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APPROACH FOR REAL – TIME IMAGE RECOGNITION

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Анотація. В цій роботі застосовано новий підхід до створення паралельно-ієрархічних (ПІ) мереж із процедурою неітараційного навчання, яка реалізована за схемою і яка застосовувалась до послідовностей зображень (образів) – плямових зображень лазерних пучків випромінювання. Використовуючи загальну ідею структурної організації штучних нейронних мереж за схемою: вхідний прошарок → прихований прошарок → вихідний прошарок, можна синтезувати навчальну паралельно-ієрархічну мережу, в якій у якості вхідного прошарку використовувати 1–ий рівень мережі, в якості прихованого прошарку – проміжні рівні, а в якості вихідного – вихідний прошарок, який традиційно застосовується у штучних нейронних мережах.

Abstract. In this work new approach for parallel-hierarchical (PH) networks learning[1] having applied to the real-time image sequences in extended laser paths[2] is proposed. It's possible to synthesize PH network with learning abilities by using the general idea of artificial neural networks structured organizations on the scheme: input layer - hidden layer – output layer. The 1-st network level should be used as input layer, next levels should be used as a hidden layer and the last level should be used as an output one, as it is traditionally in artificial neural networks.

Keywords: parallel-hierarchical network, laser path, real-time image sequences, dichotomia principle

1. INTRODUCTION

Nowadays the necessity of wider application of optoelectronic systems with automatic adjustment of a 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 a 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.

To create effective image convertors that function in the Real Time Scale (RTS) some special methods are required. They have to provide optical input, fast and compact processing, flexible and simple image classification. Modern computing devices are productive enough (up to 10^{14} operations per second). However, this index doesn't include the time required for data entering.

Besides, computing devices process data taking into account time consequence. The commands are given and executed according to tree-like laws. This means that all intellectual procedures based on the hierarchical principle only. Therefore, there are tasks within the scope of which fast image processing throughout the whole RTS is impossible even with the help of the most advanced technologies. These devices are not able to provide *apriori* the combined productivity required to implement RTS. The possible solution of this problem is the concept of specialized parallel optoelectronic convertors. This concept makes it possible to use parallel optic channels to enter and process images. The further processing needs such an arrangement of parallel channels that would provide noiseproof and fast pre-processing compact description and flexible image classification.

The general methodology of the compact image presentation is given in accordance with the scheme of *coarse* - *fine* processing. The coarse processing consists of image quantization and is followed by its division into spatially-connected segments[3]. The results of this coarse processing are separate segments structured in some fields according to their connectivity indexes. These image segments are formed from spatially connected pixels of a quantified image and then create connectivity fields. Then separate segments undergo the *fine* processing scheme.

2. METHODOLOGY

2.1. Models of PH network

Let's consider the network method of parallel-hierarchical information processing at a model level. Let there be $S\ (S = 1, 2, 3\ldots)$ nonempty element sets, giving information. The elements number is called its length (symbol L_μ — set length μ). The number of different elements in a set is called the dimensionality of the given set (symbol R_μ). Let's consider the mathematical model of the parallel decomposition of the set μ and prove the validity of the following formula:

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

where $a_i \neq 0$, R-dimensionality of the given set.

From the identical elements subsets are formed, elements of one and the same subset are determined as a_k, $k = \overline{1,R}$, n_k - the number of elements in k subset (that is multiplicity of a_k - number), a_j - optional element of the set $\{a^k\}$, selected on the j-step, $j = \overline{1,R}$, $a^0 = 0,\ n_0 = 0.$

The proof:

$$\sum_{j=1}^{R}\left(n-\sum_{k=0}^{j-1}n_k\right)\left(a^j-a^{j-1}\right)=\left(n-n_0\right)\left(a^j-a^{j-1}\right)+\left[n-\left(n_0+n_1\right)\right]\left(a^2-a^1\right)+\left[n-\left(n_0+n_1+n_2\right)\right]\times$$
$$\times\left(a^3-a^2\right)+\ldots+\left[n-\left(n_0+n_1+\ldots+n_{j-1}\right)\right]\left(a^j-a^{j-1}\right)+\left[n-\left(n_0+n_1+\ldots+n_{j-1}+n_j\right)\right]\times$$
$$\times\left(a^{j+1}-a^j\right)+\ldots+\left[n-\left(n_0+n_1+\ldots+n_{R-2}\right)\right]\left(a^{R-1}-a^{R-2}\right)+\left[n-\left(n_0+n_1+\ldots+n_{R-1}\right)\right]\left(a^R-a^{R-1}\right)=$$
$$=na^0+a^1\left[n-n_1-n+\left(n_0+n_1\right)\right]+a^2\left[n-\left(n_0+n_1\right)-n+\left(n_0+n_1+n_2\right)\right]+\ldots+$$
$$+a^j\left[n-\left(n_0+n_1+\ldots+n_{j-1}\right)-n+\left(n_0+n_1+\ldots+n_{j-1}+n_j\right)\right]+\ldots+a^{R-1}\left[n-\left(n_0+n_1+\ldots+n_{R-2}\right)-\right.$$
$$\left.-n+\left(n_0+n_1+\ldots+n_{R-1}\right)\right]+a^R\left[n-\left(n_0+n_1+\ldots+n_{R-1}\right)\right]=na^0+n_1a^1+n_2a^2+\ldots+$$
$$+n_ja^j+\ldots+n_{R-1}a^{R-1}+n_Ra^R=\sum_{j=1}^{R}n_ja^j=\sum_{i=1}^{n}a_i\,,\quad n_0=a^0=0,\; n_0+n_1+\ldots+n_{R-1}=n.$$

Let's show, that model (1) corresponds with the parallel coding algorithm of information massif. At the first algorithm step an arbitrary number a^1 is selected from number set $t_1=\{\,a_i\,\},\; i=\overline{1,\,n}$, $a_i\neq 0$ and multiplied by *n*, that corresponds to the first component of the right part (1). For the analysis of the next steps of algorithm, let's introduce into consideration number sets $z_2,\ldots z_j\,,\; z_{j+1},\ldots\; z_R$ which are formed according to the following rule.

Nonzero numbers, which take place in $(j+1)$ - step of the algorithm are the elements of the set z_{j+1}. They are the difference of each of the elements of the set z_j and the optional number, selected out of this set at the *j*-step of the algorithm.

According to this rule, form set z_2 $z_2=\{\,a_i-a_1\,\},$ where n_1 — multiplicity of the number a^1. So z_2 consists of $(n-n_1)$ of the nonzero elements. From the set z_2 select an optional element and write (a^2-a^1) for it. As a result of the second step number (a^2-a^1) is multiplied by the number of set z_2 element, that's by number $(n-n_1)$. The obtained product $(n-n_1)\;(a^2-a^1)$ corresponds with the second component of the right part (1).

Using the mathematical induction method, show that the product

$$\left(n-\sum_{k=0}^{j-1}n_k\right)\left(a^j-a^{j-1}\right)\tag{2}$$

is formed at an optional j-step of the algorithm. The model is good, as shown above, for $j=1,\,2.$ Suppose the model is good for the j -step of the algorithm. Show, that it is also valid for the *(j+1)* - step. According to the rule, formulated above, form set z_{j+1}. And considering the effect of induction:

$$z_j=\left\{a_i-a^{j-1}\right\},\qquad i=1,\ldots,\left(n-\sum_{k=0}^{j-1}n_k\right).$$

Now select an optional element from the set z_j and denote it as a^j-a^{j-1}. Then set z_{j+1} has the form:

$$\left\{ \left(a_i - a^{j\text{-}1}\right)\left(a^j - a^{j\text{-}1}\right)\right\} = \left\{a_i - a^{j\text{-}1}\right\}, \qquad i = 1,\ldots,\left(n - \sum_{k=0}^{j} n_k \right).$$

From the set z_{j+1} select an optional element $a^{j+1} - a^j$, multiply it into the number of nonzero elements in this set:

$$\left(n - \sum_{k=0}^{j} n_k \right) \left(a^{j+1} - a^j\right)$$

Then, the model is good for the $(j+1)$ - step. The obtained product corresponds $(j+1)$ - element of the right part (1).

So, formula (1) is proved. Conversion of the set μ in set μ^1, assigned by formula (1) let call conversion operator *G*.

The described procedure is satisfying at each consequent hierarchical level up to a last level $k_{\max}$ in which matrix $A_{k_{\max}}$ contains the single element. Then $T\left(L\left(P\left(A_{k_{\max}}\right)\right)\right) = \varnothing$. The serial application of operators G, P, L, T can be represented as execution of an operator F: $F\left(A_k^T\right) = T\left(L\left(P\left(G\left(A_k^T\right)\right)\right)\right) = A_{k+1}^T$. The serial application of operator F can be represented as $F^k\left(A_1^T\right) = F^{k-1}\left[F\left(A_1^T\right)\right]$. Then all multilevel process can be presented in the following functional form:

$$F^{k_{\max}-1}\left[T\left(G\left(\bigcup_{i=1}^{n} M_i \right)\right)\right] = \left\{a_{11}^k \mid k = 2, 3, \ldots, k_{\max}\right\}. \tag{3}$$

Thus, the result of processing in PH network is represented as pattern vector.

Let's prove the formula:

$$\underset{t=2}{\overset{k}{\Phi}}\left[T\left(G\left(\bigcup_{S=1}^{S} \mu_S \right)\right)\right] = \bigcup_{t=2}^{k} a_{11}^t \tag{4}$$

where μ_S - initial sets $(S = 1,\ 2,\ 3,\ldots)$, a_{11}^t - decomposition elements of the initial sets, obtained in one at each level, leading off with the second.

The proof: Let s=l, that is there is only one initial set. In this case decomposition degenerate into conversion according to formula (1)

Suppose, the given decomposition has the space for S sets. Let's prove, that it has the space for S+1 set.

$$\overset{k}{\underset{t=2}{\Phi}}\left[T\left(G\left(\bigcup_{S=1}^{S+1}\mu_S\right)\right)\right]=\overset{k}{\underset{t=2}{\Phi}}\left[T\left(G\left(\left(\bigcup_{S=1}^{S}\mu_S\right)\cup(\mu_{S+1})\right)\right)\right] = \overset{k}{\underset{t=2}{\Phi}}\left[T\left(G\left(\left(\bigcup_{S=1}^{S}\mu_S\right)\cup G(\mu_{S+1})\right)\right)\right] =$$

$$= \overset{k}{\underset{t=2}{\Phi}}\left[T\left(G\left(\left(\bigcup_{S=1}^{S}\mu_S\right)\cup T(G(\mu_{S+1}))\right)\right)\right] = \overset{k}{\underset{t=2}{\Phi}}\left[T\left(G\left(\left(\bigcup_{S=1}^{S}\mu_S\right)\cup\overset{k}{\underset{t=2}{\Phi}}\left[T\left(G\left(\mu_{S+1}\right)\right)\right]\right)\right)\right] =$$

$$= \left[\bigcup_{t=2}^{k} a_{11}^{t}\right]\cup\left[\bigcup_{j=1}^{R_{\mu_{S+1}}}\left(n_{\mu_{S+1}}+\sum_{k=0}^{j=1} n_{k_{\mu_{S+1}}}\right)\cdot\left(a^{j}-a^{j-1}\right)\right],$$

As was to be proved.

The given formula can be rewritten as follows:

$$\overset{k}{\underset{t=2}{\Phi}}\left[T\left(G\left(\bigcup_{S=1}^{S}\left(\bigcup_{i=1}^{n}a_i\right)\right)\right)\right] = \bigcup_{t=2}^{k}a_{11}^{t} \tag{5}$$

So, the network method of parallel-hierarchical method of information processing consists of the serial application of conversion operator G and transposition operator T to initial sets $\bigcup_{S=1}^{S}\mu_S$, one time and then the functional Φ $(k-1)$ - times. At each level obtain one corresponding element a_{11}^{k} of decomposition S -initial sets, where a_{11}^{k} - is the output information of the network parallel-hierarchical decomposition. This information is diagonal sets, consisting of one diagonal multiple common element.

If for the initial S -files apply conversion operator G then you obtain decomposition of lines in every file:

$$\mu_1^1 = \bigcup_{i=1}^{R_1^1}a_{1i}^{i}\ ,\ \ \mu_2^1 = \bigcup_{i=1}^{R_2^1}a_{2i}^{i}\ ,\ \ \dots\ ,\ \ \mu_s^1 = \bigcup_{i=1}^{R_s^1}a_{si}^{i}\ , \tag{6}$$

where μ_s^1 set with number S at the l-st level. Then for *k*-level set number l is μ_l^k, R_s^1 - elements number in the *S* - set at the 1-st level and R_l^k elements number in the S -set at *k*-level. As R_s^1 takes different values for each set, number in μ_1^T is equal to the maximal number from R_s^1, that is $\max\{R_1^1,R_2^1,\dots,R_S^1\}=R^1$. Then write R^1 for the maximal set length at the first level.

From formula (4) follows:

Corollary 1: The maximal number of hierarchical levels is more by one of general dimensionality of all initial sets

Corollary 2:

$$\sum_{j=1}^{S}\sum_{i=1}^{n_S}a_{ji} = \sum_{t=2}^{k}a_{11}^{t}. \tag{7}$$

The proof: As since the number of parallel decomposition S elements are less by one than the number of levels, that elements a_{11}^t are less by one, than level number, that is $(k-1)$. As transformation (5) is one-valued and reversible and also assigned with $k-1$- element, the initial elements sum is invariant to the given transformation (5), so $\sum_{j=1}^{S}\sum_{i=1}^{n_S} a_{ji} = \sum_{t=2}^{k} a_{11}^t$ is true, which was to be proved.

Corollary 3: The length of algorithms is assigned as follows:

$$L = R^1 + \sum_{t=1}^{k} P^{t+1} - \left(n^t - 1\right), \tag{8}$$

where $P^t = \max \left\{R_1^t, R_2^t + 1; R_3^t + 2; \ldots ; R_{n^{t-1}}^t + n^{t-1} - 1\right\}$, and n^{t-1} - set number in matrix $A_{t-1}^{\bullet}$ which pass into the t-level for further transformation, $t = \overline{1,k}$.

The proof: Let's use the method of mathematical induction. Let $k=1$, then $n^1 = 1,\ P^{t+1} = 0,$ and $L = R^1$. Let (8) is true for $k = q$ that is:

$$L = R^1 + \sum_{t=1}^{q} P^{t+1} - \left(n^t - 1\right), \tag{9}$$

Let's prove, that (8) is true also for $k = q+1$:

$$L = R^1 + \sum_{t+1}^{q+1} P^{t+1} - \left(n^t - 1\right) = R^1 + \sum_{t=1}^{q} P^{t+1} - \left(n^t - 1\right) + P^{q+2} - \left(n^{q+1} - 1\right),$$

As since there only single diagonal on the last level and there are exactly two diagonals on the last but one level than $P^{q+2} - \left(n^{q+1} - 1\right) = 2$, then $L = R^1 + 2 + \sum_{t=1}^{q} P^{t+1} - \left(n^t - 1\right)$ which was be proved.

Algorithm length is increased by two, by increasing the level number by one, as length of the last level became equal to 2, it became last but one and appears one more last single level. The corollary is proved.

2.2. PH network learning

By analogy with RBF networks[4] the problem of offered PH network training practically is reduced to the idea of inspected tutoring of output layer elements. Using general idea of artificial neuron network structural organization under the scheme: input layer — hidden layer — output layer, it is possible to synthesize trained PH network, in which the 1st level of network will be used as a input layer, levels $2 \div k$ will be used as the hidden layer, and we will use the output level as target layer(Fig. 1) traditionally used in neural networks.

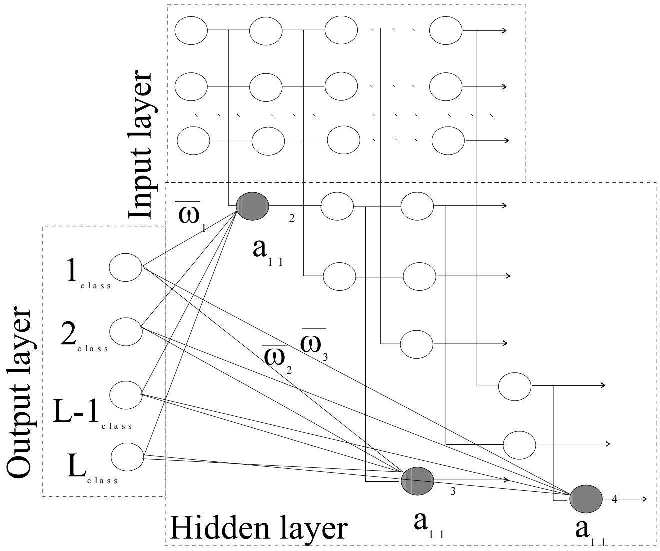


Fig. 1. Three-level structure of PH network

Using a corollary 3, defining the length of network algorithm, it is possible to determine the number of the latent layer elements and also to formalize a procedure of calculation the hidden layer elements number. The averaged values of weight factors $\overline{w}_1 \div \overline{w}_{k-1}$ are determined thus:

$$\overline{w}_t = \frac{\sum_{p=1}^{N} w_t^{(p)}}{N}$$, where N – dimensionality of learning sample P, $t = \overline{1, k-1}$.

Using the property of invariance of the sum of primary elements ($\sum_i a_i$) of the PH network to the sum of tail elements ($\sum_{t=2}^{k} a_{11}^{t}$) it is not difficult to form a system of equations to obtain such tuning coefficients $w_1 \div w_{k-1}$ in the form (10), as to easily form normalizing equation (11):

$$\begin{cases} w_1 = \dfrac{\sum\limits_{t=2}^{k} a_{11}^t}{(a_{11}^2 + \sum\limits_i a_i^2)} \\ w_2 = \dfrac{\sum\limits_{t=2}^{k} a_{11}^t}{(a_{11}^3 + \sum\limits_i a_i^3)} - \dfrac{w_1 a_{11}^2}{(a_{11}^3 + \sum\limits_i a_i^3)} \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ w_{k-2} = \dfrac{\sum\limits_{t=2}^{k} a_{11}^t}{(a_{11}^{k-1} + \sum\limits_i a_i^{k-1})} - \dfrac{w_1 a_{11}^2 + w_2 a_{11}^3 + \cdots + w_{k-3} a_{11}^{k-2}}{(a_{11}^{k-1} + \sum\limits_i a_i^{k-1})} \\ w_{k-1} = \dfrac{\sum\limits_{t=2}^{k} a_{11}^t}{(a_{11}^{k} + \sum\limits_i a_i^{k})} - \dfrac{w_1 a_{11}^2 + w_2 a_{11}^3 + \cdots + w_{k-2} a_{11}^{k-1}}{(a_{11}^{k} + \sum\limits_i a_i^{k})} \end{cases} \quad (10)$$

In expressions (10) and (11) $\sum\limits_{t=2}^{k} a_{11}^t$ – are standard, $\sum\limits_i a_i^k$, $a_{11}^2 \div a_{11}^k$ – are current components (features) of the image to be identified. To normalize the results of the PH network with tuning coefficients, which are obtained on the basis of coefficients of the type (10), we use the main feature of the PH network – $\sum\limits_{t=2}^{k} a_{11}^t = \sum\limits_i a_i$. Then the left side of the normalizing equation (11) will represent the ratio of the sum of product of averaged value of tuning coefficients and tail elements to the sum of tail elements of the network, while the right side if the identification is right is nearing one, that is $d \to 1$. The degree of this proximity to one reflects the measure of similarity of the images to be identified. Ideally, if the identification is right, $d \approx 1$.

$$d = \frac{\overline{w}_1 a_{11}^2}{\sum\limits_{t=2}^{k} a_{11}^t} + \frac{\overline{w}_2 a_{11}^3}{\sum\limits_{t=2}^{k} a_{11}^t} + \cdots + \frac{\overline{w}_{k-2} a_{11}^{k-1}}{\sum\limits_{t=2}^{k} a_{11}^t} + \frac{\overline{w}_{k-1} a_{11}^{k}}{\sum\limits_{t=2}^{k} a_{11}^t} = \frac{\sum\limits_{t=2}^{k} \overline{w}_{t-1} a_{11}^t}{\sum\limits_{t=2}^{k} a_{11}^t}, \quad (11)$$

Using the normalizing equation (11), in which $\overline{w}_1 = \overline{w}_2 = \cdots = \overline{w}_{k-2} = \overline{w}_{k-1} = 1$, it is possible quite easily to carry out the preliminary procedure of image classification using value d, and then, in accordance with the system (10) to form tuning coefficients $\overline{w}_1 \div \overline{w}_{k-1}$, carrying out the procedure if determination of weight coefficient for every class.

Particularly, when making real time image classification and analyzing, for example, neighboring shots of a multimedia image, normalizing equation (11) will be the following:

$$d = \frac{\left(a_{11}^2\right)^{j+1}}{\left(\sum\limits_{t=2}^{k} a_{11}^t\right)^j} + \frac{\left(a_{11}^3\right)^{j+1}}{\left(\sum\limits_{t=2}^{k} a_{11}^t\right)^j} + \cdots + \frac{\left(a_{11}^{k-1}\right)^{j+1}}{\left(\sum\limits_{t=2}^{k} a_{11}^t\right)^j} + \frac{\left(a_{11}^{k}\right)^{j+1}}{\left(\sum\limits_{t=2}^{k} a_{11}^t\right)^j}, \quad (12)$$

where $\left(\sum_{t=2}^{k} a_{11}^{t}\right)^{j}$ and $\left(a_{11}^{2}\right)^{j+1} \div \left(a_{11}^{k}\right)^{j+1}$ – is the sum of tail elements and value of tail elements of , accordingly, the previous (j)[th] and the next ($j+1$)[th] shots, j is the number of a shot, $j = \overline{1, m-1}$.

Taking into account the feature (7) PH network, normalizing equation (12) will be the following.

$$d = \frac{\left(a_1\right)^{j+1}}{\left(\sum_{t=2}^{k} a_{11}^{t}\right)^{j}} + \frac{\left(a_2\right)^{j+1}}{\left(\sum_{t=2}^{k} a_{11}^{t}\right)^{j}} + \cdots + \frac{\left(a_{N-1}\right)^{j+1}}{\left(\sum_{t=2}^{k} a_{11}^{t}\right)^{j}} + \frac{\left(a_N\right)^{j+1}}{\left(\sum_{t=2}^{k} a_{11}^{t}\right)^{j}} . \tag{13}$$

Then, so that to normalize the result of incoming data processing ($a_1 \div a_N$) of the ($j+1$)[th] shot, it is possible to substantially reduce identification time in the PH network for the time of processing of the (j+1)[th] shot, because during realization of the equation (13) it is not necessary to determine tail elements $\left(a_{11}^{2}\right)^{j+1} \div \left(a_{11}^{k}\right)^{j+1}$ when processing the ($j+1$)[th] shot. In comparison with known structures of neural networks, in which it is not possible to use incoming data of the (j)[th] shot for the procedure of identification of the ($j+1$)[th] shot in output layer, it is possible to do in the network under examination, which helps to reduce identification time.

2.3. The method for image coordinate definition on extended laser paths

During the analysis of the sequence of fast changing images on extended laser paths there appears a problem of definition of the centre of the beam trace. Under the influence of various environmental factors a cross-section image of a laser path (in the plane perpendicular to the direction of the beam) becomes dithered, with its shape constantly changing with time. Thus it is next to impossible without analysing the preceding images in the sequence to determine such a "power" centre $\alpha_e^i = (x_e^i, y_e^i)$ of the current (*i*-th) beam image, which would be permanent during the analysis of the image sequence $\Omega = (\omega_0, ..., \omega_{N-1})$ of the extended laser path in question. The power centre must not move when analysing a path which never changes its direction and therefore the location of its power centre is to be permanent, that is $\alpha_e^i = \alpha_e^{i-1}, i = 1..N-1$, where N – is the number of images in the sequence. In case when a beam changes its direction the calculated power centre must be automatically shifted and match the new position and features of the beam. During image analysis the method of location of an image centre is used with the help of absolute moments of order 0 and 1. Thus for quantized image of $m \times n$ size with weight factors *B (x, y) x=0.m-1, y=0.n-1* the absolute moment *m* of order *j, k* is determined as below:

$$m_{j,k} = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} B(x,y) \cdot x^{j} \cdot y^{k} \tag{14}$$

Then the image centre $\alpha = (x, y)$ is found out from the ratio of the moments:

$$\alpha = \left(\frac{m_{11}}{m_{01}}, \frac{m_{11}}{m_{10}} \right) \tag{15}$$

For weight factors in formula (14), the brightness of the given image element *B(x,y)=I(x,y)* is widely used. In this work as weight factors we take also a simple coherence Δ_k under analysis (hereinafter simple coherence) and normalized coherence $\overline{\Delta}_k$ of *k*-th cross-section where the value of brightness of the given point *I(x,y)* (16) belongs to. To find the simple and normalized coherence all the range of image brightness is broken into separate sections with predetermined step ∂I. Thus, for example, if an image has 256 levels of grey ($I(x,y) \in [0..255]$, *max(I)=255*) and the step is $\partial I = 1$, then to the *i*-th section only those points will be related that have *i* brightness. At any other step the *i*-th section will have points with the brightness as $I(x,y) \in [\partial I \cdot i \; .. \; \partial I \cdot (i+1) - 1\;]$. A point with *I(x,y)* intensity belongs to section number.

$$R(x,y) = \left[{I(x,y)}/{\partial I} \right] \tag{16}$$

where *[x]* – is an integral part of *x*.

Two points (x_1, y_1) and (x_2, y_2) are called coherent if they are adjacent, i.e.

$$\max\{|x_1 - x_2|, |y_1 - y_2|\} = 1 \tag{17}$$

and if they belong to one section or two neighbouring sections.

Therefore, each image point (*x, y*) is defined by the coherence $\delta(x,y)$ – that is the number of points associated with it. (max{ $\delta(x,y)$ }=8).

The coherence Δ_k of the *k*-th section is the sum of all points pertaining to it. It can calculated according to the formula:

$$\Delta_k = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} if\left(R(x,y) = k, \delta(x,y), 0\right), \qquad k = 0..\max(R) \tag{18}$$

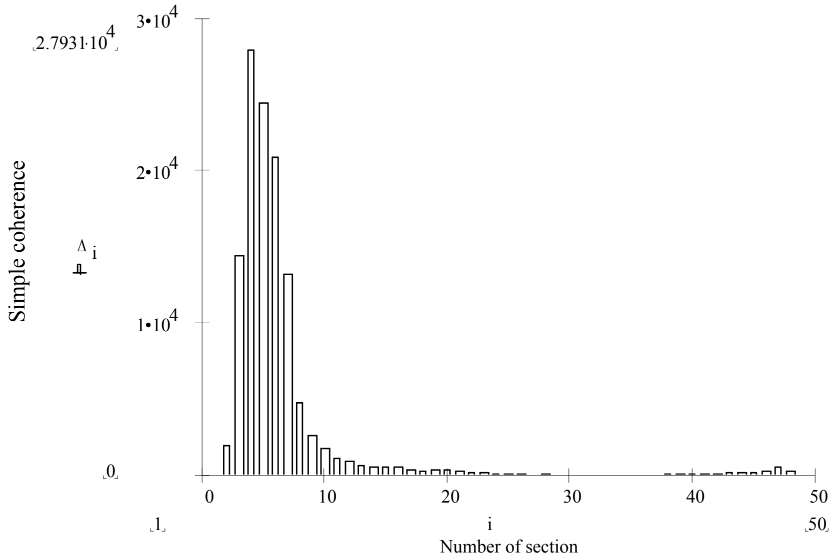
Except the coherence Δ_k it is important to define the quantity of section elements

$$\sigma_k = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} if\left(R(x,y) = k, 1, 0\right), \qquad k = 0..\max(R) \tag{19}$$

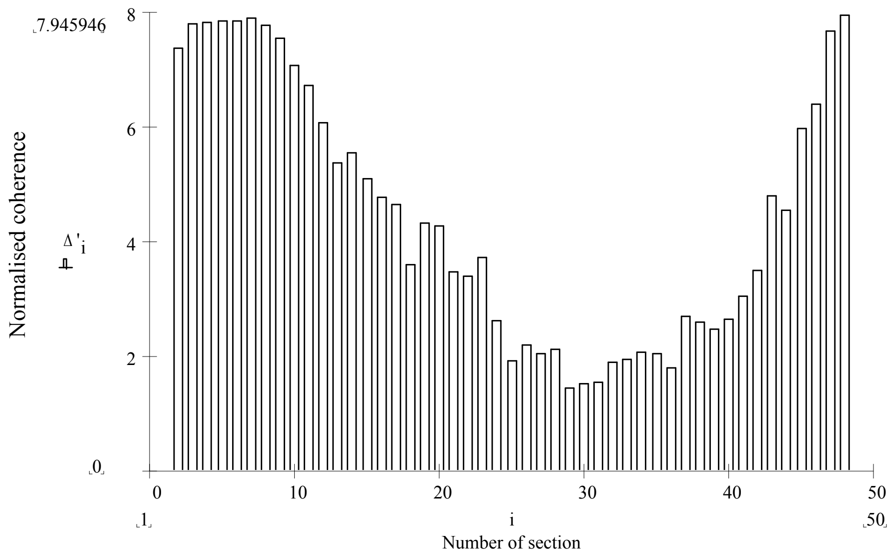
Then the relative coherence may be represented as

$$\overline{\Delta}_k = \frac{\Delta_k}{\sigma_k}. \tag{20}$$

A sample of simple and relative coherence for one of images on an extended laser path is given at figure 2.



a



b.

Fig. 2. Diagrams of simple (a.) and normalized (b.) coherence for a laser beam image

The centre found out with the method of moments is not invariant to the change of the shape and orientation of a laser path image and therefore the location of the centre of an image changes significantly along the path.

This study proposes a method for defining a certain small area δ^{i-1} in the vicinity of the centre of the preceding spot on the path. If the centre of the current spot α_e^i falls within this area the direction of the extended laser path does not change and consequently the power centre coordinates remain intact. Otherwise power centre coordinates are calculated according to the algorithm below.

For the definition of area δ^{i-1} a recurrent method of balancing - division of an image into "equivalent" areas. At the *j*-th step balancing of the active area of the spot image is done along 4 directions resulting in 4 equalization curves. Two equilibrium curves are defined along 0X and 0Y axes of the Cartesian coordinate system and the other two in the Cartesian system rotated at 45^0 along the 0X' and 0Y' axes (as shown in Fig.3). The active area at the first step covers the entire spot image. The weight coordinates *B(x,y)* prove the availability of the point (*x,y*) within the active area; if it outside the active area its weight coefficient is equal to zero and consequently this point does not affect the result of balancing.

$$N_x^j(x) = \frac{\sum_{i=0}^{n-1} B(x,y)\cdot y}{\sum_{i=0}^{n-1} B(x,y)}, \qquad N_y^j(y) = \frac{\sum_{i=0}^{m-1} B(x,y)\cdot x}{\sum_{i=0}^{m-1} B(x,y)},$$
$$N_{x'}^j(x') = \frac{\sum_{i=0}^{n'-1} B(x',y')\cdot y'}{\sum_{i=0}^{n'-1} B(x',y')}, \qquad N_{y'}^j(y') = \frac{\sum_{i=0}^{m'-1} B(x',y')\cdot x'}{\sum_{i=0}^{m'-1} B(x',y')} \tag{21}$$

Equalization curves have its maximum and minimum values at the *j*-th step of balancing, thus defining on the appropriate axis of values (for example, for a equalization curves directed along the 0X - OY will be the value axis) the range of possible values $\left[\min(N^j)..\max(N^j)\right]$. The overlapping segments of these areas form area D^j (as shown on Fig. 4), which will be the active area for the next step of recurrence. If an area consists of more than one point, the transition is made to another recurrent step. If the area consists of one point this point is considered to be the power centre of a spot image.

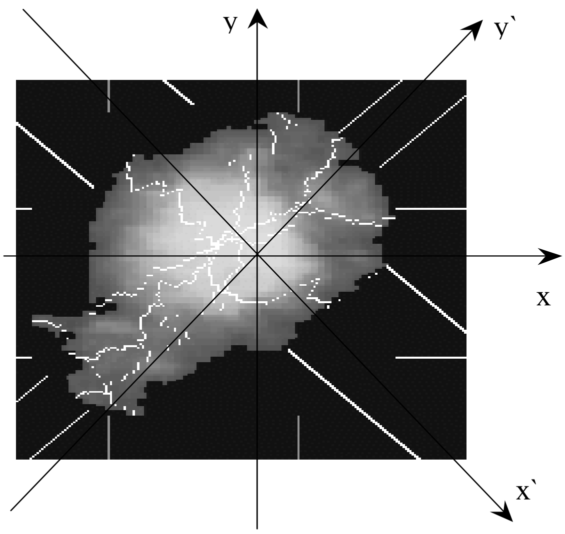


Fig. 3. Equalization curves in two coordinate systems

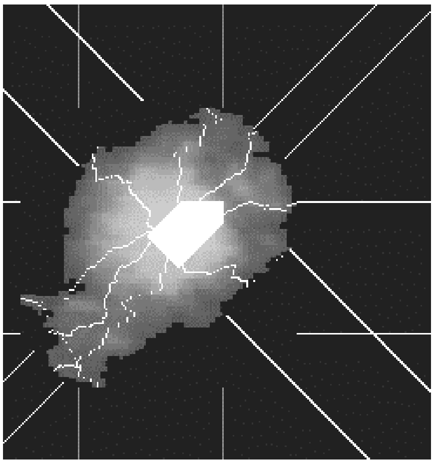


Fig. 4. The active area obtained at the 1-st step of balancing

When analysing a bean section image it is quite useful to pick a certain part the image on the threshold basis and to delete the background. In this study we use the method of threshold limiting[3] and the threshold itself is chosen depending on the weight coefficient used.

As is shown at the coherence diagrams (Fig. 2) the spot images under analysis feature two local maximums of coherence values for the sections relating to the background (the first maximum $\Delta_{\max 1}$) and to the object (the second maximum $\Delta_{\max 2}$) respectively. It is quite evident that the sections preceding the first maximum relate to the background and those to the right of it - to the data part of the image, i.e. to the object. It is necessary to determine the boundary section $\Delta_{\lim}$ that divides all of the sections into two groups: the sections to the left of the boundary ($k < \Delta_{\lim}$) that constitute the background, and the sections to the right ($k \geq \Delta_{\lim}$) that refer to the data part of the spot image.

Three methods of defining a boundary section have been considered:

1-st method: the background possesses the sequence of sections lying to the right of the first maximum of the coherence diagram. The coherence of these sections does not exceed the coherence of the previous section $\Delta_{k-1} \geq \Delta_k$, i.e. it causes a monotonous slope on the coherence diagram. The drawback of this method is the availability of small local extremums within the range of background sections it the step between the sections is small (∂I =1) and large brightness range (for example, when *max(I(x,y))=255*).

2-nd method: definition of the minimum coherence value $\Delta_{\lim}$ when it is possible to classify all sections into two groups, i.e. when the condition below is satisfied

$$\Delta_k > \Delta_{\lim}, \quad k \in [max1..\lim] \tag{22}$$

This minimum value is minimum coherence value between the two maximums.

$$\Delta_{\lim} = \min\{\Delta_k\} \quad k \in [max1..max2] \tag{23}$$

3-d method: by analogy with method 2 it deals with the normalized coherence $\overline{\Delta}$. The normalized coherence diagram has more delineated maximums since the values of the sections that are related to the central point of a spot tend to the maximum value. The same process is typical for sections of background points.

$$\overline{\Delta}_{\lim} = \min\left\{\overline{\Delta}_k\right\} \quad k \in [\overline{max1}..\overline{max2}] \tag{24}$$

where $\overline{max1}$, $\overline{max2}$ are the numbers of maximums' sections of the normalized coherence diagram.

In the experiments we used the set of 269 images. Results of the algorithm work are presented on fig. 5.

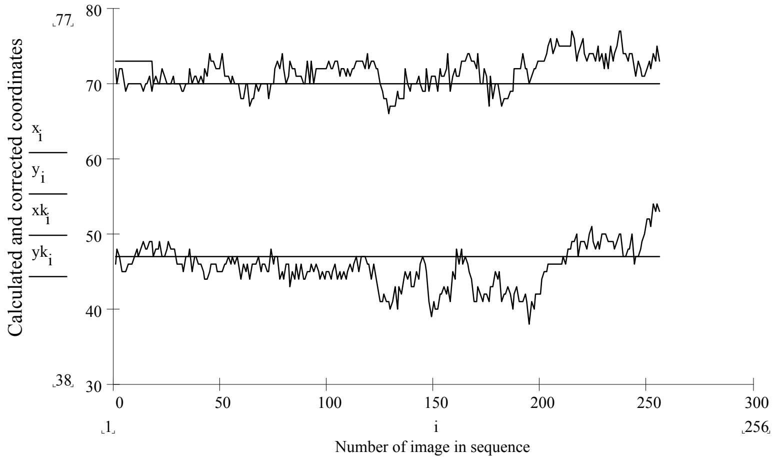


Fig. 5. Calculated and corrected by hitting to δ area on non 0 step of balancing. All images in sequence have the same corrected coordinates

While processing a sequence of images the use of the normalizing equation for two adjacent images, the first of which is considered the standard one, is possible. Then the normalizing equation assume the following form:

$$d = \frac{\overline{w}_1 (a_{11}^1)^j}{\sum_{t=1}^{k} (a_{11}^t)^{j-1}} + \frac{\overline{w}_2 (a_{11}^2)^j}{\sum_{t=1}^{k} (a_{11}^t)^{j-1}} + \cdots + \frac{\overline{w}_{k-1} (a_{11}^{k-1})^j}{\sum_{t=1}^{k} (a_{11}^t)^{j-1}} + \frac{\overline{w}_k (a_{11}^k)^j}{\sum_{t=1}^{k} (a_{11}^t)^{j-1}} = \frac{\sum_{t=1}^{k} \overline{w}_t (a_{11}^t)^j}{\sum_{t=1}^{k} (a_{11}^t)^{j-1}}.$$

where the tuning coefficients $\overline{w}_1 \div \overline{w}_k$ are obtained preprocessing the first images of the set; $(a_{11}^t)^j, (a_{11}^t)^{j-1}$ – tail elements of current and previous images accordingly. In the course of the sequence of images processing the data represented on figure were obtained.

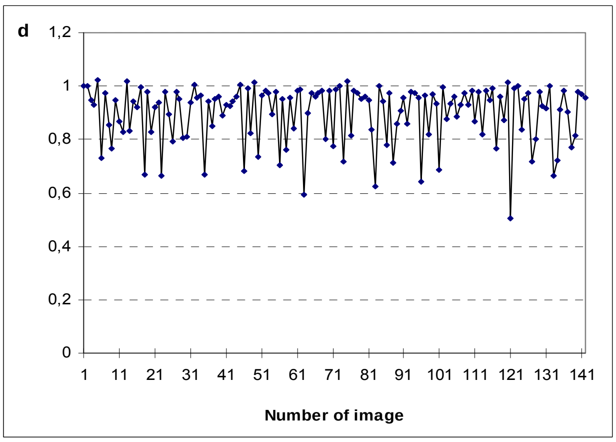


Fig. 6. Results of laser path images processing on trained PH network

For further processing it is necessary to select only defined values d, which are greater than some threshold. For example, for a processed laser trace (Fig. 6.) some d's obtain small values and their initial images might be excluded. Thereby we can remove "bad" images from a laser trace and then process them similarly.

These experiments show that for the images of long laser traces, it is not possible to measure exactly the coordinates of their energy center because of various destabilizing factors. The is why a coordinate-measuring method on the basis of analyzing mutual location of neighboring laser images is introduced in this work. The result of analyzing such mutual location of two neighboring images is a corrected result of the energy center coordinates of the current image. Such principle of the power center coordinates measurement allows to exclude the usage of inexact procedures based on various approximating operators.

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