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Computer Simulations of Association-Based Image Search Mechanisms Basing on Theory of Active Perception

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Abstract—We discuss an approach to development of an associative memory model from the viewpoint of the theory of active perception. The theory of active perception allows one to develop the tree-based memory model without the defects of the *kd*-tree and the *vp*-tree. Applications of the proposed model for solving problems of an image search by content from database are described. Also, we present the results of computer simulations directed at searching of similar and distorted images.

Keywords: associative memory, image search by content, theory of active perception

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INTRODUCTION

The increase in the volume of the stored visual information leads to necessity of developing new and effective methods of memory organization and access. An application of the associative memory is one of possible ways to solve this problem [1]. Unlike the random-access memory, in the case of the associative memory the data access is performed by the content but not by the address. This mechanism is much alike the human perception system. For example, when seeing a part of the man's image a person can recall the whole image [2]. When comparing with the random-access memory, the associative memory is able to correct errors as well as to search through similar images.

The most widely known associative memory models are developed in the neural network theory. K. Steinbuch [3] proposed one of the first of such models ("Lenrmatrix"). This model deals with binary vectors and uses the Hebbian learning rule. The further development of the idea of the associative memory is related to the works of D. Willshaw, G. Palm and D. Hopfield as well as to the model based on the oscillatory neural network [4].

When designing image search systems one focuses on the development of methods of generation of a feature description of an image and on the data access. The generation of a feature description of an image may be done globally (over the entire image) or locally. In the case of the global description, the hashCode methods are often used. For example, they are the semantic locality-sensitive hashing [5], hashes on the basis of the discrete cosine transform, the Radon transform, the image block average value [6]. The local description of images is usually done basing on SIFT and SURF methods [7]. To organize a search in the multidimensional feature space the *kd*- and *vp*-trees are used [8].

The known approaches to the problem of an image search are not without drawbacks. For example, when constructing the *kd*-tree there is a possibility of formation of an unbalanced tree due to adding a feature descriptions of images into the tree, which results in a decrease of the efficiency of the search. The disadvantage of the semantic hashing method is that with increasing of the length of the binary feature vector the distance between the objects increases and consequently the number of the images that are necessary to look through increases. High computational complexity is the main problem of the known methods of generation of the feature description an image.

In the present paper, we develop an associative memory model from the viewpoint of the theory of active perception (TAP) [9]. The model is applicable for solving problems of a search in image databases.

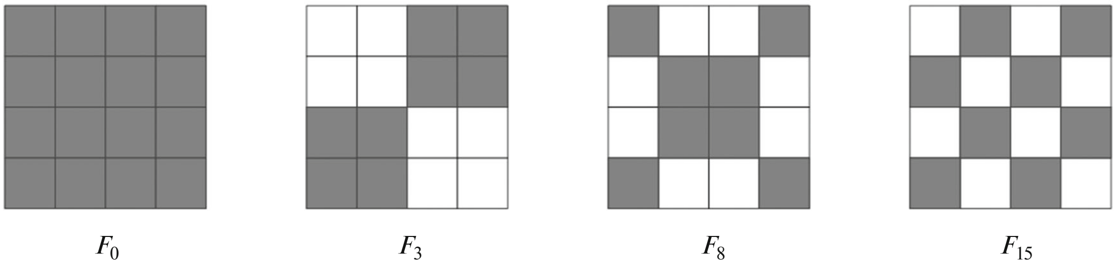

Fig. 1. Filters realizing differentiation transformation.

THEORY OF ACTIVE PERCEPTION

The theory of active perception provides solutions of two main problems of image processing that are image pre-processing and generation of its feature description [9]. From the standpoint of TAP, image pre-processing involves an integration operation; and the formation of the feature description involves a differentiation operation. The result of the first transformation is the set of the "visual" masses $\|m_{ij}\|$. The result of the second transformation is the vector $\boldsymbol{\mu} = (\mu_0, \mu_1, \mu_2, \ldots, \mu_{15})$. The differentiation transformation is fulfilled with the aid of 16 filters some of which we show in Fig. 1. The gray color denotes "+1" and the white color denotes "−1".

In Fig. 1, the filters look like the Walsh filters of the Hartmut system, however the way of their application differs since they are applied to an image only after the integration transformation was fulfilled.

In contrast to all the other known transformations, the pair of the transforms the first of which is the integral transformation and the second is the differential one are defined by the U-transform as the composition of a "true" (in the sense of the sequence of the carrying out) integro-differential transformation.

The section "Group Algebra" is the part of TAP. It deals with an analysis of dependences between spectral expansion coefficients. The found dependences can be used at the step of the decision-making process and understanding of the analyzed signal. Let a coordinate defined binary operator $V_i \in \{V_i\} \equiv \mathbf{V}$ corresponds to the filter $F_i \in \{F_i\} \equiv \mathbf{F}$. Then it is possible to assign the operator V_i or $\bar{V}_i$ to the component $\mu_i \neq 0$ of the vector $\boldsymbol{\mu}$ depending on the sign of the component. As the result, a subset of the operators from $\{V_i\}$ whose constructions are analogous to the construction of the filters, but different values of the elements of the matrix $(+1 \leftrightarrow 1, -1 \leftrightarrow 0)$ is associated with the vector $\boldsymbol{\mu}$. After defining operations of the set-theoretic multiplication and summation on the set of the operators $\{V_i\}$, we obtain an image description algebra in terms of the two-dimensional Boolean functions. The group algebra of the analyzed signal (the step of synthesis) is generated at the set of these operators. It consists of:

(1) A family of algebraic structures (the so-called complete groups) $P_n = \{P_{ni}\}$ of the form $P_{ni} = \{V_i, V_j, V_k\}$ and the cardinality 35. Each group is isomorphic to the complex neuron. The complete groups allow one to find out the correlative relations between the operators.

(2) A family of the algebraic structures (the so-called closed groups) $P_s = \{P_{si}\}$ of the form $P_{si} = \{V_i, V_j, V_k, V_r\}$ and the cardinality 105. Each group is isomorphic to the supercomplex neuron and formed from the pair of in a certain way related complete groups. The closed groups allow one to find out correlative relations between the complete groups.

An image can be formed for the complete and closed groups basing on the composing these groups operators. The image of the operator is a compact from eight elements; the image of the complete group is the compact from four elements; the image of the closed group is the compact from eight elements. For the operator and the group the mass is defined that is the sum of the image readings in the image of the group or the operator. Taking account of possible inversions of the operators included into the description of the complete and the closed groups there are 140 complete and 840 closed groups in all.

In comparison with the neural network theory TAP allows one to decompose the set of images into classes without learning. Next, the basic transformation of TAP, that is the U-transformation, has the minimal computational complexity since the simplest operations (the multiplication and summation) are used for it realization.

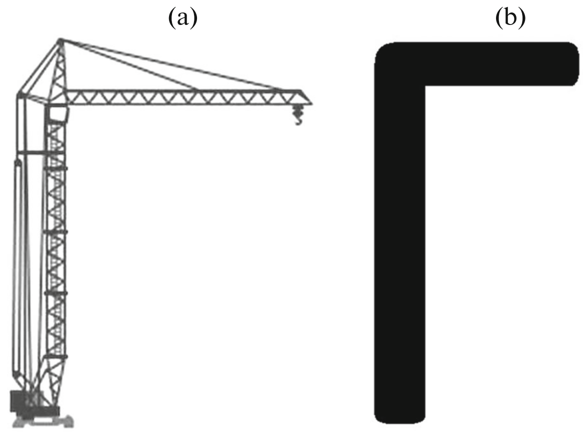

Fig. 2. Associatively connected images: (a) crane; (b) letter “Г”.

APPROACH TO DEVELOPMENT OF ASSOCIATIVE MEMORY

In psychology an association is the natural connection between two or some mental processes (such as sensation, ideas and so on), which is expressed in the fact that the appearance of one of them leads to appearance of the other or certain mental processes [10]. It is known that the concept “associational” only reflects the fact of the presence of connections between the data and has nothing to do with the mechanism of the data storage [1]. In the frame of the coverage, the operators (the groups) allow one to find out the connections between the descriptions of the images: if the images A and B have same descriptions D_A and $D_{B,}$ they can be regarded as the associatively connected. For example, the spectral coefficients of the images shown in Fig. 2 (see Table 1) have the same signs, and consequently they can be treated as the associatively connected.

TAP allows us to describe a mechanism of creation of connections between a pair of images; however, it does not describe the memory architecture. This is why for the generation of an associative memory model we propose a hierarchical structure, which is the M-level N-ary tree combined with the coarse-fine representation of the image. Let us discuss the concept of mechanisms for memorization and sampling of images. Their realization depend on the chosen architecture of the tree.

A memorization algorithm of an image I includes the following steps:

(1) The generation of a multilevel representation D of the image I:

$$\mathbf{D} = \mathrm{DEC}\,[I, M],$$

where $\mathbf{D} = \{D_{i,j}\}$ is the set of the image areas of I, $i = \overline{1, M}$, $j = \overline{1, N^{(i-1)}}$; M is the number of the levels of the decomposition (it is equal to the number of the levels of the tree); $D_{i,j}$ is the j-th image area of the i-th level, DEC is the operator of generation of a coarse-fine representation of the image;

(2) The generation of the feature description of the multilevel representation D of the image I:

$$\mathbf{H} = \mathrm{DESC}\,[\mathbf{D}],$$

where $\mathbf{H} = \{H_{i,j}\}$ is the multilevel feature description of the image I, M is the number of the levels of the decomposition (the given value of M corresponds to the number of the levels of the tree), DESC is the

Table 1. Spectral coefficients of images shown in Fig. 2

Number of coefficient	0	1	2	3	4	5	6	7
Fig. 2a	11130	–7808	–7457	–2316	–2088	–1738	–1675	–1583
Fig. 2b	33697	–21858	–12186	–8556	–6901	–4937	–4445	–3484
Number of coefficient	8	9	10	11	12	13	14	15
Fig. 2a	–1356	–1004	1160	1520	1801	1870	1893	7652
Fig. 2b	–3281	–2393	2321	3281	3397	3556	8440	13350

operator for the generation of the coarse-fine feature description of the image, $\mathbf{H}_{i,j}$ is the description $D_{i,j}$ of the image area;

(3) The selection of the set **Node** of the nodes of the tree (at each resolution level one node is chosen) to which the image I belongs; the choice of the node is determined by the proximity of the feature description of the image to a generalizing standard defined for each node:

$$\mathbf{Node} = \text{SELNODE}\,[\mathbf{H}],$$

where SELNODE is the selection operator of the set of the nodes, $\mathbf{Node} = \{\text{Node}_i\}$, $i = \overline{1, M}$;

(4) The storage of the image in the tree:

$$\mathbf{T} = \text{PUTIM}\,[I, \mathbf{Node}],$$

where **T** is the tree, PUTIM is the storage operator of the image in the tree.

In the general form a search algorithm includes two steps:

(1) The "coarse" search, which is used to reduce the volume of the processing information taking account of the structure of the tree. It consists of offering a hypothesis about the address of the node in the tree where the required image is supposed to be (the coarse search realizes the steps 1–3 of the algorithm of the storage of the image):

$$\mathbf{Node} = \text{ROUGH}\,[\mathbf{T}, I],$$

where ROUGH is the operator of the coarse search of the image, which performs the successive run over all the levels of the tree from the coarse level to the exact one; **Node** is the address of the terminal node in the tree. For example, in Fig. 3 the address of the node in the box is equal to {1, 2, 2};

(2) The "exact" search involves the comparison of the description of the required image with the descriptions of the images stored in the terminal node T_{ij} whose address is stored in **Node**, and the choice of the resulting image as the image that has the minimal distance to the required one:

(2.1) The sampling of images from the terminal node:

$$\text{Data} = \text{GET}\,[\mathbf{T}, \mathbf{Node}],$$

where Data is the set of images stored in the terminal node with the address **Node**, GET is the sampling operator of the images from the tree;

(2.2) The comparison of the images from Data with the required image:

$$\text{IND} = \underset{k \in \overline{1,|\text{Data}|}}{\arg\min}\, \text{FINE}\big[\text{Data}(k), I\big],$$

where Data (k) is the k-th image stored in the node T_{ij}, IND is the index of the found image, FINE is the operator of the "exact" search, |Data| is the power of the set Data.

The input data for the developed algorithms of the image storage and search are:1) The multilevel representation of the image:

$$\mathbf{D} = \text{DEC}\,[I, M];$$

(2) The feature description of the image in terms of the operators (**HV**):

$$\mathbf{HV} = \text{GETV}\,[\mathbf{D}],$$

(3) The feature description of the image in terms of the complete groups (**HFG**):

$$\mathbf{HFG} = \text{GETFG}\,[\mathbf{D}],$$

where $\mathbf{HFG} = \{\text{HFG}_{i,j}\}$ is the feature description in terms of the complete groups, $i = \overline{1, M}$, $j = \overline{1, N^{(i-1)}}$, GETFG is the operator for generation of the feature description in terms of the complete groups, $\text{HFG}_{i,j}$ is the description of the image area $D_{i,j}$ that contains the information about the complete groups and their masses;

(4) The feature description of the image in terms of the closed groups (**HCG**):

$$\mathbf{HCG} = \text{GETCG}\,[\mathbf{D}],$$

where $\mathbf{HCG} = \{\text{HCG}_{i,j}\}$, $i = \overline{1, M}$, $j = \overline{1, N^{(i-1)}}$, GETCG is the operator for generation of the feature description in the terms of the closed groups, $\text{HCG}_{i,j}$ is the description of the image area $D_{i,j}$ that contains the information about the closed groups and their masses.

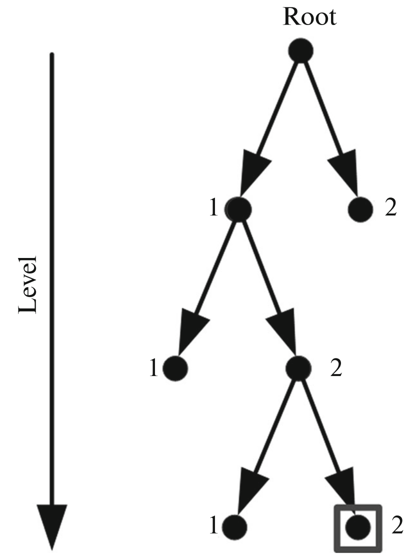

Fig. 3. Node address.

The algorithm for selection of the set of the nodes includes:

(1) The algorithm for selection of the area of interest of the image at the i-th level;

(2) The algorithm for selection of the node at the i-th level.

Let us examine the possible approaches to the selection of the area of interest at the i-th resolution level:

(1) The analysis of descriptions of all the image areas at the i-th resolution level. When using this approach at the i-th level we choose the area that is not connect with the area at the $(i - 1)$-th level. The reason for using this approach is the highest noise immunity of the operators and groups with the maximal masses;

(2) At the i-th resolution level ($i > 2$), we choose the area, which is (a) the daughter of the area that has been chosen for analysis at the $(i - 1)$-th level and (b) includes the operator (the group) with the maximal mass. At that:

(2.1) At the first resolution level the feature description of the initial image is examined as a whole;

(2.2) At the second resolution level, we choose the area for examination basing only on the masses of the operators and groups (that is without considering the parent area).

(3) At the i-th resolution level ($i > 2$), we choose the area, which is the daughter of the area that has been chosen for examination at the $(i - 1)$-level and includes the operator V_0 with the maximal mass. At that:

(3.1) At the first resolution level, the feature description of the initial image is examined as a whole;

(3.2) At the second resolution level, the area for examination is chosen taking account of the mass of the operator V_0 only.

The trees of two kinds are proposed for the images storage. The architecture of the tree of the first kind is generated taking account of the structure of the feature description of the image. With regard to the whole image as well as of any of its subarea, the feature vector can be generated in terms of the 30-dimensional vector of the masses of the operators, the 140-dimensional vector of the masses of the complete groups and the 840-dimensional vector of the masses of the closed groups. As the "N-ary tree", we denote the tree that uses such feature description.

The architecture of the tree of the second kind uses the possibility to convert the feature description of the image to the binary vector. That allows one to use the binary tree for storing the images. This architecture is denoted as the "binary tree".

Taking account of the proposed algorithms for selecting the area of interest, let us examine algorithms for defining the node of the tree for the image at the i-th resolution level placement:

(1) For the N-ary tree ($N = 30, 140, 840$) they are:

(1.1) An analysis of the description of the area of the image that has been selected at the i-th level taking account of the parent area. For this, we choose the operator or the group (complete or closed) with the maximal mass. The selected operator (group) specifies the node where the image is placed ($3 \times 2 = 6$ models are accessible; 3 is the number of possible descriptions, which are the operators, complete and closed groups);

(1.2) An analysis of the descriptions of all the areas of the image at the i-th level without taking account of the parent area. For this, we combine the masses of the operators (groups) from all the parts of the image and then select the operator (group) with the maximal mass. The selected operator or group defines the node in which the image is placed ($3 \times 1 = 3$ models are accessible).

(2) For the binary tree they are:

(2.1) An analysis of the description of the area of the image that has been selected at the i-th level taking account of the parent area. For this, on the basis of the operators (groups) the binary description of the selected area is generated; then we define the node (the generalizing standard) up to which the Hamming distance from the obtained feature description is minimal ($3 \times 2 = 6$ models are accessible);

(2.2) An analysis of the descriptions of all the areas of the image at the i-th level without taking account of the parent area. For this, we define the area whose feature description contains the operator (group) with the maximal mass. Then for the selected area we generate the binary description; after that we choose the node of the tree up to which the Hamming distance from the obtained description is minimal ($3 \times 1 = 3$ models are accessible).

Let the set of the images Data be the result of the coarse search. Having in mind to define images that belong to the set Data, at the last level of decomposition it is proposed to compare the descriptions in terms of the operators of the images that are the most similar to I (the realization of the operator FINE):

$$\mathrm{IND} = \underset{k \in \overline{1,|\mathrm{Data}|}}{\arg\min}\, \mathrm{DIST}[HV_I, HV_k],$$

where DIST is the operator of calculation of the distances between the descriptions, IND is the index of the image whose description is the most close to the required image I, HV_k is the description of the k-th image from the set Data and HV_I is the description of the required image I.

Taking into account a rapid increase of the number of nodes when using the complete and closed groups ($N = 140$ and $N = 840$), in what follows we develop the model of the N-ary tree for operators only. Consequently, below we will test $2 + 1 + 6 + 3 = 12$ models.

COMPUTER SIMULATIONS

The aim of our computer simulations was to estimate the stability of the proposed models for the search of images subjected to various distortions. To define the quality of our search criterion we used the number of the distorted images incorrectly chosen from the database. We considered the following distortions: the Gaussian noise, rotations of images, scaling of images, a reduction of the image resolution and the image screening. We also estimated the ability of the proposed models to search similar images.

In our computer simulations we used images whose minimal heights and widths were 2048 readings; the size of the database was 5×10^5 images. The reliability of a search of an image without distortions was 100%.

In Table 2, we present the values of the errors of the search averaged over the types of distortions for different models.

During the computer simulations, we found that when using the binary models based on the complete groups where the selection of the area at the i-th level is carried out taking account of the parent area, conflicts with the possibility to define the belonging of the image to the left or to the right node of the tree. This is why in Table 2 we show the test results for ten but not for twelve models as it was mentioned above.

In Tables 3–7, for different types of distortions we present the percent of incorrectly found images obtained with the aid of the model No. 1.

Independent of the model the time necessary to add an image into the tree is 0.015 s, the time of the "coarse" search is 0.05 s, the time of the "exact" search is 0.03 s; and the total time of the search was 0.08 s.

The size of the description of an image stored in the database depends on the level of resolution where this description was generated. The size of the description of one part of the image is 30 bits. Consequently, at the 4-th level of the tree the size of the description is $64 \times 30 = 1920$ bits and on the 6-th level, it is 30720 bits.

In Table 8, we list the timing characteristics for different methods of image search.

In Table 9, we present the estimates of running times for different algorithms when calculating the hashes. We analyzed the algorithms based on the discrete cosine transform (DCT), the Marr-Hildreth

Table 2. Averaged value of errors of searches

Model number	Selection of area at i-th level	Selection of node at i-th level	Type of tree	Value of error
1	Taking account of area at $(i-1)$-th level; operator with maximal mass	Operator with maximal mass	N-ary	25.97
4	Taking account of area at $(i-1)$-th level; operator V_0 with maximal mass	Operator with maximal mass	N-ary	27.09
7	Without account of area at $(i-1)$-th level	Operator with maximal mass	N-ary	31.79
10	Taking account of area at $(i-1)$-th level; operator with maximal mass	Minimal distance to generalizing standard—vector of 30 elements	binary	46.79
12	Taking account of area at $(i-1)$-th level; closed group with maximal mass	Minimal distance to generalizing standard—vector of 840 elements	Binary	75.94
13	Taking account of area at $(i-1)$-th level; operator V_0 with maximal mass	Minimal distance to generalizing standard—vector of 30 elements	Binary	52.48
15	Taking account of area at $(i-1)$-th level; operator V_0 with maximal mass	Minimal distance to generalizing standard—vector of 840 elements	Binary	63.73
16	Taking account of area at $(i-1)$-th level; operator V_0 with maximal mass	Minimal distance to generalizing standard—vector of 30 elements	Binary	49.97
17	Without account of area at $(i-1)$-th level; complete group with maximal mass	Minimal distance to generalizing standard—vector of 140 elements	Binary	58.03
18	Without account of area at $(i-1)$-th level; closed group with maximal mass	Minimal distance to generalizing standard—vector of 840 elements	Binary	59.45

Table 3. Error of search when distorting image by normal noise

Level of noise (dB)	20	10	0
Value of error	0	0	1

Table 4. Error of search under reduction of resolution of image

Size of averaged area (in readings)	10 × 10	30 × 30	50 × 50	70 × 70	90 × 90
Value of error	0	0	2	3	5

Table 5. Error of search under scaling of image

Scaling coefficient in vertical direction	0.3	0.6	0.9	1.1	1.5	1.9	0.3	0.6	0.9	1.1	1.5	1.9
Scaling coefficient in horizontal direction	0.3	0.6	0.9	1.1	1.5	1.9	1.1	1.5	1.9	0.3	0.6	0.9
Value of error	3	2	1	1	0	0	2	2	1	2	1	0

Table 6. Error of search under rotation of image

Angle of rotation	1°	2°	3°	4°	5°	6°	7°	8°	9°
Value of error	20	36	48	59	69	76	83	88	92

Table 7. Error of search under overlapping of images

Percent of overlapping	5	15	25	35
Value of error	17	67	86	90

Table 8. Estimate of time of search of image

Algorithm/ Parameters	Size of database	Time of search (in seconds)	Description in use stored in database	Method to organize search
1	2×10^4	1.05	GIST, 512 elements [5]	Search based on *kd*-tree
2	2×10^4	0.38	GIST, 512 elements [5]	Exhaustive search
3	1.29×10^7	0.146	GIST, 30 bit [5]	Exhaustive search
4	1.29×10^7	0.75	GIST, 256 bit [5]	Exhaustive search
5	2×10^4	4.3×10^{-4}	GIST, 30 bit [5]	Exhaustive search
6	2×10^4	1.4×10^{-3}	GIST, 256 bit [5]	Exhaustive search
7	1×10^7	0.1	TAP [11]	Exhaustive search
8	1×10^7	0.5	TAP, (noisy image search) [11]	Exhaustive search
9	5×10^5	0.08	TAP (4 level—1920 bit, 6 level—30720 bit)	Tree search
10	1×10^6	1.26	GIST [12]	Exhaustive search

operator (MH), the Radon transform (Radial) and the mean value of the image block (BMB). Also in the same table, we show the size of the memory occupied by a hash.

In Table 10 we give the computing time of the proposed feature description of an image averaged over 5×10^5 images.

In Fig. 4, the results of searching of similar images are shown.

Our computer simulations results in the following conclusions:

(1) In contrast to the structure of the *kd*-tree the structure of the tree used in the proposed models is fixed, balanced and does not change during generation of the database. This allows one to increase the search efficiency.

(2) When comparing Table 9 and Table 10 it is seen that the computing time of the feature description we propose is less than the computing time of the known descriptions. Taking into account that the real-

Table 9. Performance characteristics of methods of calculation of hashes

	DCT [6]	MH [6]	Radial [6]	BMB [6]	GIST [12]
Time of calculation of description (in seconds)	9.7	3.6	1.3	0.6	0.035
Size of description (in bits)	64	576	320	49	30720

Fig. 4. Associatively related images.

ization of the computing algorithms was done with the programming language R the processing power has to increase if the compiled languages are used.

(3) In contrast to the known methods of the image search by content, in the proposed approach we use the strategy of the successive refinement of the position of the image in the memory address space. This corresponds to perception systems where the "preference" is given to the procedures that are moving forward from an approximate solution to the exact one with an input of new information at each step [13].

(4) Analyzing Tables 3–7 we conclude that the search method based on the proposed model of the associative memory is highly stable when searching for images distorted by scaling, the additive noise or whose resolutions were reduced; it is less stable when images are rotated or in the case of overlapped images.

(5) The model based on the N-ary tree shows the best results when searching the distorted images. Then in decreasing order it is followed by the models of the binary tree that use operators, complete groups and closed groups, respectively.

(6) The proposed model of the organization of the memory is similar to the methods of global hash-coding. At that the structure of a hash includes the description obtained basing on the operators (for solving the problem of the "exact" search) as well as the address of the image in the structure of the tree (the numbers of the nodes of the tree). However, in contrast to the method of the semantic hashing the number of the searched images does not depend on the size of the description.

Table 10. Time of calculation of multiscale description (in seconds)

Level/Type of description	Operators	Complete groups	Closed groups
4	0.58	0.60	0.61
6	0.93	1.27	1.76

CONCLUSIONS

In the present paper, we propose the approach to generating the associative memory models based on the theory of active perception. Practical applications of such models are the image search by content. Our results show that with regard to time characteristics the proposed models are as good as the known approaches to search for similar images; and in some cases, they are even better.

Our computer simulations confirm that our models possess certain properties of the associative memory. Namely, they are an ability to complement the images, correct them and to carry out a search of similar images.

We test the proposed models on the database consisting from 50000 images. If it is necessary to increase the number of stored images, we can simultaneously use more than one model of the memory each of which stores a subset of the input set of images. In this case, a parallel search can be helpful. The division of the whole set of images between a number of models allows one to keep constant the time of the "exact" search. Note there is a possibility to parallelize the step of the "exact" search.

The aim of our future studies is to improve the time characteristics of the methods of generation the feature description of images and to develop schemes of interaction between the models for storing a larger number of images.

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