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Hybrid image registration methods: A Review

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ABSTRACT

This paper presents a review of hybrid image registration techniques (methodologies) that have been used in the medical field. This paper aims to present the survey of methods and methodologies available in context to image registration techniques according to a hybrid approach used to get images registered. Image registration is the first step in digital image processing which include the geometric alignment of sensed and reference images. Different areas of image processing like computer vision, remote sensing and medical image analysis have different methods for image registration along with different challenges associated with individuals. In this paper, work related to the hybrid image registration process is presented. In the hybrid approach, the individual superiority or advantage of different methods are combined in order to get the better results in comparison to individual approach.

Key words: Image registration, feature and intensity-based techniques, hybrid techniques.

1. INTRODUCTION

In case of image analysis processes like image fusion, there are necessary or important pre-processing stages that cannot be ignored.

A persistent problem in the image processing emerges when images captured at different time frames or by different modalities from distinct viewpoints need to be analyzed for further processing[1]. The analysis of images is necessary because information content present in one image is complementary to the other image taken by different modalities or at different time. Image registration is an important aspect while talking about image processing and analysis. The process of superimposing the images into one another is referred as image registration so that misalignment or differences are analyzed and corresponding features can be related [2]. The reason for misalignment between the two images is because of taking the images from different viewpoints, sensors position variations, capturing characteristics ,patient or object movement [3]. There is widespread application area where image registration process is used such as remote sensing, medical image analysis, robot vision ,computer vision, pattern recognition etc. [4]. In medical image analysis, image registration plays an important role. Accurate and on time treatment for a patient is of undeniable importance. The different type of scans conducted for the diagnosis of the disease from which the patient is suffering, may not provide complete information and may lead to false diagnosis. The images taken from different modalities provides complementary information [5]. In medical image processing application, registration of two or more images is of great importance so that the scans providing the complementary information need to be registered and then analyzed.

Different areas of image processing like medical image analysis , remote sensing and computer vision and have different methods for image registration along with different challenges associated with individuals. Like in the medical image analysis field, ultrasound imaging has much popularity in because of its low cost and real time information acquisition. Regardless of this much popularity, while analyzing the acquired images of ultrasound face challenges when dealing with intensity-based image registration. The main point is that the supposition regarding the noise and artefacts in case of ultrasound are somewhat different as compared to those of MRI/CT [6]. In case if any organ imaged with different modality or sensor at different time or from different angle then it is not necessary that it provide with the same information, organ is captured differently in each case. The reason of this is the physical principle involved with the imaging modality is different in every imaging modality e.g. CT, MRI, PET, SPET etc. Further analysis of the images is done using image fusion process in which the data from different modalities is integrated to form a single image with combined information.[7].

In case of remote sensing, large number of algorithms or methods are available for image registration. Gupta and Patil[8] discussed different techniques with emphasis on Fourier Mellin transform method. Along with these algorithms different challenges or difficulties are also associated with this particular field e.g. geometric distortion (translation ,scaling, rotation) and radiometric variations (spectral content difference, sensors, radiance change)[9].

There are number of ways to categorize the different image registration methods [3], [10]–[12]. According to [10], registration methods are reviewed with respect to imaging modality, image dimensionality (n-D, where n=1,2,3.....), registration basis, geometric transformation, user interaction, optimization procedure, subject, and object of registration. In the field of remote sensing [11] presented a review of different classes of techniques. A detailed survey for deformable image registration is presented in [13]. The basis for survey is deformation models, matching criteria, and optimization methods.
In this review we will discuss the basic process of image registration. The review mainly covers the hybrid image registration techniques in details. The intensity based and feature based image registration process and their components are also discussed.

2. GENERAL PROCEDURE FOR IMAGE REGISTRATION

The general procedure for image registration is as given in Table 1 for each type of image registration e.g. intensity based, feature based and hybrid approach.

Table 1: Procedure of different types of image registration

Feature based	Intensity based	Hybrid approach
• Acquire reference and sensed images. • Pre-processing (de-blurring, sharpening) • Feature Extraction or detection (lines, points regions etc.) • Feature matching (Normalised cross-correlation, mutual information, entropy information etc.) • Outlier Rejection if any • Estimating transformation (translation, rotation, affine or B-spline etc.) [14]	• Acquire reference and sensed images. • Apply initial transformation on sensed image • Similarity metric calculation • Optimisation of similarity metric • Checking whether images are registered or not • Update transformation parameters if not registered.	• Acquire reference and sensed images. • Combine or hybrid intensity and feature values • Similarity metric calculation • Optimisation of similarity metric using hybrid optimisation approach [15][16].

3. FEATURE BASED METHODS

It is broadly classified as manual and automatic image registration. Figure 1 shows the basic flow chart for feature-based image registration. While considering manual image registration, the human operator plays an important role, operator select the control points which are easy to recognize visually in sensed and reference image. In such manner operator is required to selecting and matching features.

The challenges associated with manual image registration are time consuming, tedious, laborious and repetitive task. These techniques may results in inconsistency, less accuracy [17]. For the automated image registration, there are two main methods for registration, one is area-based and another one is feature-based. While we talk about area-based methods, a window of some points is selected from the sensed image and compared with the same window in the reference image.

The similarity measure is generally normalized cross correlation in this case. This correlation measure is not reliable when the case of multimodality and grey level variation came into picture. The process of feature-based methods basically involves the three steps mainly that are feature extraction, outlier removal and feature matching. Different algorithms are available for each step. Feature based methods register images based on the features present in the images, and these features can be segmented from the images but the segmentation part is tough to deal with and results in error in final registration [18].

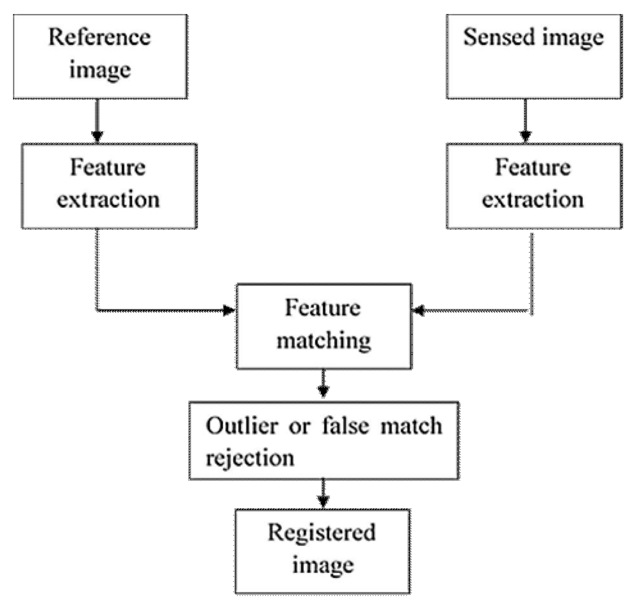

Figure 1: Flow chart for feature- based image registration

A method is introduced in which control points (CPs) are selected based on the scale-invariant feature transform (SIFT). The preliminary registered image is subdivided into chips of 64×64 pixels, and each chip is matched with corresponding chip using normalised cross correlation (NCC) [16]. An automatic image registration method was proposed [19], which combines the image segmentation and SIFT approaches in remote sensing application. The main points of the approach are as follows.

1. Convert into single-band image
2. Image segmentation
3. Use SIFT descriptors
4. Obtaining the set of matching points
5. Outlier rejection and
6. Final selected features and geometric transformations required for registration.

Table 2: Different transformations for image registration

TRANSLATION	$\begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \delta_x & \delta_y & 1 \end{matrix}$	$x=w+\delta_x$ $y=z+\delta_y$	Rigid Transformations	Affine transformations
ROTATION	$\begin{matrix} \cos\theta & \sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{matrix}$	$x = w\cos\theta - z\sin\theta$ $y = w\sin\theta + z\cos\theta$		
IDENTITY	$\begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{matrix}$	$x = w$ $y = z$		
SCALING	$\begin{matrix} \delta_x & 0 & 0 \\ 0 & \delta_y & 0 \\ 0 & 0 & 1 \end{matrix}$	$x= \delta_x w$ $y= \delta_y z$		
SHEAR (horizontal)	$\begin{matrix} 1 & 0 & 0 \\ \alpha & 1 & 0 \\ 0 & 0 & 1 \end{matrix}$	$x = w + \alpha z$ $y = z$		
SHEAR (vertical)	$\begin{matrix} 1 & \beta & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{matrix}$	$x=w$ $y= \beta w + z$		

A method for landmark identification and matching the location in pair of images for thoracic CT data is presented. A lung mask is created by segmentation process to ensure that the points or landmarks detected are within the lung volume. After landmark identification, a partial-automatic system was introduced to match the landmarks (as voxels) in the base scan with the corresponding points in the next scan[20]. The registration in this work was performed using 'elastix version 3.9'. Elastix is an image registration toolkit which is based on the National Library of Medicine Insight Segmentation and Registration Toolkit (ITK).

An approach that involves preregistration and fine registration steps is presented by [9]. For pre-registration process the scale-invariant feature transform (SIFT) technique together with appropriate outlier separation technique was used. After this pre-registration, for fine-tuning process, the maximization of mutual information using a modified Marquardt – Levenberg search strategy in a multiresolution framework as a similarity measure and transformation model used was Affine. An feature based method was proposed in [21], in which key points are extracted using SIFT from sensed and reference images and brute force matcher is used to match the key points. In order to discard the false match, the ratio between closest distance to the second closest distance is taken and it should not be greater than 0.8. RANSAC is used for key points mapping.

4. INTENSITY BASED METHODS

These basically involves comparison of pixels or voxel values of the image based on the statistical measure. The design criteria for intensity-based image registration is given as

$$\beta *= argopt\left(S_M\left(G(x), H\left(T_\beta(x)\right)\right)\right) \qquad (1)$$

where G and H are the images to be registered, S_M is the similarity measure (intensity based) calculated over the overlapping area of two images. The two images are said to be registered according to the above mentioned approach through T_β when similarity measure S_M is optimised by $\beta *$ [21].

There is number of 'similarity measure' available for intensity-based image registration.
Mutual Information (MI)

$$I(A,B) = \sum_{a,b} P_{A,B}(a,b)\, log \frac{P_{A,B}(a,b)}{P_A(a).P_B(b)} \qquad (2)$$

where $P_A(a)$ & $P_B(b)$ are marginal probability mass functions and $P_{A,B}(a,b)$ is joint probability mass function. By measuring the distance between the joint distribution $P_{A,B}(a,b)$ and the distribution associated with the case of complete independence $P_A(a).P_B(b)$The distance between $P_A(a).P_B(b)$ (, MI measures the degree of dependence of A and B by means of the relative entropy. Mutual Information proves to be efficient in 3D-3D multimodality image registration. MI in terms of entropies is given as

$$I(A, B) = H(a) + H(b) - H(a, b) \qquad (3)$$
$$= H(a) - H(a\backslash b) \qquad (4)$$
$$= H(b) - H(b\backslash a) \qquad (5)$$

H(a), H(b) are entropies for A and B, H (a, b) being the joint entropy of A and B, H(a\b) and H(b\a) are the conditional entropies of A given B and B given A respectively.

These entropies are given as

$$H(A) = -\sum_a P_A(a).logP_A(a) \qquad (6)$$

Normalised cross correlation

$$R = \frac{\sum_{(i,j)\in T}\left(I_{fl}(i,j) - I'_{fl}\right)\left(I_{DRR}(i,j) - I'_{DRR}\right)}{\sqrt{\sum_{(i,j)\in T}\left(I_{fl}(i,j) - I'_{fl}\right)2}\,\sqrt{\sum_{(i,j)\in T}\left(I_{DRR}(i,j) - I'_{DRR}\right)2}} \quad (7)$$

where $(i,j) \in T$ is the overlap region , I'_{fl} and I'_{DRR} are mean values of images in the overlap region [18]. Mutual information as a common data will be used to register multi modal enrollment in [23].

5. HYBRID IMAGE REGISTRATION

It involves integration of best part of the two or more different attributes like intensity or feature based approaches. Hybridization can be done at two levels,

A) At similarity metric level: Instead of relying alone on surface or anatomical structures, image intensity values can also be used along with these in order to form a similarity metric that will have a useful value everywhere all through the image [15].

B) At optimization level: At optimization level, the optimization of similarity metric is done. There are several local and global optimization techniques available to optimize a similarity measure. In case of local optimization approaches needs good initial start or value for estimation so that it will not get stuck at local minima. In order to deal with such situations, concepts of two different approaches can be used together to get the best result as compared with individual [24].

Hybrid image registration technique is the one which combines the best part of different attributes and in this way, it compensates for any shortcoming of the individual methods. Medical field is the wide area of application of image registration where image registration can be used for treatment planning and intervention, atlas building and comparison, fusion, diagnosis, disease following up, assisted guided surgery etc. Image registration is used for almost every anatomical structure or organ of human body like retina[25] , breast[26], brain [27], heart[28], pelvis[29], bones[30], knee[31], prostate[32] etc.

A hybrid technique in which best part of feature - based and intensity-based methods was used is presented by [33],[34],[35]. The important aspect of this work was that it uses small number of extracted features i.e. scale invariant salient region features and to find the resemblance between individual region features, RCPM (Regional component matching) and region configural matching (RCFM) was used. The proposed technique was tested on pair of aerial images and on mono or multimodality medical images [23]. A hybrid approach was introduced in which two procedures were introduced where patient specific biomechanical modelling is introduced which is followed by intensity-based image registration for 4D CT images datasets of lung cancer patients. This hybrid approach was compared with five different methods and it shows better results in terms of target registration error.[36]

A novel method [32] for image registration PHPM (PSDM Constrained Hybrid Point Matching) was proposed. A PSDM (Personalized Statistical Deformable Model) is constructed and combines with the best features of MIND (Modality Independent Neighbourhood Descriptor) and RPM (Robust Point Matching) technique. The prostate MR and TRUS (Transrectal Ultrasound) images were accurately registered with TRE (Target Registration Error) of approx.1.44mm for all subjects. For registration accuracy validation the proposed PHPM method was compared with the PSDM constrained RPM method (PRPM), the SMM constrained RPM method (SRPM), and the TPS-RPM method (TRPM).

A method for brain image registration was proposed [37], in which feature points were extracted at tissue contour using WEC (wavelet-based edge correlation) feature extraction and SURF along with Haar wavelet as a feature descriptor was used. These feature point descriptors were then used to matching corresponding points and coordinate transformation between adjacent images was established. For the features point matching, the local constraints are taken into account. RANSAC algorithm was used with perspective transformation for image registration. Different transformations used in image registrations is shown in Table 2. The accuracy of proposed method was verified using correlation coefficient (CC) and root mean square error (RMSE). A non-rigid hybrid registration technique that combines any intensity-based algorithm with a feature-based component is presented in [29] which includes iterative dual energy minimization and results better than individual approach.

A hybrid approach for registering images was proposed by Shen et. al. [38] in which enhanced mutual information was used as the similarity measure and hybrid optimisation technique using Powell's method for local search capacity and cuckoo search for global search capacity. The successiveness of the proposed method was expressed in term of success rate and registration error. The optimization process initiated with the global search approach (i.e. cuckoo search in this method), and the outcome required should be near-to-optimal solution. If the solution stops improving in given no. of iterations, then this obtained solution is considered as the convergence of CS and the local search (Powell's method) started around the optimal solution obtained by CS to enhance the accuracy of the solution. Figure 2 shows the pictorial representation of the hybrid approach.

CS is reinitiated for next round if the optimal solution is not achieved. The comparison of results of proposed method were made with the Powell's method and Cuckoo search optimizer, and it showed the remarkable difference. Another hybrid method was also proposed for multimodal (CT and MR) medical image registration by introducing

Table 3: Some hybrid techniques to get better results in comparison to individual approach

Hybrid Method	Imaging modality	Dimensionality	Author
Spatial features with mutual information (EMPCA- MI)	Multimodal Retinal Images (Canon CR-1 and SLO system)	2D	[44]
DSC similarity criterion with novel hill-climbing optimisation algorithm	Dermatology image database.	2D	[45]
PSO with two concepts of GA (crossover and subpopulation)	CT and MR images	3D	[46]

Table 4: Performance parameters involved in image registration

Performance Parameter	Method	Datasets/images	Author
Hausdorff distance	Hybrid based	fMRI	[47]
Computational cost (sec), RMSE, CC, MI, JE, NMI, ECC, KLD	Hybrid based	Tissue slices of brains	[37]
Root mean square error	Feature based	Images of the coastal plain of North Carolina and Landsat TM, Daedalus scanner and SPOT	[17][48]
TRE (Target registration error)	Intensity based	Preoperative CT (3D) image to one or more X-ray projection (2D) images	[49]
TRE, Computational time	Intensity based	Simulations using a synthetic 1-D signal, fMRI images, torso phantom	[50]
ALE, MLE, MIE and AIE IN PIXELS, MASKED AVERAGE INTENSITY DIFFERENCE (MAID), MJ, IJ, AND JE	Hybrid	MRI images	[51]
Registration accuracy (mm)	Hybrid	CT and MR images	[46]
Median registration error	Hybrid	ETDRS images (retinal)	[52]
Registration consistency	Intensity based	Landsat Thematic Mapper (TM), Indian Remote Sensing Satellite (IRS) Panchromatic (PAN), and Radarsat Synthetic Aperture Radar (SAR)	[53]

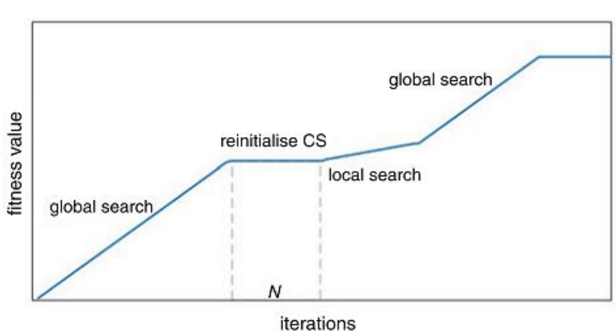

Figure 2: Sketch map of optimization process [36]

metropolis scheme in GA which prevents it from getting trapped in local minima[39]. The shortcoming of global search and local search optimisation methods was also shown in [40]. To overcome that, in this method Steepest gradient is used as starting point for PSO and provides an accurate, effective and robust way for elastic brain image registration. Another hybrid approach was also presented for elastic 2D CT abdominal image registration. Using hybrid of feature points results in better lesion recognition[41]. For image guided surgery, a hybrid approach was presented for breast surgery (supine MR and prone DCE MR images of the patient) in which a patient specific biomechanical modal was created using FEM method along with rigid intensity based image registration[26]. One another hybrid approach was presented for dental panoramic X-ray images registration in which wavelet-based decomposition was carried out on reference and sensed image, intensity based (MI), feature based (SIFT) along with outlier removal (RANSAC) was all clubbed in this approach. On comparison with other methods

,the proposed method results in 0.7805 normalized cross-correlation coefficient (NCCC) and 0.1040% percentage relative root mean square error (PRRMSE) [42].

A hybrid Particle swarm optimisation (PSO) approach in which mutual information was used as a similarity metric and two basic concepts of GA i.e. crossover and subpopulation are used with PSO for 3-D medical image registration was proposed in [24]. Brain MR and CT images were registered using individual GA, PSO and hybrid PSO. The performance of hybrid PSO was found to be better in terms of RMSE (Root mean square error). Another hybrid approach using GA (Genetic algorithm) with Powell's method for image registration was presented in [43]. The gradient mutual information used as a similarity metric. The parametric solution obtained by GA is given to Powell's method as an initial input and global solution is achieved by Powell's method. Experimental results compared with the mutual information genetic algorithm (MIGA) and it shows comparable difference between errors of both methods.

6. COMPARISON WITH INDIVIDUAL APPROACH AND ASSOCIATED PERFORMANCE PARAMETERS WITH DIFFERENT TECHNIQUES

There are hybrid techniques that shows better results in comparison to the individual feature or intensity-based approaches. Table 3 shows some of these techniques and table 4 shows the performance parameters involved for these techniques.

7. CONCLUSION

When analysing the information obtained from different sources or sensors, at that moment image registration is the thing that can't be ignored and considered as an important task. This paper gives the survey of image registration from the very basic things like what image registration is, its different types, why it is needed etc. Although a lot of work has been done in the field of image registration, but image registration using hybrid approach with deep learning-based image registration is an open issue.

In the upcoming time, there is a need of method that will recognise the task in hand, and take suitable actions to solve the problem with appropriate solution. That method may be based on combination of various approaches like deep learning with hybrid approach.

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