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Registration Based Retrieval using Texture Measures

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Abstract
The aim of the study presented in this manuscript was to develop and analyze registration based retrieval of medical image using texture measures. Three main methods are implemented in this work. The first method includes Affine transformation, Demons and Affine with B-spline. The second method implemented is medical image retrieval system using content based medical image retrieval. GLCM, LBP and GLCM with LBP are used for texture based retrieval. Shape based retrieval is processed using canny edge with the Otsu method. From registration based retrieval, Affine with B-Spline performs well and produces best result by increasing the retrieval rate and the next better performances are given by Demons and Affine registration. The results showed that the best results for registration based retrieval are given by Affine with B-Spline registration based retrieval using GLCM+LBP with (100/50). Based on more relevant retrieved images, Brain (100/50) and Knee (100/50) observed to have more relevant retrieved images.

Keywords: Medical imaging; Registration; Retrieval; Clinical diagnosis

Introduction

Representation of images is an important trait, where features are most useful for representing the contents of images and can effectively code the attributes of the images (Information available from MIT vision and modeling group) also using sound speed imaging technique Huthwaite [1] and voxel imaging by Oreshkin [2]. Feature extraction of the image in the database is most often conducted off-line Shyu [3], Smeulders et al. [4], Mojsilovis [5]. So computation complexity is not a major issue. The feature extraction uses features like texture and shape and is combined for multifeature technique. These are used most often to extract the features of an image Ma [6], Liu [7], Manjunath [8], and Lu [9]. The general feature extraction techniques used are given below. GLCM (Gray Level Co-occurrence Matrix), LBP (Local Binary Pattern) and GLCM with LBP are used for texture based medical image retrieval. Texture in CBIR (Content Base Image Retrieval) can be used for two purposes Weszka [10] and Rasoulian [11]. First, an image can be considered to be a mosaic that consists of different texture regions. These regions can be used as examples to search and retrieve similar affected and non-affected areas. Second, the texture can be employed automatically to refer the content of an image automatically or semi-automatically. For effective evaluation of diagnosis process registration, retrieval and registration based retrieval techniques has to be improved. In the recent years, retrieval of brain images was studied (see the research of Quddus and Basir [12], or Ibanez [13]. Nevertheless, it is observed that, image guided intervention is useful for the effective clinical diagnosis [14].

The aim of this research stands on developing and analyzing registration based retrieval system to assist in clinical diagnosis. This will surely help physicians and radiologists in their case based reference and evidence based reasoning in diagnosis.

Methodology

The ultimate goal of every medical image retrieval system is the real clinical integration with other systems in a well-organized and effective manner. It is based on the patient complaint and clinical examination using various imaging techniques. After imaging process the images are stored in the database and the framework is referred in Figure 1. Table 1 refers registration of images involving registration techniques.

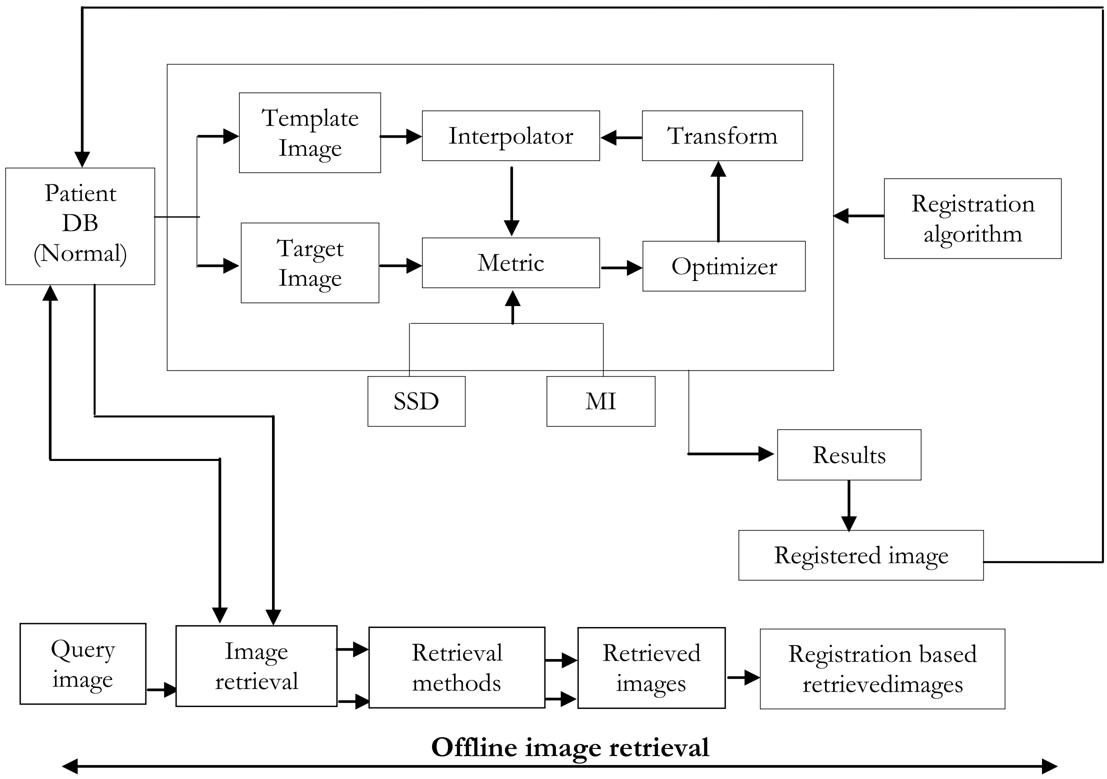

Figure 1. Medical image registration based retrieval framework

A geometrical transformation is applied to one of the two images to bring the two images into spatial alignment. Gradient descent optimizer prevents the algorithm from going systematically too far in the direction of gradient, in which the step of the gradient is reduced if the change of direction is too abrupt.

Texture Feature Extraction using GLCM

GLCM creates a matrix with the direction and distances between pixels, and then extracts meaningful statistics from the matrix as texture features Haralick et al. [15]. GLCM texture features commonly used are shown in the following: GLCM is composed of the probability value, it is defined by $P(i,j|d, \theta)$which expresses the probability of the couple pixels at θ direction and d interval. When θ and d is determined, $P(i,j|d,\theta)$ showed by $P_{i,j}$. Distinctly GLCM is a symmetry matrix; its level is determined by the image gray-level. Elements in the matrix are computed by the Eq(1).

$$P(i,j|d,\theta) = P(i,j|d,)/ \sum_i \sum_j P(i,j|d,\theta) \quad (1)$$

GLCM expresses the texture feature according to the correlation of the pair of pixels gray-level at different positions.

Table 1. Registration of images

S.No	Registration	Equation
1	Affine	$$A = \begin{bmatrix} a_1 & a_3 \\ a_2 & a_4 \end{bmatrix} = \underbrace{\begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}}_{\text{rotation}} \underbrace{\begin{bmatrix} S_{x1} & 0 \\ 0 & S_{x2} \end{bmatrix}}_{\text{scaling}} \underbrace{\begin{bmatrix} 1 & S_{x1} \\ 0 & 1 \end{bmatrix}}_{\text{shear}}$$ $T = (t_{1,1}, t_{1,2}, \ldots t_{i1,i2}, \ldots t_{n1,n2,})^T$ $R = (r_{1,1}, r_{1,2}, \ldots r_{i1,i2}, \ldots r_{n1,n2,})^R$ T refers Test image and R refers Reference image. S is the Scaling factor.
2	Demons	$$\vec{v} = \frac{(f - r) \times \vec{\nabla} r}{\left\|\vec{\nabla} r\right\|^2 + \frac{(f-r)^2}{k^2}}$$ K is a normalization factor to compensate for the mismatch between two images. For fixed point P, r is the gray scale of reference image R, and f is for floating image F. The offset for fixed point P between two images. ∇r is the gradient of the image.
3	Affine with B-Spline	The value of the displacement of pixel I $u(x_i, y_i) = \sum_j \vec{u_j} B_j(x_i, y_i)$ $B_j(x,y)$ are called the basic functions. $W_{i,j} = B_j(x_i,y_i)$ weights to emphasize that the (u_i,v_i) are known linear combinations of the (u_j,v_j).

Two-dimensional surface textures can be described by two complementary measures. They are gray scale contrast and local spatial patterns. The LBP value for the center pixel (a,b) of the image f(a,b) is calculated using the Eq(2), where i=0 to n,

$$LBP(a,b) = \sum_i U(f(a,b)-f(a_i,b_i))2^i \tag{2}$$

where U(x) the threshold function which is defined in the Eq(3):

$$U(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{3}$$

Shape Feature Extraction using Canny Edge with OTSU Method

The Otsu method has the important property that it is based entirely on computations performed on the histogram of an image. It selects a global threshold value by maximizing the separability of clusters in gray levels. The image is represented in L gray levels (0,1, ...L-1). The number of pixels N at level i is denoted by f_i; then, the total number of pixels equals $N = (f_0 + f_1 + \ldots + f_{L-1})$. For a given gray level image, the occurrence probability p of gray level is given by the Eq(4) and (5).

$$p_i = f_i / N, \; p_i \geq 0 \tag{4}$$

$$\sum_{i=0}^{L-1} p_i = 1 \tag{5}$$

Database

The database is formed from personally collected medical images from clinics and health care centers and benchmarked web image databases especially for particular modalities. Registration based retrieval is tested on these images.

- The Brain MRI database is composed of 20 T1 and T2 weighted Brain images of 5 different sets.
- The Liver MRI database consists of T2 weighted images. The database is composed of 20 T2

weighted images of 5 different sets.

- The database of Knee MRI is composed of 20 sagittal Knee images of 5 different sets.

The performance of the medical image retrieval system techniques is analyzed by the following measures. The level of retrieval precision, accuracy, retrieval efficiency, and error rate were illustrated by Muller et al. [16]. Precision and recall values illustrated by Thomas Desealers [17], summarizing (R,P(R)) pairs for varying numbers of retrieved images. The classification error rate CER is defined by Thomas Desealers [17] and is given in Table 2.

Table 2. Performance Estimation

No	Performance measure (abbreviation)	Description and Equation (All are given in Percentage % value)
1	Precision (P)	P = (number of relevant images retrived) / (total numbe rof images retrieved) P = r/n
2	Recall (R)	R = (number of relevant images retrieved)/(total number of relevant images in Database) R = r/m
3	Error Rate	Error rate = (number of irrelevant images retrieved)/(total number of images retrieved)
4	Efficiency	Retrieval efficiency = (number of relevant images retrieved)/(total number of images retrieved) if no. retrieved > no relevant = (number of relevant images retrieved)/(total number of relevant images) if otherwise
5	APR (Average Precision rate) AQR (Recall rate)	$APR(q) = \sum_{n=1}^{NR}(P_q)*(1/N_R)$ where q =0 to n , N_R =Total number of images , P_q =Total Precision rate $ARR(q) = \sum_{n=1}^{NR}(R_n)*(1/N_R)$ where q =0 to n , N_R = Total number of images, R_n = Total retrieval rate
6	Corrective Error rate (CER)	If the most similar image is relevant. from the correct modality $CER = \sum_{q\in Q}(0)*(1/\|Q\|)$ Otherwise $CER = \sum_{q\in Q}(1)*(1/\|Q\|)$ where $q_{\in 0}$ and $Q_{\in}1$
7	Classification of images	Relevant Irrelevant

Results and Discussion

The analyzed results for Registration based retrieval using Affine, Demons and Affine with B-Spline registration based retrieval using feature extraction are given below. Due to limitation of space, only the best retrieved results of images are shown. For registration based retrieval, CBMIR is implemented for Affine, Demons and Affine with B-Spline registration based retrieval.

Figure 2 show texture based retrieval using GLCM for Brain, Liver and Knee images with APR and ARR of (93/47) %. For Brain and Knee images, similar images are retrieved. For Liver image, Chest image which is extremely of different modality is retrieved. For Texture based retrieval using LBP Brain, Liver and Knee images with APR and ARR of (60/30) % is retrieved. For Brain image, Liver is the perceptually very different images retrieved. For Liver image, Brain is the physically dissimilar image retrieved. Irrelevant images are not retrieved for Knee image. By using GLCM+LBP for Brain, Liver and Knee images with APR and ARR of (80/40)% is achieved. For Brain image using GLCM+LBP; Knee and Liver are the perceptually very different images retrieved. However, irrelevant images are not retrieved for Liver and Knee images using GLCM+LBP and are given in Table 3.

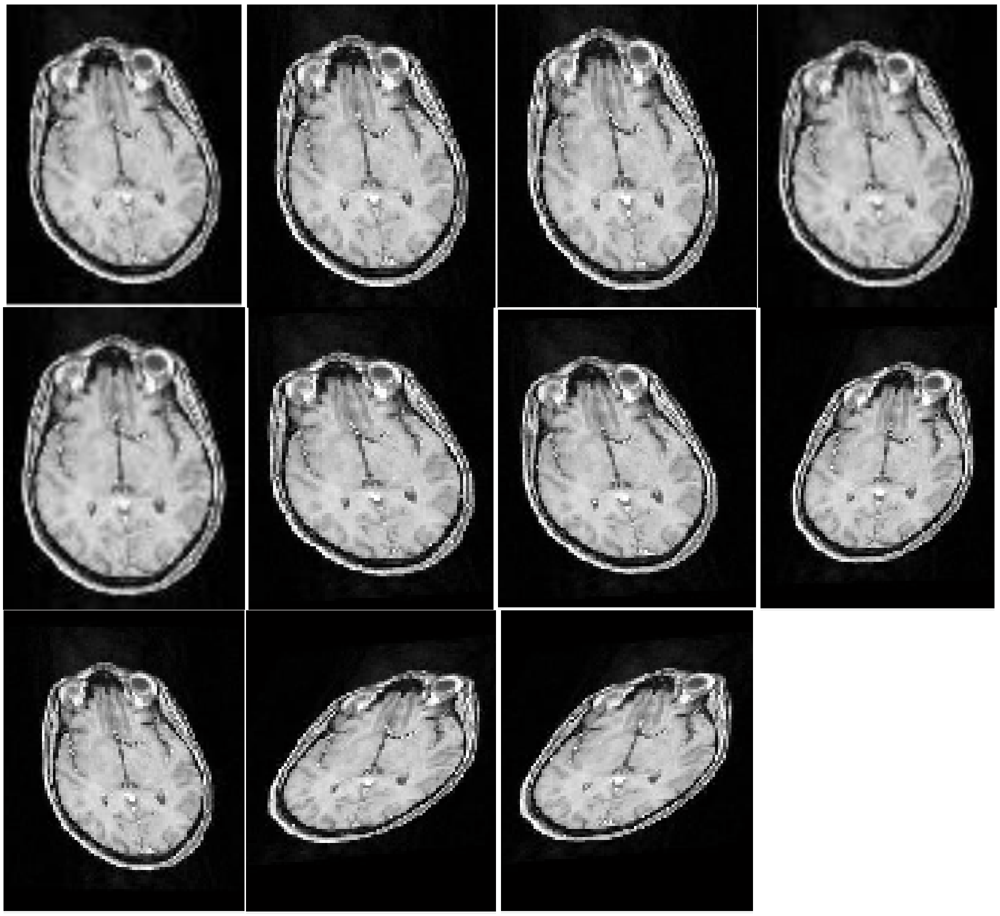

Figure 2. Affine registration based retrieved brain images using GLCM

Table 3. Overall Performance evaluation by (precision /recall) calculation from retrieved images using texture basedextraction techniques

Images	GLCM	LBP	GLCM+LBP	APR	ARR
(Precision/Recall) values for Affine registration based retrieval					
Brain	100/50	60/30	60/30	73	37
Liver	80/40	40/20	100/50	73	37
Knee	100/50	100/50	100/50	100	50
APR	93	67	87	-	-
ARR	47	33	43	-	-
(Precision/Recall) values for Demons registration based retrieval					
Brain	100/50	100/50	100/50	100	50
Liver	100/50	80/40	100/50	93	47
Knee	100/50	80/40	100/50	93	47
APR	100	87	100	-	-
ARR	50	43	50	-	-
(Precision/Recall) values for Affine with B-Spline registration based retrieval					
Brain	100/50	60/30	100/50	87	43
Liver	100/50	40/20	100/50	80	40
Knee	100/50	100/50	100/50	100	50
APR	100	67	100	-	-
ARR	50	33	50	-	-

Table 3 shows the overall performance evaluation. The reason for GLCM to perform well in texture based retrieval is, it calculates texture features according to the correlation of couple pixels gray levels at different positions. On applying Affine transformation, the pixel distribution is changed. Because of the inherent property of GLCM, it performs well. Since LBP based only on the orientation of pattern distribution it does not work well. But when both are combined, GLCM with LBP it performs well because of its combined advantage. For Affine registration based retrieval using texture based techniques, based on the APR and ARR, GLCM with (93/47)% of (APR/ARR) was found to perform better in retrieval than GLCM+LBP and LBP. Knee images with (100/50) % of (APR/ARR) were found to be retrieved more than Brain and Liver images. GLCM perform well in texture based retrieval. Since, it calculates statistics based on distance and direction between pixels on the deformed image. For Demons, registration based retrieval for Brain, Liver and Knee images (APR/ARR), GLCM with (100/50) % of APR and ARR found to perform well in retrieval of Brain, Liver and Knee images. Based on more relevant retrieved images, Brain images are retrieved more with (100/50) % of (APR/ARR). The Brain image with (100/50) % of (APR/ARR) found to be retrieved more. Affine with B-Spline retrieves more images with higher precision values. Brain and Knee images have higher retrieval rate. For Affine with B-Spline registration based retrieval, the Knee images with (100/50) % of (APR/ARR) found to be retrieved more than Brain and Liver images. The textural smoothness is more in Knee images than Brain and Liver images. Based on the (APR/ARR) GLCM and GLCM with LBP of (100/50) % found to perform well in retrieval of Brain, Liver and Knee images. But when both are combined, GLCM with LBP it performs well because of its combined advantage. The Knee images with (100/50) % of (APR/ARR) found to be retrieved more than Brain and Liver images. Based on more relevant retrieved images Liver images are found to be retrieved more with (100/50) % of (APR/ARR). The reason is the textural smoothness and contrast is more in Knee images than Brain and Liver images. Drastic changes are found for Liver images. However, lesser internal organs with variations in the texture level are found for Brain images.

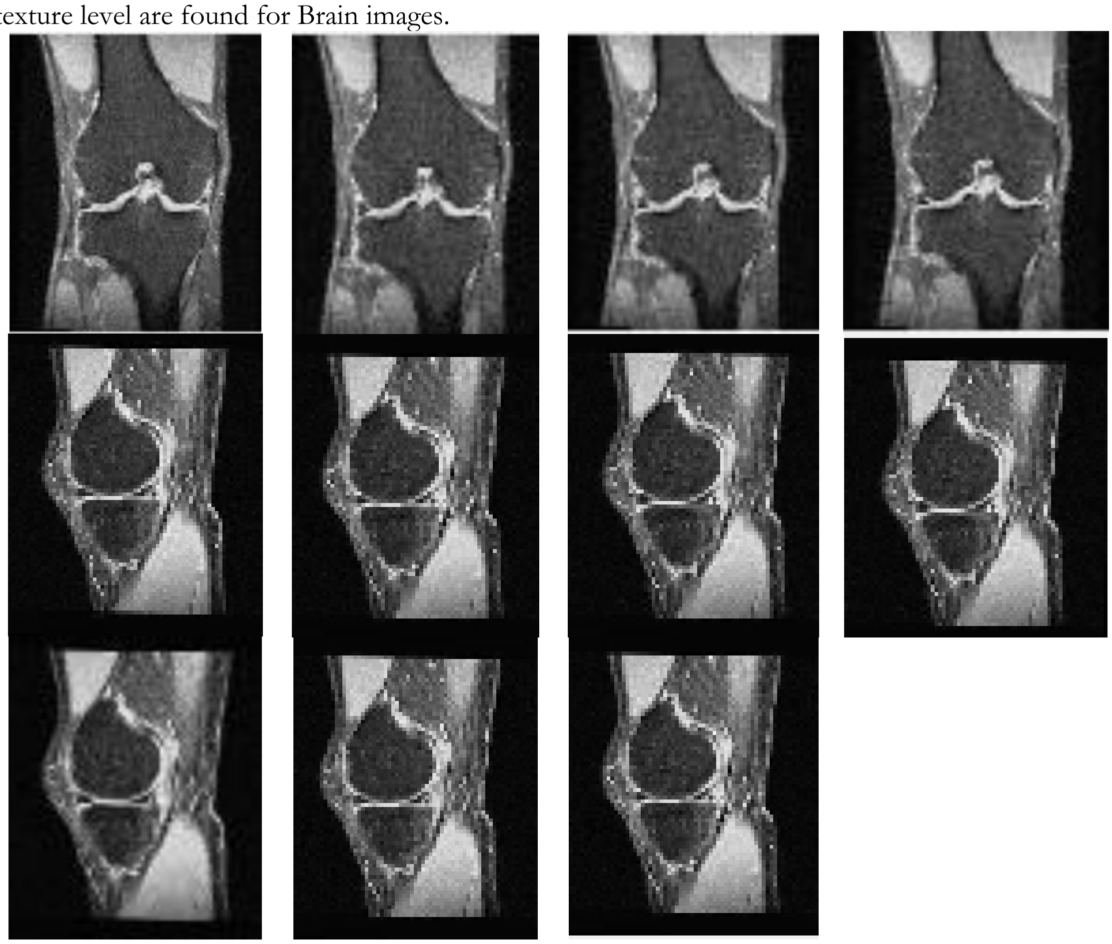

Figure 3. Affine with B-Spline registration based retrieved knee images using canny edge with Otsu method

Figure 3 shows Canny edge with Otsu method using Demon registration based retrieval for Brain, Liver and Knee images with APR and ARR of (87/43) %. Irrelevant images are not retrieved for Brain image; Chest is the irrelevant image retrieved for Liver image. Brain is the irrelevant image retrieved for Knee image.

Table 4 shows the overall precision and recall calculation from the performance evaluation using shape based retrieval techniques for Brain, Liver and Knee images. From the retrieval techniques used, shape is found to have a lesser retrieved rate. The features used in shape based retrieval search for exact size and shape which is not possible in medical images because of their difference in orientation. This makes the retrieval difficult and retrieves only the lesser image which is most similar image for the given query alone. This is an added advantage but, only lesser images are retrieved. More relevant retrieved images are found for Knee than Brain and Liver images respectively.

Table 4. Overall Performance evaluation by (precision /recall) calculation from retrieved images using shape based extraction technique

Images	(Precision/Recall) values	APR	ARR
(Precision/Recall) values for Affine registration based retrieval			
Brain	60/30	60	30
Liver	40/20	40	20
Knee	80/40	80	40
APR	60	-	-
ARR	30	-	-
(Precision/Recall) values for Demons registration based retrieval			
Brain	100/50	100	50
Liver	80/40	80	40
Knee	80/40	80	40
APR	87	-	-
ARR	43	-	-
(Precision/Recall) values for Affine with B-Spline registration based retrieval			
Brain	100/50	100	50
Liver	60/40	60	40
Knee	100/50	100	50
APR	87	-	-
ARR	47	-	-

The variation changes produced by (translation, rotation and shear) using affine transformation, changes the orientation. Hence decreases the retrieval rate. Canny edge preserves edge details and Otsu operates on selected global threshold value by maximizing the separability of clusters in gray levels. For Affine registration based retrieval, the (APR/ARR) of shape is (60/30) %. Demons achieving the purpose of non-rigid registration based retrieval with lesser orientation changes. Demons when combined with canny edge preserves the edge details, this increases the retrieval rate.

Table 5 shows the overall performance evaluation using multifeature based retrieval for registered images. The textural and shape are the two major properties while dealing with images and hence when combined produce best results. The (APR/ARR) for Affine is (100/50)%. The reason is, GLCM preserves the textural properties of images which plays the major role in retrieval of images and Canny edge preserving edge details and Otsu operates on selected global threshold value by maximizing the separability of clusters in gray levels. Based on the former statement, Liver and knee images are found to be retrieved more with (100/50) % of (APR/ARR) for Affine registered image. Since the Affine registered image has changes in its direction orientation and with a drastic change in the pixel distribution, has found lesser results for texture and shape based retrieval. Since Demons used here, is a deformable transformation, the pixel distribution variation is lesser when compared with the query image. Hence the APR and ARR of multifeature is (93/47) % of (APR/ARR) % for Demons registration based retrieval. Liver and Knee images are found to be retrieved more with (100/50) % of (APR/ARR) % than Brain. Affine with B-Spline transformation is smooth and continuous with lesser disorientation in images. Hence on applying, Co-occurrence matrix, it captures features of a texture using spatial relations of similar gray tones is the reason for providing higher retrieval rate than Affine and Demons. The (APR/ARR) of shape is (100/50) % for Affine with B-Spline registration based retrieval and all the three images found to be retrieved with (100/50) %.

Table 5. Overall Performance evaluations by (precision /recall) calculation from retrieved images using shape basedextraction technique

Images	(Precision/Recall) values	APR	ARR
(Precision/Recall) values for Affine registration based retrieval			
Brain	60/30	60	30
Liver	100/50	100	50
Knee	100/50	100	50
APR	87	-	-
ARR	43	-	-
(Precision/Recall) values for Demons registration based retrieval			
Brain	80/40	80	40
Liver	100/50	100	50
Knee	100/50	100	50
APR	93	-	-
ARR	47	-	-
(Precision/Recall) values for Affine with B-Spline registration based retrieval			
Brain	100/50	100	50
Liver	100/50	100	50
Knee	100/50	100	50
APR	100	-	-
ARR	50	-	-

A real surgical guidance rather than clinical decision making process is needed. Such access methods are necessary to make the systems accessible to a larger group of people and applications and to gain experience that goes far beyond a validation of retrieval results. It has been found that the proposed system is capable of producing accurate and highly consistent retrieval rate in an interoperable manner for clinical diagnosis. By feature based retrieval using texture and multifeature, the retrieval rate is observed to be high for both before and after registration. Texture based retrieval is well suited for Knee images. For shape based retrieval, the retrieval rate is observed to be increased using Affine with B-Spline registration technique. An interesting observation is, retrieval of images performs well in both before and after registration of images using multifeature based technique. Brain, Liver and Knee images performs equally well for multifeature based retrieval. Hence in respective with the particular imaging organ, Registration based retrieval using multifeature could be performed effectively. Affine with B-Spline registration technique is most suitable in retrieval of images using texture, shape and multifeature. From the extreme analysis, it is concluded that, the best results for registration based retrieval is given by Affine with B-Spline registration based retrieval using GLCM+LBP with (100/50). Based on more relevant retrieved images, Brain (100/50) and Knee (100/50) observed to have more relevant retrieved image.

List of abbreviations

CBIR	Content Based Image Retrieval
GLCM	Gray Level Co-occurence Matrix
LBP	Local Binary Pattern
P	Precision

R	Recall
A	Accuracy
APR	Average Precision Rate
ARR	Average Recall Rate

Conflict of Interest

The author declares that they have no conflict of interest.

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