ANALYTICAL CLASSIFICATION OF MULTIMODAL IMAGE REGISTRATION BASED ON MEDICAL APPLICATION

Mohammad Reza Keyvanpour[1], Somayeh Alehojat[2]
[1]Department of Computer Engineering, Alzahra University, Tehran, Iran
[2]Department of Computer Engg., Islamic Azad University, Qazvin Branch, Qazvin, Iran

ABSTARCT

In the last two decades, computerized image registration has played an important role in medical imaging. One of the important aspects of image registration is multimodal image registration, where is used in many medical applications such as diagnosis, treatment planning, computer guided surgery. Not specified the relationship between the intensity values of corresponding pixels, the difference between images contrast in some areas than other areas, mapping the intensity values in an image to multiple intensity value in other images, are challenging problems in multimodal image registration. Due to importance of image registration in medical, identification this challenges seem necessary. This paper will have a comprehensive analysis on several types of multimodal image registration methods and will express its affect on medical images. To reach this goal, each method will investigate according to its affect on the field of medical imaging and challenges facing each method will evaluate analytically. So that recognition these challenges play an effective role in choosing an appropriate registration method.

***KEYWORDS*:** Image registration, medical image registration, multimodal image registration, information theory

I. INTRODUCTION

Image registration is the problem of alignment two or more image of different viewpoint, at different times or with different kinds of imaging sensors. Registration is important application in many image processing and is used in many medical imaging applications. One of the important aspects of image registration is multimodal image registration, so that different sensors are used for imaging of an image. In this case, the image registration provide tools for gathering information from various device and are created a more detailed views.In recent years, multimodal image registration is one of the challenging problems in medical imaging. Due to changes in the rotation and size, differences in brightness and images contrast, is difficult for a physician to combine mentally all image information carefully. Moreover, the radiotherapy techniques using manual adjustment on the MRI and CT brain images may require several hours to be analysis [1, 2]. Therefore, an image registration technique is required until to transfer all image information to a general information system.
Essentially, image registration methods are divided into three categories based on landmark, segmentation and voxel. Major challenges in multimodal image registration are variety of intensity images obtained from different sensors. Since voxel based methods is applied directly on image gray values, they are more general. Due to importance of medical images, speed and accuracy of registration process should be considered. Accordingly, this paper introduces the medical image registration methods and will be introduced types of multimodal image registration, then these measure compare with measures such as speed, accuracy, computational complexity. Finally, we were trying to evaluate this methods effect in the field of medical imaging. The rest of this paper is organized as follows: In section 2, the related work and proposed definitions for image registration and multimodal medical image registration is introduced. We describe medical image registration

methods in section 3. In section 4, the proposed framework for classification of multimodal methods is presented and section 5 evaluates these methods. Section 6 includes the conclusion.

II. RELATED WORK

Generally, image registration is the process of image component transformation to a coordinate system that from image processing viewpoint, the most interesting and possibly most difficult step is to determine the proper transformation that transform these components to normal coordinates [3]. A system for performing image registration algorithms uses of machine vision, image processing, machine learning and artificial intelligence [2, 4]. In recent decades, imaging changes identification in remote sensing has been much attention [5, 6]. In radiographic, images automatically compare and match and in mammography, cancer cases is easily determined [7, 8]. Image registration can be applied in the diagnosis and identification steps, such as face detection, handwriting recognition, stereo matching and motion analysis [3, 4]. One of the important aspects of image registration is when various devise used to imaging of a scene. .Therefore, an image registration technique is required to transfer all image information to a general information system. In this case, the goal is to display images so that to facilitate diagnostic for physicians to find the desired image information similarities and differences [9]. More recently developed fully automated methods essentially revolve around entropy [10] and mutual information [11, 12]. In this way we can understand that image registration in recent years applied to one of the important areas in image processing.

III. MEDICAL IMAGE REGISTRATION METHODS

Image registration is the problem of alignment two or more image of different viewpoint, at different times or with different kinds of imaging sensors. Registration is important application in many image processing and is used in many medical imaging applications. One of the important aspects of image registration is multimodal image registration, so that different sensors are used for imaging of an image. In this case, the image registration provide tools for gathering information from various device and are created a more detailed views.In recent years, multimodal image registration is one of the challenging problems in medical imaging. Image registration is used in analyzing medical images for diagnosis, in machine vision for stereo matching, in astrophysics to adjust images with different frequencies and many other areas. In medicine, patients often in order to better diagnosis or treatment is imaging with multiple radiology sensors. Due to changes in rotation or difference in image contrast, is difficult for a physician to combine mentally all image information carefully. Therefore, an image registration technique is necessary to transfer all image information to an overall system.

As shown in Figure (1), image registration is used to gather information from various sensors and provide more detailed views. Main methods of image registration are divided into three categories: intrinsic, extrinsic and non image. Since intrinsic methods are used mainly for multimodal image registration, these methods will review.

Intrinsic methods are classified into landmark, voxel and segmentation based.

Landmark extraction and image segmentation in some registration methods is difficult while voxel based methods are practical and more general [13].

3.1 Landmark based registration

Landmarks are based on anatomy i.e. clear and visible points, which usually are determined by the user interaction or are geometric i.e. local areas such as maximum curvature, corners, etc, so that usually are defined in an automated method. In landmark based registration, a set of specific points is compared with the first image content. These algorithms use of criteria such as average distance between every landmark or distance between landmark with the lowest frequency.

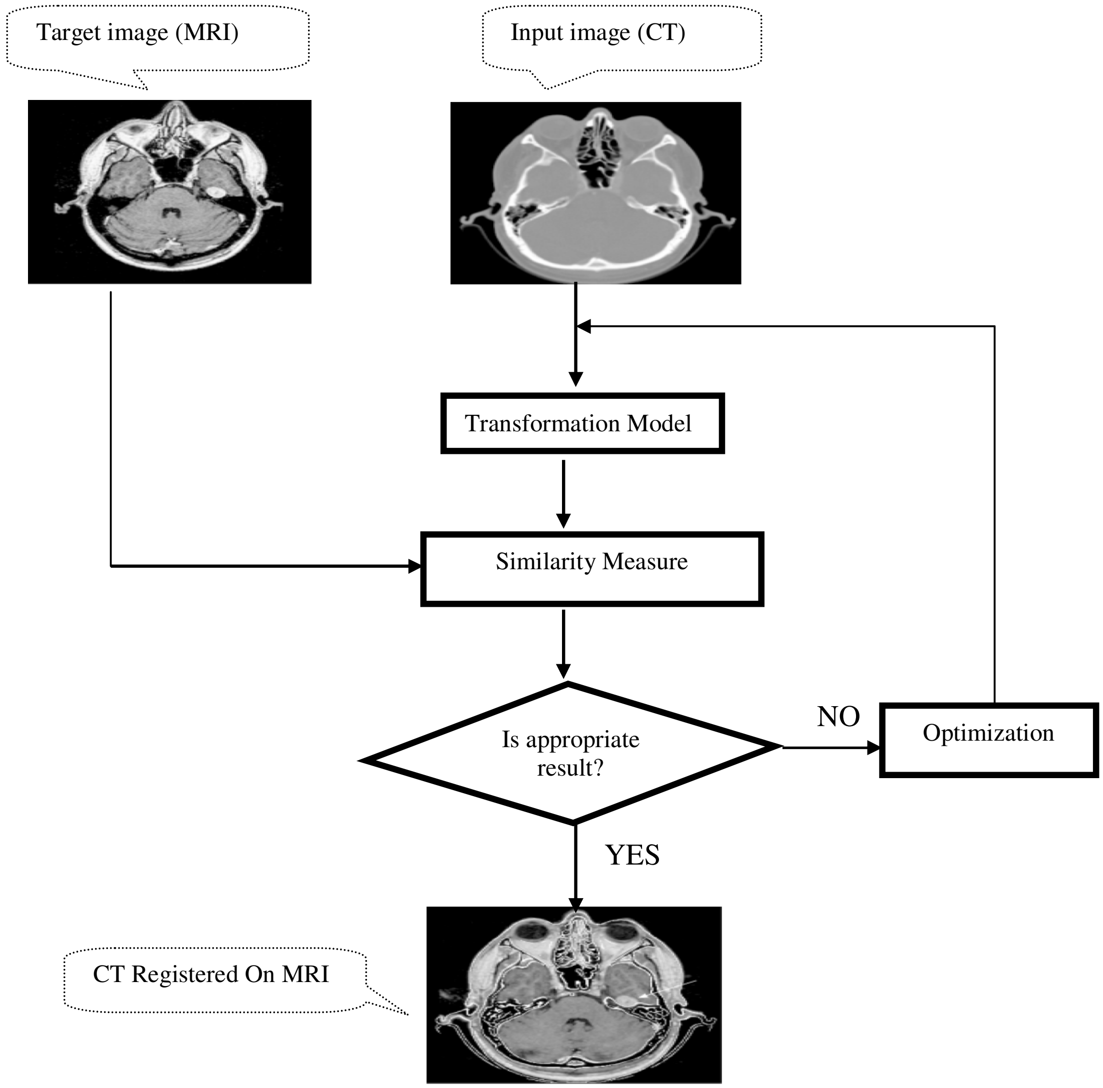

Figure (1): a multimodal image registration system

3.2 Segmentation based registration

Segmentation based registration is rigid where have been extracted from similar image structures to be registered, and they can also be deformable model where an extracted structure from one image is elastically deformed to fit the second image. Rigid model based approaches are probably the most popular methods currently in clinical use. Their popularity relative to other approaches is due to the head-hat method which relies on the segmentation of the skin surface from CT, MR and PET images of the head. Another cause is the fast chamfer matching technique for alignment of binary structure by means of a distance transform.

3.3 Voxel based registration

This method directly is applied on the image gray values and does not require to preprocessing and user interaction. There are two distinct methods: decrease the content of gray value image to a series of scalars and orientations. Second for all images content, has been used through the registration process. Methods using all image content, can be applied to almost every field of medicine with the use of any transformation to be used. as shown in figure (2), Since multimodal image registration is affected by the intensity and methods based on the intensity are applied of gray values image, these category of methods are used for multimodal image registration.

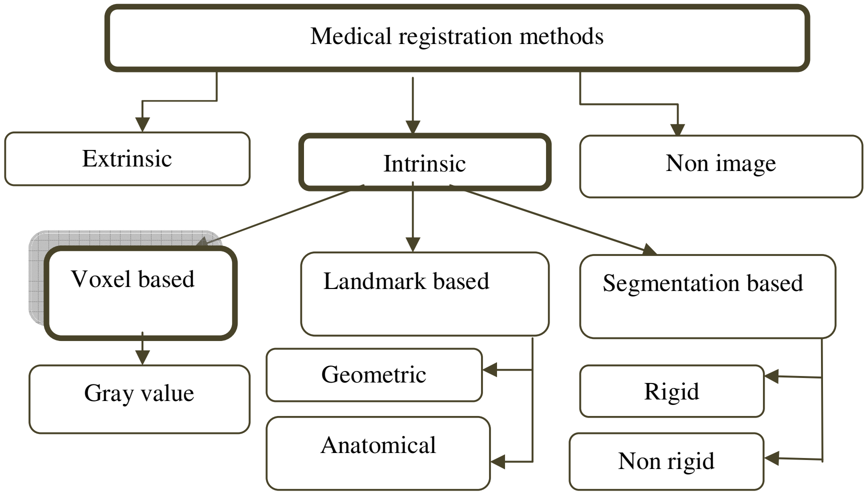

Figure (2): medical registration methods classification

IV. PROPOSED FRAMEWORK FOR MULTIMODAL IMAGE REGISTRATION METHODS

Multimodal image registration is one of challenging issue in the field of medical imaging. Therefore, choose the method with minimum error for medical image registration may seem important. In this section, various methods of multimodal image registration and the challenges of each method will explained. In medicine, patients often in order to better diagnosis or treatment is imaging with multiple radiology sensors. Due to changes in rotation or difference in image contrast, is difficult for a physician to combine mentally all image information carefully. Therefore, an image registration technique is necessary to transfer all image information to an overall system. As shown in figure (3), using this classification, a suitable method for multimodal medical image registration can be selected.

This section includes the proposed framework for classification of multimodal image registration methods and applications and challenges of each method in the field of medical imaging will be evaluated.

4.1 Information theory based methods

In recent decades, Information theory is used to effectively in multimodal image registration. In this part, measures of information theory and its applications in medical image registration is expressed.

4-1-1- Entropy

Shannon entropy for an image is calculated based on probability distribution of image gray values. When different sensors are used for imaging, display the intensity of an area in two images, is different. Consequently, the aim is reducing variance than the registration obtained .

The histogram in entropy based methods contains the combination of gray values in each of the two images for all corresponding points. When images are aligned correctly, joint histogram shows exact clusters of gray values.

In order to measure the joint histogram distribution of two images, Shannon entropy is used, its formula is shown in equation (1).

$$H(I_1, I_2, T_\alpha) = -\sum_{a,b} p_{I_1,I_2}(a,b) \log p_{I_1,I_2}(a,b) \qquad (1)$$

$$a = I_1(x_1, y_1) \qquad (2)$$

$$b = I_2(T_\alpha(x_1, y_1)) \qquad (3)$$

I_1 and I_2 are two images that geometrically marked with T_α transformation, So that pixels (x_1, y_1) in I_1 with an intensity, is correspond to the pixel $T_\alpha(x_1, y_1)$ in the I_2 with b intensity . While $P_{I1,I2}(a, b)$, that express a highly probable value pairs in the image I_1 and I_2 is correspond to the image intensity b. with finding T_a, is minimized entropy transformation and images registered [14] .

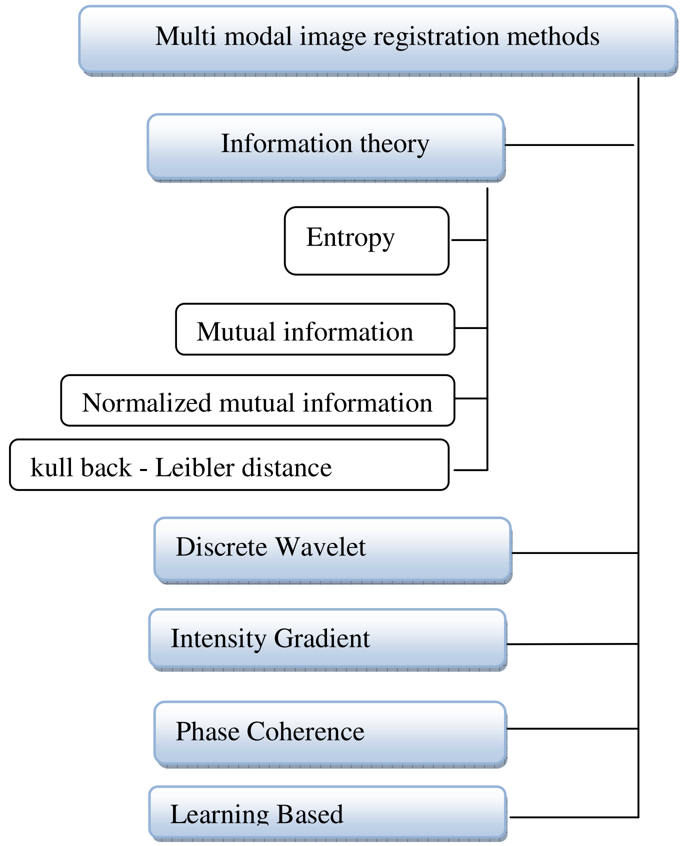

Figure (3): classification of multimodal image registration methods

4-1-2- Mutual Information

Shannon entropy problem is that lower values can lead to false match. For example, if only one element have been within the area of overlap of the two images, is produced a sharp peak in the joint distribution, Thus reduced the amount of entropy. Mutual information is one of the automatic image registration methods in medical imaging where it offers a measure of dependence between two images.

Equation (4) is mutual information definition so that I (I_1, I_2, T_α) is mutual information measure that aligned with T_α transformation.

$$I(I_1,I_2,T_\alpha)=H(I_1)+H(I_2)-H(I_1,I_2,T_\alpha) \qquad (4)$$

H (I_1), H (I_2) is based on border probability of intensity values in overlapping area of images.

4-1-3- Normalized Mutual Information

Size of parts with overlapping images, to impress the measure of mutual information in two ways: First, low overlapping, reduces the number of samples, so that is low statistical power of estimating the probability. Second, with increasing misalignment, which usually is associated with reduced overlap, the measure of mutual information increases. When total entropy increase marginal entropy is connected faster. Thus, a measure of normalized mutual information was provided less sensitive to changes that are overlapping [14].

4-1-4-Kull back–Leibler Distance

This method is based on a priori knowledge of the expected joint intensity distribution estimated from aligned training images. One of the key features is the use of the expected joint intensity distribution between two pre-aligned, training images as a reference distribution. The goal is to align any two images of the same or different acquisitions such that the expected distribution and the observed joint intensity distribution are well matched. In other words, the registration algorithm aligns two different images based on the expected outcomes. The difference between distributions is measured using the Kullback - Leibler distance (KLD). The KLD value tends to zero when the two distributions become equal. The registration procedure is an iterative process and is terminated when the KLD value becomes sufficiently small [15]. The Kullback - Leibler distance between the two distributions is given by equation (5):

$$D(PT\,||Pref) = \sum_{i1,i2=0}^{255} \mathrm{PT}(\mathrm{i1},\mathrm{i2}) \log \frac{\mathrm{PT(i1,i2)}}{\mathrm{Pref(i1,i2)}} \qquad (5)$$

The idea behind the registration technique is thus, to find a transformation T_0, acting on the floating image, that minimizes the KLD between the joint intensity distribution P_{T0} and the reference distribution P_{ref}. Or, in formula (6):

$$T_0 = \arg\min\nolimits_{\mathrm{T}} D\,(P_T \,||\, P_{\mathrm{ref}}) \qquad (6)$$

4.2 Discrete wavelet

In this method, firstly multimodal images are decomposed by wavelet transformation. Then calculated an energy mapping of detailed images from the subclass and is used genetic algorithm to obtain the absolute minimum total distance between the energy maps [16].

4.3 Intensity Gradient

The idea of applying this method is to determine similarity between images based on all images so that the image structure can be defined by changes in intensity. In this method, an image intensity change can be detected via the image gradient and considered the normalized gradient field, which is purely geometric information. Computation gradient is less sensitive and allow deal with noisy image [17].

4.4 Phase Correlation

The main challenge in automatic multimodal image registration is inconsistency in the intensity values and or contradiction between patterns and missing data between images. A method based on local phase dependency is not sensitive to the variation intensity, contrast or noise and provides efficient method for providing important characteristic of image. In multimodal image registration, a feature extraction method based on local fuzzy correlation measure is described. This feature show the behavior of local phase structure at various scales in near sharp image features. With a reference image and an input image, algorithm making the mapping of local fuzzy dependency for both images and estimation of transformation parameters will do registration using an objective function [18].

4.5 Learning Based Method

In learning based methods, Instead of using a universal, but a priori fixed similarity criterion such as mutual information, a similarity measure is learned, such that the reference and correctly deformed floating images receive high similarity scores. In other words, objective function is to maximize the correlation between input and reference images and to achieve the desired results, not preset preprocessing images [19, 20].

Multi modal image registration is the task of inferring a spatial transformation T for a reference image I_r and its corresponding floating image I_f. Given a similarity function s that quantifies the compatibility of aligned reference-floating image pairs, the optimal transformation of (I_r, I_f) is found by maximizing the similarity over all possible transformations, such as equation (7):

$$T^* = \arg\max_{T \epsilon \tau} s\,(I_r, I_f \circ T) \qquad (7)$$

Our goal is to train a similarity function s over a sample of pre-aligned image pairs such that the empirical cost of mis-registration. Figure (4) show an overview of a learning-based image registration system.

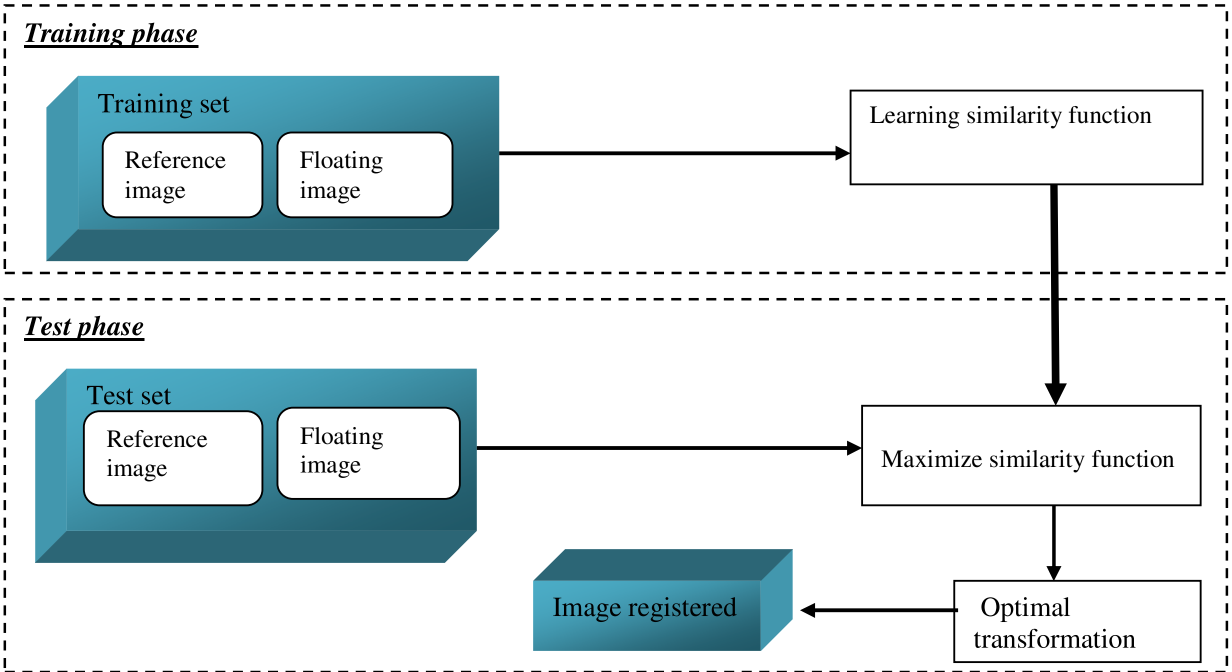

Figure (4): An Overview of a learning-based image registration system

V. EVALUATION OF MULTIMODAL MEDICAL IMAGE REGISTRATION VARIOUS METHODS

Generally, multi modal image registration methods are divided into three categories based on landmark, segmentation and voxel. As was expressed earlier, multimodal registration have more publicity on some medical images, Since medical imaging requires two principles accuracy and speed, in selecting an appropriate method of multimodal image registration according to these principles are important. Table (1) and table (2) evaluate amount of influence each of these methods on multimodal medical image registration process. The functional measures that considered in our evaluation of multimodal medical image registration are as follows:

- User Interaction: A multimodal image registration method usually is intensity based. They are in general fully automatic without the need for user interaction.
- Speed: A multimodal image registration method must guarantee high speed.
- Accuracy: A multimodal image registration approach must provide high accuracy in dealing with medical data.
- Computational complexity: This property express that how many iteration dose the algorithm need to find the optimal solution.
- According to studied the evaluation criteria can be seen that, methods based on voxel are effectiveness than other methods.

VI. CONCLUSION

Not specified the relationship between the intensity values of corresponding pixels, the difference between images contrast in some areas than other areas, mapping the intensity values in an image to multiple intensity value in other images, are challenging problems in multimodal image registration. Due to importance of image registration in medical, identification this challenges seem necessary. This paper had a comprehensive analysis on several types of multimodal image registration methods and expressed its affect on medical images area. To reach this goal, each method was investigated according to its affect on the field of medical imaging. Results of several studies, indicate that among several existing methods in multimodal image registration, voxel based methods is more important. Because of voxel based methods are applied on the image intensity values, are more important. Since, the main challenge in multimodal registration is diversity of image intensity obtained from different sensor, select the method that can identify the multimodal image registration main requirements (speed and accuracy) in the medical field, is the other objectives of this paper.

Table (1): evaluation of multimodal medical image registration methods

Computational complexity	**Accuracy**	**Speed**	**User interaction**	**Challenge**	**Similarity measure example**	**General approach**	**Evaluation / approach**	
high	low	low	interactive	User interaction	Nearest Iterative point	Determine the geometric features matching interactive	landmark	**Multi modal medical image registration**
Almost low	Almost low	Almost low	Automatic and semi automatic	Dependency between accuracy and segmentation	Chamfer	alignment of binary structures by means of a distance transform	segmentation	
low	high	high	automatic	……….	Information theory	using all the image content with computation of gray value	voxel	

Table (2): Multimodal registration methods analysis

accuracy	speed	User interaction	Challenge	General approach	evaluation / approach	
low	high	automatic	Local maximum	Measuring joint histogram distribution with different intensity	Information theory	Multimodal registration
Almost high	Almost high	automatic	Don’t responsible in depth and internal area of image	Fast wavelet transform for energy mapping from first function	Wavelet transform	
high	high	automatic	Observed based	definition image structure using intensity change with gradient calculation	Intensity Gradient	
Almost low	Almost low	Semi automatic	Don’t responsible with change in rotation or size	A feature based method based on Phase dependency that use of weighted mutual information	Phase Coherence	
high	high	automatic	Network train	Maximize the similarity using a learning based method	Learning based	

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Authors

Mohammad Reza Keyvanpour is an Associate Professor at Alzahra University, Tehran, Iran. He received his B.s in software engineering from Iran University of Science & Technology, Tehran, Iran. He received his M.s and PhD in software engineering from Tarbiat Modares University, Tehran, Iran. His research interests include image retrieval and data mining.

Somayeh Alehojat received her B.s. in software engineering from Islamic Azad University, Guilan, Iran. Currently, she is Pursuing M.s in software engineering at Islamic Azad University, Qazvin Branch, Qazvin, Iran. Her research interests include image registration and neural networks.