Chapter 3

Mono-Modal Image Registration

This chapter aims to present novel image registration methods. Image registration is the process of mapping points from one image to corresponding points in another image. The registration geometrically aligns two images (the reference and sensed images). Image registration is a crucial step in all image analysis tasks in which the final information is gained from the combination of various data sources. Typically, registration is required in remote sensing, multispectral classification, environmental monitoring, change detection, image mosaicking, weather forecasting, creating super-resolution images, integrating information into geographic information systems etc. Algorithms used for image registration are broadly classified as monomodal and multimodal image registration. In monomodal applications, the images to be registered belong to the same modality, as opposed to multimodal registration tasks, where the images to be registered stem from two different modalities. Aim of monomodal image registration is to gain larger 2-D view or 3-D representation of scanned scene or to find and evaluate changes in the scene which appeared between the consecutive images acquisitions. The methods proposed in this chapter are grouped into spatial domain methods and transform domain methods. Main contributions, advantages, and drawbacks of the proposed methods are discussed.

3.1 Spatial Domain Methods

This section offers registration techniques and framework to aid in the selection of appropriate technique for a specific problem. Knowledge of the cause of distortions present in images to be registered should be used as much as possible in designing a method for particular application. The class of transformation and its complexity determine the general type of method to be used. Spatial methods operate in the image domain, matching intensity patterns or features in images. Some of the feature matching algorithms are outgrowths of traditional techniques for performing manual image registration, in which an operator chooses corresponding control points (CPs) in images. Two algorithms that are combined approach of feature-correlation and contour based image registration are implemented.

3.1.1 Combined approach of cross-correlation and features

This approach is based on the extraction of salient structures or features in the images. Significant regions like lines, region boundaries, roads, rivers or points of region corners, line intersections, points on curves with high curvature are understood as features here. They should be distinct, spread all over the image and efficiently detectable in both images. They
are expected to be stable in time to stay at fixed positions during the whole experiment. The number of common elements of the detected sets of features should be sufficiently high, regardless of the change of image geometry, radiometric conditions and presence of additive noise. In this method edges of images are extracted in color vector space by using color gradients.

For a scalar function \( f(x, y) \), the gradient is a vector pointing in the direction of maximum rate of change of \( f \) at coordinates \((x, y)\). Let \( r, g \) and \( b \) be the unit vectors along the \( R, G \) and \( B \) axis of \( RGB \) color space.

\[
\begin{align*}
u &= (\partial R/\partial y)r + (\partial G/\partial y)g + (\partial B/\partial y)b \\
\end{align*}
\]

Let \( g \) is function of \( x \) and \( y \) and quantities \( g_{xx}, g_{yy} \) and \( g_{xy} \) be defined in terms of the dot product of these vectors, as follows

\[
\begin{align*}
g_{xx} &= u.u = |(\partial R/\partial x)|^2 + |(\partial G/\partial x)|^2 + |(\partial B/\partial x)|^2 \\
g_{yy} &= v.v = |(\partial R/\partial y)|^2 + |(\partial G/\partial y)|^2 + |(\partial B/\partial y)|^2 \\
g_{xy} &= u.v = (\partial R\partial R/\partial x\partial y) + (\partial G\partial G/\partial x\partial x) + (\partial B\partial B/\partial x\partial y)
\end{align*}
\]

Direction of maximum rate of change of \( c(x, y) \) is given by an angle

\[
\theta(x, y) = \frac{1}{2} \tan^{-1} \left( \frac{2g_{xy}}{g_{xx} - g_{yy}} \right)
\]

Where \( c(x, y) \) is arbitrary vector in RGB color space. \( \theta(x, y) \) is image and element of \( \theta(x, y) \) are angles at each point that the gradient is calculated. \( F(\theta(x, y)) \) is gradient image given by Equation (3.7)[1].

\[
F(\theta(x, y)) = \left\{ \frac{1}{2} [(g_{xx} + g_{yy}) + (g_{xx} - g_{yy}) \cos 2\theta + 2g_{xy} \sin 2\theta] \right\}^{\frac{1}{2}}
\]

Algorithm

- One of the images is referred to as the reference or source and the second image is referred to as the target or sensed.
- Extract features of both images.
- Find correspondence between image features such as points, lines, and contours by correlation method.
- Knowing the correspondence between a numbers of points in images, a transformation is then determined to map the target image to the reference images, thereby establishing point-by-point correspondence between the reference and target images. The experiment is performed on different datasets.
Implementation on SCOE dataset to correct translation

Figure 3.1 shows sample images of SCOE-1 and SCOE-2, features are extracted from the images to increase the accuracy of method. Correlation between reference and sensed image is calculated. The change of each similarity measure is plotted as a function of translation. Figure 3.1(e) shows that the sample correlation coefficient is maximized correct position. Figure show that the registration errors in feature based correlation method are smaller than the simple correlation based estimator.

![Sample images of SCOE-1 and SCOE-2](image.png)

Observation It is observed that maximum is sharpened the correlation plot. In this way, the method is less sensitive to intensity differences between the reference and sensed images. Method is fast to implement and useful for real-time applications.

3.1.2 Contour based image registration

This technique is the primary approach currently taken to register two images whose type of misalignment is unknown. If images are taken from varying viewpoints of a scene with smooth depth variations, then the two images will differ depending on perspective transformation. A concept of color segmentation has been used in proposed algorithm to extract contours. Given a set of color of interest, obtain mean of color \(m'\). For segmentation classify each RGB pixel in image as having a color in the specified range or not. Euclidean distance is used to measure similarity. \(z'\) is an arbitrary point in RGB space and \(T\) is threshold. Euclidean distance between \(z'\) and \(m'\) is given by

\[
D(z, m) = \|z - m\| = \left[ (z - m)^T (z - m) \right]^{\frac{1}{2}}
\]

\[
D(z, m) = [(z_R - m_R)^2 + (z_G - m_G)^2 + (z_B - m_B)^2]^{\frac{1}{2}}
\]
Here $RGB$ denotes $RGB$ components. The locus of points such that $D(z, m) \leq T$ is a solid sphere of radius $T$ and point contained within, or on the surface of the sphere satisfy specified color criterion. Coding these two sets of points in the image with black and white produces a binary, segmented image. After segmentation remove noise by “Gaussian” filter, threshold blurred image and obtain contour of an object[1].

**Algorithm**

- Using color segmentation scheme, closed- boundary region (counter) is found.
- Feature points, often referred to as control points of reference image are corresponded with feature points in the data image. The center of gravity of these regions is used as control points. The correspondence between control points is determined.
- Spatial mapping is determined using these matched control points.

Control points for point matching play an important role in the efficiency of this approach. Thus accuracy of point matching lays foundation for accurate registration. Points can be selected which are known to be rigid, stationary and easily pin-pointed in both datasets.

**Implementation on Jupiter dataset to correct translation**

Image mosaicks are useful for a variety of tasks in vision and computer graphics. A particularly convenient way to generate mosaicks is by “stitching” together many ordinary photographs. Existing algorithms focus on capturing static scenes. In this experiment, centers of gravity of corresponding sub images are treated as corresponding feature points. Knowing the correspondence between a points in images, a transformation is then determined to map the target image to the reference images, thereby establishing point-by-point correspondence between the reference and target images. Figure 3.2 (a) and (b) shows Jupiter images with red regions. For registration of Jup1 and Jup2 contours of red colors are extracted by proposed method. Center of gravity for these counters is calculated. Centroid of contours i.e. $(x, y)$ coordinates of centre of gravity of Jup2 are corresponded with centroid of Jup1 contour.

![Figure 3.2: (a) Original image Jup-1 (256 x 256). (b) Translated image Jup-2(256 x 256). (c) Counter extracted from Jup-1. (d) Counter extracted from Jup-2. (e) Mosaick of Jup-1 and Jup-2.](image-url)
Implementation on Berry dataset to correct rotation

Similar procedure of red color segmentation is implemented to obtain counters of Berry images. Figure 3.3(a) shows the Berry image and 3.3(b) shows berry image rotated by \( 90^0 \). Counters of red region are extracted and angle between x-axis and major axis of counter is calculated to find angle of rotation. It is observed that calculated angle of rotation is \( 88.85^0 \).

Figure 3.3: (a) Original image Berry1 (256 \( \times \) 256). (b) Berry2 rotated by \( 90^0 \) (256 \( \times \) 256).

Implementation on Clown dataset to correct rotation and stretching

In previous work, the method of image registration with an affine transform is presented. However, the affine transform is generally not capable of image registration between a frame and a panorama. The previous method is improved to estimate projective transform parameters. In this experiment image correction of rotated and stretched image of Clown is done by point mapping method. In this method features are extracted by thresholding and edge detection technique. In the proposed experiment points of intersection of corresponding sub images are treated as corresponding feature points. Projective transformation is applied on image to correct stretched image. Implementation details are shown in Figure 3.4.

Figure 3.4: (a) Clown1 original image(adopted from MATLAB toolbox)(600 \( \times \) 400). (b) Clown2 original image stretched and rotated (600 \( \times \) 400). (c) Image corrected by projective transformation.

Observation  Feature based methods do not use the gray values to describe matching entities and hence overcomes the limitations of spatial methods. The main advantage of feature based method lies in the filtering out the redundant information. Accuracy of this method is more but the limitation is, it is manual and slow. It is confirmed that this improved method could estimate image registration parameters under conditions that hindered the previous method.
3.2 Transform Domain Methods

Transform-domain methods find the transformation parameters for registration of the images while working in the transform domain. Such methods work for simple transformations, such as translation, rotation, and scaling. Two methods are implemented in transform domain.

3.2.1 Fourier Transform method

Frequency-domain methods find the transformation parameters for registration of the images while working in the transform domain. Such methods work for simple transformations, such as translation, rotation, and scaling. Applying the phase correlation method to a pair of images produces a third image which contains a single peak. Correlation theorem has one more useful property. Correlation theorem states that, the Fourier Transform of the correlation of two images is the product of Fourier Transform of one image and complex conjugate of Fourier Transform of other. The Fourier Transform of an image $f(x,y)$ is a complex function, each function value has real part $R(\omega_x, \omega_y)$ and an imaginary part $I(\omega_x, \omega_y)$ at each frequency $(\omega_x, \omega_y)$ of frequency spectrum.

$$F(\omega_x, \omega_y) = |F(\omega_x, \omega_y)| e^{-\phi(\omega_x, \omega_y)}$$\hspace{1cm}(3.10)

Where $|F(\omega_x, \omega_y)|$is magnitude and $\phi(\omega_x, \omega_y)$ is phase angle

$$|F(\omega_x, \omega_y)|^2 = R^2(\omega_x, \omega_y) + I^2(\omega_x, \omega_y)$$\hspace{1cm}(3.11)

$$\phi(\omega_x, \omega_y) = \tan^{-1}\left[ \frac{I(\omega_x, \omega_y)}{R(\omega_x, \omega_y)} \right]$$\hspace{1cm}(3.12)

Cross power spectrum of two images is defined as

$$F(\phi_x, \phi_y) = \frac{F_1(\phi_x, \phi_y) F_2(\phi_x, \phi_y)}{|F_1(\phi_x, \phi_y) F_2(\phi_x, \phi_y)|}$$\hspace{1cm}(3.13)

Shift theorem guarantees that phase of cross power spectrum is equivalent to the phase difference between the images. The phase of cross power spectrum is represented in its spatial form, i.e. by taking the inverse Fourier Transform of the representation in the frequency domain, then we will have a function which is an impulse. Proposed method is used to correct translation in images[2].

Algorithm

- Extract features (edges) of reference and sensed image.
- Find Fourier Transform of reference and sensed image.
- Calculate cross power spectrum by using Equation (3.13).
- Calculate inverse Fourier Transform, we get third image which contains a single peak. This impulse is approximately zero everywhere except at displacement.
- The location of this peak corresponds to the relative translation between the images.
Implementation on SCOE dataset to correct translation

If an acceleration of the computational speed is needed or if the images were acquired under varying conditions or they are corrupted by frequency-dependent noise, then Fourier methods are preferred rather than the correlation like methods. A class of algorithms, which may be used to determine similarity in a far more efficient manner than methods currently in use, is implemented in Figure 3.5. There may be a saving of computation time of two orders of magnitude or more by adopting this new approach. The problem of translational image registration, used for an example throughout, is discussed.

Figure 3.5: (a) Edges extracted from SCOE-1 (300 x 225). (b) Edges extracted from SCOE-2 (300 x 225). (c) Cross power spectrum for SCOE 1 and SCOE 2 in frequency domain.

Observation The method entails determining the location of the peak of the inverse Fourier Transform of cross power spectrum phase. Since the phase difference for every frequency contributes equally, this technique is particularly well suited to images with narrow bandwidth noise. It is effective technique for images obtained under different illumination condition. But if we extract image features and then apply Fourier method accuracy increases. The proposed matching method requires computation of one FFT to compute Fourier spectra for both images and one IFFT’s to compute impulse function. The computational time savings are more significant if the images, which are to be registered, are large.

3.2.2 Fourier Transform to correct rotation

In proposed algorithm Fourier based image registration is used for images which are rotated with respect to each other shown in Figure 3.6. Rotational movement without translation can be deduced in a similar manner as translation using phase correlation by representing the rotation as a translational displacement with polar coordinates. Rotating an image rotates the Fourier Transform of that image by same angle of rotation, we compute the phase of cross power spectrum as a function of the rotation angle estimate $\phi$ and use polar coordinates $(r, \theta)$ to simplify equation. This gives a function.

$$G(r, \theta; \phi) = \frac{F_1(r, \theta) F_2^*(r, \theta - \phi)}{|F_1(r, \theta) F_2^*(r, \theta - \phi)|}$$  \hspace{1cm} (3.14)

Algorithm

- Find Fourier Transform of both images.
- Convert them to polar coordinate system.
- Find complex conjugate of second image (* indicates complex conjugate).
- Use Equation (3.14), to find $\phi$, apply rotational transformation on rotated image for each $\phi$ and select $\phi$ where it matches with reference image.

**Implementation on Earth dataset to correct rotation**

In order to implement the proposed image registration algorithm, Earth data set is used. Dataset consists of images from same sensors but acquired at different angles. This dataset is especially selected to increase the degree of difficulty that the image registration algorithm will deal with. Figure 3.6 shows implementation details.

![Figure 3.6](image)

Figure 3.6: (a) Image of earth taken from satellite (600 x 600). (b) Rotated image of the same scene (600 x 600), (Figures adopted from MATLAB toolbox.). (c) Registered images in same coordinate system. (d) Registered image overlaid on original image.

**Observation** A general-purpose technique for image registration has been presented. It has several key elements. This method is time consuming because of difficulty in testing for each $\phi$. Fourier methods offer advantages in noise sensitivity and computational complexity. Since Fourier methods rely on their invariant properties, they are only applicable for certain well defined transformations such as rotation and translation.

### 3.2.3 Wavelet Transform based image registration

Earlier work utilized cross-correlation as a similarity metrics to compare features such as gray levels, edges. Registration of image using Wavelets is being discussed in this section. The proposed method uses the Wavelet multiresolution property to extract feature points and
normalised cross-correlation to find similarity between feature points in reference image and sensed image. In the first level Discrete Wavelet coefficients corresponding to Db2 mother Wavelet are computed for both reference and sensed image. Coefficients are used for affine transformation. Wavelet Transform decomposes an image into various sub images based on local frequency content. Using discrete Wavelet Transform, a function $f(t)$ can be represented by

$$f(t) = \sum a_{j,k} \psi_{j,k}(t)$$  \hspace{1cm} (3.15)

Where $a_{j,k}$ are Wavelet coefficients, $\psi_{j,k}(t)$ is basis function, $j$ is scale, $k$ is translation of mother Wavelet $\psi(t)$. Two dimensional DWT can be obtain by applying DWT across rows and columns of an image. The two dimensional DWT of image $f(x, y)$ is

$$f(x, y) = \sum_{j,k} C_{J0}(k, l) \phi_{j,k,l}(x, y) + \sum_{S=H,V,D} \sum_{J=J0}^{\infty} \sum_{k,l} D_{j}^{S}[k, l] \psi_{j,k,l}^{S}(x, y)$$  \hspace{1cm} (3.16)

Where $C_{J0}$ is approximation coefficient, $\phi_{j,k,l}(x, y)$ is scaling function, $D_{j}^{S}$ is set of detail coefficients and $\psi_{j,k,l}^{S}$ is set of Wavelet function. The DWT coefficients are computed by using a series of low pass filter $h[k]$, high pass filters $g[k]$ and down samplers across both rows and columns. The results are the Wavelet coefficient the next scale. The filter bank approach to calculate two dimensional dyadic DWT is shown in Figure 3.7. The Wavelet coefficients are of smaller spatial resolution as they go from finer scale to coarser scale. The coefficients are called the approximation (A), horizontal detail (H), vertical detail (V) and diagonal detail (D) coefficient.

In Wavelet Transformation due to sampling, the image size is halved in both spatial directions at each level of decomposition process thus leading to a multi-resolution signal representation.

![Figure 3.7: Two-dimensional orthogonal Wavelet decomposition.](image-url)
Implementation on SCOE dataset to correct translation

The performance of the proposed algorithm is tested on SCOE images. VR images of SCOE captured by levelled camera translated in x-direction are used for experiment. In the experiments, images are decomposed into $N = 2$ levels. Cross correlation is used as similarity criteria. Figure 3.8 (c) and (d) shows multiresolution signal decomposition.

Figure 3.8: (a) Original image SCOE-1 (300 $\times$ 225). (b) Translated image SCOE-2 (300 $\times$ 225). (c) Wavelet decomposition at level 2 by Harr Wavelet for SCOE-1. (d) Wavelet decomposition at level 2 by Harr Wavelet for SCOE-2.

**Observation**  It is observed that combinational approach of Wavelet-correlation combination shows good results than simple correlation method. Even Wavelet can be used in case of multimodal image registration. The experimental results show that the proposed algorithm can select sufficient control points semi-automatically to reduce the local distortions caused by local height variation, resulting in improved image registration results. Another important advantage resides in the fact that the registration with respect to large-scale features is achieved first and then small corrections are made for finer details.

### 3.3 Applications

The registration methods applied in three major research areas are as follows

- Computer vision and pattern recognition—For numerous different tasks such as segmentation, object recognition, shape reconstruction, motion tracking, stereo mapping and character recognition.

- Medical image analysis—including diagnostic medical imaging, such as tumor detection and disease localization, and biomedical research including classification of microscopic images of blood cells, cervical smears and chromosomes.
- Remotely sensed data processing-for civilization and military applications, in agriculture, geology, oceanography, oil and mineral exploration, pollution and urban studies, forestry and target location and identification.

Although these three areas which have contributed a great deal to the development of registration techniques, there are still many areas which have developed their own matching techniques. Template registration is used in recognizing or locating a pattern such as an atlas, map or object model in an image, it is also used for character recognition, signature verification and waveform analysis. Viewpoint registration i.e. registration of images taken from different viewpoints is used to determine depth or shapes in an image and temporal registration i.e. registration of images of same scene taken at different times or under different conditions is used in detecting and monitoring of changes or growths. In medical image analysis it is used in Digital Subtraction Angiography i.e. registration of images before and after radio isotope injections to characterize functionality, it is also used in Digital Subtraction Mammiography to detect tumors, early cataract detection etc. Temporal registration is also used for remotely sensed data processing like natural resource monitoring, surveillance of nuclear plants, urban growth monitoring etc.

3.3.1 Image mosaicking on Infra-Red dataset

Main application of image registration is in remote sensing for image mosaicking of surveyed area for monitoring of global land usage; landscape planning etc. A camera typically has a limited field of view. A lens with a wide field of view incurs substantial distortion. In addition, capturing the entire scene with the limited camera resolution compromises the image quality. Image mosaicking algorithms register or stitch a sequence of images into a composite image.

![Sample images from Track-1 to Track-15 (256 x 256).](image)

**Observation**  By finding transformation between two frames the second frame is transformed with respect to first one and they are combined to form mosaick. Here image is selected and all other images are registered with respect to the reference image, and mosaick is created. In this case the overlapping area is taken from one of the images, so there is no effect of blurring in the mosaick image. Table 3.1 shows the point of maximum match
using different methods. Figure 3.10 shows mosaick of a set of 15 IR images from Track-1 to Track-15.

Table 3.1: Location of maximum match for IR dataset.

<table>
<thead>
<tr>
<th>S.1.</th>
<th>Image combination</th>
<th>Correlation</th>
<th>Fourier</th>
<th>Wavelet</th>
<th>Feature Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>T1-T2</td>
<td>44</td>
<td>45</td>
<td>45</td>
<td>44</td>
</tr>
<tr>
<td>2</td>
<td>T2-T3</td>
<td>51</td>
<td>50</td>
<td>49</td>
<td>50</td>
</tr>
<tr>
<td>3</td>
<td>T3-T4</td>
<td>19</td>
<td>21</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>4</td>
<td>T4-T5</td>
<td>22</td>
<td>21</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>5</td>
<td>T5-T6</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>6</td>
<td>T6-T7</td>
<td>57</td>
<td>59</td>
<td>59</td>
<td>58</td>
</tr>
<tr>
<td>7</td>
<td>T7-T8</td>
<td>30</td>
<td>32</td>
<td>33</td>
<td>31</td>
</tr>
<tr>
<td>8</td>
<td>T8-T9</td>
<td>22</td>
<td>24</td>
<td>24</td>
<td>23</td>
</tr>
<tr>
<td>9</td>
<td>T9-T10</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>18</td>
</tr>
<tr>
<td>10</td>
<td>T10-T11</td>
<td>60</td>
<td>63</td>
<td>61</td>
<td>62</td>
</tr>
<tr>
<td>11</td>
<td>T11-T12</td>
<td>28</td>
<td>28</td>
<td>27</td>
<td>27</td>
</tr>
<tr>
<td>12</td>
<td>T12-T13</td>
<td>50</td>
<td>50</td>
<td>51</td>
<td>49</td>
</tr>
<tr>
<td>13</td>
<td>T13-T14</td>
<td>27</td>
<td>27</td>
<td>27</td>
<td>27</td>
</tr>
<tr>
<td>14</td>
<td>T14-T15</td>
<td>13</td>
<td>14</td>
<td>13</td>
<td>14</td>
</tr>
</tbody>
</table>

3.3.2 Image mosaicking on SCOE images

An arbitrary set of images of Saraswati College of Engineering, Kharghar, Navi Mumbai were collected, using a panoramic set up. To capture the images the camera was mounted on a leveled tripod. While capturing the images camera was operated in manual mode where all camera parameters like aperture, shutter speed, focal length were constant. Since images are taken from different planes, the topology of mosaick was unknown. The motion between the images was unknown and was not assumed to be constant.

Observation Transformation between two frames is calculated by using different algorithms. The second frame is transformed with respect to first one and they are combined to form mosaick. In this case the overlapping area is taken from one of the images, so there is no effect of blurring in the mosaick image. Table 3.2 shows the point of maximum match using different methods for translation in x and y direction. Pictorial information of the same is also available in graph. Mosaick in Figure 3.12 consists of a set of 6 images from SCOE-1 to SCOE-6.
Table 3.2: Location of maximum match for SCOE dataset.

<table>
<thead>
<tr>
<th>s.n</th>
<th>Image Combination</th>
<th>x-trans</th>
<th>y-trans</th>
<th>x-trans</th>
<th>y-trans</th>
<th>x-trans</th>
<th>y-trans</th>
<th>x-trans</th>
<th>y-trans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SCOEl-SCOE2</td>
<td>157</td>
<td>157</td>
<td>156</td>
<td>159</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>SCOE2-SCOE3</td>
<td>163</td>
<td>164</td>
<td>163</td>
<td>163</td>
<td>164</td>
<td>163</td>
<td>164</td>
<td>163</td>
</tr>
<tr>
<td>2</td>
<td>SCOE3-SCOE4</td>
<td>220</td>
<td>223</td>
<td>219</td>
<td>220</td>
<td>223</td>
<td>220</td>
<td>223</td>
<td>220</td>
</tr>
<tr>
<td>3</td>
<td>SCOE4-SCOE5</td>
<td>163</td>
<td>161</td>
<td>162</td>
<td>161</td>
<td>161</td>
<td>161</td>
<td>161</td>
<td>161</td>
</tr>
<tr>
<td>4</td>
<td>SCOE5-SCOE6</td>
<td>120</td>
<td>118</td>
<td>118</td>
<td>119</td>
<td>118</td>
<td>119</td>
<td>118</td>
<td>119</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.3.3 Image mosaicking of Hiranandani Images.

Images are captured using hand held camera with some overlapping area by keeping camera parameters constant. Before taking the pictures, it should be known that there are some limitation and some important points about image capturing for image mosaick. Since all the formula and all the assumption for this project is the pin hole camera model, hence any camera which behave very different from the pin hole camera model will create undesirable result.
Observations  By finding transformation between two frames the second frame is transformed with respect to first one and they are combined to form mosaic. Here first image is selected and all other images are registered with respect to the reference image, and mosaic is created. In this case the overlapping area is taken from one of the images, so there is no effect of blurring in the mosaic image. Table 3.3 shows the point of maximum match using different methods. Mosaic in Figure 3.15 consists of a set of 15 images from H-1 to H-15 that are in VR band.

3.4 Discussion

- For three different sets of images SCOE1-SCOE-6, T1 to T15 and H-1 to H-15 experiments are carried out. Some of the algorithms and proposed methods are compared on the basis of point of match. Table-3.1 to Table-3.3 shows results for various methods.

- In pixel based method cross correlation is used as similarity measure. It is observed that in natural images like buildings or scenery, method shows match at multiple points. The feature based method makes use of features like point of intersection, edges, corners, centers of contours etc. for matching sample template with reference image. The method combining image features with correlation method have many advantageous properties of both feature-based and intensity based. It overcomes the limitation of intensity based method.
Table 3.3: Location of maximum match for Hiranandani dataset.

<table>
<thead>
<tr>
<th>s.n</th>
<th>Image combination</th>
<th>correlation</th>
<th>Fourier</th>
<th>Wavelet</th>
<th>Feature method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>H1-H2</td>
<td>63</td>
<td>62</td>
<td>61</td>
<td>61</td>
</tr>
<tr>
<td>2</td>
<td>H2-H3</td>
<td>110</td>
<td>111</td>
<td>113</td>
<td>114</td>
</tr>
<tr>
<td>3</td>
<td>H3-H4</td>
<td>62</td>
<td>63</td>
<td>62</td>
<td>63</td>
</tr>
<tr>
<td>4</td>
<td>H4-H5</td>
<td>79</td>
<td>77</td>
<td>80</td>
<td>82</td>
</tr>
<tr>
<td>5</td>
<td>H5-H6</td>
<td>147</td>
<td>147</td>
<td>149</td>
<td>150</td>
</tr>
<tr>
<td>6</td>
<td>H6-H7</td>
<td>93</td>
<td>92</td>
<td>93</td>
<td>95</td>
</tr>
<tr>
<td>7</td>
<td>H7-H8</td>
<td>72</td>
<td>74</td>
<td>74</td>
<td>75</td>
</tr>
<tr>
<td>8</td>
<td>H8-H9</td>
<td>73</td>
<td>74</td>
<td>74</td>
<td>74</td>
</tr>
<tr>
<td>9</td>
<td>H9-H10</td>
<td>88</td>
<td>88</td>
<td>89</td>
<td>90</td>
</tr>
<tr>
<td>10</td>
<td>H10-H11</td>
<td>83</td>
<td>84</td>
<td>83</td>
<td>82</td>
</tr>
<tr>
<td>11</td>
<td>H11-H12</td>
<td>79</td>
<td>79</td>
<td>81</td>
<td>80</td>
</tr>
<tr>
<td>12</td>
<td>H12-H13</td>
<td>81</td>
<td>81</td>
<td>81</td>
<td>82</td>
</tr>
<tr>
<td>13</td>
<td>H13-H14</td>
<td>85</td>
<td>84</td>
<td>89</td>
<td>89</td>
</tr>
<tr>
<td>14</td>
<td>H14-H15</td>
<td>128</td>
<td>126</td>
<td>128</td>
<td>129</td>
</tr>
</tbody>
</table>

- Contour based method do not use the gray values for matching and hence overcomes the limitations of spatial methods. Feature based method filter out the redundant information. Accuracy of this method is more but the limitation is, it is manual and slow.

- In frequency based method accuracy is more than correlation method. But if we extract image features and then apply Fourier method accuracy increases.

- These are some of the observations about methods used for registration of images which are in same spectral band. Conclusion is combined approach of feature and Fourier Transform is the best option for monomodal image registration.

Image registration is difficult when images are obtained through different sensor types. Mutual Information, Entropy, Hotelling Transform and Radon Transform are some of the approaches that can be used for multimodal image registration. These methods are explained in detail in Chapter 4.