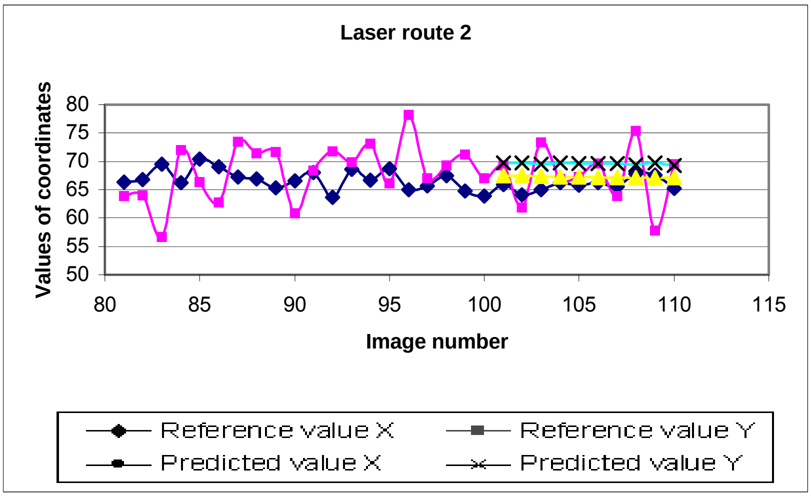
For the prediction of power center coordinates it is possible to use a variant of calculation of function of future value of coordinates with the use of linear regression [14].

The equalization for function has a type of *a*+*bx*, where:

$$a = \overline{Y} - b\overline{X}\,,\; b = \frac{n\sum xy - \left(\sum x\right)\left(\sum y\right)}{n\sum x^2 - \left(\sum x\right)^2}$$

Results of prediction of power center coordinates of images for the 4 laser routes are brought around to Fig. 8. Values of coordinates are shown on the graphs X and Y for the 30 images (from 81 till 110) and predicted values of coordinates X and Y for the 10 images (from 101 till 110).





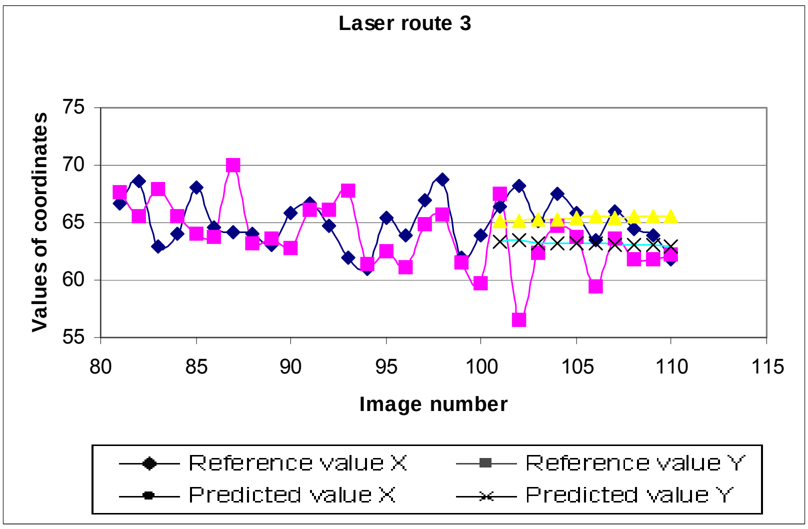


Fig. 8. Results of prediction of power center coordinates of images for 4 laser routes

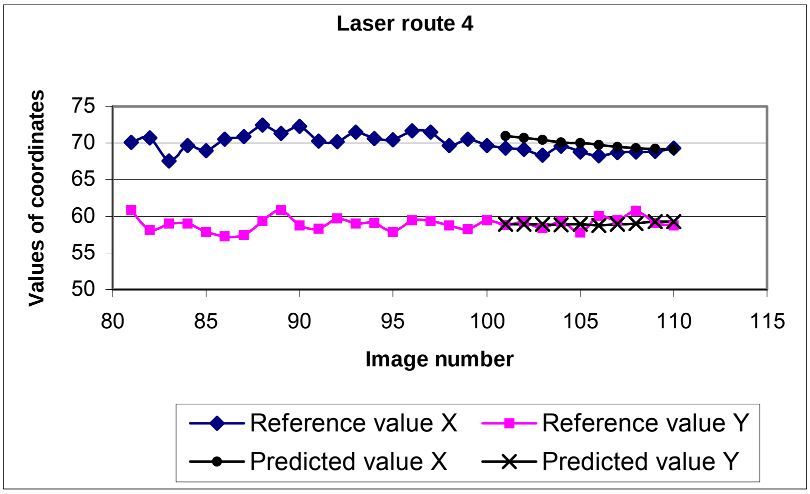


Fig. 8. Results of prediction of power center coordinates of images for 4 laser routes (continuation)

VARIATION 4

Prognostication on the basis of neural network with the use of the Back Propagation learning algorithm 13.

For constructions of network the 2 input layers, 2 output layers and 1 hidden layer with the 10 neurons was used. Results of prognostication are shown on Fig. s 9 and 10, where a prognosis is led for the 20 values (x original of x- prediction, y-original, y- prediction) in diagrams separately for x and for y.

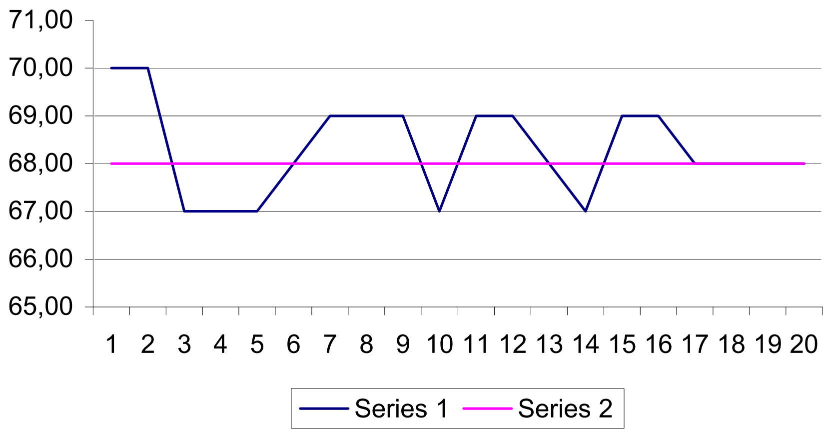


Fig. 9. Results of prognosis with the use of Back Propagation learning algorithm for x

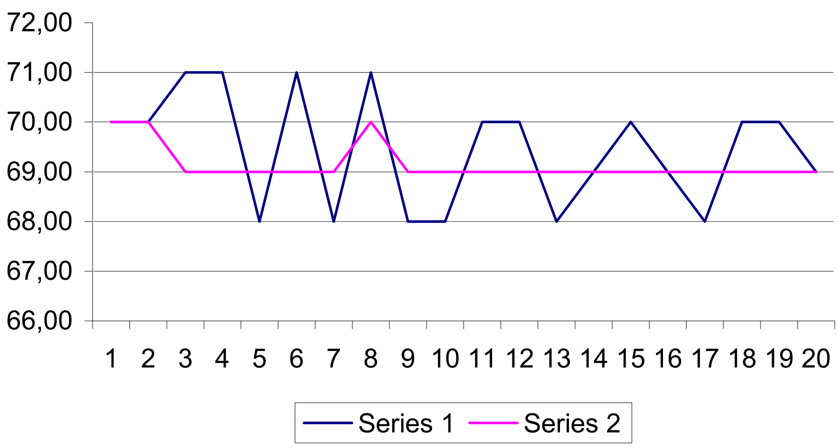


Fig. 10. Results of prognosis with the use of Back Propagation learning algorithm for y

VARIATION 5

Prognostication on the basis of neural network with the use of the Radial Basis Function (RBF) learning algorithm [10].

For constructions of network the 2 input layers, 2 output layers and 1 hidden layer with the 10 neurons was used. Results of prognostication are shown on Fig. s 11 and 12, where a prognosis is led for the 20 values (x original of x- prediction, y-original, y- prediction) in diagrams separately for x and for y.

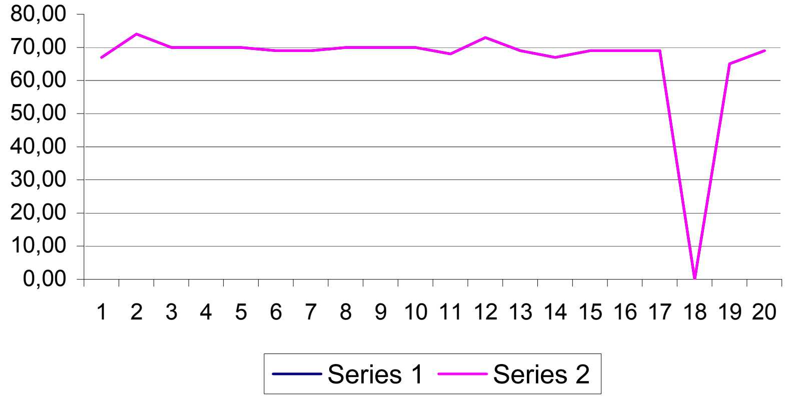


Fig. 11. Results of prognosis with the use of Radial Basis Function learning algorithm for x

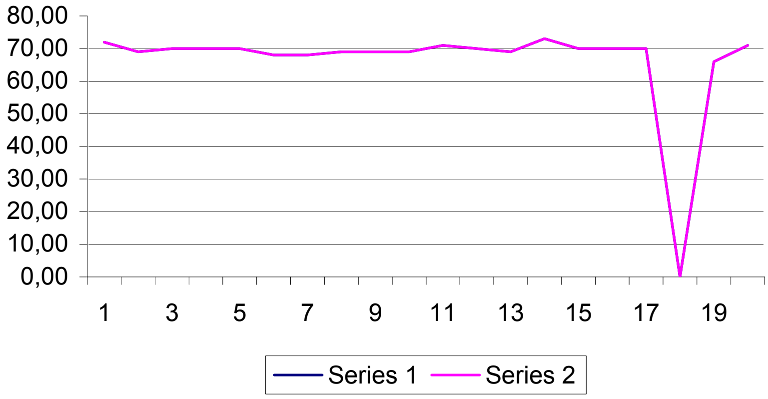


Fig. 12. Results of prognosis with the use of Radial Basis Function learning algorithm for y

RESEARCH PROSPECTS

The analysis of the problem of extrapolation of laser images trajectory shows, that the extrapolation by one point, which as a rule is energy or geometrical centre of the image is not absolutely correct and can not ensure high measurement accuracy. Besides, the fluctuation character of process being observed (for instance, laser line) requires application of statistical methods, both for extrapolation itself, and for evaluation of its quality. More adequate condition of the problem is application of some intermediate preparation of the image (or set of preparations), which is stable to image fluctuations resulting from the object movement, fluctuations of the channel of propagation and other reasons. The procedure of generation of the preparation must possess robustness and adaptability properties. Taking into consideration the absence of precise construction methods of such preparations the application for their generation the technology of self-learning neural networks seems to be expedient. In the given paper the variants of definition, generation methods of the image preparations and solution of the extrapolation problem are considered. The opportunity of construction of self-learning adaptive neural network intended for generation of preparations in real time is discussed. The suggested approach aimed at the solution of the problem of trajectory extrapolation is based on statistical estimation methods.

CONCLUSION

We have proposed a learning algorithm for determining the coordinate reference point of laser imaging. Complexities of proposed function allow making real-time processing with comparatively simple hardware. This is achieved by approximating the edge lines of images such that c_2, c_3 [5] and c_7 approximation coefficients and also some 6×6 unmonogenous equation systems are used to learning calculations, and ordinary energy centers finding for rest calculations. The simulation results gave 1,1-1,2 maximal reference point determination error, which is smaller, then in traditional approximation methods [2], at some ones. Proposed methods may be utilized at pattern recognition and image compression because of correlation between correlation of approximation coefficients and phase of image.

In evaluating the fractal dimensions for laser patch, it becomes a big problem exact extracting outlines. In this paper we are used an edge lines of image. To extract real outlines more exactly, digital image filters should be used.

To increasing the results accuracy it is expedient to make any iterations, taking as preliminary the values of earlier determined etalon coordinates and data, used at forming equations coefficients of (5). At second iteration using, the accuracy will increased.

To decreasing the number of rejected images and establish derivation of the perturbations the set which is approximated as a set corresponding to 3D set of threshold values, with various coefficients should be used. For selection of optimal edges dynamic tunnelling system of their setup [6] is suggested.

The different variants of learning algorithms realization were investigated. The experiments shows, that most perspective are the learning algorithms applying linear regress and training on neural networks basis using Radial Basis Function learning algorithm.

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