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A Registration Technique for Medical Images using Fuzzy- SIFT Matching

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ABSTRACT
Registration is a decisive, primary step in image analysis that helps to obtain absolute information by combining multiple data sources. This pre-processing task is one of the most essential measures in medical images making them useful for different applications such as classification, change detection and image fusion. With the advent of multiple modalities that yield numerous images, registering them becomes a challenging issue. Conventional approaches for image registration incident a meagre performance due to their vulnerability in scale and intensity variations. In this paper we propose an optimized FUZZY- SIFT Matching technique for image registration. Initially Scale Invariant Feature Transform (SIFT) is applied to extract key points from images. Images are segmented to regions based on Fuzzy C-means clustering approach which produces clusters. Key points are matched based on their gradient orientations from the clusters of both reference image and target image and finally image warping is performed by applying piecewise linear transformation function. Experimental results indicate that the proposed method improves the match performance compared to other usual methods in terms of correct-match rate and aligning accuracy.

Keywords
Medical Images, Registration, SIFT, Clustering, DoG filter, Piecewise linear transformation

1. INTRODUCTION
In medical imaging, image registration process is used to extract complementary information from different modalities. In image registration, one image is treated as the reference image and the other is treated as target image. The target image is transformed to match the reference image. This alignment process could be achieved by matching the image features followed by image registration. Image registration is a key step to register the images in medical imaging. The correction process of medical images requires registration of images. It is the process of superimposing images of the same patient taken at different times, from different perspectives. It geometrically aligns the base image and the reference image by transforming different sets of data into one coordinate system.

For clinical use, medical images are often collected and stored digitally. In medical imaging, registration is performed on the medical images and it allows us to compare two time period images of a patient. In image analysis, final registered image is considered for the study of diseases progression.

Commonly used image registration methods for multi-band images are region based, moment based, region and feature based and FFT based methods. Feature based image registration is generally composed of three steps: Extraction of image features and their descriptors, matching of these descriptors and forming relation between the images. Among feature based methods, moment based methods are more favourable. Best known examples of moment based methods are Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF). The main difficulties in registration are the ambiguity in detecting the same points in both images and matching them based on their local features. Also even after appropriate alignment, there can be artefacts at the alignment boundaries as images may differ in colour, and in lighting conditions. Latest studies in the literature make use of local invariant descriptors to depict and match the image features under various changes. Focusing on these issues, we put forward an optimized approach that is invariant to scale, time, sensor and viewpoint.

This paper proposes an algorithm where SIFT and Fuzzy -Clustering together is used to determine the similar points in the overlapping areas of both the images. These corresponding points define the underlying transformation matrix between the frames. The rest of the paper is organized as follows, Section II describes the related works, Section III deals the proposed methodology, Section IV experimental results and discussions followed by concluding remarks.

2. RELATED WORKS
Most change detection systems employ registration as a first necessary step to obtain accurate geometrical alignment of the images before image comparison. Barbara Zitova et al [1] proposed that image registration process can be broadly classified into two categories namely intensity-based and feature based methods. The intensity-based approach does not choose any salient feature or object from an image. On the other hand, in feature -based approach unique features like identifiable line intersections, endpoints, corners, edges etc. are selected and are described. Therefore in matching process the intensity based methods are applied when there is lot of characteristic information about the shape and formation of the object is present. It mainly relies upon the information provided by Gray levels or the colors present in the image.

Lemieux et al., [6] 1998 proposed Affine registration but is not suitable for more complex deformations. Wachowiak, M.P et al. [15] (2006) used high performance registration using optimization techniques. Damas, S et al., [3] (2011) proposed evolutionary computation for registering two medical images. A new divergence measure was explored by Martin et al. [9]

(2007). F-information measure was introduced by Pluim.J.P.W et al. [11] in 2004. Maes, F et al [8] (2003) proposed medical image registration using mutual information. These conventional approaches for image registration result into a meagre performance due to their vulnerability in scale and intensity variations.

Collignon et al., [2] used joint entropy as a criteria for the registration of CT and MRI data. Parzen density estimation is also described for computing this entropy. Pelizzari et al [10]., described surface based methods and these methods are used to register Pet and MRI imagery.

Viola et al., [14] has suggested many technical details and these details are based on the relationship between mutual information and other measures of registration. In the work of Linkster [7] entropy plays a role in the field of neural networks.

Salvi et al., [4] proposed a recent range of image registration methods and it includes Principal Component Analysis(PCA). This method achieves less accurate solution. Kyriacou et al., [5] proposed a simple uniform expansion model and it is subsequently used in a normal-to-normal atlas registration.

Rohlfing et al. [12] imposed a volume preserving strategy and it is used to register contrast-enhanced MR breast images. Staring et al., [13] used high dimensional MI to tackle deformable registration of Cervical MRI.

3. METHODOLOGY

3.1 Key Point Generation

An optimized registration method for medical images is proposed. This registration includes three methods namely 1) Key point Generation 2) Cluster formation and Matching 3) Image Transformation.

Figure 1 represents the architecture of the newly proposed registration method. Firstly SIFT key points are being produced for both the reference and target images which are those images of same patient but taken from different perspectives. In parallel these images are clustered using Fuzzy C-Means and those key points are located in the above said clustered images. Then cluster to cluster matching take place in both the images using their gradient orientation as the appropriate feature. Finally matched points acts as transformation parameters for proper alignment of the target image to form the registered image. In this feature extraction and matching, first step is to detect each point that has to be matched with the features of another image. Each detected point and its neighbourhood are described by feature descriptor which is used to match with the points in another image. It is important that the same points must be detected in both images and the detected points should be characterized as uniquely as possible. The SIFT algorithm developed by Lowe is invariant to image translation, scaling rotation, and partially invariant to illumination changes and affine 3D projection. The SIFT algorithm has four main steps: (1) Scale Space Extrema Detection, (2) Key point Localization, (3) Orientation Assignment and (4) Description Generation.

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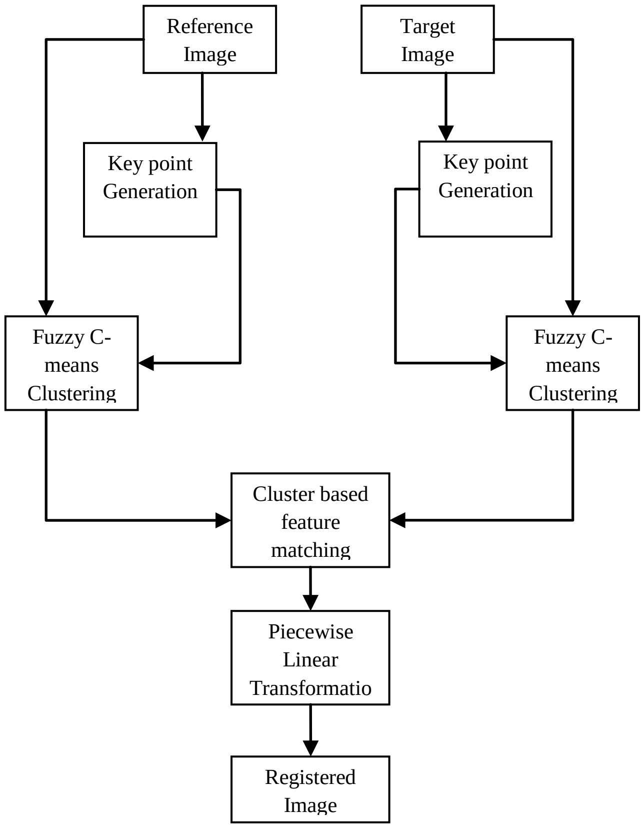


Fig.1. Proposed Registration Method

The first stage is to identify location and scales of key points using scale space extreme in the difference-of-Gaussian (DoG) functions with different values of σ.

The DoG function is convolved of image in scale space separated by a constant factor k as in equation (1).

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) \times I(x, y) \qquad (1)$$

Where, G is the Gaussian function and I is the image.

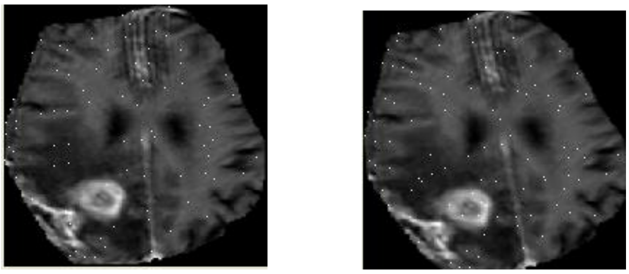
Then the Gaussian images are subtracted to produce a DoG, after that the Gaussian image is sub sampled by factor 2 and it produces DoG for sampled image. A key point is then detected by comparing the 3×3 neighbourhood which forms a total of 26 neighbours by taking the local maxima and minima of D(x, y, σ).

In second stage, key point's candidates are localized and refined by eliminating the key points where the unstable is found. In the third stage, the orientation of key point is obtained based on local image gradient. The last stage is to compute the local image descriptor for each key point based on image gradient magnitude and orientation at each image sample point in a region centered at key point. These samples building a 3D histogram of gradient location and orientation forms a 4×4 array location grid and 8 orientation bins in each sample which is 128-element dimension of key point descriptor. These key points with orientation forms the feature set.

3.2 Cluster Formation and Matching

Clustering data is a familiar practice for analyzing statistical data, which finds application in many fields.

C-means is the clustering algorithm used to determine the natural spectral groupings present in a data set. FCM has turn out to be the most recognized and dominant method in cluster analysis. Figure.2. shows Input images with SIFT key points.



(a) **(b)**

Fig.2. Input images with SIFT key points. (a) Reference image (b) Target image.

Initially cluster centres are selected randomly. An Euclidean distance measure is calculated with respect to the pixel values and the degree for each pixel is being estimated based upon the distance measure. Greater the distance lower will be the degree and smaller the distance higher will be the degree. FCM minimizes the objective function as,

$$J = \sum_{i=1}^{C} \sum_{j=1}^{n} (u_{ij})^m D(x_j, v_i) \qquad (2)$$

u_{ij} represents the membership degree of jth pixel value in the ith cluster,

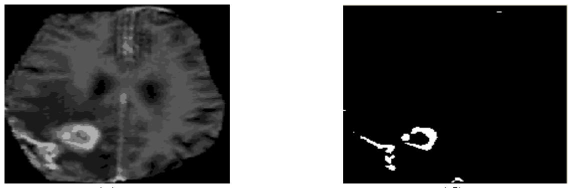
v_i represents the ith cluster center,

D represents the square of Euclidian distance that measures the similarity between a pixel value and a cluster center,

$m >=1$ the degree of fuzzyfication.

The sum of the memberships for each pixel must be unity. Each pixel generates a degree for each cluster and the one which has the greatest degree of all is assigned to the exact cluster. This process iterates and all pixels are grouped as clusters as the cluster centre updates for each iteration. The previously generated key points are located in these clustered images. Once clusters with key points tend to exists feature matching occurs with respect to the gradient orientation. The feature points are grouped based on the cluster mapping. Clusters with highest number of matching features are known to be the parameters of transformation. Feature points out of clusters are neglected. These matched and filtered feature points are used to determine the parameters of the transformation model between the images. Mapping function parameters are found simultaneously with the feature correspondence. Local errors do not influence the registration process globally. Figure 3 shows Clustered images using fuzzy C-means.

(a) **(b)**



(c) **(d)**

Fig.3. Clustered images using fuzzy C-means. (a) Reference image (b)Cluster formation in reference image (c)Target image (d) Cluster formation in target image

Image Transformation

To determine the piecewise linear transformation function between the image pairs, first triangulation of control points are performed in one image which will automatically obtain corresponding triangles in the other image. Normally Dirichlet tessellation is used for triangulation. Then for each pair of triangles corresponding mapping functions are determined to register them. Boundary triangle planes are extended to determine mapping outside triangulated areas. The overall mapping function is then obtained by piecing together the linear mapping functions.

Local weighted mean uses information about local control points only by forming polynomials to register local areas in the image. The algorithm calculates the radius of influence of the polynomial as the distance from the centre control point to the farthest point used to infer the polynomial. The transformation of an arbitrary point is determined by the weighted mean of all polynomial passing over the point inside the radius of influence. In the proposed work, cluster SIFT matching method of registration, achieves an improved accuracy of 95.54%. Figure 4 shows the registered image and it is obtained by using Fuzzy-SIFT matching technique.

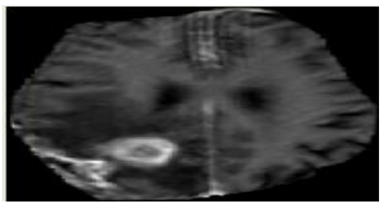


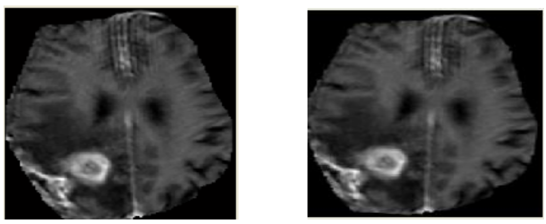
Fig.4. Registered Image

4. EXPERIMENTAL RESULTS

The proposed system is implemented using Mat lab.

Datasets

The system was evaluated in the specific case of Glioma evolution analysis. Our proposed method is implemented on real human brain MRI dataset tumor images of 30 patients. Figure 5 shows the input images.



(a) **(b)**

Fig.5. Input images. (a) Reference image (b) Target image

In this section, the performance of the proposed registration technique in remote sensing image pairs is evaluated experimentally for PSNR (peak signal to noise ratio) and RMSE (root mean square error) rates. Algorithm is tested against five different pairs of images and their accuracy is shown.

The key points, PSNR and RMSE values obtained for the image sets are given in Table 1.

Table 1. Key points, peak signal to noise ratio, root mean square error resulted from the proposed registration method

Image pairs	Key points	PSNR	RMSE
a	3133	32.11	3.23
b	2502	29	5.71
c	3705	38.28	4.4
d	4113	32.05	3.33
e	2830	28.69	5.56
Mean		32.026	4.446

Figure 6 shows the plot of key points, peak signal to noise ratio, root mean square error for five different image pairs.

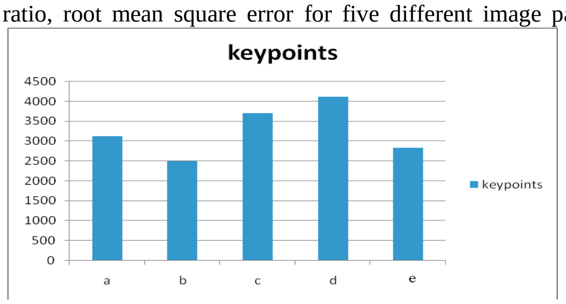


Fig.6.Total no.of key points resulted from the proposed registration method for five different image pairs (a,b,c,d,e)

PSNR measures the image quality by calculating the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It evaluates the proposed registration algorithm by comparing the reference and the registered image pairs. The higher the PSNR, the better will be the quality of the registered image. Figure 7 shows the plot of PNSR for the five different image sets

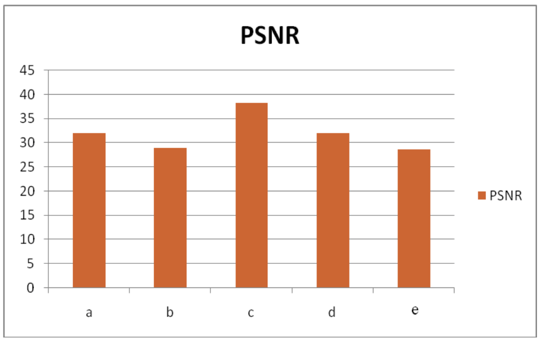


Fig.7. PSNR (in decibels) resulted from the proposed registration method for five different image pairs (a,b,c,d,e)

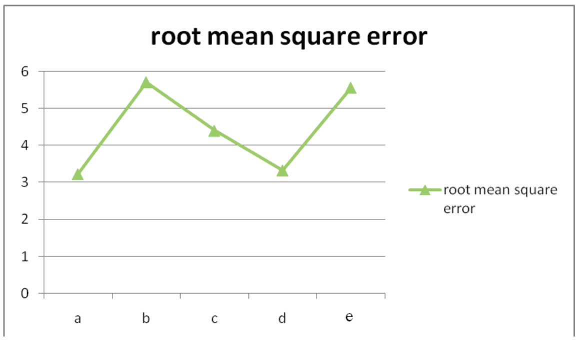


Fig .8. Total Errors (in percentage) resulted from the proposed registration method for five different image pairs(a,b,c,d,e)

RMSE denotes the difference between values predicted by the model and the values actually observed.

The accuracy of the proposed algorithm is evaluated from the calculated error rate. Figure 8 shows the plot of RMSE for the five different image sets.

Accuracy calculated from the root mean square error resulted from the proposed registration method is shown in Table 2.

TABLE 2. Accuracy calculated from the root mean square error resulted from the proposed registration method

Image pairs	RMSE	Accuracy
a	3.23	96.77
b	5.71	94.29
c	4.4	95.6
d	3.33	96.67
e	5.56	94.44
Mean	22.23	77.77
Avg	4.446	95.554

Total Errors (in percentage) resulted from the proposed registration method for five different image pairs (a,b,c,d,e) is referred in figure 9.

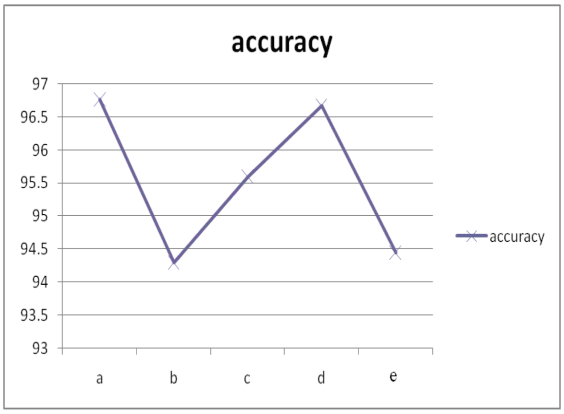


Fig.9.Total Errors (in percentage) resulted from the proposed registration method for five different image pairs (a,b,c,d,e)

5. CONCLUSION

A family of features based on groups of scale invariant interest points has been generated. The geometrical and illumination invariance of these features makes them particularly applicable for solving difficult correspondence problems. The importance of sub-pixel / sub-scale localisation of key points, critically improves the accuracy of descriptors. To reject outliers Fuzzy C- means clustering selects a set of feature matches that are loosely consistent with a global 2D transformation. In future, registered images obtained by using Fuzzy-SIFT matching technique can also be used in change detection technique to determine the pathological changes in two time period images of a patient. In Image segmentation, registered images can also be used to obtain better segmented region.

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