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Systems for Searching for Magnetic Resonance Images using the Matrix of Maximum Singularities

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Abstract. *Compared to images of a more general nature, medical images possess a number of specific peculiarities. This requires the development of specialized methods and software in order to obtain, process, store, and analyze them. The paper presents and implements models of a system for content-based search in a magnetic resonance (MR) images database, based on some wavelet transforms. The Matrix of the Maximum Singularities (MMS) descriptor, which demonstrates stability with respect to some qualitative factors leading to changes in the MR image content, has been constructed by means of a wavelet transform*.

1. Introduction

The development of modern diagnostic medical equipment leads to the accumulation of huge amounts of medical images belonging to different modalities. The comparison of a medical-diagnostic image with previous images of the same modality belonging to the same patient or with similar images of other patients is one of the main activities in medicine and scientific research. For this purpose, images need to be stored, retrieved from databases and transferred. The amount and volume of collections containing such images are a prerequisite for the development of effective indexing, retrieval, recognition and identification methods that are fast, reliable and accurate.

The currently developed methods for extracting graphical information are divided into two main groups [21]:

- Text-Based Image Retrieval (TBIR);
- Content-Based Image Retrieval (CBIR).

Regardless of the mass spread of TBIR-systems, the indexing metadata used by them (key words, image names, etc.) require a considerable amount of time and human resources, which gradually limits their application.

The information in CBIR-systems is described by the Feature Vector (FV), which is a set of numerical parameters defined on the basis of individual visual features or their combination, such as shape, texture, colour, brightness, etc. The main advantage of these systems is the full automation of the algorithm of indexing and retrieving data from a database based on their primitives without using any additional information about them. This turns the development of such systems into a fast growing scientific field, yet their efficiency is still much lower than that of TBIR-systems.

A major drawback of the CBIR-systems is the so-called semantic rupture [19, 20]. When the user compares two images, he first compares their semantic content, whereas the system's assessment is based on the visual characteristics of the image (low-level characteristics) – colour, shape, texture, etc. The minimization of this semantic gap is one of the main tasks whose solutions are needed in order to improve the quality of these systems. In an attempt to address some of the shortcomings of the two types of systems, hybrid systems are proposed. Their components are both TBIR-systems and CBIR-systems [2, 18].

Due to some peculiarities of medical images, the methods for retrieving general-purpose images cannot be expected to be also directly applicable to medical databases. This requires the creation of Text-Based Medical Image Retrieval (TBMIR) and Content-Based Medical Image Retrieval (CBMIR) subclasses of the text and contextual search systems respectively. They are designed to retrieve images from medical bases.

The effectiveness of using such clinical cases in diagnostic and scientific activities is related to the improvement of Picture Archiving and Communication

System (PACS) systems and the development of relevant information technologies. The initial developments of medical image retrieval systems are text-based requests or requests based on matching accurate data from the respective database. The metadata used is manually entered information about the content of the database image, as well as clinical and other patient information. In PACS systems, there is not a FV selection module, and the textual information contained in the Digital Imaging and Communications in Medicine (DICOM) protocol is commonly used to index the image. Therefore, such TBMIR-systems have specific applications, as this indexing structure is oriented toward the identification of particular medical cases and is often not targeted at large-volume bases. Therefore, the development of algorithms for the automatic indexing of the content of images in pattern extraction systems is a topical task in the field of processing, analysing, recognizing and identifying medical images. The wide range of applications of these algorithms, from computer-based diagnostic solutions to methodological and research activities, is a major impetus for the development of CBMIR-systems in these fields.

In the development of CBMIR-systems, some of their peculiarities distinguishing them from general images should be taken into account. V. Kovalev [9] identifies three such parameters: incompatibility of image classes, insignificant intra-class differences, and specificity of class-defining signs. This requires the development of specialized algorithms for automatic indexing of their content and recognition. It is necessary to distinguish the cases in which a patient's actual image has to be compared with images of their previous studies from those when comparison is carried out for the purpose of a comparative analysis of the normal and pathological conditions. In the first case, it is sufficient to use common visual features, while in the second case differences are due to specific features, typical of the respective type of pathology, and thus specialized training is required.

CBMIR-systems use features (such as texture, structure, scale presentation, etc.) of the images or their regions in order to build the indexed base necessary for the efficient retrieval of these biomedical images. In the field of medicine, the characteristics of the absolute colour or the level of grey are usually of very limited distinctive power, with the exception of some special exploration images. The descriptor functions based on textures play an important role as powerful distinguishing visual features. One of the first methods for presenting textural features are Haralick's classic co-occurrence matrices [6]. The different information and statistical properties of Haralick's classic co-occurrence matrices and their generalizations are often used as hallmarks in CBMIR-systems.

The strongly expressed texture of MR images, compared to that of images from most modalities (for example, without ultrasound), is a consequence of the physical principles for their production [14]. In [9, 10], generalized co-occurrence matrices are proposed for analysing the three-dimensional (volume) textures and their use as descriptors of a CBMIR-system for extracting MR images. The brightness level, the absolute value of its gradient, and the angle between the vectors of the gradients in the respective voxels of the image are the basic parameters for the construction of these matrices.

A characteristic feature of most of the methods for constructing FVs in systems for pattern-based extraction is their single-scale spatial domain. The multiscale transformations are a convenient method for analyzing inhomogeneous structures because this analysis is performed simultaneously in the physical and frequency spaces. According to Heisenberg's principle, the spatial and frequency resolution are in an inversely proportional dependence. Since the sharp changes in the intensity of the image are observed at small scales, its analysis can be performed at a good spatial resolution [1].

This section provides a brief overview of a very small part of image methods and characteristics that construct the descriptor spaces of the corresponding CBMIR-systems. More detailed information on the topic can be obtained, for example, from [4, 15].

The purpose of this paper is to build and implement some models of a CBMIR-system for extracting images from large databases of MR images. In defining the FV of the system, we use the fact that the peculiarities of the image are usually the bearers of its basic information. On the other hand, it is known that wavelet transforms are a suitable registrar of these non-smoothed structures in the image [11].

The dimension of the descriptor space directly affects the qualities of the system. In order to build the indexed base of the system, a special matrix of maximum singularities is introduced. Experimental studies have been conducted to establish the qualities of this matrix as a search system descriptor.

The paper is organized in the following manner: *Section 2* contains a short description of the wavelet transformations used. *Section 3* introduces the matrix of maximum singularities for indexing MR images, whereas *Section 4* provides some wavelet-based models of the recognition system. In the next two parts, a comparative analysis of the proposed algorithms is carried out, and the stability of one of them with regard to some qualitative factors has been established. The experimental results from the sensitivity analysis of the proposed descriptor are presented in *Section 7*, and the last section contains concluding notes on the analysis of the models of the

CBMIR-system models that have been constructed, as well as on the characteristics of the proposed descriptor.

2. Wavelet transformations

In this section, we will describe three wavelet transformations used in the present work. Their detailed descriptions are contained in [3, 11, 17].

The one-dimensional Discrete Dyadic Wavelet-Transformation (DDWT) is realized by convolutions, which cascadedly calculate wavelet-coefficients. The signal undergoes low-frequency and high-frequency filtration, followed by dyadic downsampling. This decomposition can be repeated for the low-frequency component up to the maximum possible level. Separately, two-dimensional image transformation is carried out by constantly applying the one-dimensional one to the rows and columns of the corresponding array. This results in four two-dimensional blocks containing respectively the coefficients of the low-frequency approximation of the image and the three detailed images W^H, W^V and W^D, which include the corresponding high-frequency structures in horizontal, vertical and diagonal directions.

In many applications, in particular, in recognition tasks, it is necessary to use translationally invariant transformations. The DDWT does not inherit this property from the continuous wavelet-transformation. There are different approaches to maintaining this invariance at its discreet realization [3]. One such transformation that is used in this paper is the Discrete Stationary Wavelet Transform (DSWT). It is realized like the DDWT, but without the subsequent downsampling. Its frequency resolution is provided by upsampling the wavelet filters in each iteration.

The next transformation, which is used, is a two-dimensional à trous algorithm (ATR), proposed by Holschneider et al. [7]. The implementation of the fast wavelet transform is similar to the discrete transformation (in the case of a bi-orthogonal basis); however, there is not any subsequent decimation. The one-dimensional convolution filters for calculating approximation and detailing coefficients at level j are obtained by inserting $2^j - 1$ zeros between every two coefficients of the filters describing the corresponding scaling functions and wavelets. This filter extension results in "holes" (*trous* in French), hence the name of the algorithm.

The two-dimensional image decomposition algorithm is implemented by consistently applying the one-dimensional convolution along the rows and columns of the image. However, unlike DDWT and DSWT, here the detailing coefficients are filtered with one-dimensional high pass filters in one direction only, which results in only two detailed images W^H and W^V, i.e., no low-pass filtering perpendicular to the direction of the high-pass filtering is now performed.

The third transformation used in this paper is the Repagular Wavelet-Transformation (RWT), introduced by Poliakova and Krylov [17] in order to increase the accuracy when separating image contours. A family of functions localized at one point is used as a base wavelet. Its scale change occurs not by dilation transformation, as it does with the common wavelet transform, but by using functions of different regularity.

If $s(t)$ is a signal with limited energy and $\psi(t,a)$ is the base wavelet (with a regularity parameter *a*), its continuous RWT can be set with the convolution

$$W_s^r(a,b) = s(t) * \bar{\psi}_a(b),$$

where $\bar{\psi}_a(t) = \psi(-t,a)$.

In the applications of the RWT for the base wavelet, the function $\tilde{\psi}(t,a) = 2^{-ta}$ is often used and the corresponding convolution is realized using the filter

$$\left\{G_a^{\psi}(n)\right\}_{n=0}^{2(N_a-1)} = \left\{-2^{-(N_a-1)a}, \ldots, -2^{-2a}, -2^{-a}, -1,\ 1,\ 2^{-a}, 2^{-2a}, \ldots, 2^{-(N_a-1)a}\right\},$$

where $2N_a$ is the number of filter coefficients. The values of the parameter a of the repagular wavelet-transform can be set by the formula $a = 2^{-j}\alpha_0$, where α_0 is any fixed number from the interval $(0,1)$, and $j = 0, 1, 2, \ldots$. The change of j results in modifying the regularity parameter, i.e., the transition from one level of permission to another in the RWT is done by changing parameter *a*.

3. Matrix of maximum singularities

The wavelet-transform, as a function of the scale, is known to be an image regularity indicator, i.e. it provides the connection between its local peculiarities and the corresponding wavelet-coefficients. At small scales, the local maxima of a wavelet transform characterize the irregular structures of the signals. These singularities carry the essential information about them, contained in a relatively small number of wavelet coefficients [12, 13].

We will use this fact to index MR images in the recognition task by constructing a special matrix. Let $I(s,p,q)$ be the array of data obtained from the nuclear magnetic resonance tomography, where s is the number of slices (the cross-section of the object), and p and q are the indexes of the image in slice s. As a result of the transformation of this array, for example by the RWT, the corresponding matrices of wavelet coefficients are obtained. The matrix obtained by projecting the largest (in terms of absolute value) elements of the matrices found for the image I, will be called its Matrix of the Maximum Singularities (MMS) and will be denoted as M_I^R.

When applying the DSWT, three such matrices will be obtained: M_I^{SH}, M_I^{SV} and M_I^{SD}, corresponding to the three arrays of detail coefficients. Whereas with ATR there will be two such matrices (M_I^{TH} and M_I^{TV}) for the MR image I.

Figure 1 shows an indexed image obtained by the RWT algorithm as well as its respective MRI slices.

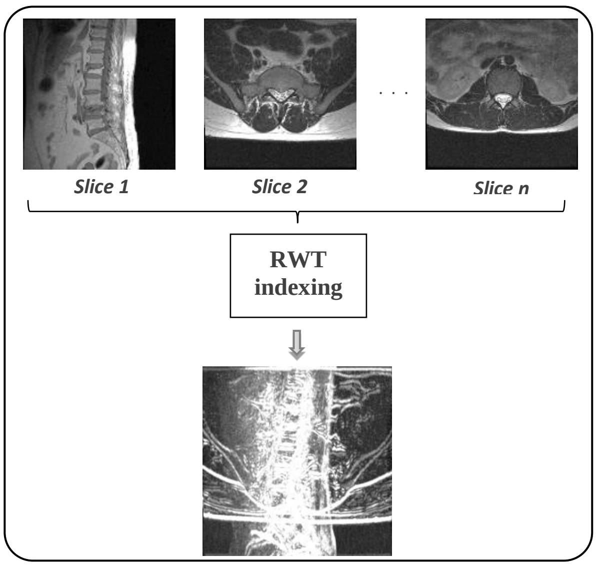


Figure 1. Indexed image with the RWT algorithm and its corresponding MRI slices

4. Recognition system models

In order to construct the corresponding model of the search system in a database with MR images through MMS, a base of halftone images is used $\Omega = \left\{ I_i\left(s, p, q\right), i \in \Im \subset \mathrm{N} \right\}$. For the given base Ω, following the criterion of the relative change of Shannon's entropy, the optimal level j_{opt} of image decomposition is defined for each of the examined wavelet transformations [16]. Then the corresponding indexed bases obtained from Ω will belong to the type:

$$\Theta^S = \left\{ M_I^{SH}\left(j_{opt}\right), M_I^{SV}\left(j_{opt}\right), M_I^{SD}\left(j_{opt}\right), I \in \Omega \right\};$$

$$\Theta^T = \left\{ M_I^{TH}\left(j_{opt}\right), M_I^{TV}\left(j_{opt}\right), I \in \Omega \right\}$$

and

$$\Theta^R = \left\{ M_I^{R}\left(j_{opt}\right), I \in \Omega \right\}.$$

The similarity of the corresponding MMS characteristics can be estimated by some metric function, for example, by the Frobenius norm – $\rho\left(I, I_0\right) = \left\| M_I^\theta - M_{I_0}^\theta \right\|_F$, $\theta \in \left\{ SH, SV, SD; TH, TV; R \right\}$.

The result of the content-based search in the database Ω is the set of similar (relevant) images

$$\Re = \left\{ I_{i_0} \mid \rho\left(I_{i_0}, I_0\right) \le \varepsilon^\theta, i_0 \in \Im \right\},$$

where the parameters ε^θ are additionally set by the user. n cases, where I_0 is contained in base Ω, the relationship $\varepsilon^\theta \approx 0$ is executed for each $\theta \in \left\{ SH, SV, SD \right\}$, $\theta \in \left\{ TH, TV \right\}$ or for $\theta = R$.

5. Comparative analysis tests of the proposed CBIR-system models

The methods evaluating the systems for extracting information from medical databases are less developed compared to those related to images of a general nature. The lack of publicly available specialized test medical information bases, similar to that of Harvard Medical School [8], the need for expert assessors, as well as the confidentiality of the data, are among the main problems in assessing the performance of CBMIR-systems. This also explains the lack of such research on medical image search systems in most publications on this topic, and in the cases where this has been done, different metric estimates are used, based on the analysis of the results obtained from the system's performance [11]. For this purpose, the so-called relevance measures (precision, recall, etc.) or metric functions are most commonly used.

To evaluate the performance of the three algorithms implementing the relevant models of the constructed search system, L_2-normalized and correlation distances are used in the feature space. For this purpose, a MR images database has been created based on a study of 30 patients carried out with a MRI General Electric Medical System 1.5T at Dr. St. Cherkezov Hospital in Veliko Tarnovo. The results are obtained from three types of studies: Abdomen, Cervical Spine (C-Spine) and Lumbar Spine (L-Spine). The medical images are in the DICOM output format and, before being fed into the input of the system, they are converted into grayscale.

Table 1 shows the results obtained from the research evaluating the search system in respect to the proposed metric functions for each of the examined wavelet transformation.

Table 1. Metric evaluation of the quality of the system

Type of study	SWT		RWT		à trous	
	Correlation distance	L_2 distance	Correlation distance	L_2 distance	Correlation distance	L_2 distance
Abdomen	0.958	0.137	0.96	0.0753	0.66	0.29
C-Spine	0.95	0.077	0.97	0.044	0.73	0.17
L-Spine	0.9355	0.131	0.969	0.09	0.72	0.28

From the experimental results obtained, it can be seen that, with regard to the proposed metrics assessing the quality of the CBMIR-system, the RWT algorithm retrieves more appropriate images compared to the other two.

6. RWT-algorithm stability with respect to some quality factors

The stability of the proposed algorithm in the search system is established by the sensitivity of the MMS by changing the content of the image. For this purpose, experimental research and appropriate statistical analysis have been conducted. The impact of three sets of factors (contrast, brightness and noise) on the number of the matching elements of the relevant descriptor MMS has been examined. To this end, additional images are generated based on each of the images from the already formed collection of medical data, applying the following levels to the analysed factors:

- contrast – $5\%, 10\%, 15\%$;
- brightness – $5\%, 10\%, 15\%$;
- Rician noise – $1\%, 5\%, 15\%$.

The statistical dependence of the qualitative factor F and the quantitative sign X can be determined by means of a one-way analysis of variance (One-Factor ANOVA) [5]. The number of matching elements of the respective descriptor matrices is set to be the quantitative attribute X. The equality of the general variances can be evaluated according to Cochran's criterion. *Table 2* shows the data of the factor $F\left(F_1, F_2, F_3\right)$, which may be respectively contrast, brightness and Rician noise, according to this criterion at a significance level $\alpha = 0.05$.

Table 2. Applying Cochran's criterion to the different groups of factors

Type of study: Abdomen C-Spine L-Spine	Factor group		
	F_1	F_2	F_3
G	0.477	0.352	0.6026
G_{tabl}	0.6167		

The results obtained for all the examined groups of factors show that the zero hypothesis for the uniformity of the variances is valid at the given level of significance. Therefore, ANOVA can be used to determine the impact of the individual factors on the examined magnitude. The two variances (factorial and residual), generated respectively by the factor and by accident, are compared using the Fisher-Snedecor's criterion. The data under this criterion, at a significance level $\alpha = 0.05$, is given in *table 3*.

The results obtained for all the examined groups of factors show that the hypothesis concerning the equality of the two variances is valid at the given significance level. Therefore, group averages do not differ significantly for all three factors, i.e., the RWT algorithm is stable when there are changes in contrast, brightness and Rician noise.

Table 3. Applying Fisher-Snedecor's criterion to different groups of factors.

Type of study: Abdomen C-Spine L-Spine	Factor group		
	F_1	F_2	F_3
F	0.52	0.739	2.4
F_{tabl}	3.63		

7. Analisis of the sensitivity of the mms, as a descriptor in the RWT-model of the CBMIR-system

To study the sensitivity of the descriptor matrix MMS in the RWT-algorithm in relation to some changes in the content of the MR image, the Matrix of Averages (MA) is used. The MA is obtained like the MMS, but the operator used to design the local wavelet maxima is replaced by the averaging operator. In other words, the elements of the MA are the arithmetic mean values of the wavelet coefficients (in terms of positions) of all slices of the tomographic image. The sensitivity of the pair of descriptor matrices is established by quantitative evaluations obtained by comparing their response to some changes in the content of the MR image, known in advance. These quantitative evaluations are determined by the L_2-normalized distance and the correlation distance.

Two images have been selected for basic tomography images in this comparative analysis of the pair of descriptors. The first is 3D MRI data (human cranium) from Matlab and the other is a real MR (C-Spine) image from the database, by means of which the comparative analysis of the proposed algorithms was carried out. Their contents are altered by adding ten levels of Rician noise to each section of the image. The two descriptors, MMS and MA, are then determined for each corresponding group of the original image and its ten versions received with a subsequent increase in the noise level. *Figure 2* shows the indexed images of 3D MRI data (human cranium) from Matlab, respectively via MMS and MA descriptors in the RWT algorithm.

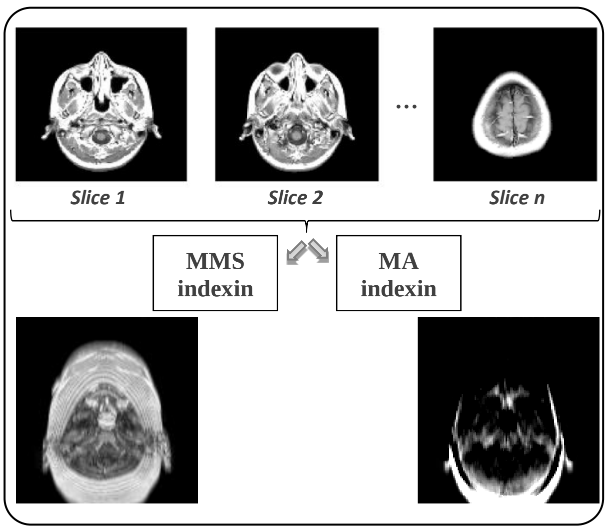
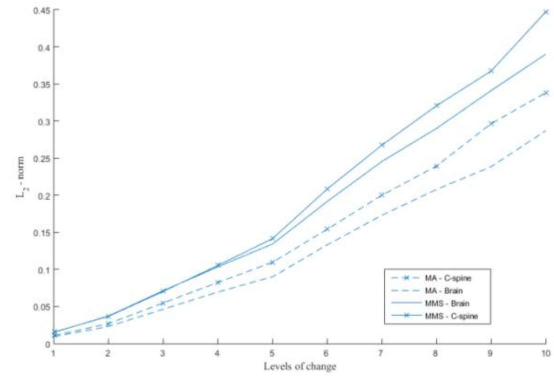


Figure 2. Indexing 3D MRI data (human cranium) from Matlab by means of MMS and MA

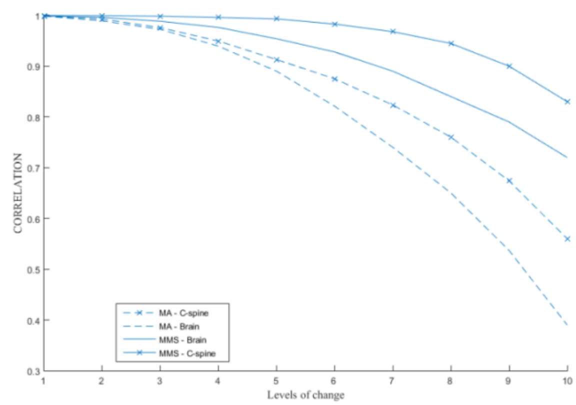
The difference degree of the image and its versions with changed content is estimated by calculating the distance between their descriptors in the indexed space. The results obtained are presented in *figure 3*.

The MMS descriptor shows a higher sensitivity than the MA one. Its lower sensitivity can be explained by the fact that the descriptor MA is inherently “integral”.

Singularities and non-smooth structures contain the most important part of the image information [13]. Finding the singularity points is in the basis of determining the local deformations in the image and, therefore, they are used for calculating local descriptors in some CBMIR-systems. Computer medical diagnostics through images from different modalities is also connected with the study of such points from the so-called suspicious areas in order to find pathological changes.



(a) L_2-normalized distance



(b) correlation distance

Figure 3. MMS and MA sensitivity to changes in the contents of the MR image

In signal analysis, the discrete wavelet transform has a lower frequency-time resolution than the continuous transformation. However, the features of the images locally affect the wavelet coefficients of the discrete transform. They are identified by the change in the local maximums of these coefficients at small scales.

The MMS descriptor matrix is constructed by designing these maximums. Thus, its elements identify the pixels, in whose neighborhood significant changes in the content of a certain slice of the MR image are observed. The elements of the MA descriptor are obtained by means of an operator averaging the wavelet coefficients, which leads to a certain “smoothing” of these singularities. This is a theoretical confirmation of the results obtained from the comparative analysis of the sensitivity of the MMS and MA regarding the changes in the content of the MR image.

8. Conclusion

The experimental results show that the constructed system for searching content indexed by the local peculiarities of the MR images is a satisfactory solution to the given task. The metric functions used (L_2 -normalized distance and correlation distance) represent the stability of the proposed algorithms for the CBIR-system in terms of the sensitivity of the MMS descriptor introduced in the paper. The comparative analysis of the proposed algorithms establishes the superiority of the RWT algorithm over the other two. This algorithm is more precise when retrieving relevant images from the MR image database. It is determined by means of the values of the metric functions considered, with allowable changes in the content of the images.

In addition, the paper presents a one-way ANOVA for the RWT algorithm. The results of this analysis show the stability of the algorithm with regard to the qualitative factors: contrast, brightness and Rician noise.

The equality of the variances of the corresponding normally distributed general populations is established using Cochran's criterion. The Fisher-Snedecor's criterion then shows that the group averages of the number of matching elements of the respective MMS of the RWT system are approximately equal. This means that we have some stability of the algorithm regarding the factors considered. In addition, the better sensitivity of the proposed descriptor has been established in comparison with the averaging MA descriptor in terms of changes in the content of the MR image.

The acceptable size of the MMS descriptor space, the sensitivity of the descriptor introduced and the established robustness of the RWT algorithm, in terms of contrast, brightness and Rician noise, are among the major advantages of the proposed CBIR-system models.

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