CHAPTER 5: OPTIMIZATION METHODS FOR IMAGE MATCHING

5.1 Correlation Based Image Matching

Many feature-based registration methods have been proposed in literature. One of the methods is normalized cross correlation (NCC) that computes the normalized cross-correlation of the matrices of sensed and reference. The resulting matrix contains the values from -1.0 to 1.0. This method will provide correct registration only for the images having uniform brightness and no occlusion. Another method is determining sum of squared differences (SSD) which is sum of square of Euclidean distance between the corresponding pixels. SSD value near to zero indicates the best match. But it takes more time compared to normalized cross correlation method.

An affine transformation may be expressed as a combination of translation, rotation and scaling, all operating in the plane of the image. Let us consider an image function \( f \) defined over a \((w, z)\) coordinate system, undergoes geometric distortion to produce an image \( g \) defined over an \((x,y)\) coordinate system. This transformation may be expressed as

\[
g(x,y) = T \{f(w,z)\}
\]  

The model between two registration images can be represented by affine transformation.

\[
\begin{pmatrix}
  x \\
  y
\end{pmatrix} = S \begin{pmatrix}
  \cos \theta & -\sin \theta \\
  \sin \theta & \cos \theta
\end{pmatrix} \begin{pmatrix}
  w \\
  z
\end{pmatrix} + \begin{pmatrix}
  dx \\
  dy
\end{pmatrix}
\]
Where $S$ is the scaling factor, $\theta$ is the rotation angle and $dx$ and $dy$ are the translation value in x and y direction.

In correlation based image registration algorithm, we need to scan the reference image and search the maximum correlation between reference image and sensed image. This section describes the two proposed methods. Increment Sign Correlation coefficient (ISC) converts brightness values into binary codes and computes correlation.

### 5.1.1 Increment Sign Correlation Coefficient (ISC)

In this method, we are checking sign of increasing and decreasing in brightness by scanning both the images from left to right and top to bottom. This method will provide robust result even in noisy condition and occlusion. It is a descriptive statistic which is used when data is organized into groups and in that group how strongly it resembles each other.

It first converts pixel brightness values into corresponding binary codes $b_1, b_2, \ldots, b_{n-1}$ based on the brightness increment information. For the reference image, the binary code vector $b_r^f$ is generated, if next pixel brightness is higher than current pixel then make it 1 otherwise 0. Similarly, the binary codes $b_i^f$ for sensed image are calculated.

The increment sign correlation coefficient (ISC) between $b_r^f$ and $b_i^f$ is defined [40] as follows.

$$
ISC = \frac{1}{n} \sum_{i=1}^{n} \{b_r^f b_i^f + (1 - b_r^f)(1 - b_i^f)\} 
$$

### 5.1.2 M-estimator Correlation Coefficient (MCC)

Some estimation technique requires prior knowledge, and many times it is not available. So in this type of cases, we require estimation
technique which does not depend on prior knowledge. This technique is called Maximum likelihood estimation. It is based on mean brightness and standard deviation of two input images.

Let \( m_1 \) and \( m_2 \) represent the masks for sensed and reference images respectively [40] and \( f_i \) and \( F_i \) are defined as the pixel brightness values in sensed and reference images respectively. Compute the mask \( m_1 \) from residues \( x_i = f_i - \bar{f} \) for each pixel \( i=1, 2,...,n \) and mean brightness value \( \bar{f} \) of the sensed image as follows.

\[
m_1 = \begin{cases} x_i & \text{if } x_i < k_1 \\ k_1 \text{sgn}(x_i) & \text{if } x_i \geq k_1 
\end{cases} \tag{5.4}
\]

Where \( k_1 = 1.345\sigma_x \) and \( \sigma_x \) is the standard deviation of sensed image brightness residues.

Compute the mask \( m_2 \) from residues \( y_i = F_i - \bar{F} \) for each pixel \( i=1, 2,...,n \) and mean brightness value \( \bar{F} \) in the reference image windows of the same size as sensed image as follows.

\[
m_2 = \begin{cases} y_i & \text{if } y_i < k_2 \\ k_2 \text{sgn}(y_i) & \text{if } y_i \geq k_2 
\end{cases} \tag{5.5}
\]

Where \( k_2 = 1.345\sigma_y \) and \( \sigma_y \) is the standard deviation of reference image brightness residues.

Compute the MCC between the masked sensed and reference image as follows.

\[
MCC = \frac{\sum_{i=1}^{n} m(i)(f_i-\bar{f})(f_i-\bar{f})}{\sqrt{\sum_{i=1}^{n} m_2(i)(F_i-\bar{F})^2} \sqrt{\sum_{i=1}^{n} m_1(i)(f_i-\bar{f})^2}} \tag{5.6}
\]

Where \( m(i) = \sqrt{m_1(i) \times m_2(i)} \)

Return the window position having the maximum value of MCC indicating the best match.
5.1.3 Results and Discussion

Figure 5. 1 Set 5.1.1: (a) Original Image (b) ISC of Original (c) Template Image (d) ISC of Template

Figure 5. 2 Set 5.1.1: (a) ISC Profile (b) Registered Image
Figure 5.3 Set 5.1.2: (a) Original Image (b) ISC of Original (c) Template Image (d) ISC of Template

Figure 5.4 Set 5.1.2: (a) ISC Profile (b) Registered Image
Figure 5. 5 Set 5.1.3: (a) Original Image (b) ISC of Original (c) Template Image (d) ISC of Template

Figure 5. 6 Set 5.1.3: (a) ISC Profile (b) Registered Image
Figure 5. 7 Set 5.1.1: (a) Original Image (b) Template Image (c) MCC Profile (d) Registered Image

Figure 5. 8 Set 5.1.2: (a) Original Image (b) Template Image (c) MCC Profile (d) Registered Image
Chapter 5: Optimization Methods for Image Matching

Figure 5. 9 Set 5.1.3: (a) Original Image (b) Template Image (c) MCC Profile (d) Registered Image

<table>
<thead>
<tr>
<th>Image Set</th>
<th>Image Size</th>
<th>Elapsed time (ISC) (sec)</th>
<th>ISC</th>
<th>Elapsed time (MCC) (sec)</th>
<th>MCC</th>
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</thead>
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<td>Two Kids (Occlusion)</td>
<td>75 * 100 34 *30</td>
<td>7.389379</td>
<td>0.7716</td>
<td>10.194402</td>
<td>0.0012</td>
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<tr>
<td>Satellite image (Scaling)</td>
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<td>0.9015</td>
<td>27.311679</td>
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</tr>
<tr>
<td>Car image (Rotation)</td>
<td>200 * 112 100 * 56</td>
<td>12.826444</td>
<td>0.5745 (incorrect)</td>
<td>68.220294</td>
<td>0.000306</td>
</tr>
</tbody>
</table>

Table 5.1 Correlation Parameters Comparison

Above figures shows results of ISC method and MCC method on three different cases respectively. The comparison of computational time required by the ISC and MCC registration methods are given in above table. The values are for an Intel Core 2 duo laptop with 4 GB RAM in a MATLAB environment. In first case, sensed image is having poor brightness, occlusion and noise and from the results we can see that we get perfect registration in both the case, even in this worst input.
In the second case, sensed image is scaled, again we got perfect alignment. In the third case, sensed image is rotated; ISC does not provide proper registration whereas MCC provides perfect results. It is clear that ISC requires significantly less time as compared to other method for all types of case. But it provides incorrect result when sensed image is rotated. The result shows that the algorithm is an efficient way of image registration with M-estimator. This algorithm will take much more time for high resolution images so not suitable for bigger size images.

## 5.2 Mutual Information Based Medical Image Registration

Medical image registration is very important for detection and diagnosis of disease. When the images are acquiring by different sensors or at different time then mutual information based techniques will provide good results.

### 5.2.1 Image Similarity using Mutual Information

Mutual Information (MI) has emerged in recent years as a very effective measure of image comparison. It is intensity based method so it takes into account spatial relationship between pixels.

#### 5.2.1.1 Entropy

Entropy is a measure of information. Any image is basically matrix which consists of various intensity values which are random in nature. Shannon entropy probability distribution function is defined by the following equation.

\[
H(A) = - \sum_a P_A(a) \log_2 P_A(a) \quad \text{(5.7)}
\]
Entropy measures the uncertainty inherent in the distribution of a random variable.

### 5.2.1.2 Joint Entropy

MI is intensity based similarity measure and is closely related with joint entropy of two images which can be calculated from the following equation.

\[
H(A,B) = - \sum_{a,b} p_{A,B}(a,b) \log_2 p_{A,B}(a,b)
\]  

(5.8)

Joint entropy and conditional entropy are simple extensions that measure the uncertainty in the joint distribution of a pair of random variables, and the uncertainty in the conditional distribution of a pair of random variables. Images are registered when one is transformed relative to the other to minimize the joint entropy.

### 5.2.1.3 Joint Histogram

Individual entropies can be easily calculated from Joint histogram. A joint histogram is a multidimensional histogram created from a set of local pixel features. An entry in a joint histogram counts the number of pixels in the image that are described by a particular combination of feature values. Each entry is the number of times intensity in one image corresponds to an intensity b in the other. Row number is intensity of image 1, i.e. 1st row is the occurrence of intensity 1 in image 1. Column number is intensity of image 2, i.e 1st column is the occurrence of intensity 1 in image 2.

Usually a discrete joint histogram is considered to estimate the joint PDF for the calculation of MI. attempting to compute the overlapping regions; we should maximize the individual entropies and minimize the joint entropy. An image of single amplitude has a less disperse histogram than an image of many grey scales and the lower dispersion implies lower entropy.
5.2.1.4 Mutual Information

Mutual information between two images is calculated from individual entropy and Joint entropy as follows.

\[
MI(A, B) = H(A) + H(B) - H(A, B)
\]

(5.9)

Advantage in using mutual information over joint entropy is it includes the individual entropy. Maximizing the mutual info is equivalent to minimizing the joint entropy. After registration joint entropy increases as matching is achieved so the correspondence of pixel to pixel increases, which in terms increase the mutual information.

5.2.2 Simplex Search Method for Optimization

This is a direct search method that does not use numerical or analytic gradients. If \( n \) is the length of \( x \), a simplex in \( n \)-dimensional space is characterized by the \( n+1 \) distinct vectors that are its vertices. In two-space, a simplex is a triangle, in three-space, it is a pyramid. At each step of the search, a new point in or near the current simplex is generated. The function value at the new point is compared with the function’s values at the vertices of the simplex and, usually, one of the vertices is replaced by the new point, giving a new simplex. This step is repeated until the diameter of the simplex is less than the specified tolerance.

Nelder-Mead simplex algorithm as described in Lagarias et al. [113]. This algorithm uses a simplex of \( n + 1 \) points for \( n \)-dimensional vectors \( x \). The algorithm first makes a simplex around the initial guess \( x_0 \) by adding 5% of each component \( x_0(i) \) to \( x_0 \), and using these \( n \) vectors as elements of the simplex in addition to \( x_0 \). (It uses 0.00025 as component \( i \) if \( x_0(i) = 0 \).) Then, the algorithm modifies the simplex repeatedly according to the following procedure.
The term *unconstrained* means that no restriction is placed on the range of $x$. Unconstrained minimization is the problem of finding a vector $x$ that is a local minimum to a scalar function $f(x)$.

The general algorithm is given below.

Step 1: Construct the initial working simplex $S$.

Step 2: Repeat the following steps until the termination test is satisfied. Calculate the termination test information. If the termination test is not satisfied then transform the working simplex.

Step 3: Return the best vertex of the current simplex $S$ and the associated function value.

It is based on ordering (worst, second worst and best), finding Centroid, applying transformation over accepted point and compute reflection point, expansion point, contraction point and shrinking point.

**5.2.3 Algorithm**

1. Read the two images, reference image and sensed image. It is assumed that the sensed image differs by rotation, scaling and translation as compared to reference image.

2. Apply RST transformation on sensed image by selecting appropriate initial value of angle, scaling factor and translation.

3. Compute joint histogram which reflects combine occurrence in both the images. Also compute individual entropies and joint entropy using equations (5.7) and (5.8) respectively.

4. Determine mutual information using equation (5.9) and then apply simplex search optimization algorithm described in section 5.2.2 which provides final RST values used to register sensed image.
5.2.4 Results and Discussion

Figure 5.10 (a) Reference MRI image (276 X 230) (b) Sensed MRI image (563 X512)

Figure 5.11 Registered image

Figure 5.11 Registered image
Figure 5.12 (a) Joint Histogram before registration (b) Joint Histogram after registration

Figure 5.13 (a) Reference MRI image (328 X 251) (b) Sensed MRI image (652 X 548)
Figure 5. 14 Registered Image

Figure 5. 15 (a) Joint Histogram before registration (b) Joint Histogram after registration

<table>
<thead>
<tr>
<th>Image set</th>
<th>Before Registration</th>
<th>After Registration</th>
<th>Elapsed time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H(A)</td>
<td>H(B)</td>
<td>H(A,B)</td>
</tr>
<tr>
<td>Set 1</td>
<td>4.6879</td>
<td>3.5569</td>
<td>7.9567</td>
</tr>
<tr>
<td>Set 2</td>
<td>7.4970</td>
<td>7.5661</td>
<td>14.7611</td>
</tr>
</tbody>
</table>
From the table 5.2, it can be observed that the entropy of reference and sensed images are very low because it contains very low information in terms of gray level. It does not include whole range 0 to 255. The joint entropy gives more average information compared to marginal as it consider the gray levels of both images. After registration joint entropy increases as matching is achieved so the correspondence of pixel to pixel increases, which in terms increase the mutual information.

5.3 Implementation of Image Registration Using PSO

There are many optimization techniques available like Simulated Annealing, Random search technique, genetic algorithm, memetic algorithm, Ant colony optimization, Differential evolution, Particle Swarm Optimization (PSO), Nelder Mead Optimization, Levenberg Marquadt and many more. Out of these, PSO is suitable for continuous optimization problem because it is highly non linear, non differentiable and non convex.

Image matching and registration has great practical applications in the field of remote sensing, computer vision and medical imaging. How best we can able to determine the template image fits into target image poses many problems to be solved. The registration process will involve scaling, rotation, shifting, shearing and other non linear transformations which make it difficult to automate the process and manual attention is required. Evolutionary optimization methods can be used for automatic matching of images.

In this method, PSO is used to register satellite images using mutual information as objective function. Satellite images have been taken in which preprocessing is already done otherwise we have to do radiometric correction on raw images which include LUT corrections,
stagger correction, correction for block and line losses etc. Some users also expect geometric corrections also to be done on these images. Challenges to register satellite images are mainly because they are linear arrays of CCDs; many such lines together form an image. (The normal images are taken from frame cameras). Here every linear array image is a frame and you can look forth for variations in camera orientations between every such frames of linear array giving rise to internal distortion within the image. A corrected satellite image can be free of such distortions.

5.3.1 Particle Swarm Optimization Method

There are many methods available for optimization problem. Methods are either deterministic or probabilistic in nature. Deterministic method gives exact solutions and do not use any random technique and rely on the thorough search of the feasible domain. But the disadvantages of deterministic method is it is not robust and can only be applied to restricted class of problems and Often too time consuming or sometimes unable to solve real world problems.

Particle Swarm Optimization is an iterative, learning based method introduced by James Kennedy and Eberhart in 1995 [60].

It is population based method and in this context, the population is called swarm and the individuals are called particles. Particles are randomly initialized within the parameter space and each particle is given an initial velocity. During iteration, position of particle is updated and a new velocity is calculated. Find the best position of the particle and generates social groups, where each particle has different logical neighbors. Each particle will remember its best value and X and Y coordinate of it.

For each iterative process, the particle can update its position \(x_i^k\), velocity \(v_i^k\) and moving based on the \(p_{\text{best}}\) and \(g_{\text{best}}\) as following.
\[ x_i^{k+1} = x_i^k + v_i^{k+1} \]  \hfill (5.10)

\[ v_i^{k+1} = r_1 \omega v_i^k + c_1 r_2 (p_{best} - x_i^k) + c_2 r_3 (g_{best} - x_i^k) \]  \hfill (5.11)

Where \( k \) is the current iteration, \( c_1 \) and \( c_2 \) are two positive constants, \( r_1, r_2 \) and \( r_3 \) are random number in the range \([0, 1]\). \( \omega \) is inertia that will control the influence by the former moving velocity. \( \omega \) is greater than global searching performance is better while smaller \( \omega \) would bring better local search.

Fitness function can be calculated by finding mutual information using the equation (5.9) of previous section.

In brief, The PSO algorithm will start by taking randomly particle position and velocity and fitness function is computed. Now depending on that value, particles will change its position and velocity and finally after some iteration, particles will be settled down at its appropriate matched position.

### 5.3.2 Implementation

Digital signal processing is now become core in most of the rapidly growing technologies like signal and image processing and in wireless communication. These processors are having capabilities of representing real time analog signals in digital form with fast processing speed. The TMS 320C67X series is a 32 bit floating point processor having implemented VLIW architecture. It requires one computer to create the program, embedded JTAG to load the program from computer to C6713, an AIC23 stereo codec, 4 users accessible LEDs and DIP switches, power supply, 32 bit external memory interface and VM3224K2 display card. The on board power supply provides two voltages, 1.26 V for DSP core and 3.3 V for I/O ports. DSK 6713 operates on 225 M Hz. Synchronous dynamic RAM is of 16 MB and Flash of 512 KB [118].
DSK – 6713 is an evaluation platform for the TMS320C6713 Digital signal processor from Texas instruments. It includes reference design for interfacing the DSP to other devices like SDRAM, Flash, a Codec, third party add – in card and so on. An on board JTAG emulator allows debugging the program from CCS through computer's USB port.

Code composer studio (CCS) provides an IDE to incorporate the software tools. CCS includes tool for code generation (C compiler), debugging tool, assembler and linker. The C compiler will compile the C code with extension .c and generating .asm assembly file. The assembler converts .asm file into machine language object file .obj. the linker links and combines object and library files and generates .out file which can be loaded using CCS into C6713 and run on C6713. The CCS has Graphical User Interface (GUI) using which we can view Time/ Frequency graph, Eye diagram, Constellation diagram and Images.
**TFT LCD Video Daughter card**

The DSP VM3224K2 is a TFT LCD video daughter card which support NTSC analog video signal and displays digital video data on TFT LCD display. It used NTSC up to 30 fps as a input and gives output in the form of RGB565 format. The resolution is 320 X 240 and 16 bits per pixel for video / image output. It uses power from DSP board so no additional power is required. This product is a plug in for the Texas instruments C67X starter kit.

![Figure 5.17 Real Image of TFT LCD Video Module [117]](image)

The RGB24 is more widely used in different image based applications. In RGB24 format each channel is having 0 – 255 (8 bit) so total $2^{24} = 16$ million different colors. Internally, for memory cache line efficiency this is stored as 4 bytes instead of 3 and thus one byte is lost in exchange of extra access performance. But in embedded systems the memory saving and processing time is the main requirement of any system. The RGB 565 format used 16 bit format to represent color image. So extra 2 bytes are saved and thus saved time too. In this system 5 bits for red, 6 bits for green and 5 bits for blue color. Human eye is more sensitive to green color so extra 1 bit is added to green component.
The TFT LCD Output

The Thin Film Transistor (TFT) LCD uses an RGB565 format and having 320x240 in size. The LCD panel should given pixel information periodically. So VM3224K2 module contains memory which will store 320 X 240 pixel information. LCD controller [117] provides 512 KB DRAM memory data to the LCD panel in synchronization with the horizontal and vertical sync signals. 512 KB DRAM is divided into two parts: 256 KB size in two pages. One part is for display buffer and other is used by DSP. The LCD controller generates signals to drive the LCD, and the 17-bit address generator generates pixel data addresses directed to the LCD.

Pixel locations in TFT-LCD display are shown in figure 5.13. The first number in parenthesis represents the horizontal coordinate on the LCD panel, while the second represents the vertical coordinate.

<table>
<thead>
<tr>
<th>(0,0)</th>
<th>(1,0)</th>
<th>...</th>
<th>(318,0)</th>
<th>(319,0)</th>
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<tr>
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<td>(0,238)</td>
<td>(1,238)</td>
<td>...</td>
<td>(318,238)</td>
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<td>(0,239)</td>
<td>(1,239)</td>
<td>...</td>
<td>(318,239)</td>
<td>(319,239)</td>
</tr>
</tbody>
</table>

Figure 5. 19 Pixel Locations for the Landscape Panel

5.3.3 Flowchart and Algorithm

Flowchart:
Chapter 5: Optimization Methods for Image Matching

Input Two Images Ref and Sensed

Setting Initial Variables like No. of Particles, No. of Iterations, Inertia, C1, C2

Initialize the Particle Position and Velocity

Round Particle Position and Velocity

Calculate Joint Histogram

Compute Individual Entropy and Joint Entropy

Find Mutual Information (MI) as a Fitness function

Find Pbest (Particle Best Position) and Gbest (Global Best Position)

Update Position and Velocity for Each Particle

Update Pbest and Gbest

Iteration Number > Maximum Iteration

N

Y

Registered Image
The following algorithm has been implemented for satellite image registration.

1. The first step is to read two satellite images – one reference image and another sensed image using DSK 6713. To read the images we have to convert them into .dat file format using MATLAB.
2. Open code composer studio 3.1 and connect DSP 6713 kit and then create new project using .pjt extension.
3. Open editor window and write C code. Create population of agents called particles which is uniformly distributed and save the details of the particles into two swarm matrixes (one for x and other for y coordinate) which include initial position of the particles, velocity of each particles, updated position, and fitness values / objective function.
4. If current position of particle is better than previous one then update it and also update its velocity using equations (5.10) and (5.11).
5. Calculate fitness value (using equation (5.9)) and place it at the fourth column and evaluate particle best (p_best) and global best (g_best).
6. Repeat the procedure until stopping criterion is satisfied.
7. Save the program using .c extension and then add in the current project and build the program. Then load the .out file and run the program.

5.3.4 Result and Discussion

The images have been used are taken from Bhuvan website – a Geoportal of ISRO. First set of image is of Vallabh Vidyanagar and goal is to register Shastri medan area. Second set of image is of New
Vallabh Vidyanagar and being registered academic institutions of CVM including A. D. Patel Institute of Technology.

Figure 5. 20 Set 5.3.1: Reference (500 X 700) and Sensed (300 X 200) Image of Vallabh Vidyanagar

The area which is to be registered

Figure 5. 21 Set 5.3.1 Registered Images
Figure 5. 22 Set 5.3.2: Reference (500 X 700) and Sensed (400 X 200) Image of New Vallabh Vidyanagar

The area which is to be registered

Figure 5. 23 Set 5.3.2 Registered Image
Initially particles are given random values and coordinates of each particle are stored in swarm matrix. During iteration, fitness function is calculated and accordingly particle’s position and velocity is updated and quality assessment parameters are calculated. This procedure is continued until error is reduced. The following table 5.3 and 5.4 gives parameters of image registration. In order to authenticate and consolidate the results, tenfold validation has been carried out for both the case. The result on LCD of VM3224K2 is not seen clearly so I had also placed result of CCS for better visibility using graph property of code composer studio.

<table>
<thead>
<tr>
<th>No. of Iteration</th>
<th>Entropy H(A)</th>
<th>Entropy H(A,B)</th>
<th>Mutual Information (MI)</th>
<th>X Value</th>
<th>Y Value</th>
<th>RMSE</th>
<th>PSNR</th>
<th>CC</th>
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<td>0.0395</td>
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<td>13.2208</td>
<td>1.0526</td>
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<td>128</td>
<td>48.2687</td>
<td>33.2896</td>
<td>0.4687</td>
<td>0.2300</td>
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</tbody>
</table>

Table 5.3 Ten fold validation result of Set 5.3.1
Chapter 5: Optimization Methods for Image Matching

Entropy of sensed image $H(B)$: 8.5811

Entropy of reference image: 25.0684

<table>
<thead>
<tr>
<th>No. of Iteration</th>
<th>Entropy $H(A)$</th>
<th>Joint Entropy $H(A,B)$</th>
<th>Mutual Information (MI)</th>
<th>$X$ Value</th>
<th>$Y$ Value</th>
<th>RMSE</th>
<th>PSNR</th>
<th>CC</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
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<td>1.</td>
<td>8.2461</td>
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<td>1.0097</td>
<td>101</td>
<td>66</td>
<td>60.3954</td>
<td>28.8070</td>
<td>-0.0183</td>
<td>0.1240</td>
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<td>60.8512</td>
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<td>0.1138</td>
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<tr>
<td>3.</td>
<td>8.6428</td>
<td>17.0092</td>
<td>1.0126</td>
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<td>158</td>
<td>58.6427</td>
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<td>0.0942</td>
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<td>28.8068</td>
<td>-0.0278</td>
<td>0.1135</td>
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<tr>
<td>6.</td>
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<td>1.0129</td>
<td>79</td>
<td>158</td>
<td>59.0153</td>
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<td>0.1090</td>
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<tr>
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<tr>
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Table 5.4 Ten fold validation result of Set 5.3.2
Figure 5. 24 Registered Image on VM3224K2 Daughter card

Figure 5. 25 Set up of image Registration using DSP hardware
5.4 Comparative Discussion and Summary

The proposed method uses increment sign correlation and M – Estimator which are correlation based methods and will reduce the influence of noise and occlusion very accurately. M - Estimator allows one to estimate maximum likelihood with high precision intensity changes and the geometric transformations to align two images.

At present, MRI imaging has been a major tool for diagnosis of brain diseases and image registration is important part of it. Each MRI image is different to some extent but the difference is limited. If the optimization parameters are same for all the images, the precision of image registration will be deteriorated.

In this work, the PSO based satellite image registration is done. The PSO satisfies fast searching capability. This method is iterative learning based method where particles will remember its position and depending on objective function value, algorithm will update particle’s position and velocity. To calculate accuracy of this registration, quality assessment parameters have been calculated. Moreover, the parameters like number of particles, inertia, positive coefficients, number of iterations, size of two images and fitness function will affect the registration time and registration result.