Serdica J. Computing **7** (2013), No 4, 333–342

Serdica
Journal of Computing

Bulgarian Academy of Sciences
Institute of Mathematics and Informatics

CONTENT-BASED IMAGE RETRIEVAL FOR COMPUTER TOMOGRAPHY IMAGES USING WAVELET DESCRIPTORS

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Abstract. An approach to building a CBIR-system for searching computer tomography images using the methods of wavelet-analysis is presented in this work. The index vectors are constructed on the basis of the local features of the image and on their positions. The purpose of the proposed system is to extract visually similar data from the individual personal records and from analogous analysis of other patients.

1. Introduction. The increasing penetration of modern information technologies in systems for organizing, storing, searching and transferring data is a prerequisite for the continuous increase of the amount and volume of image collections and of different types of multimedia databases. Regardless of the unified approach for constructing systems of image search content, there is no universal algorithm for indexing and searching applicable to different types of databases. For example, if shape or other obvious visual distinctions are used for standard images, the main features of medical images tend to have an implicit, hidden character [1]. In this connection, the issues of developing efficient, fast,

ACM Computing Classification System (1998): H.3.1, H.3.3, I.5.4.
Key words: CBIR, wavelet, SDWT, wavelet-maxima, medical image database.

reliable, safe and base-adapted methods for indexing and searching images for recognition and identification according to their content will continue to be open, live and dynamically developing.

2. The CBIR-system model. To build a model search system a database of images is used: $S = \{s_i\,[n,m]\}$, where $i \in I \subset \mathbb{N}$, $n,m = 0,2,\ldots,2^{k_{\max}}-1$, $k_{\max} \in \mathbb{N}$ and ψ is a fixed binary wavelet. We use *SDWT* (*Stationary Discrete Wavelet Transform*) to represent each image from S in the descriptor space: $\bigcup\limits_{i\in I}\left\{D_r^H(s_i), D_r^V(s_i), D_r^D(s_i), r=\overline{1,k}\right\}$, where $1 \le k \le k_{\max}$, and $D_r^{\Theta}(s_i)$, $1 \le r \le k$, $\Theta = H,V,D$ are the corresponding matrices of the detailing coefficients of the three ranges. It is known that the local features of the image cause significant values of the wavelet-image amplitude. *Mallat's* algorithm [2] represents the wavelet transform by lowpass and highpass analysis filters. The impulse response of the corresponding filters, as they pass through the points of a transition process in the image, respectively, the amplitude of the corresponding wavelet base, will have a local maximum [3].

The initial reduction of the dimensionality of the feature vector can be done on the basis of significant wavelet coefficients. Applying threshold processing based on a particular criterion for each level of decomposition $r = 1,2,\ldots,k$ we determine m_r^{Θ}, $\Theta = H,V,D$, respectively the largest and smallest detailing coefficients, corresponding to the wavelet maxima of the *SDWT* modulus. Thus a $3 \times k \times 2$-block-matrix of the descriptors $D_\psi(s)$, $s \in S$ is created. For the rth decomposition level each block represents a $2m_r^{\Theta}$−dimensional array: one is $P_r^{\Theta}(s)$, $\Theta = H,V,D$, consisting of the values of the local extrema, and the second, $L_r^{\Theta}(s)$, $\Theta = H,V,D$, contains their positions. A similar matrix of the descriptors $D_\psi(s_0)$ is built for the image-query s_0.

The similarity of the matrices of the descriptors $D_\psi(s)$ and $D_\psi(s_0)$ is estimated using the distance between their respective arrays:

$$\rho^i_{L^\Theta} = \min_{1\le r\le k} \rho_0\left(L_r^{\Theta}(s_i), L_r^{\Theta}(s_0)\right) \quad \text{and} \quad \rho^i_{P^\Theta} = \max_{1\le r\le k} \rho\left(P_r^{\Theta}(s_i), P_r^{\Theta}(s_0)\right),$$

$\Theta = H,V,D$, where ρ_0 is the relation *equation* in the set of real numbers, and ρ is a metric function.

The result of the content-based search in the database S is the set of similar (relevant) images $R = \{s_i,\ i \in I_0 \subset I\}$, if $\rho^i_{L^\Theta} \ge 2\lambda_r^{\Theta}\sum\limits_{r=1}^{k} m_r^{\Theta}$ and $\rho^i_{P^\Theta} \le \mu^{\Theta}$, $\Theta = H,V,D$, for each $i \in I_0$. The parameters I_0, λ_r^{Θ} and μ^{Θ} are further set

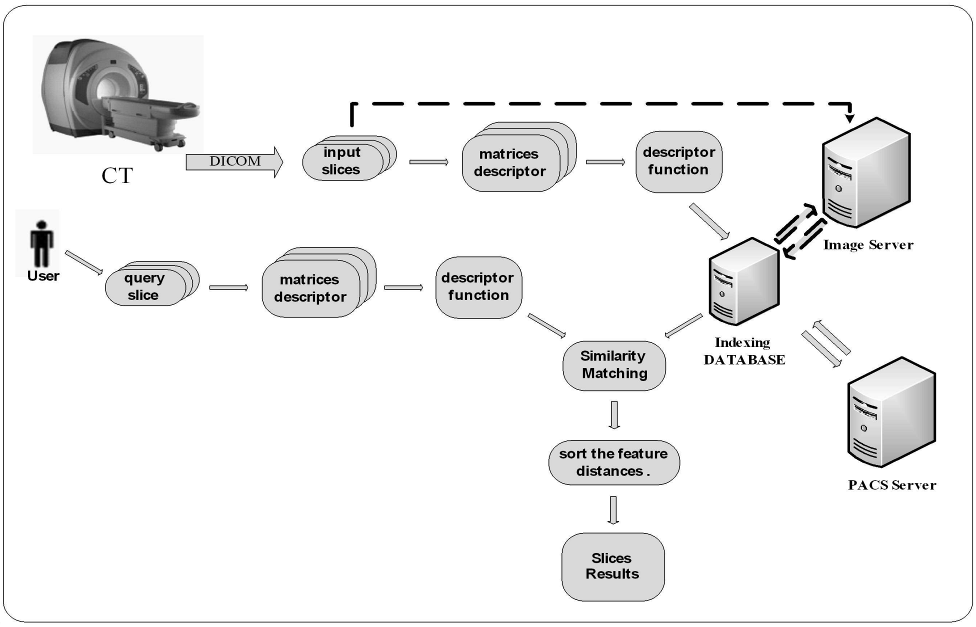

Fig. 1. A flowchart of the CBIR system

by the user. In cases where the image s_0 is contained in the S, for some $i_0 \in I_0$ we will have $\rho^{i_0}_{L\Theta} \approx 2\sum_{r=1}^{k} m^{\Theta}_{r}$ and $\rho^{i_0}_{P\Theta} \approx 0$,for$\forall\Theta = H, V, D$.

Fig. 1 shows the flowchart of the suggested model of the *CBIR* system

3. Methodology for determining the parameters of the system. To conduct the study and the analysis, as well as to determine the parameters of the proposed model of the *CBIR* system, a database of medical images is developed using a computed tomography study of 15 patients. The results thus obtained are divided into three groups: head, spine and knee joint, containing respectively 5437, 2998 and 1847 slices. The medical images are in the output format *DICOM* (*Digital Image and Communications in Medicine*), extracted directly from the CT, without previous processing which could lead to less informative data.

The parameters of the *CBIR* system are determined on the basis of the comparative wavelet analysis that has been carried out. For this purpose the following tasks are performed:

- determining the most informative decomposition level;
- choosing the analysing basis wavelet;
- minimizing the dimensionality of the descriptor space;
- investigating the stability of the system depending on different factors: rotation, varying brightness, contrast and noise.

Representatives of the following main three groups are used as analyzing basis wavelets:

- *orthogonal wavelets with a compact support:*
  - *Daubechies:db2,db3,db4,db6,db8,db10;*
  - *Coiflets:coif1,coif2,coif3,coif5;*
  - *Symlets:sym2,sym3,sym4,sym6,sym7,sym8;*
- *biorthogonal wavelets with a compact support: bior2.4, bior2.6, bior3.1;*
- *Mayer's wavelets: dmey.*

3.1. Determining the most informative decomposition level. *Shannon's* non-normalized entropy [4] is used as a criterion for determining the most informative decomposition level. For this purpose, 300 images (slices) of all the available ones in the database (10282) are sampled. For each of the patients 20 slices are randomly selected and subjected to $SDWT$ by means of the underlying wavelets of the target groups, up to the sixth level of decomposition ($k = 6$). Fig. 2 presents the results for three of the wavelets where the relative variation of the entropy has the highest values.

From the graph in Fig. 2 it is seen that after the third scale the change $\dfrac{dE}{E_r}$ decreases dramatically, i.e., the upper levels of decomposition do not cause any significant changes in the quantity of the information contained in the respective wavelet coefficients [5]. Therefore it can be assumed that the fourth level of decomposition is the most informative, i.e., $r = 4$.

3.2. Determination of the basic wavelet. In order to determine an analyzing basis wavelet, we use its "sensitivity" to the respective database [6], determined by a given metric. From the sample thus formed we choose a slice for each patient from each of the groups of anatomical organs. On their basis

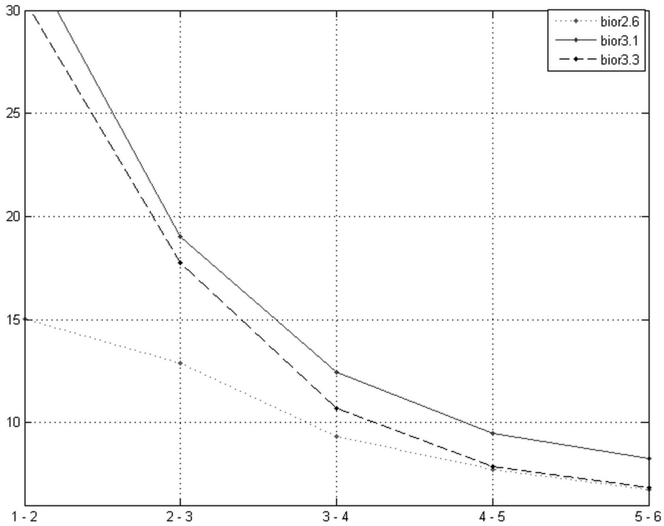

Fig. 2. The dependence of the relative entropy change rate on the level of the decomposition

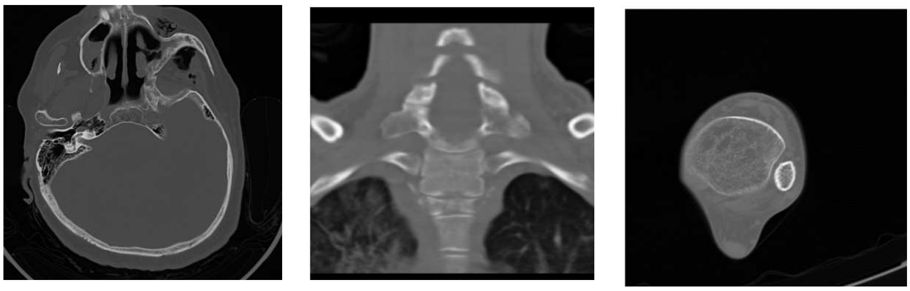

Fig. 3. Anatomical slices for head, spine and knee

five additional images are generated. They are obtained by adding the Gaussian noise having the following parameters: means $\mu = 0$, for different values of the variance: $v = 0.01$; 0.02; 0.05; 0.75; 0.1 indicated with s_v. Their descriptors matrices $D_\psi(s_v)$ and $D_\psi(s)$ are constructed for $r_{opt.} = 4$ using all the basic wavelets. In order to assess the similarity of $D_\psi(s_v)$ and $D_\psi(s)$ we use cosine distance metric, and the sensitivity of the analyzing wavelet is determined by its maximum value. Fig. 3 presents an image of each of the studied groups of anatomical organs, while Fig. 4 presents the results for three of the wavelets having the highest sensitivity to the base of medical images in question.

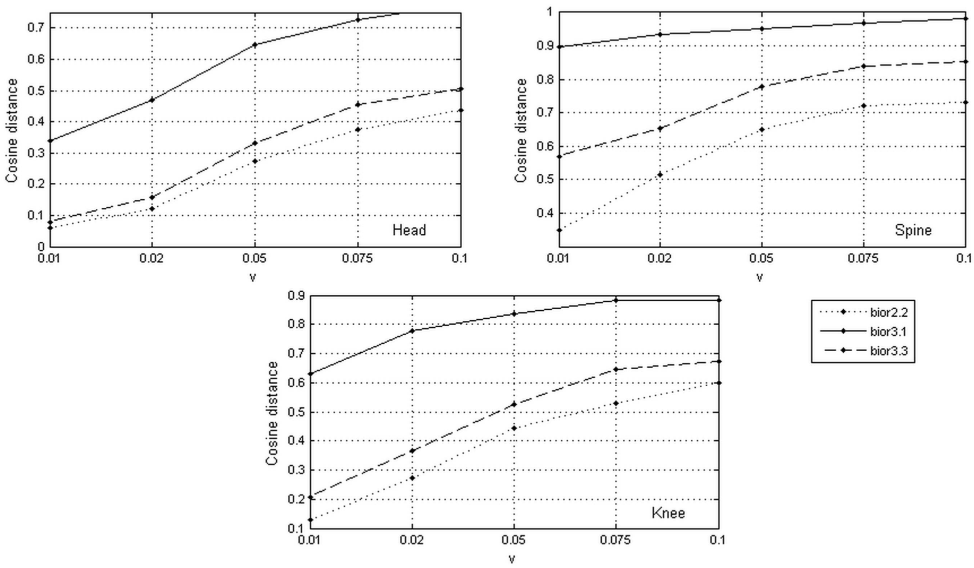

Fig. 4. Sensitivity of the basic wavelet

From the results obtained it follows that of all analyzing wavelets *bior 3.1* has the highest sensitivity for this database of medical images, a result which is confirmed by the graphs in Fig. 2.

3.3. Minimizing the dimensionality of the descriptor space. Finding the minimal length of the index vector means finding the optimal value of the parameter m. Again as an optimality criterion, we use the relative change of entropy for the already formed sample. Two types of research have been carried out for the variation interval of m: $m \in \{25, 50, 100, 150, 200, 250, 300\}$ and $m \in \{500,\ 1000, 1500, 2000, 2500, 3000\}$. In the first case the task is to search for visually similar images in the patient's record. The second group of studies that determines the optimum value of m refers to retrieving similar images from similar analysis of other patients. Fig. 5 shows the results of the study determining the optimal value of the parameter m, respectively $m = 150$ and $m = 1750$.

3.4. The stability of the algorithm in terms of the impact on different groups of qualitative factors. To study the stability of the proposed search algorithm a one-way analysis of variance is performed. The objective is to determine the effect of the four groups of factors (rotation, contrast, brightness, and noise), on the degree of divergence of the mathematical expectation of the number of matches between the feature vectors of the elements, taking into ac-

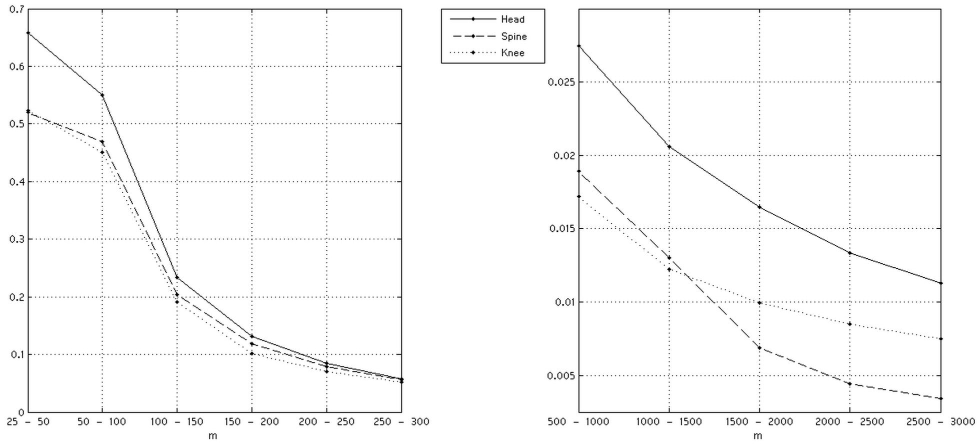

Fig. 5. Dependence of the relative entropy change rate at the individual levels of the changes m

count the positions of the specific points of the images. The applicability of the analysis is grounded with *Cochran's* criterion [7], concerning equality at grand variance.

Further, from the sample already formed four slices are selected for each of the patients examined for the three groups of anatomical organs. Additonal ones are generated on the basis of each image applying the following levels of the corresponding factor F for the factor groups to be analyzed: for rotation – -2°, -1°, 1°, 2°; for contrast and brightness – 5%, 10%, 15%; for noise (Gaussian) – 0.01, 0.02, 0.05, 0.075, 0.1.

The results of the analysis of variance at a level of significance $\alpha = 0.05$ are shown in table 1.

Table.1. Application of the Fischer-Snedecor criteria for different groups of factors

Study	groups of factors					
	rotation		contrast	brightness	noise	
	F	$F_{tabl.}$	F	F	F	$F_{tabl.}$
Head	25.42	2.76	3	0.32	0.04	3.21
Spine	3.09	2.7	1.97	0.63	3	3.13
Knee	4.91	2.76	2.78	0.33	0.08	3.21

From the obtained results according to the *Fischer-Snedecor* criteria it follows that the contrast, brightness, and the noise do not significantly affect the normal distributions signs, while the rotation has a significant impact on the investigated random variable.

4. Experimental part. The proposed model of a *CBIR*-system of medical images indexed by the maximum of the wavelet-transform modulus (Fig. 1) is a program implemented in *Matlab* using the additional packages *Image Processing Toolbox* and the *Wavelet Toolbox*. *MySQL Database Server* and *EMS SQL Manager* are used for the implementation of the database. The connection between the *Matlab* and *MySQL* database is done with a *JDBC* (*Java Database Connectivity*) protocol.

The experimental testing of the system search was conducted with the created database containing 10282 images (slices), obtained by CT studies of 15 patients in three types of research categories: head, spine and knee. The medical images are in the output format *Dicom*, *CT Siemens – Somatom Definition* and *Somatom Spirit*.

The suggested model of a search system is implemented in two main modules. The first is used to enter a new patient's analysis into the database and includes storing, structuring and indexing the results of the diagnostic imaging examination done on the patient. The second module searches for visually similar images using a given sample. This process can be implemented at two independent stages. The first stage is the process of extracting a limited set of series of slices from the individual patient's record and is only applicable to the cases where the record is included in the database. At the second stage similar images

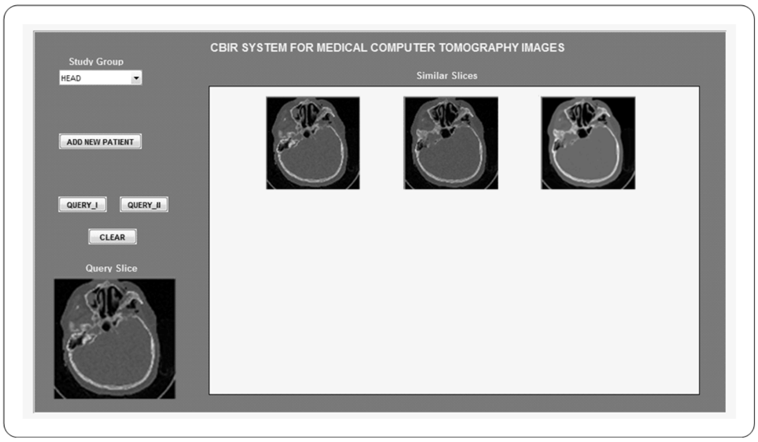

Fig. 6. CBIR-system interface

are found using a given sample in a set of series of slices in the examinations of different patients. The extraction process ends with the display of similar images ordered according to the metrics. Fig. 6 shows the interface of the *CBIR* system as well as the results of the performed experimental search. In addition, it is also necessary to assess the quality of the system in order to compare it with similar ones.

In order to test the search system a full range of slices from patients' medical analyses are used. Their number can be the reduced in order to decrease the size of the indexed database. A few slices are enough for the recognition tasks. Only the most specific slices for the particular disease can be used for the diagnosis and monitoring of clinical results, as well as for conducting a comparative analysis of images of other patients. This significantly improves the performance of the algorithm.

5. Conclusion. This paper presents a model of a system for retrieving images by content indexed through their local peculiarities, taking into account their positions in the data. The local features of the images correspond to a maximum module of two-dimensional wavelet-transformation. Together with their positions they can be used to index the tomography slices in the search algorithm. The paper also proposes a methodology for determining the optimal (according to a given criteria) parameters of a system for medical images retrieval. The suggested search algorithm is based on a comparison of the visual similarity of the images without considering the data from the header portion of the DICOM files. The results obtained lead to the conclusion that the proposed system model is a satisfactory solution to the assigned tasks. In the future it is necessary to improve the proposed algorithm in terms of its resistance to rotation, as well as to reduce the effect of noise.

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Received March 6, 2014
Final Accepted May 15, 2014