

Comparative Study of Image Registration Methods

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Abstract

The main objective of image registration is to match two or more images captured at different times by different sensors or by different angles or from different viewpoints. Image registration has become a crucial step in most of the image processing tasks used in various areas. It is a key technology which is applied for computer vision, remote sensing, image processing, medical image analysis and other fields. Medical image registration is used to find a spatial transformation to match all the anatomical points and diagnostic points on the image. In general, the majority of registration methods consist of the following four steps: feature extraction, feature matching, transform modeling, and finally image resampling. The accuracy of a registration process is highly dependent to the feature extraction and matching methods. Cross Correlation is the basic statistical approach to image registration. It is used for template matching or pattern recognition. Template is considered as a sub-image from the reference image, and the image is considered as a sensed image. The objective is to establish the correspondence between the reference image and sensed image. It gives the measure of the degree of similarity between an image and template, which can be used for image registration. Normalized Cross Correlation (NCC) method is improved by using Feature Based Method. Image are effectively represented by any of its feature such as edges, points, curves etc. and these features are effectively used for image registration. Images are applied with the filters to extract edges. Post that NCC is done to find the sharp point on NCC plot. This method restricts us with only monomodal images. For multimodal images we have used Mutual Information as a measure of similarity. A widely used measure is Mutual Information (MI). This method requires estimating joint histogram of the two images. Experiments are presented that demonstrate the approach. The technique is intensity-based rather than feature-based. Mutual Information is effectively used as similarity measure between two images which can be monomodal or multimodal. Mutual information is consider as a measure of how well one image explains the other; it is maximized at the optimal alignment. To make this more effective Contourlet transform is used. Contourlet is a recent development of transform theory as an improvement of wavelets. It is a multiscale and multidirectional, two dimensional transform. It is a combination of Laplacian pyramid and directional filter bank. The discrete contourlet transform has a fast iterated filter bank algorithm that requires order N operations for N -pixel images. the contourlet transform effectively captures smooth contours that are the dominant feature in natural images. This leads us to more efficient image registration.

Keywords: Image Registration, Normalized Cross Correlation, Steerable Pyramid, Contourlet Transform.

1. INTRODUCTION

Image Registration is the determination of a geometrical transformation that aligns points in one view of an object with corresponding points in another view of that object or another object. Relationship between type of distortion and the type of image registration is the most important

task. There are two types of distortions can be distinguished. First type is those which are type of misregistration i.e. they are the cause of misalignment between two images. The second type of distortions is usually effect of intensity values. The basic need of image registration is for integrating information taken from different sources, finding changes in images taken at different time or at different conditions. Image registration is the process of overlaying images (two or more named reference and sensed images) captured from the same scene but at different times and view points, or even by using different sensors. Therefore, it is a crucial step of most image processing tasks in which the final information is obtained from a combination of various data sources and images are not designed. These include image fusion, change detection, robotic vision, archeology, medical imaging, and multichannel image restoration. Typically, image registration is required in remote sensing applications such as change detection, multispectral classification, environmental monitoring, weather forecasting, super resolution images, and integrating information into Geographic Information Systems (GIS). It is also used in biomedical image processing applications for combining computer tomography (CT) and magnetic resonance imaging (MRI) data to obtain more complete information about the patient, monitoring tumor growth, treatment verification, and comparison of patients' data with anatomical atlases. It is also used in cartography (for map updating), computer vision (for target localization), automatic quality control, motion analysis, and target tracking.

The most fundamental characteristics of image registration technique is the type of transformation used to properly overlay two images. The primary general transformations are affine, projective, perspective and polynomial. These are all defined well mapping of one image into another. Basic image registration can be categorized in two modalities, Monomodal Image Registration and Multimodal Image Registration. Modalities refers to the means by which the images to be registered are acquired. When image registration is done with the two images of object with same sensor, it can be treated as Monomodal image registration whereas with the images from different sensors it is known as Multimodal image registration. Multimodality registration methods are often used in medical imaging as images are obtained from different scanners. It includes CT, MRI or whole body Positron Emission Tomography (PET). These images are used for tumor localization, segmentation of specific part of body and registration of ultrasound and CT images for prostate localization in radiotherapy [1,24,25,28].

1.1 Steps of Image Registration

In general, the majority of automated registration methods consist of the following four steps: feature extraction, feature matching, transform modeling, and image resampling. In the feature extraction step, manually or preferably automatically, salient and distinctive features are extracted. In the feature matching step, the correspondence between the features detected in the sensed image and those detected in the reference image is established. In order to match the extracted features, a similarity measures (such as iterative closest points (ICP), Bessel algorithm, geometric ICP, least squares error (LSE), normalized cross correlation (NCC), average magnitude difference function (AMDF), and maximization of mutual information (MMI)) are used. In the transform modeling step, the parameters of the mapping function are computed by means of the established feature correspondence. Finally, in the image resampling step, the sensed image is registered by means of the mapping function. Due to the saliency of edge features in panchromatic images and also their stability against environmental and illumination changes image edges can be extracted as primary features. Then extracted edge corners will be required control points (CPs). Consequently, more accurately extraction of edges leads to better CP detection which in turn improves the registration results. The accuracy of extracted edges and the required computational cost of the algorithm form the measures to evaluate different methods.[1, 25, 28]

1.1.1 Feature Extraction

To manually or preferably automatically extract salient and distinctive features such as closed boundary regions, edges and points. For further processes, these features can be represented by their point representatives (centers of gravity, line endings, distinctive points, moment or differential descriptors for curves), which are called control points. The proposed

method can use contourlet transform to extract strong, smooth, and connected edges from input images. There are many edge extraction methods reported. These could be grouped in two main categories: point-wise and region wise. In point wise methods, only isolated pixel values take part in the edge extraction process. They include highpass and bandpass filtering as well as Robert, Sobel, Prewitt, and Canny edge detectors. These methods have low computational costs but they cause ringing effects on extracted edges and also amplify high frequency noise (see Table 3). These methods result in disconnected edges, too. Only the Canny edge detector of this group leads to connected extracted edges, however in a blind manner, and thus may lead to wrong edges and corners. In region-wise methods, the edges are extracted using a small neighborhood of pixels. Rank-based filters, statistical methods, Fourier transform, Spline-interpolation, Laplacian based and wavelet-based are samples of region wise methods. All of these methods could extract salient and acceptable edges. However, they need heavy preprocessing leading to high computational costs. For example, in the rank-based method, instead of raw pixel values, the value near median of a neighborhood around the edge pixels is selected. In statistical methods, the distribution function of two neighboring objects is used to determine the edge pixels. Fourier transform-based edge extraction methods use the frequency responses of edge pixels. In Spline-interpolation-based methods, first the edge pixels are interpolated along a Spline and then the edge pixels are extracted. In Laplacian and wavelet based methods, the edge extraction and its verification is done in a multi resolution manner. In present work we propose contourlet transform for feature extraction.

1.1.2 Feature Matching

In this step, the correspondence between the features detected in the reference and sensed images are established. Various feature descriptors (along with spatial relationships among them) and similarity measurements are reported for this purpose. Feature descriptors include: B-Splines, chain code, snake-model, length code algorithms. Similarity measures include: iterative closest points (ICP), Bessel algorithm, geometric ICP, least squares error (LSE), normalized cross correlation (NCC), average magnitude difference function (AMDF), and maximization of mutual information (MMI).

1.1.3 Transform Modeling

In this step, the type and parameters of mapping function which aligns the sensed image to the reference image are estimated. The parameters of the mapping function are computed by means of the established feature correspondence.

1.1.4 Image Resampling

In this step, the sensed image is registered by means of the mapping function. Image values in non-integer coordinates are computed by the appropriate interpolation technique. Various survey papers for Image registration n research papers are studied as described in chapter 2. Different method of Image registration and its applications are discussed. Chapter 3 overviews various methods used for Image Registration. It includes the use of Normalizes Cross Correlation, Mutual information and Contourlet Transform for Image Registration. Also it explains about algorithm used. Based on the algorithm, various experiments are done on different images. Some are done for monomodal an some for multimodal and results obtained and discussed in chapter 4. According to the experiments done we reached to some conclusion and future scope explained in chapter 5. Chapter 6 introduces us with various references used for the study.

2. LITERATURE SURVEY

Image Registration is presented efficiently by Lisa Gottesfeld Brown and Image Registration deals with the matching of two images. Registration is the determination of a geometrical transformation that aligns points in one view of an object with corresponding points in another view of that object or another object [1, 2, 5].

Jignesh N Sarvaiya, Dr. Suprava Patnaik & Salman Bombaywala illustrates efficient use of Normalized cross correlation for image registration. Template matching is done using NCC. In

this paper, correspondence between main image and template image is established which gives the degree of similarity between them. Then, the minimum distortion, or maximum correlation, position is taken to locate the template into the examined main image [16]. Luigi Di Stefano, Stefano Mattocchia & Martino Mola used cross correlation as a method for feature matching. This method is based on the rotation and scale invariant normalized cross-correlation. Both the size and the orientation of the correlation windows are determined according to the characteristic scale and the dominant direction of the interest points [4]. There are various methods of Image Registration. Some are discussed by Lisa Gottesfeld Brown and Barbara Zitova, Jan Flusser [1, 5]. Methods are Correlation, Fourier Method, Point mapping etc. Correlation can be used effectively. Point mapping method is less sensitive to local distortions as they use control points and local similarity, they use information from special relationship between control points and they are able to consider possible matches based only on supporting evidence. It can be efficient to use method point mapping for image registration. J. Flusser used moment based approach to correct affine distortion, he has also done degraded image analysis to locate invariants in images [10, 11].

P. Ramprasad, H.C. Nagaraj and M.K. Parasuram presented a new wavelet based algorithm for registering noisy and poor contrast dental x-rays. Proposed algorithm has two stages, first stage is preprocessing stage, which removes the noise from x-ray images, Gaussian Filter has been used. Second stage is a geometric transformation stage [12]. Sangit Mitra and B.S. Manjunath explained various contour based approaches for multispectral image registration in their different papers [13]. Sh. Mahmoudi-Barmas and Sh. Kasaei have explained the edge extraction for Image Registration using Contourlet Transform. Control points are used to detect edges [14]. For multimodal images registration is explained by P.Pradeepa and Dr. Ila Vennila .Proposed method said that for two images which are multimodal registration can be done with the mutual information between two images [15]. Also Yonggang Shi have explained about multimodal image registration. Proposed method said that Mean and variance of Joint Intensity Distribution can be efficiently used for the multimodal images [16]. Nemir Ahmed Al-Azzawi with Harsa Amylia and Wan Ahmed K. Abdullah have explained about the monomodal image restration. Nonsampled Contourlet Transform with the help of Mutual information can be effectively used for monomodal image registration [17]. Manjusha Deshmukh and Udhav Bhosale explained about image registration and use of Mutual Information for image registration [24,25,30].

3. PROPOSED METHOD

Image registration is widely used in remote sensing, medical imaging, computer vision etc. In general, its applications can be divided into main groups according to the manner of the image acquisition. It can be different viewpoints (multiview analysis), different times (multitemporal analysis), or from different sensors (multimodal analysis) etc. And accordingly registration method can be used.

3.1 Cross Correlation Based Template Matching

Correlation methods are useful for registration of monomodal images, for comparison of several images of the same object. One of the fundamental task in image registration is Template matching. Template matching is the process of finding the location of a sub image, called a template, inside an image. Template matching involves comparing a given template with windows of the same size in an image and identifying the window that is most similar to the template. The basic template matching algorithm consists in measuring the degree of similarity between the template image and the reference image.

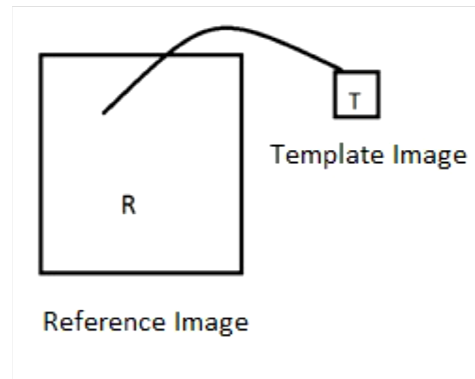


FIGURE 3.1: Template Matching $T < R$.

Then, the maximum correlation position is taken to locate the template into the examined image. Normalized Cross Correlation (NCC) is often the adopted for similarity measure due to its better robustness [4, 5]. Cross-correlation is the basic statistical approach of registration. It is often used for template matching or pattern recognition in which the location and orientation of a template or pattern is found in picture. Cross correlation is a similarity measure or match metric. For template T and image I , where T is small compared to I , the two dimensional normalized cross-correlation function measures the similarity for each translation.

$$\Gamma(u, v) = \frac{\sum [f(x, y) - f_{uv}] [t(x - u, y - v) - t]}{\{ [f(x, y) - f_{uv}]^2 [t(x - u, y - v) - t]^2 \}^{0.5}} \quad \dots (3.1)$$

Normalized cross-correlation can be used as basic approach for image registration. NCC is the simplest but effective method for similarity measure. Here we are trying to find out the location of the template image in main image. Normalized cross correlation is done for the template and the main image. Then the maximum correlated point is determined which indicates the proper position of the template in main image. The offset for the point of maximum correlation will be calculated. And accordingly template is highlighted in main image. Consider template image T which we want to match with the reference image R , as shown in Figure 3.1. Generally T is very small image compare to given reference image R . Normalized Cross Correlation is done between two and the point of maximum correlation is obtained.

Algorithm

- Calculate cross-correlation in the spatial or the frequency domain, depending on size of images.
- Calculate local sums by precomputing running sums.
- Use local sums to normalize the cross-correlation to get correlation coefficients.
- Find location of point at which maximum normalized cross correlation is obtained.
- Locate the template at that location on reference image.

Above NCC method can be improved by using Feature Based Method. Image can be effectively represented by any of its feature such as edges, points, curves etc. and these features can be effectively used for image registration. In above method, before two images be cross correlated, they are applied with the filters to extract edges.

3.2 Mutual Information

Image registration methods based on mutual information criteria have been widely used in multimodal medical image registration and have shown hopeful results. Although the information content of the images being registered is constant, the information content of the portion of each image that overlaps with other image will change with each change estimated registration

transformation. Therefore a suitable technique for measuring joint entropy is to measure with respect to marginal entropy. This measure is known as Mutual Information $I(A,B)$. It can be independently and simultaneously proposed for multimodal medical image registration.

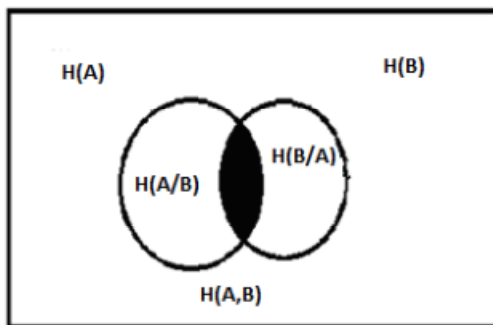


FIGURE 3.2: Mutual Information.

mutual information is employed as a similarity measure to be optimized. Since MI made its entrance into the field of medical image registration, it has been adopted by a large number of researchers [15-17, 30].

$$I(A,B) = H(A) + H(B) - H(A,B) \quad \dots\dots(3.2)$$

Where $H(A,B)$ is joint entropy and $H(A/B)$ & $H(B/A)$ are conditional entropy.

$$H(A) = -\sum P_A(a) \log P_A(a) \quad \dots (3.3)$$

$$H(A/B) = -\sum P_{AB}(a,b) \log P_{AB}(a,b) \quad \dots\dots (3.4)$$

$$H(A/B) = -\sum P_{AB}(a) \log P_{A/B}(a/b) \quad \dots\dots (3.5)$$

Mutual information is a direct measure of the amount of information common between the two images as shown in Figure 3.2. During image registration, however, different transformation estimates are evaluated, and these transformation estimates will result in varying degree of overlap between images, though it is better than joint entropy. The problem has been addressed by proposing various normalized form of mutual information that are more overlap independent. Mutual information can be consider as a measure of how well one image explains the other; it is maximized at the optimal alignment.

Algorithm

- Read Reference main image and Image to be registered.
- Use Mutual information as simillarity criteria.
- Calculate the angle of rotation and scale.
- Rotate the image with calculated angle of rotation and scale image accordingly.

3.3 Steerable Pyramid

In many early vision and image processing tasks we require oriented filters. It needs to apply the same filter, rotated to different angles under adaptive control, or wishes to calculate the filter response at various orientations. Here is an efficient architecture to synthesize filters of arbitrary orientations from linear combinations of basis filters, al-lowing one to adaptively "steer" a filter to any orientation, and to determine analytically the filter output as a function of orientation [23]. A new registration approach based on just two resolution scales is proposed. Firstly, the image datasets will be decomposed into multi-scale, multi-orientation subimages by the steerable pyramid. To improve registration accuracy and efficiency, only the lowest resolution scale and the highest-resolution scale will be used for the registration purpose. In each of these two scales, a new "magnitude sub-band" will be constructed from the multi-orientation band-pass coefficients to

extract edge information. Then, to improve registration accuracy, both raw coefficients in low-pass sub-bands and the edge features in magnitude sub-band will be used as registration feature space. The steerable pyramid can be used to construct the multiscale, multi-orientation image representation with the property of rotation- and translation-invariance. In this pyramid representation, the image is decomposed into subbands by the basis functions which are directional derivative operators with different sizes and orientations.

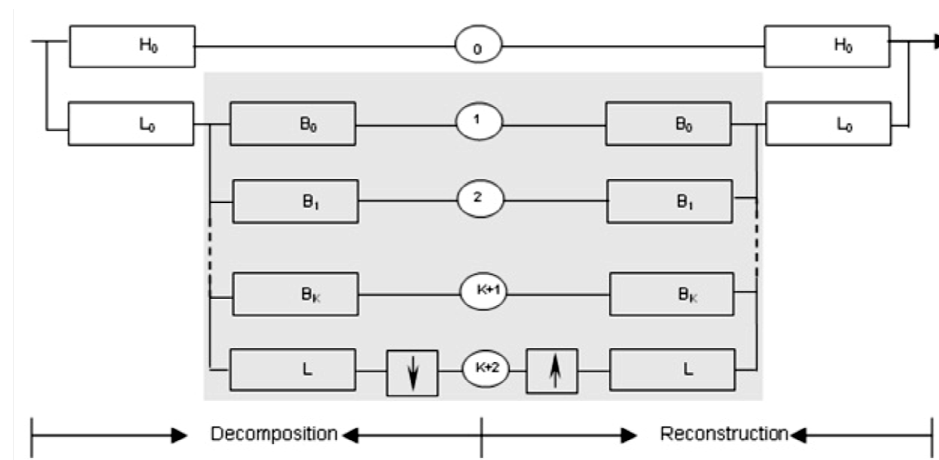


FIGURE 3.3: System diagram for the steerable pyramid.

As all the basis functions are derived by translations, dilations, as well as rotations of a single function, steerable pyramid can be thought as a “wavelet”. Similar to conventional orthogonal wavelet decompositions, the steerable pyramid is implemented by recursively dividing an image into a set of oriented subbands and a low-pass sub-image. The input image is firstly decomposed into a lowpass subband L_0 and a highpass subband H_0 . The lowpass band is then decomposed into N directional bandpass subbands B_k where $k = 0, \dots, N - 1$ and a lowpass subband L . The subbands B_k describe image directional features and are designed to be polarseparable in Fourier domain. The subbands decimated by factor 2 will be decomposed into a lower-resolution level. Finally, the multi-directional and multi-scale representation of the image can be derived from the recursive procedure. The Steerable Pyramid is a linear multi-scale, multi-orientation image decomposition that provides a useful front-end for image-processing and computer vision applications. Filters with orientation tuning are often used in the detection of lines and edges. Canny’s edge operator can be used efficiently, which is optimize to detect step edges; Canny’s system can also be used with different filter choices to detect features other than step edges. Filter that is optimized for use with an edge will give spurious responses when applied to features other than edge. For example, when the Canny edge filter is applied to a line rather than an edge, it produces two extrema in its output rather than one, and each is displaced to the side of the actual line position. On the other hand, if a filter is optimized for detecting lines, it will give spurious responses with edges. Since natural images contain a mixture of lines, edges, and other contours, it is often desirable to find a contour detector that responds appropriately to the various contour types.

Algorithm

- Read Reference main image and Image to be registered.
- Apply Steerable filter on both images.
- Use Mutual information as simillarity criteria.
- Calculate the angle of rotation and scale.
- Rotate the image with calculated angle of rotation and scale image accordingly.

3.4 Contourlet Transform

For Many signal processing tasks such as compression, denoising, feature extraction and enhancement image can be efficiently represented by Contourlet Transform (CT), which is one of several transforms aimed at improving the representation sparsity of images over the Wavelet Transform (WT). The main feature of these transforms is the potential to efficiently handle 2-D singularities, i.e. edges, unlike wavelets which can deal with point singularities exclusively. This difference is caused by two main properties that the CT possess: 1) the directionality property, i.e. having basis functions at many directions, as opposed to only 3 directions of wavelets 2) the anisotropy property, meaning that the basis functions appear at various aspect ratios (depending on the scale), whereas wavelets are separable functions and thus their aspect ratio equals to 1. The main advantage of the CT over other geometrically representations, is its relatively simple and efficient wavelet-like implementation using iterative filter banks. Due to its structural resemblance with the wavelet transform, many image processing tasks applied on wavelets can be easily adapted to contourlets.

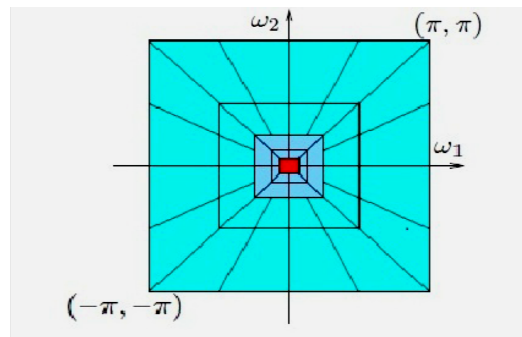


FIGURE 3.4: Frequency decompositions by the contourlet transform.

The contourlet transform was proposed as a directional multiresolution image representation that can efficiently capture and represent singularities along smooth object boundaries in natural images. Its efficient filter bank construction as well as low redundancy makes it an attractive computational framework for various image processing applications. The contourlet transform is implemented via a twodimensional filter bank that decomposes an image into several directional subbands at multiple scales. This is accomplished by combining the Laplacian pyramid with a directional filter bank at each scale. Due to this cascade structure, multiscale and directional decomposition stages in the contourlet transform are independent of each other. One can decompose each scale into any arbitrary power of two's number of directions, and different scales can be decomposed into different numbers of directions. This feature makes contourlets a unique transform that can achieve a high level of flexibility in decomposition while being close to critically sampled. Figure above shows an example frequency partition of the contourlet transform where the four scales are divided into four, four, eight, and eight directional subbands from coarse to fine scales, respectively. Figure 3.5 shows examples of possible frequency decompositions by the contourlet transform.

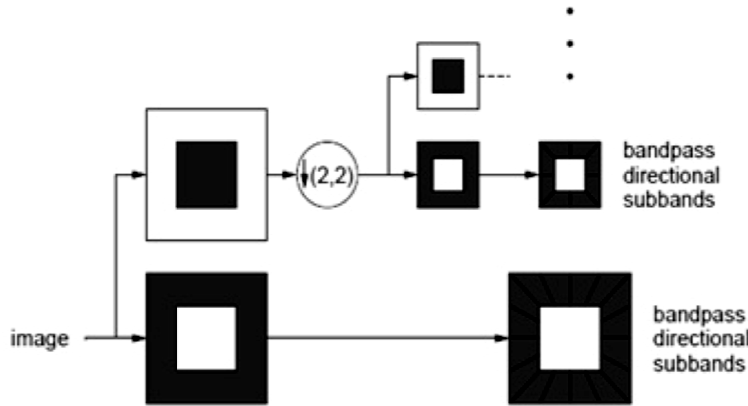


FIGURE 3.5: Contourlet transform.

In particular, by altering the depth of the DFB decomposition tree at different scales (and even at different orientations in a contourlet packets transform), we obtain a rich set of contourlets with variety of support sizes and aspect ratios. This flexibility allows the contourlet transform to fit smooth contours of various curvatures well. The major drawback of DWT in two dimensions is their limited ability in capturing directional information. In light of this, Do and Vetterli [24] developed the Contourlet Transform, based on an efficient two-dimensional multiscale and directional filter bank (DBF). Contourlet Transform not only possess the main features of DWT, but also offer a high degree of directionality and anisotropy. It allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, Contourlaet Transform uses iterated filter banks, which makes it computationally efficient ($O(N)$ operations for an N pixels image) [24].

Contourlet Transform gives a multiresolution, local and directional expansion of image using Pyramidal Directional Filter Bank (PDFB). The PDFB combines Laplacian Pyramid (LP) which captures the point discontinuities, with a DFB which links these discontinuities into linear structures. Figure 3.7, shows the flowchart of Contourlet Transform for a 512×512 image. As shown in Fig. 1, first stage of Contourlet Transform is LP decomposition and DFB is the second stage. The Contourlet Transform is a multiscale, multi resolution filter that comprised of Pyramidal filter and Directional filter. The Proposed algorithm used Laplacian Pyramidal filter as Pyramidal filter and Steerable filter as directional filter. The Contourlet Transform enhances the image with its property of decomposition and reconstruction. Laplacian Pyramid Filter The Laplacian Filter highlights regions of rapid intensity changes.

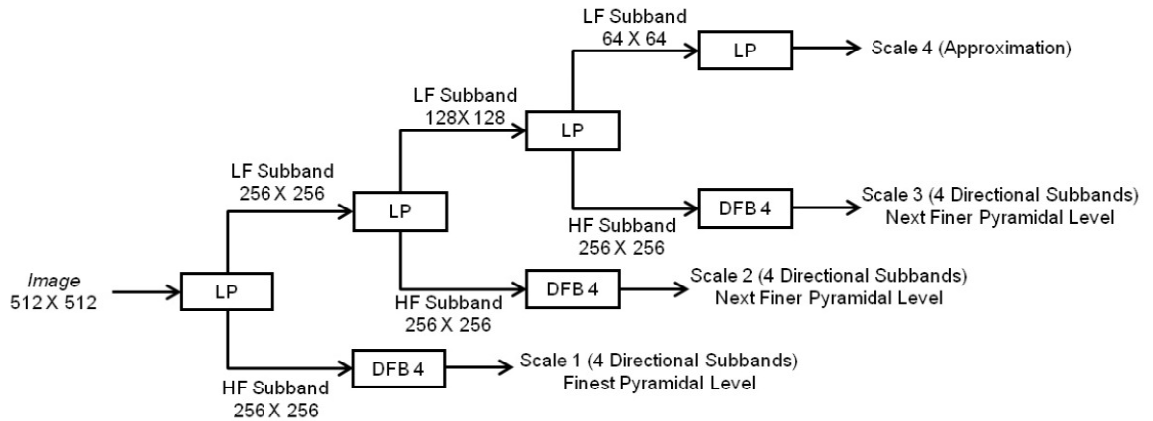


FIGURE 3.6: Flowchart of Contourlet Transform for a 512×512 image.

The Laplacian Filters smooth the input image using a Gaussian smoothing filter in order to reduce its sensitivity to noise. Laplacian pyramid filter is used to capture the edge point. Directional Filter Bank is used to link the discontinuities point in linear structures.

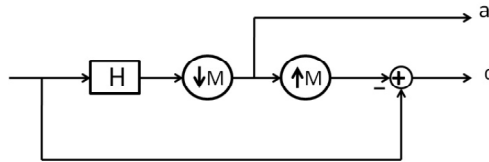


FIGURE 3.7: Construction of LP.

The Laplacian Filter decomposes the images into information at multiple scales. This filter extracts features of interest and to attenuate noise that present in the image. The applications of this filter can be image enhancement, restoration and image analysis. The efficient image coding for the image modelling is achieved by the property of the redundancy reduction of this filter. The Laplacian filter consists of Low pass filter and High pass filter. The decomposition is based on the difference between the two filters. The image is recursively decomposed into low-pass and high-pass bands. In each decomposition level the LP creates a down sampled low-pass version of the original image and a band-pass image. In Laplacian Pyramid method each input image is decomposed into a subband of low frequency of original image and a bandpass high frequency subbands. The same process is repeated for low frequency subband for the specified Contourlet decomposition level. The Laplacian Pyramid decomposition process is shown in Figure 3.6. The input image is applied to a LP filter H and then down sampled to derive a coarse approximation a (Lowpass Subband). Then the image is up sampled. The resultant highpass subbands are derived from subtracting the output of the synthesis filter with the input image. The output of Laplacian filter is followed by Directional Pyramidal Filters leads us to the contourlet transform. Here Steerable Pyramidal filter is used.

Algorithm

- Read Reference main image and Image to be registered.
- Obtain contourlet transformed of both images.
- Use Mutual information as similarity criteria.
- Calculate the angle of rotation and scale.
- Rotate the image with calculated angle of rotation and scale image accordingly.

4. RESULTS AND DISCUSSION

The proposed method was applied to register various sets of images. The following figures present the reference image, target image and registered image.

4.1 Cross Correlation Based Template Matching of Monomodal Images

Penguins' image is considered as original image for first dataset. Some part of this image is cropped which is considered as Template image. Figure 4.1 (a) show the original image and the template is extracted from original image is shown in Figure 4.1 (b). Using Normalized cross-correlation the NCC plot is obtained as shown in Figure 4.1 (c) and offset points are obtained using maximum peak in the NCC plot. Finally generated image for registration is shown in Figure 4.1 (d). Some results are obtained for various datasets as shown in Table I, which shows the offset for the point of maximum cross correlation. This offset helps to find out the place of template image in original image. Similarly for another image which is a real time image of trees, same process is done, Normalized Cross Correlation is done and plot obtained and results are obtained as shown in Table 1.

TABLE 1: Cross Correlation Coefficient.

	Actual offset	Observed offset		
	Left	Top	Left	Top
Dataset 1	151	73	151	73
Dataset 2	87	69	87	69

Dataset 1

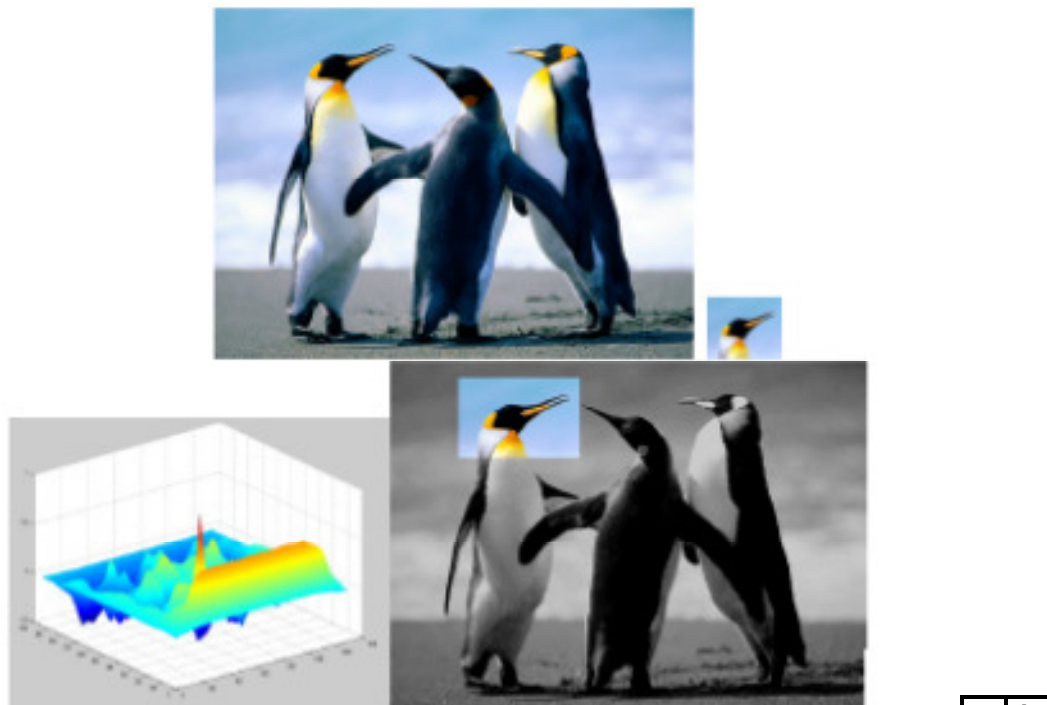


FIGURE 4.1: (a) Reference Image (b) Template Image (c) NCC Plot (d) Registered Image.

Figure 4.2 shows the offset obtained for dataset II. Figure 4.2 (a) show the original image and the template is extracted from original image is shown in Figure 4.2 (b). Using Normalized cross-correlation the NCC plot is obtained as shown in Figure 4.2 (c) and offset points are obtained using maximum peak in the NCC plot. Finally generated image for registration is shown in Figure 4.2 (d).

Dataset 2

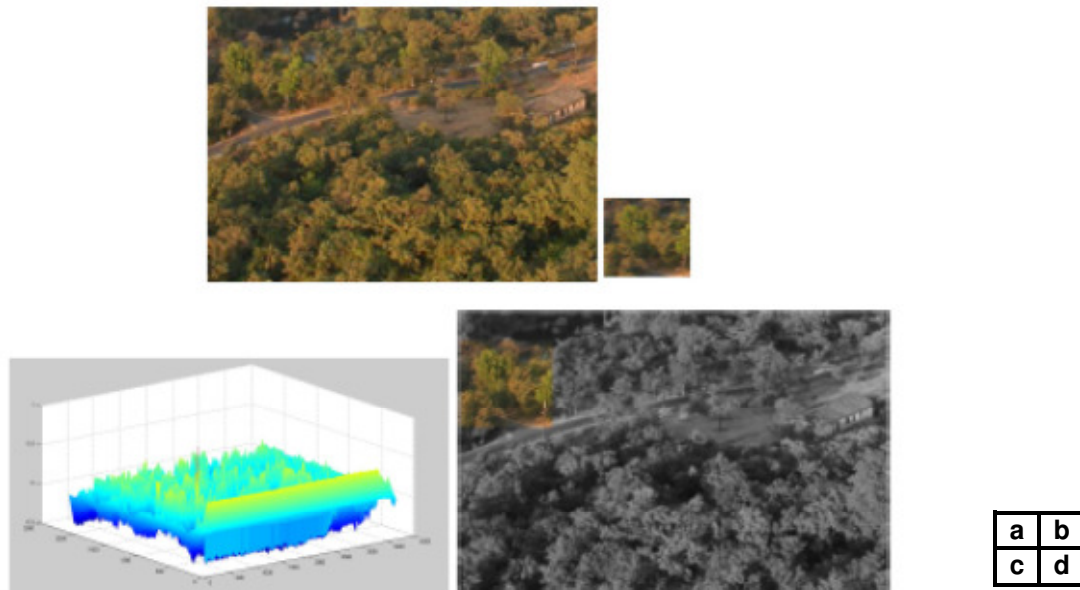


FIGURE 4.2: (a) Reference Image (b) Template (c) NCC Plot (d) Registered Image.

Observation

NCC is effective tool for similarity measure between two images. Two main drawbacks of the correlation-like methods are the flatness of the similarity measure maxima (due to the self-similarity of the images) and high computational complexity. The maximum can be sharpened by preprocessing or by using the edge or vector correlation. It is used in next section.

4.2 Feature Based Template Matching of Monomodal Images

Various feature of image can be extracted and effectively used for registration. This is the basic step in image Registration. Feature can be edges or points or curves in image. Edge detection or extraction is a preliminary step in various image processing applications. There are various methods for edge extraction such as Laplacian operator, gradient operator and various filters, out of which canny edge detector can be used very effectively. The Canny method finds edges by looking for local maxima of the gradient of I . The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is therefore less likely than the others to be fooled by noise, and more likely to detect true weak edges. Canny edge filter is applied on images. Using this filter edges are extracted and that images can be used for further processing. Correlation can be carried out on these images which results in better Normalised Cross Correlation graph and hence better matching.

Dataset 1

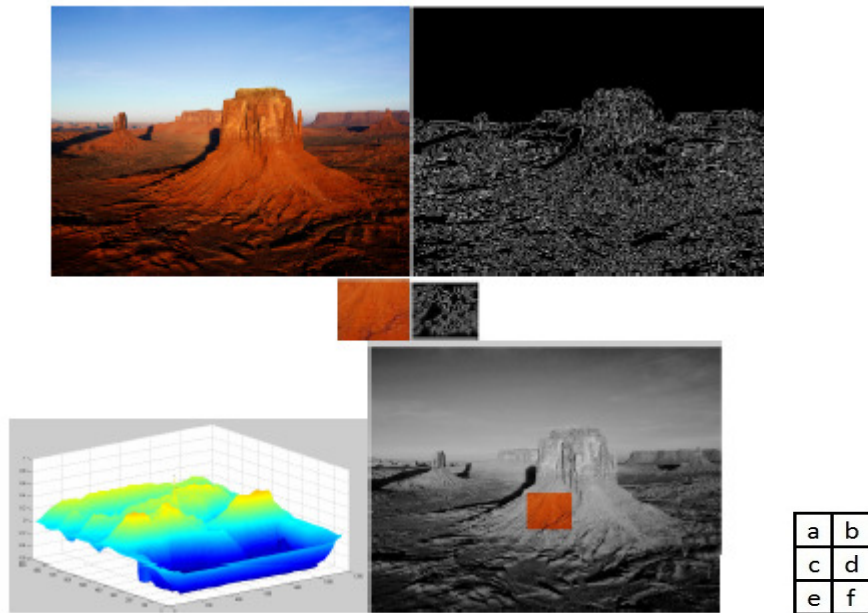


FIGURE 4.3: (a) Reference Image (b) Filtered Reference image (c) Template Image (d) Filtered Template Image (e) NCC Plot (f) Registered Image.

Dataset2

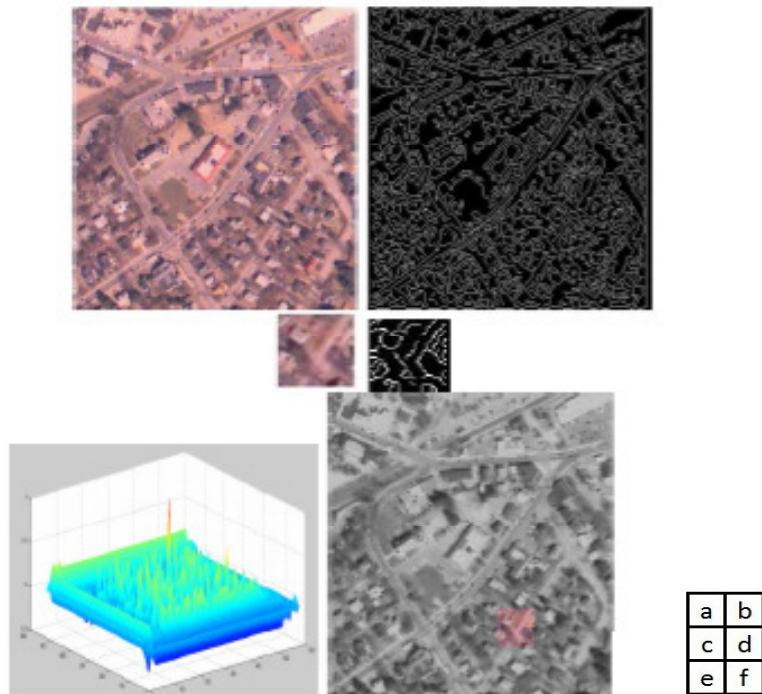


FIGURE 4.4: (a) Reference Image (b) Filtered Reference image (c) Template Image (d) Filtered Template Image (e) NCC Plot (f) Registered Image.

Observation

The maximum is sharpened by using the edge detection filter. This method fails for the multimodal images. We can use another similarity measure for such images. It is used in next section.

4.3 Mutual Information Based Monomodal Image Registration to Correct Rotation And Scale

Two monomodal images are registered using Mutual Information. Mutual information is used here as a similarity measure between two images.

Dataset

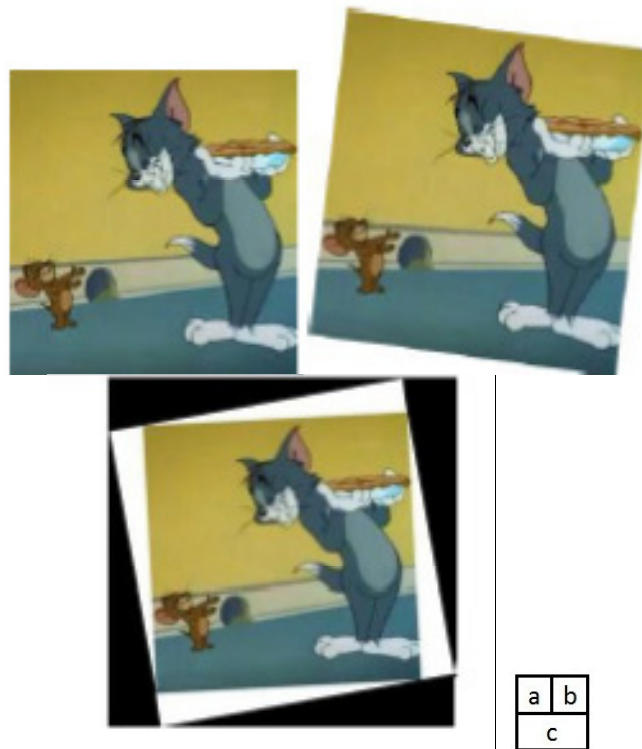


FIGURE 4.5: (a) Reference Input Image (210x210) (b) Image 2: Rotated Image (234x234) (c) Registered Image (210x210).

Observation

Mutual Information is effective tool for similarity measure between two monomodal images. Above image is rotated by angle 7 degrees. After applying Mutual information algorithm, Image is registered back but with 1 degree of difference.

4.4 Mutual Information Based Multimodal Image Registration to Correct Rotation And Scale

Mutual Information can be used as similarity measure for monomodal as well as multimodal images. Multimodal here refers to images taken by different source. Two images of same brain are used for the experiment. One is MRI of brain and other one is PET image of same brain. Mutual information is calculated for them and rotated and scales image is registered. Initially experiment is done for rotated image later followed by rotated and scaled image.

Dataset 1

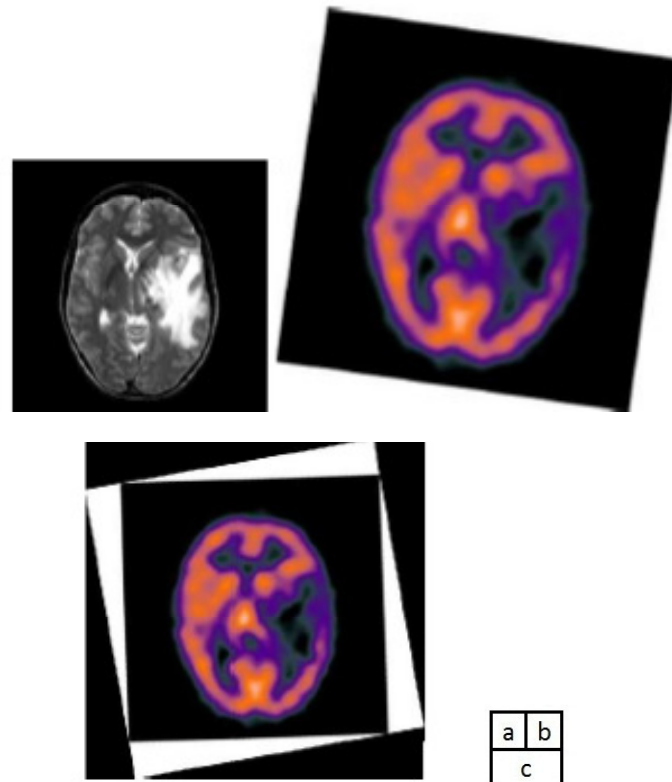


FIGURE 4.6: (a) Reference Input Image (210x210) (b) Image 2: Rotated Image (234x234, Rotation 8 degree) (c) Registered image (304x303).

Observation

Mutual Information is effective tool for similarity measure between two images, for monomodal as well as multimodal images. It has limitation of speed, when time is an important constraint one cannot use this method. Although it has some limitations entropy and mutual information are best approaches for multimodal image registration. The maximum can be sharpened by preprocessing. It is used in next section.

4.5 Steerable Transform Based Image Registration to Correct Rotation and Scale

For multimodal images mutual information can be effectively used as similarity measure and registration can be done. This registration can become more correct and effective if we use feature of images. Here features are extracted using steerable transform and then it is followed by mutual information as mapping function leads to increase in accuracy.

Dataset 1



FIGURE 4.7: (a) Reference Input Image (210x210) (b) Image 2: Rotated Image (234x234) (c) Transformed Reference Input Image (210x210) (d) Transformed Image 2: Rotated Image (234x234) (e) Registered image (210x210).

Dataset 2

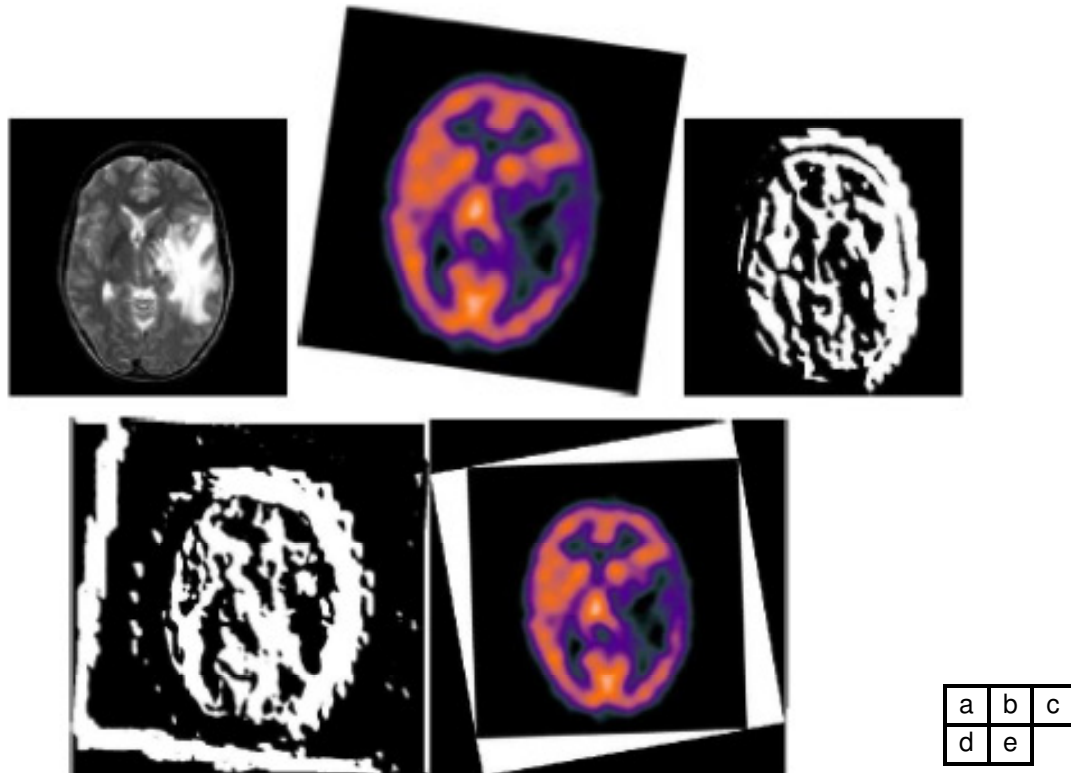


FIGURE 4.8: (a) Reference Input Image (Image size 210x210 pixels) (b) Image 2: Rotated Image (Image size 500x500 pixels, Rotation 8degree, scaled by 2) (c) Transformed Reference Input Image (Image size 374x296 pixels) (d) Transformed Image 2: Rotated Image (Image size 398x320 pixels) (e) Registered image (Image size 551x473 pixels).

Observations

It is observed that combinational approach of Steerable transform and mutual information gives better results. This combination can be used in case of multimodal image registration. To improve accuracy of registration we can use contourlet transform which is explained in next section.

4.6 Contourlet Transform Based Image Registration to Correct Rotation and Scale

For multimodal images mutual information can be effectively used as similarity measure and registration can be done. This registration can become more correct n effective if we use feature of images. Here features are extracted and then it is followed by mutual information as mapping function leads to increase in accuracy.

Dataset 1



FIGURE 4.9: (a) Reference Input Image (256X256) (b) Image 2: Rotated Image (296X296) (c) Transformed Reference Input Image (256X256) (d) Transformed Image 2: Rotated Image (296X296) (e) Registered image (256X256).

a	b	c
d	e	

Dataset 2



a	b	c
d	e	



FIGURE 4.10: (a) Reference Input Image (210x210) (b) Image 2: Rotated Image (234x234) (c) Transformed Reference Input Image (210x210) (d) Transformed Image 2: Rotated Image (234x234) (e) Registered image (210x210).

Dataset 3

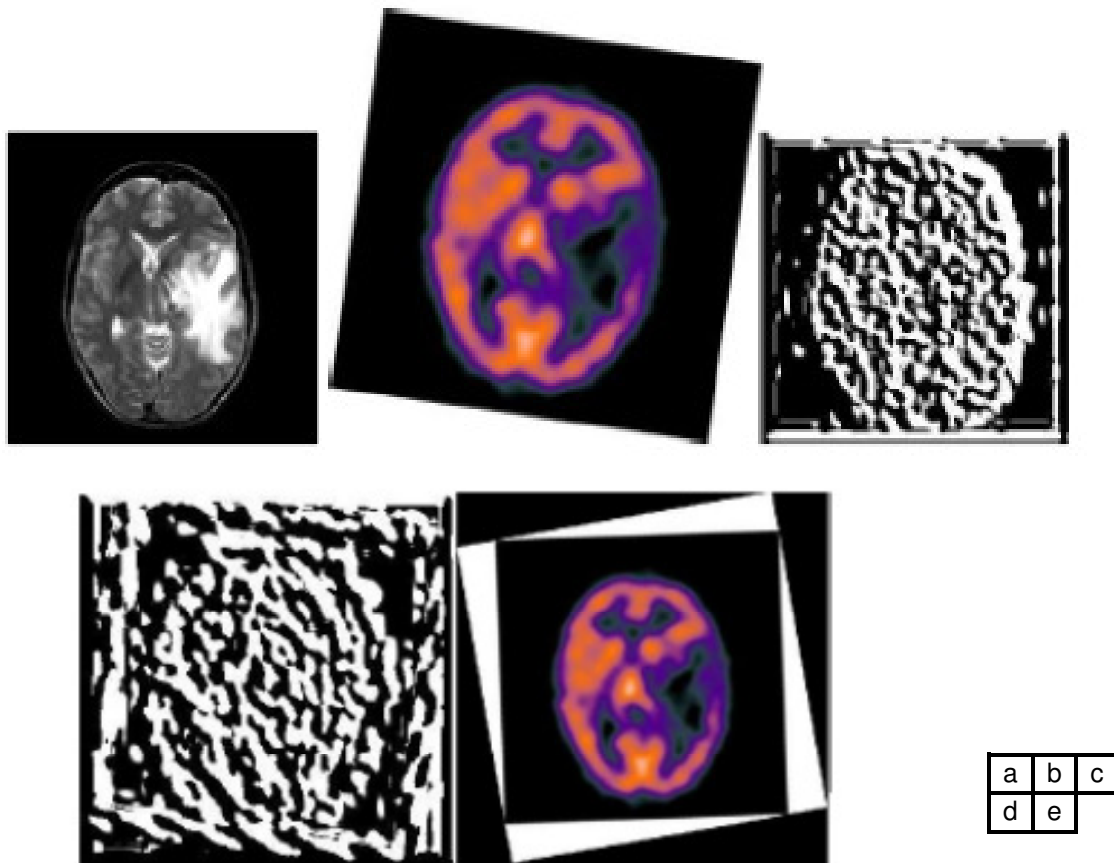


FIGURE 4.11: (a) Reference Input Image (Image size 210x210) (b) Image 2: Rotated Image (Image size 500x500, Rotation 8degree, scaled by 2) (c) Transformed Reference Input Image (Image size 374x296) (d) Transformed Image 2: Rotated Image (Image size 398x320) (e) Registered image (Image size 551x473).

Observations

It is observed that combinational approach of contourlet transform and mutual information gives better results. Even contourlet and mutual information combination can be used in case of multimodal image registration. If we involve mutual information as similarity criteria, speed decreases and hence we can not use this combination in applications where speed is required.

5. CONCLUSION AND FUTURE SCOPE

We have described a template-matching algorithm, for image registration based on NCC on similarity measures. It is clear that Normalized Cross-Correlation (NCC) is the good approach to image registration by template matching. It gives perfect template matching in the given reference image. The Maximum Cross-correlation coefficient values indicate the perfect template matching. This approach cannot be efficient for multimodal image registration. We get number of points with maximum correlation coefficient, instead only one matched point. So it will be insufficient to obtain exact offset and hence, for multimodal image registration we can go for registration using feature extraction or we can use any transform for the proper threshold value or mapping functions can also be used. Feature based method also can be used for image registration. Feature can be extracted from an image, which can help us to match two images. This feature can be points or edges in that image which can help us to match two images. When registering images with non-linear, locally dependent geometric distortions, we are faced with two basic problems—how to

match the CPs and what mapping functions to use for registration. In multimodal registration, MI technique has become a standard reference, mainly in medical imaging. Some authors combined the MI with other, preferably feature-based, methods to gain higher robustness and reliability. Mutual information can be considered as a measure of how well one image explains the other; it is maximized at the optimal alignment. This method can effectively register image but little lagging in accuracy. To increase accuracy, features of image can be extracted followed by Mutual Information as similarity measure. The dependencies across scales, space, and directions were quantitatively compared using mutual information measures. Contourlet Transform can be efficiently used for image registration. For a computational image representation to be efficient, it should be based on a local, directional and multiresolution expansion. The need for image registration is to capture fine curves in image with multiresolution, which can be efficiently done with Contourlet Transform. With this method scale is corrected and angle of rotation is corrected with the difference of 1 degree. The Contourlet Transform is capable of resolving two dimensional singularities and representing image edges more efficiently. The future development on this field could pay more attention to the feature-based methods, where appropriate invariant features can provide good platform for the registration.

6. REFERENCES

- [1] Lisa Gottesfeld Brown, "A Survey of Image Registration Techniques", Dept. of Computer Science, Columbia University, New York. Jan 12, 1992. W. Förstner, "A Feature-Based Correspondence Algorithm For Image Matching", *International Archives of Photogrammetry and Remote Sensing*, vol.26, no.3, pp.150-166, 1986.
- [2] Feng Zhao, Qingming Huang, Wen Gao "Image Matching By Normalized Cross-Correlation", Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China Graduate School of the Chinese Academy of Sciences, Beijing, China
- [3] Luigi Di Stefano, Stefano Mattoccia, Martino Mola DEIS-ARCES, "An Efficient Algorithm for Exhaustive Template Matching Based on Normalized Cross Correlation", *IEEE Computer society*, Proceedings of the 12th International Conference on Image Analysis and Processing, 2003A.
- [4] Zitova B., and Flusser J., "Image Registration Methods: A Survey," *Journal of Image and Vision ELSEVIER*, Vol. 21, pp. 977-1000, June. 2003.
- [5] Radke R. J., Andra S., Al-Kofahi O. and Royasm B., "Image Change Detection Algorithms: a Systematic Survey," *IEEE Transaction on Image Processing*, Vol. 14, No. 3, pp. 294-307, March 2005.
- [6] Makela T., Clarysse P., Katila T. and Magnin I. E., "A Review of Cardiac Image Registration Methods," *IEEE Transaction on Medical Imaging*, Vol. 21, No. 9, September 2002.
- [7] Zhengzhou, China Eugenio F., Marques F. and Marcello J., "A Contour-Based Approach to Automatic and Accurate Registration of Mmulti-Temporal and Mmultisensory Satellite Imagery," *IEEE International Geoscience and Remote Sensing Symposium*, 2002. IGARSS '02. 2002
- [8] Guo Xiao-jun, Han Li-li, Ning Yi "Feature Points Based Image Registration between Endoscope Image and the CT Image", Department of Mechanical Engineering HUANGHE S&T COLLEGE Zhengzhou, China.
- [9] J. Flusser, T. Suk, "Degraded Image Analysis: an Invariant Approach", *IEEE transaction on Pattern Analysis and Machine Intelligence* 20(1998)590-603.
- [10] J. Flusser, T. Suk, "A Moment Based Approach to Registration of Images with Affine Geometric Distortion", *IEEE transactions on Geoscience and remote sensing* 32(1994)382-387.

- [11] H. Manjunath, B. S. Mitra, 1995. "A Contour-Based Approach to Multisensor Image Registration", *IEEE Transactions on image processing*, 4(3), pp. 320-334.
- [12] P. Ramprasad, H.C. Nagaraj and M.K. Parasuram, "Wavelet based Image Registration Technique for matching Dental x-rays", *International Journal of Electrical and Computer Engineering* 4:2 2009
- [13] Sh. Mahmoudi-Barmas and Sh. Kasaei, "Contourlet-Based Edge Extraction for Image Registration", *Iranian Journal of Electrical & Electronic Engineering*, Vol. 4, Nos. 1 & 2, Jan. 2008
- [14] P. Pradeepa and Dr. Ila Vennila, "Multimodal Image Registration Using Mutual Information", *IEEE International conference On Advances in Engineering, Science And Management (ICAESM-2012)* March 30,31,2012
- [15] Yoggang Shi, "Multimodal Image Registration Using Mean and Variance of Joint Intensity Distribution", School of information and electronics, Beijing Institute of technology, Beijing 100081, China ICSP2010 Proceedings
- [16] Nemir Ahmed Al-Azzawi, Harsa Amylia Mat Sakim and Wan Ahmed K. Wan Abdullah, "MR Image Monomodal Registration Based on the Nonsampled Contourlet Transform and Mutual Information", *2010 International conference on Computer Applications and Industrial Electronics (ICCAIE)*, December 5-7, 2010, Kuala Lumpur, Malaysia.
- [17] Issac N. Bankman, "HandBook of Medical Imaging Processing & Analysis", *Academic Press*, 2000.
- [18] J. V. Chapnick, M. E. Noz, G.Q. Maguire, E. L. Kramer, J. J. Sanger, B. A. Birnbaum, A. J. Megibow, "Techniques of Multimodality Image Registration", *Proceedings of the IEEE nineteenth Annual North East Bioengineering conference*, 18-19 March 1993, 221-222.
- [19] Jignesh N Sarvaiya Dr. Suprava Patnaik Salman Bombaywala, "Image Registration By Template Matching", *2009 International Conference on Advances in Computing, Control, and Telecommunication Technologies*. 16
- [20] Duncan D., Y. Po and Minh N Do. Member IEEE, "Directional Multiscale Modeling of Images using the Contourlet Transform", *IEEE Transactions on Image Processing*.
- [21] S. Anand and R. Aynesh Vijaya Rathna, "Architectural Distortion Detection in Mammogram using Contourlet Transform and Texture Features", *International Journal of Computer Applications* (0975 – 8887) Volume 74– No.5, July 2013
- [22] William T. Freeman and Edward H. Adelson, "The Design and Use of Steerable Filters", The Media Laboratory and Dept. of Brain and Cognitive Sciences Massachusetts Institute of Technology Cambridge, Massachusetts 02139 *IEEE Trans. Patt. Anal. and Machine Intell.*, Vol. 13, No. 9, pp. 891-906, Sept., 1991.
- [23] M. N. Do and M. Vetterli, "The contourlet transform: An efficient directional multiresolution image representation," *IEEE Transactions on Image Processing*, vol. 14, no. 12, pp. 2091–2106, 2005.
- [24] Dr. Manjusha Deshmukh & Udhav Bhosale, "Image fusion and image quality assessment of fused images", Saraswati College of Engg. Navi Mumbai, India, *International Journal of Image Processing (IJIP)*, Volume (4): Issue (5), pp. 484-508.
- [25] Dr. Manjusha P. Deshmukh & Udhav Bhosale, "A Survey of Image Registration", *International Journal of Image Processing (IJIP)*, Volume (5) : Issue (3) , 2011.

- [26] Dr. Manjusha Deshmukh and Udhav Bhosle, “ *Image Registration in Time and Frequency Domain*”, In Proceedings of International Conference on Machine Vision, Image Processing and Pattern Analysis (MVIPPA 2008), World Academy of Science, Engineering and Technology, Bangkok, Thailand, Dec 2008, pages 121-127.
- [27] Dr. Manjusha Deshmukh and Udhav Bhosle, “*Image Registration for Image Fusion*” In Proceedings International Conference on Emerging Technologies and Applications in Engineering, Technology (ICETAETS 2008), Rajkot, Gujarat, January 2008, pages 1856-1860.
- [28] Dr. Manjusha Deshmukh and Udhav Bhosle, “ *Mutual Information Based Image Registration* ”, In Proceedings of International Conference on Signal Processing, World Academy of Science and Technology, Bangkok, December 2009 pages 113-118.17