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NEURAL NETWORK ALGORITHM OF IMPROVEMENT OF VECTOR TOPOGRAPHICAL MAPS ACCORDING TO THE DATA FROM EARTH REMOTE SENSING

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Abstract:

The algorithm of improvement of vector topographical maps according to the data from Earth remote sensingwas considered. The using of intelligent system, based on support vectors machines, multilayer perceptrons, feedforward neural networks, Kohonen's neural mapwas proposed. The approach to training of feedforward neural network through the use ofgenetic algorithm andKitano's graph generation grammars was considered.

Keywords: Artificial neural network, support vectors machine, Kohonen's neural map, multilayer perceptron, feedforward neural network, Kitano's graph generation grammar, genetic algorithm.

1. Introduction

The problemof timely drawing and updating of topographical maps is one of the most important current problems in different economic realms, exploitation of natural resources and safety precautions of human life and activities.

The problem can be solved by means of the analysis of the data of Earth remote sensing (ERS)by semi- or fully-automaticintelligent systems that maintain high accuracy of theproblemsolving and low time expenditures for its solving.

2. Statement of The Problem

A topographical map is prepared in geographic information system on the basis of the set of vectors layers, each of which describes location of different terrain features. Thus, the problem of improvement of topographical map reduces to the problem of improvement of the set of vectors layers. The problem of improvement of vector layer V_{old} consists in obtaining of vector layer V (1):

$$V_{old} \xrightarrow{f} V, \qquad (1)$$

where*f* is afunctional of improvement, is given by (2):

$$V = f(V_{old}, I) \quad (2)$$

where I is a satellite image or airphoto intelligence. I can be presented in a form (3):

$$I = \{i(m,n,k)\}; i(m,n,k) \in \{-1,1\};$$
$$m = \overline{1,M}, n = \overline{1,N}, k = \overline{1,K}; M, N, K \in \mathbb{N}, \quad (3)$$

Where:

- $i(m,n,k)$ is a value in spectral channel k pixel with coordinates $(m,\ n)$;

- M, N, K is number of rows, columns and spectral channels in the image I.

Let us assign to every pixel $i(m,\ n)$ set of coordinates $(x,\ y,\ z)$ in the map coordinates system: $(x,\ y,\ z) = map(m,\ n)$. Thus, data superimposition of ERS on the map vectors layers is achieved.

The task at hand in the present article is the functional f of improvement of map vector layers. This functional can be constructed different ways, however, at the present time, increasingly frequently artificial intelligence methodscame intouse, based on the machine learning theory.

This paper examines only the simplest – two-dimensional –case.Described algorithm can be applied for improvement of three-dimensional models of the scenery as well.

3. Algorithm

Recommended algorithm of improvement of topographical mapsconsists of the following steps:

1. Preprocessing of data of ERS I_{raw} – the noise correction, the conversion into the coordinate system of the map, projecting into two-dimensional map projection (z -coordinatefrom now on is taken to be equal tozero);

2. Transformation of I_{raw} from the source format of presentation of spectral channels to presentation format that is used by algorithm (4):

$$i(m,n,k) = spectral\_convert(i_{raw}(m,n,k)) = a * i_{raw}(m,n,k) + b;$$
$$m = \overline{1,M}, n = \overline{1,N}, k = \overline{1,K}; a, b \in \mathbb{N}, \quad (4)$$

where a, b are coefficients of linear transformation, chosen in accordance with the source format of presentation of spectral channels.

By virtue of the fact that typicallythe source formatis represented by unsigned integer eight-bit number, then coefficients a, b possess value (5):

$$a = \frac{2}{255},\ b = -1; \quad (5)$$

3. Classification of image pixels I with the receiving at the output of mask C (6):

$$c(m,n) = classification(i(m,n), V_{old}, I_{old}); c(m,n) \in P; \\ m = \overline{1,M}, n = \overline{1,N}; P \subset \square, \quad (6)$$

where:

- P is set of class indexes. Every index p marks one of possible object classes that can be presented in vector layer;

- I_{old} is ERS data, by which vector layer V_{old} was constructed;

4. vectorization of mask C with the receiving at the output of vector layer V.

Elements $c(m,n)$ of mask C make an element of vector layer V (point, line or polygon –depending on layer type)in the event that they have the same value (belong to one and the same class)and form tie set of points in Cartesian coordinatesrelating to the center of mask.

Vectorization can be performed by applying algorithms, described in [1] and [2].

4. Classifier

A key step of the presented algorithm is the classification of image pixels I with the receiving at the output of mask C. Classification is performed by applying the classifier $classification$. There are various ways of construction of classifier: manual, semi-automatic (with manual selection of algorithm parameters, with manual verification phaseof classification results, etc.) and automatic. Automatic methods ofconstruction of the classifier are of the greatest interestbecause of the possibility to reduce significantly the time expenditures on classification.

As the automatically adjusted classifier $classification$ solutions, based on the concepts of the artificial intelligence theory and the machine learning theory can be used.

During the preparation of the article,the classifier operating according to the following algorithm was developed:

1. Preliminary pixels classification $i(m,\ n)$ with the generation at the output of preliminary mask C_{pre}.

For preliminary pixels classification Kohonen's neural map is used;

2. Correlation of mask C_{pre} with vector layer V_{old} with the generation at the output of the list of classified and unclassified pixels $i(m,\ n)$.

Every pixel $i(m,\ n)$ is marked as classified,ifdistance measure $d\left(I(m,\ n),\ I_{old}(m,\ n)\right)$ is less or equal to certain

threshold $T; T \in \square^{+}$ that is chosen adaptively depending on image histograms I, I_{old} –the less image contrast (the more pronouncedhistogram modes and the closer histogram modes are to each other), the less value of threshold T, what is needed for sensitivity enhancement of algorithm on uniform image. Metrics d is chosen depending on task at hand – experiments showed that for improvement of topographical maps Euclidean distance measure is a reasonable choice;

3. Classifier kernel training $kernel$.

Classifier kernel trains on classified pixels $i(m, n)$;

4. Pixels classification $i(m, n)$ with the receiving at the output of mask C. If pixel $i(m, n)$ is entered in the list of classified ones, then $c(m, n) = c_{pre}(m, n)$, otherwise $c(m, n) = kernel(i(m, n))$.

5. Classifier Kernel

Classifier kernel is a set of tree-structured simple classifiers $classifier\_simple$.

Every simple classifier partitions original vector subspace $Q_{sub} \subset Q$ of vector space Q, composed of vectors $i(m, n)$, into two classes. Being related to a particular class, vector $i(m, n)$ goes down to the next tree level until it reaches one of thesinks.Every of sinks of treecorresponds to one of the resulting indexes p of possible classes.

Training of classifier kernelreduces to training of simple classifiers.

Training of simple classifiersis an iterative process, composed of the following stages:

- parameters selection of training and run of classifier;
- training of classifier by particular algorithm.

In the capacity of simple classifiers the following concepts of machine learning theory can be used:

- support vectors machine [4];
- multilayer perceptron [5];
- feedforward neural network

6. Feed forward Neural Network

Artificial feedforward neural networkcan be represented as function $y = ann(v)$ – function that produces for each input vector v the corresponding feedback y.

Artificial feedforward neural networkis composed of several neurons connected to each other by synapses, by whichsignals circulating in the network are transmitted. Every neuron has slowing down threshold that determines the

response level of the neuron to the corresponding excitation. Term "feedforward" means that in the artificial neural networkcircular paths are lacking. Every neuron of the networkexposes its input vector to transformation in accordance with its threshold value and its activation function, transmitting its output through the corresponding synapses to other neurons. Most ofartificial feedforward neural networks belong to neural networks class, training by teacher. For training of suchartificial neural network learning set V_{teach} of vectors is used, for which set of ideal feedbacks d_{teach} is known. For testing of the quality of training of the artificial neural network the test set V_{test} of vectors is used, for which ideal feedbacks d_{test} are also known . In general, fitting of artificialfeedforward neural network structure is a complicated problem. There are a number of approaches to its solution, the most developed of which is the approach with using of genetic algorithm [6] for search of optimal neural network structure, in the context ofmeansquared error functional $E(V_{test})$ (7):

$$E(ann, V_{test}) = \frac{\sum_i \left(ann\left(v_{test\ i}\right) - d_{test\ i}\right)^2}{V_{test}}; \quad i = \overline{1, V_{test}}. \qquad (7)$$

An important problem to be solved in the process of search of the optimal artificial neural networkstructure through the use of the genetic algorithm is the problem of encoding ofartificial neural network structure in the form of continuous sequence of characters sequence of chromosomes that make up a single gene of the genome of each individual.

H. Kitano in [7] suggested a coding procedure of artificial neural network structure, named Kitano's graph generation grammars. This article presentsone of the buildups of Kitano's graph generation grammars, which consists of introduction of complementary parameter W that defines the extent of analysis of initial grammar production and permits to set with the help of grammars that contain the same number of productions, networks of arbitrary size.

The artificial feedforward neural network structure can be presented in a form of loop-free direct graph. Each arc in this graph corresponds to a synapse and has its own weight settable during the network training. Each graph node corresponds to one neuron; with each node a threshold valueof corresponding neuron that adjusted during the network training is associated.

Existing in the graph arcs can be specified through the use of the vertex incidence matrix G (8) of the artificial neural network, in which the unit encodes the existence of edge directed from the vertex with number equal to the number of the row to the vertex with number equal to the number of the column, and zero, consequently, the absence of such

edge.

$$G=\begin{pmatrix} g_{11} & \dots & g_{1H_G} \\ \dots & \dots & \dots \\ g_{H_G1} & \dots & g_{H_GH_G} \end{pmatrix}; \quad g_{ij}\in\{0,1\}; \quad i=\overline{1,H_G}; \quad j=\overline{1,H_G}. \qquad (8)$$

Matrix G can be encoded through the use of productions of production grammar A (9):

$$A=\{T,T_P,T_N,F_T,F_P,F_N,S\};$$

$$T=\{0,1,\omega\}; \quad T_P=\{T_{P\ i}\}; \quad i=\overline{1,16}; \quad T_N=\{T_{N\ j}\}; \quad j=\overline{1,H_N}; \quad S\in T_N;$$

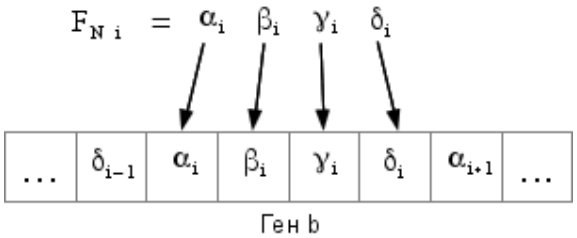
$$F_T=\{1\to\begin{pmatrix}1&1\\1&1\end{pmatrix}; \quad 0\to\begin{pmatrix}0&0\\0&0\end{pmatrix}; \quad \omega\to 0\}; \qquad (9)$$

$$F_P=\{F_{P\ 1}\to\begin{pmatrix}0&0\\0&0\end{pmatrix}, \quad F_{P\ 2}\to\begin{pmatrix}0&0\\0&1\end{pmatrix} \quad ,\dots,F_{P\ 16}\to\begin{pmatrix}1&1\\1&1\end{pmatrix}\};$$

$$F_N=\{F_{N\ i}\}; \quad F_{N\ i}:T_{N\ i}\to\begin{pmatrix}\alpha&\beta\\\gamma&\delta\end{pmatrix}; \quad i=\overline{1,H_N}; \quad \alpha,\beta,\gamma,\delta\in\left(F_N\cup F_P\right),$$

where: T, T_P, T_N, F_T, F_P, F_N, S - are sets of terminal symbols, preterminal symbols, non-terminal symbols, of inference rules for terminal symbols, of inference rules forpreterminal symbols, of inference rules fornon-terminal symbolsand starting non-terminal symbolscorrespondingly.

Grammar A is called Kitano's graph generation grammar. One grammar A corresponds to one individual of population of genetic algorithm. Elements T, T_P, T_N, F_T, F_P are fixed for every A, and, consequently, gen of individual encodes onlyproductions F_N. Productions F_N can be encoded by scheme shown at Fig. 1. Each production F_{Ni} isreflected into four chromosomes α_i, β_i, γ_i, δ_i,following each other and δ_{i-1} chromosome in single gene b of individual.



Gene b

Fig. (1). – Encoding scheme of productions F_N

Algorithm of reconstruction of matrix G of grammar A consists of the following steps:

1. initial matrix $G_1 = S$ is created;

2. $w = 1$ step of application of productions F_T, F_P и F_N is performed:

$$G_1 = S \quad \rightarrow \quad G_2 = \begin{pmatrix} \alpha_S & \beta_S \\ \gamma_S & \delta_S \end{pmatrix};$$

3. step 2 is repeated for each of productions α_S, β_S, γ_S, δ_S:

$$G_2 = \begin{pmatrix} \alpha_S & \beta_S \\ \gamma_S & \delta_S \end{pmatrix} \quad \rightarrow \quad G_3$$

;consequently, dimensionality G_3 is equal to $2^{(3-1)}$ on $2^{(3-1)}$ = 4 on 4 productions;

4. step 3 is repeated $(W-2)$ times –until matrix G_W is gotten;

5. in matrix G_W any symbol $g \in (T_P \cup T_N)$ is seen as symbol ω and according to the production is turn to zero;

6. matrix G_W is turned to matrix G according to formula (10) – consequently, in matrix G guaranteedlycircular paths will be lacking.

$$G = (g_{ij}); \quad G_W = (g_{W\ ij}); \quad g_{ij} = \begin{cases} 0, & i \geq j \\ g_{W\ ij}, & i < j \end{cases}; \quad i = \overline{1, H_G}; \quad j = \overline{1, H_G} \qquad (10)$$

Parameter W of the reconstruction algorithm of the vertex incidence matrix G determines the maximum number of neurons that can be in the resulting artificial neural network - 2^{W-1}. neurons. Considering the fact that the number of inputs and outputs of the artificial neural networkis fixed, then to the artificial neural networkdescribed by a corresponding graph, several neurons are joined:

– input neurons in sufficient quantities — are contactedby means of synapses with the sources of the graph; these synapses are channeled from the input neurons to the sources of the graph;

– output neurons in sufficient quantities — are contactedby means of synapses with the sinksof the graph; these synapses are channeled from sinksof the graph to the output neurons.

The cardinal number H_N of the set T_N has a great impact, as well as parameter W, on the quality of work of genetic algorithm, because it is the one that determines the length of the gene (as $4H_N$ chromosomes) and, therefore, the degree of “diversity”of production, encoded by the gene. The choice of H_N is made by a heuristic method, small value of H_N will lead to the degeneration of the population and its convergence to a local optimum, while the higher

value H_N , on the contrary, will increase the diversity of individuals, but will also increase the time of convergence of the genetic algorithm to,possibly, global optimum.

In comparison with the traditional version ofKitano's graph generation grammar proposed version allows to describe equally compact a neural networks with any maximum number of neurons that is achieved by means of parameter W

7. Genetic Algorithm

Genetic algorithm, used for search of the optimal artificial neural network structure and which uses for encoding of artificial neural network structureof Kitano's graph generation grammar, consists of the following steps:

1. set $V=\{v_i\};\quad i=\overline{1,H_V}$ of vectors from the studied subject area and set $d=\{d_i\};\quad i=\overline{1,H_V}$ of ideal feedbacks of artificial neural networkto corresponding vectors from V are created; on basis of sets V and d at each iteration of genetic algorithm training V_{teach} , d_{teach} and test V_{test} , d_{test} sets of vectors and feedbacks will be composed;

2. randomly an initial population of individuals is generated $B=\{b_i\};\quad i=\overline{1,H_B}$;

3. from the set V in random manner subsets V_{teach} , V_{test} are selected; for sets V_{teach} and V_{test} from set d corresponding to them subsets d_{teach} and d_{test} are selected;

4. for each individual $b_i \in B$ the corresponding grammar A_i , which produces neural network ann_i is reconstructed;

5. for each individual $b_i \in B$ the fitness function $Q(b_i)$ (11) is calculated:

$$Q(b_i)=\frac{1}{E(ann_i,V_{test})+\varepsilon};\quad \varepsilon\in\square;\quad \varepsilon<10^{-8}; \tag{11}$$

6. individuals $b_i \in B$ are sorted in descending order of fitness function $Q(b_i)$;

7. individuals with indexes $i\in\left[1,H_{B\ best}\right]$ form a set of individuals $B_{best}\subset B$, individuals with indexes $i\in(H_{B\ best},H_{B\ best}+H_{B\ cross}]$ form a set of individuals $B_{cross}\subset B$; individuals with indices $i\in(H_{B\ best}+H_{B\ cross},H_{B\ best}+H_{B\ cross}+H_{B\ mut}]$ form a set of individuals $B_{mut}\subset B$, in addition, conclusions (12)should be carried:

$$\begin{gathered} H_{B\ best} \geq 2; \\ H_{B\ cross} = \sigma H_{B\ mut}; \quad \sigma \in \square; \quad \sigma > 1; \\ H_{B\ best} + H_{B\ cross} + H_{B\ mut} = H_B; \\ B_{best} \cap B_{cross} = \varnothing; \quad B_{best} \cap B_{mut} = \varnothing; \quad B_{cross} \cap B_{mut} = \varnothing; \end{gathered} \tag{12}$$

8. individuals $b_i \in B_{cross}$ are replaced by individuals $b_{cross\ kl} = cross(b_k, b_l); \quad b_k, b_l \in B_{best}$ — that is by individuals - the results of crossing of random individuals from the set B_{best} of the best individuals of the population;

9. individuals $b_i \in B_{mut}$ are replaced by individuals $b_{mut\ k} = mutation(b_k); \quad b_k \in B_{best}$ — that is by individuals — the results of mutations of random individuals from the set B_{best} of the best individuals of the population;

10. if the best individual of the population b_1 was the best and met the stop condition $Q(b_1) > P$ no less than I previous algorithm iterations without interruption, then one proceeds to step 3, otherwise stop of the algorithm is performed.

Parameter P is the level that defines adequate quality of training of artificial neural network.

On completing of stop execution of the genetic algorithm of the artificial neural network, generated by grammar A_1 of the corresponding individual b_1 of the final population is taken as the best.

The genetic algorithm has the following parameters:

– $H_V; \quad H_{V\ teach} = \{V_{teach}\}; \quad H_{V\ test} = \{V_{test}\}$ - define the sizes of training and test sample of vectors; values of these parameters depend on the subject area and the complexity of the classification problem to be solved and required artificial neural network;

– $H_{B\ best}; \quad H_{B\ cross}; \quad H_{B\ mut}; \quad \sigma$ - determine the number of individuals maintained during the transition to the next iteration of the genetic algorithm, replaceable on the results of crossovers and mutations, respectively;

– $cross$, $mutation$ - functional of crossover and mutation respectively;

– P – defines the upper quality level of training of the best artificial neural network, sufficient to stop the algorithm;

– I determines sufficient to stop the algorithm number of iterations, at which, in a row, stop conditions for the best individual should be repeated; obviously, the more I, the greater the probability of convergence of the algorithm to the optimum steady — toartificial neural network giving the same quality of learning result for arbitrary V_{teach} and V_{test}.

8. Experiment

To test the validity of the proposed method for improvementof topographical maps several experimentswere set up, one of which will be discussed further. The experiment is to specify and complement the topographical map of the field traverse“Malinishchi”, located on the border of Ryazan and Pronsk Districts of the Ryazan Region and named after the village of Malinishchi located at this field traverse.

As the satellite image I_{old} we took a satellite image of the part of thefield traverse “Malinishchi”, made by the satellite “Landsat — 7” (camera "ETM +") onMay 22, 2000, on its basis updated topographic map $\{V_{old}\}$ was created. The problem of the developed algorithm consists in specifying of original topographical cartof the part of the field traverse “Malinishchi”and complement of the resulting map withinformation about the wholefield traverse. Specifying and complement of topographical map were performed with help of the satellite image I, dated on 23 May, 2006, made by the satellite "Landsat — 7" (camera "ETM +").

In comparison with a topographicalmap $\{V_{hand}\}$, compiled for I manually, the algorithm demonstrated high accuracy of the result, having classified incorrectly less than 5% of the pixels $i(m, n)$.

On the average, the accuracy of the algorithm reaches 93% of correctly classified pixels $i(m, n)$ in comparison with the manual classification.

9. Summary

During the experiments, the developed algorithm showed the following advantages:

- high accuracy of the result –not less than 93 % of the pixels of the original Earth remote sensing data are classified correctly;
- lowtime expenditures — 30 — 40 ms.at 6-channel image of size 4000 by 4000 pixels (typical satellite image) that allows to achieve 25 FPS;
- high level of automation of the specifying process.

The disadvantages of the developed algorithm are high complexity of its implementation and the necessityof prior automatic adjusts of the classifier to improve its time characteristics.

10. Conclusion

The developed algorithm showed high time efficiency – a satellite image I with dimensions $M = 4000, N = 4000, K = 6$ can be processed in the average per 30 — 40 ms that is enough for 25 frames per

second (25 FPS) – the frequency sufficient for forming a video sequence, a smooth and continuous for the visual system of an average person).

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