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A Review on the Process, Components and Performance of Medical Image Registration

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Abstract- In medical image analysis, registration is the process of aligning two or more input images of the same organ into a single more informative image. Registration process involves the estimation of optimal transformation that best aligns the objects of interest in the input images. The performance of registration method is measured on the basis of accuracy, reliability, robustness and efficiency. This study has two main objectives. Firstly, to systematically present the process and main components of medical image registration and secondly to report the important parameters for its performance. Our approach of review is unique from already published work because we have performed detailed investigation on the process and performance of medical image registration. The knowledge on the work that has been developed in the area is mathematically presented in a compact form. The contribution is to provide useful platform for the researchers and clinicians in the field and a reference for those searching for literature on the process, components and performance of medical image registration.

Keywords- **:** Medical Image Analysis; Image Registration; Registration Components; Registration Performance.

I. Introduction

Over the last few decades, medical imaging techniques have brought a lot of changes in the way disease being treated and the type of operation being done. The advancement in medical imaging techniques lead to the advancement in image guided surgery (IGS) [1] and radiation therapy. IGS and radiotherapy uses medical imaging techniques for disease identification, classification, treatment planning, monitoring and evaluation of disease and detection of progression in structural and functional organs. These advanced techniques have the advantages of quick recovery, non-severe surgical
trauma and reduced length of stay and cost in hospital [2]. Currently, medical imaging techniques can help a clinician in qualitative diagnosis and proper decision making in the diagnostic process. Moreover, the tumor is accurately resected based on the information obtain image information. Real time precise information during IGS and radiotherapy is available now to the clinicians due to the integration of intra-operative imaging with navigation technology.

In medical imaging, registration process integrates information from multiple images. The process of image registration is done by geometrically aligning/mapping matching points (image pixels or voxels) from two or more images [3-7]. The aim of registration is to find a spatial transformation that aligns the points in one image to the corresponding points in the second image suppressing the geometrical deformation between the two of them [8]. This concept is presented graphically in Fig.1. Fig. 1 shows the mapping of coordinate frames and anatomical structures in one image of the same organ to their corresponding positions in another image of that organ. The moving image or the image being deformed is called source image and the fixed or un-deformed image to which it is compared is called the target image [9]. For a 2D image the problem is posed as finding a transformation T such that

$$[x, y] = [x', y'] + T([x', y']) \qquad (1)$$

Where the object at coordinates $[x, y]$ in the target image is at coordinates $[x', y']$ in the source image. The definition can be easily extended to any number of dimensions.

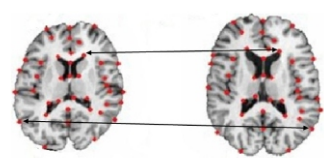

Fig. 1. An example of corresponding points for two brain images of the same patient: The tissue location pointed by the arrow on the left image (x, y) corresponds to the tissue location pointed by the arrow on the right image ($x' y'$).

In medical image registration, images of a human organ may be acquired with the same or different modalities, either from same or different viewpoints and times. The purpose is to carry out accurate diagnosis and to perform successful treatment. Several types of imaging modalities are now available with different types of mechanisms to extract information (structural and functional) from human organs. For example, computed tomography (CT) and magnetic resonance imaging (MRI) are used to extracts anatomical information. On the other hand, single photon emission computed tomography (SPECT) and positron-emission tomography (PET) are used to extract functional information [10]. Integrating multiple types information [11] (functional and anatomical) from human organ is necessary in IGS and radiotherapy. It helps the surgeon in the proper diagnosis and treatment planning of a patient.

Spatial transformation is an important component of image registration in which spatial relationship between the images is determined. In spatial transformation model, the registration method can be categorized as linear and Non-linear. Linear registration includes rigid and affine while nonlinear registration include nonrigid and deformable. Fig. 2 shows a general overview of linear and nonlinear brain image registration.

As shown in the Figure, the linear registration is performed by translating, rotating, scaling, and shearing the images. On the other hand, nonlinear deformable registration mapped voxel-to-voxel correspondences between input images. Medical image registration is widely used in IGS and radiotherapy for the accurate voxel by voxel mapping of complex images with large-scale local and global deformations. Medical image registration also enhances the planning, execution and evaluation of surgical procedures. In the registration process, a special association between source image IMS and target image IFT is established during transformation as shown in the Fig.2. The correspondence between transformations signals are usually performed either locally or globally in a linear and non-linear fashion.

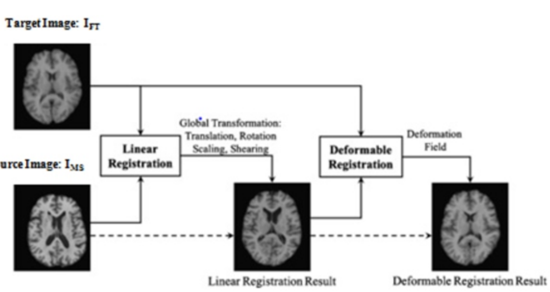

Fig. 2. A general procedure of brain image registration

The objective of this paper is to describe the available knowledge on medical image registration process/ components and performance in a systematic form.

This work attempts to provide a theoretical foundation and compact platform for researchers by presenting the important aspects of medical image registration (components and performance). It will help clinicians by providing relevant and quantitative information on diagnostic, surgical and treatment planning which will eventually improve their knowledge on this challenging area of research.

The rest of the paper is organized as follows: Section II provide a detail overview of registration process and components. Section III present and analyzes the performance parameters for the registration approach Experimental evaluation of existing registration approaches is presented in section IV. Section V summarizes this paper.

II. Registration Process and Components

In general, registration is the process of transformation *T* from one image to another one. In the registration of two images, we generally consider two images for transformation. One image is considered as fixed also called target image i.e. $I_{FT}(x)$ and the other is considered as moving also called as source image i.e. $I_{MS}(x)$.

Source and target images are defined in their own spatial domain (source image: $\Omega_{MS} \subset R^d$ and target image: $\Omega_{FT} \subset R^d$).

In the registration of medical images, a transformation function *T(x)* is determined which map one image (source image) to another (target image). In other words, transformation function align/map one image (source image) according to the coordinates of another image (target image) i.e. $T : \Omega_{MS} \subset R^d \rightarrow \Omega_{FT} \subset R^d$[12]. The aim of registration is to maximize the similarity *S* or minimize the cost function *C* with respect to the transformation function *T*. It is an optimization problem [13] and is given by

$$T' = \arg\min_T C(T; I_{FT}, I_{MS}) \qquad (2)$$

or

$$T' = \arg\max S(T; I_{FT}, I_{MS}) \qquad (3)$$

In the above equations, the optimum transformation is represented by T′ while optimization is represented by arg *m* in and arg max I_{FT} and I_{MS} are the target and source images, respectively. In equation 2 *C* is the cost function while in equation 3, *S* is the similarity metric. These two metric shows how well the two images are aligned.

In the registration process geometrical transformation between separate images are determined and are accordingly aligned. The purpose is to obtain complementary and maximum information. Registration process is performed iteratively, moving or source image is transformed to the coordinates of target or fixed image. After the transformation, similarity metrics between moving and fixed images (source and target) are estimated. In the last step, the final and more informative image is created, if the similarity metrics are satisfied. The registration process is continued several times until the perfect alignment of two input images. Fig. 3 graphically shows the complete process of image registration. The description of registration component shown in the Figure is represented in the subsequent sections. In the registration process, the coordinates of one image (source) is transformed to the corresponding coordinates of another image (target) iteratively.At each iteration, the optimizer check maximum similarity measure and if it is not achieved, the process is repeated. This process is continued until the transformation function optimally aligns source image features into their corresponding target image space.

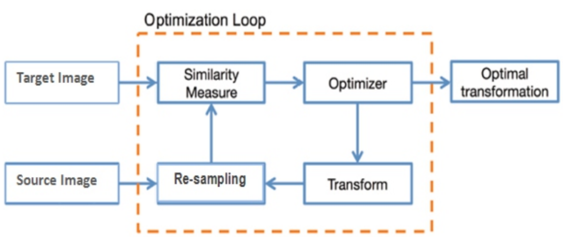

Fig.3.The process/components of registration

A. Transformation

In image registration, transformation is mapping function that associate spatial information in one image to those in another or in physical space [14]. The transformation function transformed moving source image into the fixed target image coordinate system, as shown in Fig.4. The general equation for the transformation is:

$$T:\Omega_{MS} \subset \mathbb{R}^2 \rightarrow \Omega_{FT} \subset \mathbb{R}^2 \qquad (4)$$

Where T maps each point $x_i \in \Omega_{MS}$ to $T(x_i) \in \Omega_{FT}$.

An important role of the transformation function in the registration is to use information obtained from the corresponding coordinates for the deformation of one image (source) to the geometry of the other (target)[15]. The type of transformation is associated with the number of dimensions of the image. Transformation is described by the number of parameters, or "degree of freedom". Rigid or linear transformation is usually required for the registration of 2D undistorted images while deformable transformation is mostly used for the registration of 3D images obtained at different phases during the respiratory cycle[16].

Fig.4. Transformation of moving source image to the coordinates of fixed target image

1) Rigid Transformation

Rigid transformation is the type of transformation in which the distance between points in the image are preserved[17]. For example, point-to-point distance and angles between strait lines remain unchanged[18].Images of the same subject are mostly co-registered with rigid transformation. Rigid registration involve rigid transformations such as the mapping of different head positions obtained from multiple scans[19]. Rigid transformation can be described with translations and rotations only. This type of transformations is also called Euclidean transformation because it preserves the Euclidean distance. Euclidean transformation can be expressed mathematically as

$$x' = T_{e^x} = \begin{bmatrix} R & t \\ 0^{\mathrm{T}} & 1 \end{bmatrix} \qquad (5)$$

In the above equation R represent the orthogonal rotation matrix, the translation vector is represented by t and a null vector by 0. Euclidean transformation depends on the dimensions. For instance for 2D images, the transformation is defined as

$$T = \begin{bmatrix} R & t \\ 0^{\mathrm{T}} & 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & t_x \\ \sin\theta & \cos\theta & t_y \\ 0^{\mathrm{T}} & 0 & 1 \end{bmatrix} \qquad (6)$$

In equation (6), the angle of rotation is represented by θ. Translation on x-axis is represented by t_x while on y-axis it is represented t_y. The degree of freedom in rigid transformations is less than affine, projective and deformable transformations. The degrees of freedom in two-dimensional rigid transformation are three, one for the rotation of image and two for the translation of image. In three dimensional rigid transformations, the degrees of freedom are six i.e. three for the rotations of image and three for the translations of image.

Fig.5 shows the rigid transformation of two MRI images of same subject obtained acquired with different scan sessions each using a different MR Scanner. A rigid transform T is an image coordinate transformation composed of a translation vector (Tx, Ty, Tz) and a rotation matrix defined by three Euler angles (θ, Φ, Ψ) as

$$T = f(Tx, Ty, Tz, \theta, \phi, \psi) \qquad (7)$$

By applying the registration transform to the initial source image I_{MS}, a new image $\tilde{I}_{MS}$ is generated spatially aligned with the target image I_{FT}. This allows the extraction of complementary information from the two images.

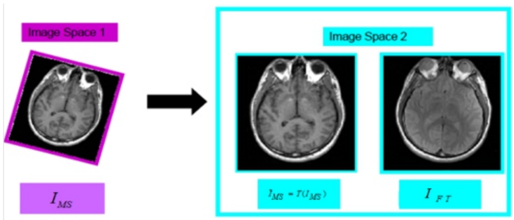

Fig.5. Rigid transformation of two MRI images of same subject acquired with different scan sessions each using a different MR Scanner

2) Deformable Transformations

Rigid transformations do not have enough degrees of freedom or flexibility to accommodate local shape differences. Moreover, rigid transformation is also not suitable in images containing tissue with spatially varying tissues. Such types of images with local shape differences and spatially varying tissues requires deformable (non-rigid) transformation[15]. Deformable transformations allows many possible deformations of one image into another[20]. It is a non-uniform mapping between images and measure small, varying discrepancies by deforming source image to match the other. Deformable transformations allow locally changing deformation.

In deformable registration the voxel-to-voxel correspondences between source image I_{MS} and target image I_{FT} is established during transformation. Fig. 6 shows the process of deformable registration. In the Figure, determining the deformation field is a high-dimensional ill-posed optimization problem. Deformation smoothness is imposed to avoid implausible deformations and to preserve topology. Deformable transformations are effectively used to describe the spatial relationship between images. These applications include multimodal image registration, inter and intra-patient registration and longitudinal studies[21].

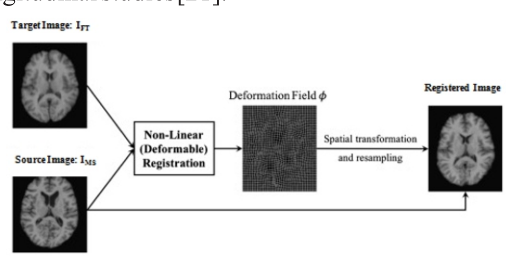

Fig.6. An overview of deformable medical image registration

Deformation always occurs in the registration of images obtained from multiple imaging modalities.

Moreover, modalities such as mammography and ultrasound also create internal deformations[15]. Multi-modal image registration is an essential technique in several medical procedures such as diagnosis, treatment planning, therapeutic procedures and interventional surgical guidance. Deformable transformation is required in intra-patient registration. In these types of registration, deformable transformations accommodate deformation in tissue. It is due to natural changes over time in the patient anatomy or due to interventions. Similarly, deformable transformation also play a key role in inter-patient registration and properly accommodate the substantial variability across individuals[14].

In non-rigid [22] registration, the geometric transformations can be divided into either physically based models or a basis function expansion. The earlier is depicted by partial differential equations of mechanics while the later is derived from the interpolation [23].A realistic deformation is mostly estimated with physical models. However, these models are simple and are suitable for the estimation of small deformations. Using physically based models for complex deformations a significantly higher computational effort will be required. Therefore, future research is required for the development of advanced biomechanical models and continuum biomechanics.

B. Re-sampling/Interpolation

In the registration process, after the derivation of spatial transformation, re-sampling and interpolation are performed which compensate the unnecessary impenetrable movement and create registered image. The pixel values (elements) of the deformed source image at a coordinate determined by the fixed target image are estimated using the process of interpolation[16].Interpolation depends on similarity measure, or transformation. The interpolation of values obtained from source image at given coordinate in the target image provide several benefits during registration process. The sparsely populated areas in the deformed source image are usually caused by deformable transformation. Interpolation is spatially required in such cases to estimate the pixels values of deformed source image at the coordinate determined by the target image. Nearest neighbor, linear and cubic convolutions are commonly used interpolation methods for image registration.

C. Similarity Measures

The terms image quality assessment and image similarity assessment are closely related. Image quality depends on the visible differences between fixed image (target image) and moving/deformed image (source image) [24]. Similarity measure is an important component of medical image registration which

evaluate and compares the source and target images. It is based on pixel intensities and patterns, cross-correlation, anatomical structures and mutual information[25-32].
Similarity measure is estimated on basis of modality involved, angle of view and time interval [33]. In the registration process, at every iteration similarity is checked between input images. If the measure of similarity is not according to the requirement of successful registration then the process is optimized to further determine the best alignment between two images (source and target) as shown in Fig. 3. Let F be similarity function, T be registration transformation, then the degree of similarity $\Psi(.)$ between source image I_{MS} and target image I_{FT} is calculated as

$$F(I_{MS}, I_{FT}, T) = \Psi(T(I_{MS}), I_{FT}) \quad (8)$$

In the registration process, pixels of the source and target images are mapped at the same image coordinate. For example, the first pixel in target image represent the first pixel in source image while the second pixel in target image represent the second pixel in source image and so on. Some of the popular measures for estimation of registration performance are Mutual Information (MI), Correlation-Coefficient (CC), Mean Square Error (MSE), Sum of Square Difference (SSD [34] and Peak Signal-to-Noise Ratio (PSNR). The performance of the registration is evaluated on the bases of these similarity measures.

1) Mutual Information (MI)

In image registration, mutual information (MI) [35] estimates the degree of dependency between source and target images. MI is a popular tool for image registration and it maximizes the similarity between two images. MI provides optimal transformation between source and target images. The transformation matrix includes rotation, translation, scaling and shear. MI is extensively studied for the medical image registration over several years. The robustness and accuracy of rigid registration in multimodal images can be easily measured with MI.
The main aim of MI in the registration is to properly map source and target images and maximizes the quantity of information in a registered image. MI is used for the registration of two-dimensional (2D) and three dimensional (3D) images [36,37]. Mutual information assumes a statistical relationship that can be captured by analyzing the images' joint entropy [38][39][40]. Mathematically as

$$MI(I_{FT}, I_{MS}) = \sum_{x} \sum_{y} \mathrm{P}_{I_{FT}I_{MS}}(x,y) \log \frac{\mathrm{P}_{I_{FT}I_{MS}}(x,y)}{P_{I_{FT}}(x) P_{I_{MS}}(y)} \quad (9)$$

In the above equation, joint probability of pixels for both images (source and target) is represented by $\mathrm{P}_{I_{FT}I_{MS}}$ while the probability distribution of each image is represented by P. The value of entropy is maximum when the mapping of two images is poor. Therefore, the value of entropy needs to be minimized for the best mapping between source and target images. MI has been widely used for several types of applications in registration of medical images and it is considered as popular metric for determining the robustness and accuracy of registration.
Using MI, the performance of three different registration approaches developed by Alam, Fakhre, et al. [41] (approach-1), Lombaert, Herve, et al. [42] (approach-2) and Rahunathan, Smriti, et al. [43] (approach-3) are shown in Table 1. In the Table, 6 image pairs (source and target image) rotated at different angles are evaluated and their MI is calculated. Registration approach having maximum MI between two images is considered optimal registration.

TABLE 1
USING MI THE PERFORMANCE OF THREE DIFFERENT REGISTRATION APPROACHES

Sample Image	Theta (degrees)	Approach-1	Approach-2	Approach-3
		MI	MI	MI
Pair-1	15	1.6017	1.5033	1.4405
Pair-2	30	1.1868	1.0798	1.2668
Pair-3	45	1.3238	1.4561	1.2156
Pair-4	60	1.92604	1.8902	1.33872
Pair-5	75	2.0313	1.9799	1.2464
Pair-6	90	3.4866	2.6153	1.5243

2) Mean Square Error (MSE)

Accuracy of the registration algorithm depends on the mean square error (MSE) value and it evaluates the quality of the registration [44, 45]. As similarity measure MI considers only pixel values for comparing source and target images. In order to compare two images with pixel positions (geometry), mean square error (MSE) is an optimal parameter for estimating the similarity between source and target images.
Mean square error represents the average of the squares of the "errors" between fixed target image and moving source image. The error is the amount by which the values of the fixed image differ from the moving image. For given two images, the MSE is used to measure the registration quality, mathematically

$$MSE(I_{MS}, I_{FT}) = \frac{1}{N} * \sum_{i=1}^{N} (I_{MS_i} - I_{FT_i})^2 \quad (10)$$

Where I_{MSi} and I_{FTi} are intensity of ith pixel of the source image I_{MS} and target image I_{FT}, and N is the number of considered pixels. A lower value of MSE means lower similarity error and higher similarity between the two images.

3) Peak Signal-to-Noise Ratio

Peak Signal to-Noise-Ratio (PSNR) is a valid quality measure for evaluating the performance of registration. It measure the difference between source and target images [46]. PSNR measures the quality of moving source image (reconstructed, recovered or corrupted) with respect to its original fixed target image. The higher the PSNR, the better moving source image has been reconstructed to match the fixed target image and the better the registration algorithm. PSNR is measured in logarithmic decibels (dB) scale. If p is the largest possible value of the signal, MSE is the difference between source and target image, then PSNR is define as

$$PSNR = 20\log_{10}\left(\frac{P}{MSE}\right) \tag{11}$$

The PSNR metric is mostly used to describe the quality of denoised image. In image registration, PSNR is estimated on the basis of dynamic range and the MSE of the image. The obtained PSNR for two images with different dynamic ranges and corrupted with the same amount of noise will be different. It is due to the difference in dynamic ranges. However, PSNR is a best and commonly used image quality metric in the registration process.

4) Sum of Squared Difference (SSD)

Sum of Squared Difference (SSD) is a popular similarity measure based on pixel computation. It is widely used in the monomodality medical image registration [47]. It is based on pixel by pixel intensity differences between the two images (source and target)[48]. SSD accumulate the square of intensity difference between the fixed target image I_{FT} and deformed moving source image I_{MS}.

Mathematically it is expressed as

$$SSD = \frac{1}{N}\sum\sum\sum(I_{FT}(x,y,z) - I_{MS}(x+v_x, y+v_y, z+v_z))^2 \tag{12}$$

Where N denotes the total number of voxels in the source image I_{MS} after the application of deformation field $\vec{v}$. The SSD measure is widely used for serial MR registration. For small number of pixels with high intensity differences between the two images, the sensitivity of SSD is also high. This type of situation is usually occur, if contrast material is injected into the patient veins or arteries between the acquisition of two images.

5) Cross Correlation (CC)

Cross-correlation (CC) is an important similarity measure in the registration of medical images with linear relationship. CC metric is widely used for intramodality registration and for the estimation of similarity between two images [49]. CC is an ideal metric for the registration of medical images whose intensities are linearly related [50]. The values of correlation coefficient range between -1 and +1. In case of strong similarity among the pixels of input images, the value of CC falls in positive range. In case of low similarity between images, the value of CC falls in negative range. In other words, if the absolute value of a CC is higher, the more will be the linear relationship between input (source and target) images. In order to estimate the degree of relationship between two quantities, Pearson presented a mathematical equation for correlation coefficient, as shown in equation 13 [51].

$$CC(I_{MS}, I_{FT}) = \frac{\sum_x (I_{MS_x} - \overline{I_{MS}})(I_{FT_x} - \overline{I_{FT}})}{\sqrt{\sum_x (I_{MS_x} - \overline{I_{MS}})^2 \sum_x (I_{FT_x} - \overline{I_{FT}})^2}} \tag{13}$$

Where $\overline{I_{MS}}$ the mean pixel value of source image I_{MS} in the overlapping region and $\overline{I_{FT}}$ is the mean pixel value of target image I_{FT} in the overlapping region.

The performance of single modality (monomodal) and multi-modality (multimodal) image registration are evaluated with correlation coefficient. In IGS and radiation therapy, correlation coefficient is considered as a useful similarity metric because in these applications, the images are mostly obtained from same modality. However, in multi-modal image registration, this similarity metric is not considered a favorable choice [52]. In medical image registration, CC can be easily implemented and there is no to calculate the probability densities at every iteration. Furthermore, CC is insensitive to geometric distortion and intensity in-homogeneity.

D. Optimization

The goal of registration is to obtain maximum and complementary information through geometrical transformation and mapping [53]. This process is performed iteratively, until the similarity measures are fulfilled and as result a registered image is generated. If the measures of similarity is not perfectly achieved the registration process is repeated. The repetitions continue till the optimization of transformation parameters. Optimization is an important process in image registration because it optimally aligns the intensity values in two images. Since optimization modify the parameters differences in images, as a result, the two input images (source and target)become perfectly aligned [54].Optimization is an iterative process, it continuously perform the operation till the identification of optimum parameters for mapping[55]. Currently various registration problems are successfully solved with the help of available optimization techniques. The proper mapping of corresponding information in image registration can be done with the help of available optimization techniques. However, each optimization technique uses its own mechanism for mapping in image registration. Moreover, the performance of registration greatly depends on the chosen optimization technique [56].

III. Performance of Registration

The performance of registration algorithm is measured on the basis of accuracy, reliability, robustness and efficiency. Moreover, registration performance also depends on the, resource requirements, algorithm complexity and clinical use. The performance (efficiency and accuracy) of registration algorithm plays an important role in IGS. Proper registration of related information in multiple images provides a basis for treatment and follow up process[8]. Efficiency, accuracy and robustness are the important parameters for the evaluation of registration algorithm. Using these parameters, registration algorithm can be used as a clinical tool for patient safety and healthcare.

The accuracy, efficiency, reliability and robustness of image registration algorithm depend on many parameters. These parameters include modality, similarity measures, transformation, optimization, effects on image contents and implementation mechanisms[57].

A. Accuracy

Accuracy is the direct measure of the registration and it is the difference between the true and estimated values. With reference to image registration, accuracy can be expressed for the estimated registration parameters. Accuracy can also be referred to the mean or root mean squared distance between corresponding points in the two images. Accuracy in registration is very important in clinical applications because it greatly help surgeon to make an incision on the proper place[58]. Registration technique is more accurate of it gives better results in terms of both quality and quantity. The qualitative accuracy of medical image registration technique is generally based on visual inspection by trained medical experts. In other words, the medical experts see if the related structures are successfully lying on the top of each other. The quantitative accuracy of medical image registration technique depends on mathematical or statistical techniques. These techniques quantitatively measure the accuracy of registration. Although, accuracy validation is difficult but essential to clinical application of medical image registration techniques.

B. Reliability

Reliability is the number of times the algorithm succeeds in finding the correct answer with reference to the total number runs performed. In other words, reliability of registration technique means that the algorithm should complete the assigned task incessantly in a reliable fashion. For example if the image registration is performed for n numbers of image pairs out of which m numbers of image pairs are registered correctly then the reliability of the algorithm is m/n. The reliability of registration technique is estimated on the basis of success rate and capture range[59]. The number of successful registration in the whole procedure against the number of all registrations is called the success rate while in capture range, the distance from the reference point to the first 1mm subinterval for which the registration is successful in less than 95% of all cases.

C. Robustness

Robustness tells about the impact of variations in certain parameters on image registration. Robustness measures the degree of stability of the registration algorithm. It can be measured with respect to noise, illumination variations, occlusion, non-overlapping region etc. In other words, robustness of a registration algorithm refers to its capability to perform effectively in rowdy environment [60]. A registration algorithm is robust or stable if it should not produce unpredictable results in somewhat different or abnormal situations. Since medical images are mostly inconsistent due to natural behavior. Therefore, registration algorithm should also be robust to properly manage small differences in the multiple images obtained from the same organ during image-guided surgery (IGS)[61].

D. Efficiency

The computation complexity/ efficiency show how much time is required to execute the algorithm. In other words, the efficiency of registration technique is evaluated on the basis of computation times it takes during execution. The efficiency of registration algorithm is an important parameter in IGS and other clinical application because timely respond with accurate alignment is always desired[62]. The efficiency of rigid registration is generally high due to simplicity in the transformation process and the use of less number of parameters for alignment. Deformable registration algorithm, on the other hand, is slow because it is affected by the detection of many parameters and asymmetric transformation. The efficiency of deformable registration algorithm can be improved by using symmetric transformation. Moreover, the efficiency can also be improved by using minimum number of parameters for correspondence.

E. Algorithm Complexity, Resource Requirements and Clinical use

The performance of registration is also estimated on the basis of resource requirements and the complexity of an algorithm. These two measures go hand in hand. For example, if a complex registration algorithm is required for images with high deformation and complexity, then the resources required to perform such a task will also be higher. On the other hand, images with low complexity required minimum resources and can be aligned with less complex rigid registration. Resource requirements and algorithm complexity are also related to clinical applications. In real time applications such as surgical interventions, a registration algorithm should be efficient because it will alternatively increase the required resources. The clinical use of registration method depends on several factors such as feasibility and computational efficiency. In clinical application, the medical expert analyze registration algorithm on the basis of feasibility and efficiency.

The performance of the image registration also depends on the performance of its components i.e. feature selection, feature correspondence etc. For example, in feature correspondence, the performance can be represented by true positive probability, which is termed as correct match rate in the community of image registration. Among the n numbers of features, correctly matched features are m then the correct match rate is given by m/n. In summary, till now it is not possible for a single registration algorithm to perform perfectly and meet all of the above parameters.

IV. Experimental Evaluation of Existing Registration Approaches

The performance of the two existing registration approaches is evaluated on 2D MRI slices of glioma patients. The size of images used in the experiments was 234×310 pixels. The existing registration approaches were implemented in Matlab and tested on an i7 core 3.3 GHz with 16 GB RAM.

The registration approaches has been used to register the fixed target image and moving source image deformed at different levels. In order to qualitatively visualize the whole process, the results are presented in several steps.

The registration performance of selected registration approaches based on MSE, PSNR, SSD, CC and computation time are shown graphically in Fig.7, Fig.8, Fig.9, Fig.10 and Fig.11.

In Fig. 7, MSE at different deformation levels between target and source images before deformation, after deformation, using existing approach 1 and approach 2 are graphically shown. In the Fig., MSE is zero before deformation, high after deformation, minimized up to some level with registration approach 2 and almost near to zero in registration approach 1. This shows that the performance of registration can be measured using MSE.

The performance of registration can also be measured with peak signal to noise ratio (PSNR). The higher the PSNR, the better will be the registration between images. The PSNR between two images after deformation, with approach 1 and with approach 2 is

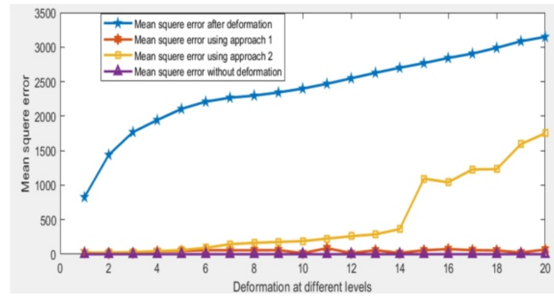

Fig.7. Mean square error of different registration approaches, before deformation and after deformation.

shown in Fig. 8. In the Fig., the high value of PSNR show that a particular registration algorithm tried to perfectly resembled the deformed source image with fixed target image.

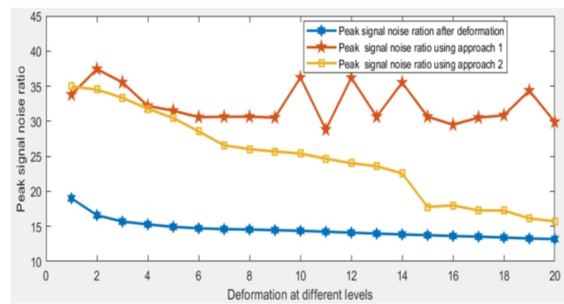

Fig.8. Peak signal noise ratio of different registration approaches, before deformation and after deformation.

The performance of registration approaches evaluated with Sum of square difference (SSD) metric as shown in Fig.9. In the Fig., the value of SSD is at the lowest points before image deformation and at the highest points after image deformation. In the Fig., the value of SSD is closed to the minimum levels in case of registration approach 1 and it is maximum in case of registration approach 2. This shows that the performance of approach 1 is better than approach 2.

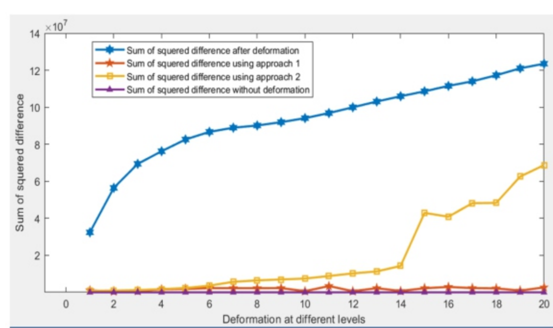

Fig.9. Sum of square difference of different registration approaches, before deformation and after deformation.

One of the objectives of registration algorithm is to maximize cross correlation and minimize cost. In this study, we have also evaluated the performance of two existing registration approaches with cross correlation (CC) similarity metric. Cross correlation measure the similarity between the intensities/features of two images. The CC obtained for approach 1, approach 2, before deformation and after deformation is shown in Fig. 10. In the Fig., the CC obtained for registration approach 1 is almost 1 which shows that the registration is perfectly performed.

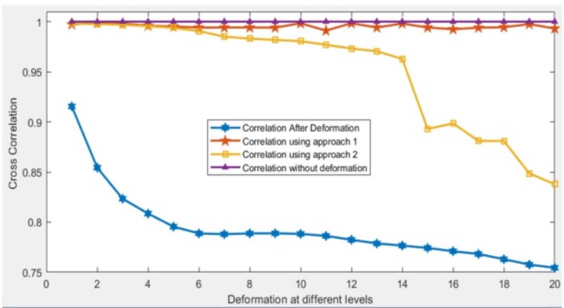

Fig.10. Cross Correlation difference of different registration approaches, without deformation and after deformation.

The performance of registration algorithm is better if it takes minimum computation time and less memory space during execution. The computation time of two registration approaches are shown in Fig.11. The obtained result show that the registration approach 1 takes minimum execution time to complete the registration process for the input images as compared to registration approach 2.

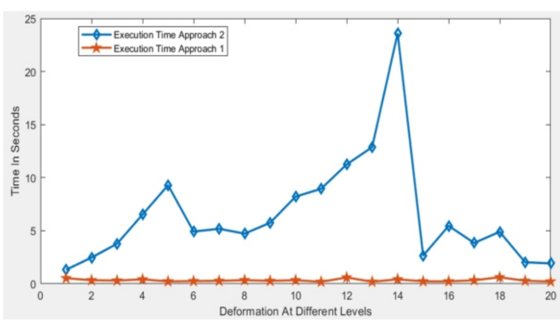

Fig.11. Computation Time of different registration approaches.

V. SUMMARY

Registration is a challenging task in medical image analysis due to different imaging conditions, variability in anatomical structures and elasticity of the body and organs. In this paper, we have provided a comprehensive knowledge in a compact form on the medical image registration process, its components and performance. The major components involve in the registration process are transformation, interpolation, similarity measure and optimization. The performance of registration is measured on the basis of accuracy, efficiency, reliability, resource requirements, algorithm complexity and clinical use.

In this review, it has been found that each component in registration process plays an important role. Moreover, the performance of registration also depends on several factors including efficiency, accuracy, reliability, robustness, algorithm complexity, clinical use and resource requirements.

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