CHAPTER 1

INTRODUCTION

1.1 IMAGE PROCESSING

Acquisition of images or producing the input image is called imaging. Image processing (Alberto Martin and Sabri Tosunoglu 2000, Zelelew et al 2008) is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or, a set of characteristics or parameters related to the image. Most image processing techniques involve treating the image as a two dimensional signal and applying standard signal processing techniques to it. Image processing may be analog, optical or digital.

Digital image processing is developing the ultimate machine that could perform the visual functions of all images, that is, it is an enhancement by improving image quality, by filtering the noise and restoration of images, by performing compression to save storage area and channel capacity during transmission. It is a rapidly evolving field with growing applications in many areas of science and engineering. Digital image processing is the use of computer algorithms to perform image processing on digital images. Digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the buildup of noise and signal distortion during processing. Since images are defined for two or more
dimensions, digital image processing is modeled in the form of Multidimensional Systems.

The main criterion of registration is to fuse the sets of data with the variations, if any or with their similarities into a single data. These sets of data are acquired by sampling the same scene or an object captured at different point of time or from different perspectives, in different coordinate systems. It is used in computer vision, medical imaging, military automatic target recognition, and compiling and analyzing images and data from satellites. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements.

Image registration is used in astrophotography to align images taken in space. Using control points which are automatically or manually entered, the computer performs transformations on one original image to make major features align with a transformed image. Image registration is an essential part of panoramic image creation. There are many different techniques that can be implemented in real time and run on embedded devices like cameras and camera-phones.

1.2 IMAGE REGISTRATION

Image registration is the process of transforming different sets of data into one coordinate system. The data may be multiple photographs, data from different sensors, from different periods of time, or from different viewpoints. Generally registration is the most challenging among all the tasks in image processing. This is because aligning of images to overlap the common features and differences if any, is to be emphasized for immediate visibility to the naked eye.
There is no general registration algorithm (Chris Davatzikos and Jerry Prince 1994, Studholme et al 1996, George Matsopoulos et al 1999, Rueckert et al 1999, Wolberg and Zokai 2000, Christensen and Johnson 2001, Johnson and Christensen 2002, Yang-Ming Zhu 2002, Jan Kybic and Michael Unser 2003, Fookes and Maeder 2004, Bentoutou et al 2005, Pere Marti-Puig 2006, Dennis Healy and Gustavo Rohde 2007, Matungka et al 2008, Khaissidi et al 2009, Shu Liao and Albert Chung 2010), which can work reasonably well for all images. A suitable registration algorithm for the particular problem must be chosen or developed, as they are adhoc in nature. The algorithms can be incorporated explicitly or implicitly, or even in the form of various parameters. This step determines the success or failure of image analysis. The method generally involves determining a number of corresponding control points in the images and from the correspondences, determining a transformation function (Brown 1992, Stefan Kiebel et al 1997) that will determine the correspondence between the remaining points in the images. This technique may be classified based on four different aspects given as follows: (i) the feature selection (extracting features from an image) using their similarity measures and a correspondence basis, (ii) the transformation function, (iii) the optimization procedure, and (iv) the model for processing by interpolation.

Amongst the numerous algorithms developed for image registration so far, methods based on image intensity values are particularly excellent as they are simple to automate as solutions to optimization problems (Ashburner et al 1997, Mark Jenkinson and Stephen Smith 2001, Mark Jenkinson et al 2002, Jan Kybic and Michael Unser 2003, Mark Wachowiak et al 2004, Stefan Klein et al 2007, Michael Sdika 2008). Pure translations, for example, can be calculated competently and universally as the maxima of the cross correlation function.
(Balasubramanian and Porkumaran 2005) between two images (Dennis M. Healy and Gustavo Rohde 2007, Moigne et al 2002, Zhang et al 2000). Additional commands such as rotations, combined with scaling and shears, give rise to nonlinear functions which must be resolved using iterative nonlinear optimization methods (Dennis Healy and Gustavo Rohde 2007).

1.2.1 Medical Image Registration

The purpose of registration is to visualize a single data merged with all the details about these sets of data obtained at different times or perspectives or co-ordinate systems. Such data is very essential in medicine for doctors to plan for surgery. The most common and important classes of image analysis algorithm with medical applications (George Matsopoulos et al 1999, Yang-Ming Zhu 2002, Adam Wittek et al 2006, David Frakes et al 2008) are image registration and image segmentation. In Image analysis technique, the same input produces a relatively detailed description of the scene whose image is being considered. Hence the image analysis algorithms (Christophoros Nikou et al 2001, Barbara Zitova and Jan Flusser 2003, Candocia 2003) perform registration as a part of image analysis towards producing the description. Also, in single subject analysis, the statistical analysis is done either before or after registration. But in group analyses, the statistical analysis is done after registration. Though registration transforms the different sets of data into one co-ordinate system, the data sets are required for comparison and/or integration.

In the medical imaging field, image registration is regularly used to combine the complementary and synergistic information of images obtained from different modalities. A widespread problem when registering image data is that one does not have direct access to the density functions of the image intensities. They must be estimated from the image’s data. A
variety of image registration techniques have been used for successfully registering images that are unoccluded. This is generally practiced with the use of Parzen windows or normalized frequency histograms (Fookes and Maeder 2004).

1.3 CLASSIFICATION OF IMAGE REGISTRATION METHODS


Dimensionality specifies two techniques, spatial dimensions only and the other is time series with spatial dimensions. In both, there are 2D-2D, 2D-3D (Smadar Gefen et al 2008), 3D-2D and 3D-3D.

Nature of registration may be extrinsic or intrinsic. Extrinsic may be invasive or non-invasive and intrinsic may be Landmark based, Segmentation based, Voxel property based (Anand Joshi et al 2007) or Non-image based registration. Landmark based registration is either anatomy based registration or geometry based registration. Segmentation based registration is rigid image registration (Mehdi Hedjazi Moghari and Purang Abolmaesumi 2007) or elastic or non-rigid registration (Jessica R. Crouch et al 2007, Oscar Camara et al 2007, Stefan Klein et al 2007, Yong Li et al 2007, Mark Holden et al 2008, Siwei Yang et al 2008). Voxel property based image registration is reduction to scalar/vector or using full image content and intrinsic may also be non-image based image registration.
**Nature of transformation** may be Nonreflective Similarity where the shapes and angles are preserved, rigid, affine (Luca Lucchese et al 2006), projective or curved (Peng Wen 2008), polynomial (order 2, 3 or 4), piecewise linear, or LWM (Local Weighted Mean) image registration.

**Domain of transformation** is global or local domain (Gulcin Caner et al 2006). The Nonreflective Similarity, rigid, affine, projective or curved and polynomial are global transformations that considers entire image and piecewise linear and lwm are local transformations that considers different regions within an image. **Interaction** is non interactive, semi automatic or automatic registration method. **Degree of Freedom** is 3 as Translation using x, y values, Rotation using θ value and Scaling using s value are considered. **Optimization procedure** is parameters computed for or parameters searched for.

**Modalities** is monomodal and also termed as intramodal using modalities like autoradiographic, Computed Tomography (CT) or Computed Tomographic Angiography (CTA), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Portal, Single Photon Emission Computed Tomography (SPECT), Ultra Sound (US), video or Xray or Digital Subtraction Angiography (DSA) or multimodal (Stefan Henn and Kristian Witsch 2003, Orchard 2007) and also termed as intermodal image registration using any of the two modalities mentioned above. It also includes modality to model or patient to modality. **Subject** is intrasubject, intersubject or atlas image registration. **Object** is head, thorax, abdomen, pelvis and perineum, limbs or spine and vertebrae.

The images considered for investigation in this thesis falls under 2Dimensions-2Dimensions (2D-2D) spatial dimensions for monomodal image registration and 2D-2D time series with spatial dimensions for
multimodal image registration. Intrinsic for landmark based geometric transformations, affine model based on points and voxel property based using the full image content. Nature of transformation is affine; domain of transformation is global image registration. Interaction is automatic image registration. Optimization is the parameters computed for minimization of RIU. Modalities include both intramodal where the image is monomodal which uses CT and MRI-T1 weighted registered and MRI-T2 weighted registered images and intermodal where the image is multimodal image registration using CT - MRI-T1, CT - MRI-T2 registered with axial, sagittal and / or coronal projections. Subject is intrasubject for monomodal image registration and intersubject for multimodal image registration. Object selected is head and brain or skull image registration is considered.

1.4 IMAGE REGISTRATION TECHNIQUES

Image registration is classified as intensity based (Andriy Myronenko and Xubo Song 2010) and feature based image registration (Dana Paquin 2007, Stephen DelMarco et al 2007). Further classification is based on linear transformations, or elastic or nonlinear transformation.

In addition, spatial methods operate in the image domain, matching intensity patterns or features in images. 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. The location of this peak corresponds to the relative translation between the images. Unlike many spatial domain algorithms, the phase correlation method is resilient to noise, occlusions, and other defects
typical of medical or satellite images. The phase correlation uses the fast fourier transform to compute the cross-correlation between the two images, which results in large performance gains. The method can be extended to determine rotation and scaling differences between two images by first converting the images to log polar coordinates. Due to properties of the fourier transform, the rotation and scaling parameters can be determined in a manner invariant to translation.

1.5 IMAGE REGISTRATION PROCESS

Image registration is an essential step in imaging problems where the valuable information contained in more than one image is registered. Information obtained from multiple images appear at different poses, using different sources and is of complementary nature are aligned. Hence spatial alignment is needed for proper integration of useful information from the separate images. This procedure is called registration. Figure 1.1 shows the flowchart of the image registration process.

Given an original image, the goal is to perform any transformation, such that this image is similar to the original image and is called as a transformed image. The transformations that may be performed are translation, rotation and / or scaling. This method of registration leads to monomodal image registration or could also be termed as intramodal image registration. Also the original image and transformed image may be of different modalities and while registering them it leads to multimodal image registration or could also be termed as intermodal image registration. For the registration process there are different modalities like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), Ultra Sound (US), etc., that could be involved. In this thesis, CT,
MRI-T1 Weighted and MRI-T2 Weighted modalities are considered. There are three types of projections of brain images, namely, axial (transaxial), sagittal and frontal (coronal). All these three types of projections are used for MRI-T1 and MRI-T2 brain images. For CT only axial and sagittal projections of brain images are used.

![Flowchart of Image Registration Process](image)

**Figure 1.1 Flowchart of Image Registration Process**

Over the course of a neurosurgical procedure, the brain may change its shape in reaction to mechanical and physiological changes associated with the surgery. Hence registration is required. It is necessary to find the best transformation function that aligns two images by maximizing a similarity.
1.5.1 Transformations

A transformation is the process of mapping points to other locations. Transformations are fundamental part of image processing and are used to position images, to shape images, to change viewing positions and even to change how something is viewed (eg., the type of perspective that is used).

The three main types of affine transformations are: Translation, Rotation and/or Scaling. These basic transformations can also be combined to obtain more complex transformations.

1.5.1.1 Translation

Translations are simple to implement. If a point $x$ is to be translated by $t$ units, then the transformation is given by Equation (1.1).

$$y = x + t$$

(1.1)

where

$y$ – new point on plane

$x$ – old point on plane

$t$ – translation value

In 2D matrix terms, this transformation is expressed by Equation (1.2)

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} d_{x_1} \\ d_{x_2} \end{bmatrix}$$

(1.2)
where

\[ y_1, y_2 \quad – \quad \text{new point on plane representing two axes} \]

\[ x_1, x_2 \quad – \quad \text{old point on plane representing two axes} \]

\[ d_{x_1}, d_{x_2} \quad – \quad \text{translated values with } x_1, x_2 \text{ parameters} \]

**1.5.1.2 Rotation**

In two dimensions, rotation is described by a single angle. Consider a point at co-ordinate \((x_1, x_2)\) on a two dimensional plane. A rotation of this point to new co-ordinates \((y_1, y_2)\), by \(\theta\) radians around the origin, is generated by the transformation given by Equation (1.3).

\[
y_1 = \cos(\theta)x_1 + \sin(\theta)x_2 \\
y_2 = -\sin(\theta)x_1 + \cos(\theta)x_2 \tag{1.3}
\]

where

\[ y_1, y_2 \quad – \quad \text{new point on plane representing two axes} \]

\[ x_1, x_2 \quad – \quad \text{old point on plane representing two axes} \]

\[ \theta \quad – \quad \text{rotated value} \]

A rotation of \(\theta\) degrees is performed as in Equation (1.4).

\[
\begin{bmatrix}
y_1 \\
y_2
\end{bmatrix} =
\begin{bmatrix}
\cos(\theta) & \sin(\theta) \\
-\sin(\theta) & \cos(\theta)
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2
\end{bmatrix} \tag{1.4}
\]
1.5.1.3 Scaling

Scaling is needed to change the size of an image, or to work with images whose voxel sizes differ between images. These represent scalings along the orthogonal axes, and are represented using Equation (1.5). It can be represented in matrix form by Equation (1.6).

\[ y_1 = s_{x_1} \cdot x_1 \]
\[ y_2 = s_{x_2} \cdot x_2 \]  \hspace{1cm} (1.5)

where

\[ y_1, y_2 \quad \text{– new point on plane representing two axes} \]
\[ x_1, x_2 \quad \text{– old point on plane representing two axes} \]
\[ s_{x_1}, s_{x_2} \quad \text{– scaled values} \]

\[
\begin{bmatrix}
  y_1 \\
  y_2
\end{bmatrix} =
\begin{bmatrix}
  s_{x_1} & 0 \\
  0 & s_{x_2}
\end{bmatrix}
\begin{bmatrix}
  x_1 \\
  x_2
\end{bmatrix}
\]  \hspace{1cm} (1.6)

1.6 PERFORMANCE ANALYSIS

The algorithms for monomodal and / or multimodal brain image registration are simulated in MATLAB. The purpose of the simulation is to study the effect of registrations with various transformations using the different similarity measures (Alexis Roche et al 1998, Alexis Roche et al 1999, Darko Skerl et al 2006, Stefan Martin and Tariq S. Durrani 2007). The main aim is to determine the Mutual Information (MI) (Josien Pluim P.W. et al 2000, Emiliano D’Agostino et al 2003, Mert R. Sabuncu and Peter

1.6.1 Performance Metrics

In order to qualitatively analyze the performance of the algorithms and compare with existing algorithms, the following metrics are used in this thesis. To quantify the similarity of images similarity measures are used. The choice of similarity measure depends on modality of images to be registered. Correlation coefficient, Normalized sum of squared intensity differences, and Ratio of image uniformity are used for monomodal and Mutual Information is used for multimodal image registration.

**Mutual Information (MI):** MI is a measure of similarity. It measures the similarities between the image intensities of corresponding voxels in both images. MI will be maximized when both the images are aligned. MI is given by Equation (1.7) as \( I(X, Y) \).

\[
I(X, Y) = \sum_{y \in Y} \sum_{x \in X} p(x, y) \log \left( \frac{p(x, y)}{p_1(x)p_2(y)} \right) \tag{1.7}
\]
where

\[ X, Y \] a point in the images.

\[ p(x,y) \] Joint distribution function of points \( X \) and \( Y \) in images

\[ p_1(x), p_2(y) \] Marginal distribution functions of points \( X \) and \( Y \) in images.

The values of MI are non-negative and symmetric. The values of MI range from zero to High. High MI indicates large reduction in uncertainty. Low MI indicates small reduction and zero indicates that the two variables are independent.

**Correlation Coefficient (CC):** CC is a measure of how well the original and transformed images are identical. CC has the value 1, if the two images are absolutely identical, value ‘0’, if the two images are completely uncorrelated and ‘-1’, if they are completely anticorrelated, that is, if one image is the negative of the other. CC is given by Equation (1.8).

\[
CC = \frac{\sum (x_i - x_m)(y_i - y_m)}{\sqrt{\sum (x_i - x_m)^2} \sqrt{\sum (y_i - y_m)^2}}
\]  

(1.8)

where

\[ x_i \] intensity of the \( i^{th} \) pixel in image1

\[ y_i \] intensity of the \( i^{th} \) pixel in image2

\[ x_m \] mean intensity of image1
If the range of CC is less than 0.10 then there is no linear relationship between the two images. If CC is between 0.10 to 0.29 then CC is small, if CC is between 0.30 to 0.49 then CC is medium and if CC is between 0.50 to 1.00 then CC is large.

**Computation Time for Registration (CTR):** The time taken by the algorithm to perform the registration process.

**Normalized Sum of Squared Intensity Differences (NSSD):** Two models may be compared using their NSSDs as a measure of how well they explain a given set of observations. The unbiased model with the smallest NSSD is generally interpreted as best explaining the variability in the observations and is called the Normalized Sum of Squared Intensity Differences or Normalized Minimum Variance Unbiased Estimator.

The goal of NSSD is to find the corresponding (correlated) pixel within a certain disparity range \( d(d(E(\ldots), d_{max}) \) that minimizes the associated error and maximizes the similarity as given by Equation (1.9).

\[
SSD = \sum_{(i,j) \in W} (I_1(i,j) - I_2(x+i,y+j))^2 \tag{1.9}
\]

where

\[I_1(i,j)\] original image

\[I_2(x+i,y+j)\] transformed image

The values of SSD is normalized to give NSSD with values obtained between 0 and 1 given by Equation (1.10) as NSSD.
NSSD = \frac{a_{SSD}}{\text{Norm}(a_{SSD})} \quad (1.10)

where

- $a_{SSD}$: Sum of Squared Intensity Differences
- $\text{Norm}(a_{SSD})$: Matrix Norm of $a_{SSD}$

NSSD has a higher computation complexity as it involves numerous multiplication operations. To overcome the tradeoff between precision and accuracy, NSSD is used. NSSD ranges between 0 to 1. As NSSD tends to 0, the deviations of errors are minimum and when images are aligned and will increase with misalignment.

**Ratio of Image Uniformity (RIU):** It finds the transformation that minimizes the standard deviation of the ratio of image intensities. This ratio is computed on a voxel-by-voxel basis from the transformed image and the original image that results from the current estimate of the registration transformation. RIU is expressed by Equation (1.11).

$$
RIU = \frac{1}{N} \sum_{k(i,j), l(i,j), m(i,j)} (R(I_k(i,j)) - \bar{R})^2 
$$

\begin{align*}
RIU & = \sqrt{\frac{1}{N} \sum_{k(i,j), l(i,j), m(i,j)} (R(X_{k(i,j)}) - \bar{R})^2} \\
\end{align*}

(1.11)

where

- $R(X_{k(i,j)})$: voxels in the intermediate ratio image $I_k(i,j)$
- $I_k(i,j)$: original image
- $\bar{R}$: mean value of the ratio of image intensities
From Equation (1.11), $R(X_{i,j})$ is the voxels in the intermediate ratio image of the original image $I_1(i,j)$ and is given by Equation (1.12) and $\bar{R}$ is the mean value of the ratio of image intensities and is given by Equation (1.13).

$$R(X_{i,j}) = \frac{I_1(i,j) | X_{i,j}^T \sum_{l \in [i-i,j],[j,j] \cap I_2(x+i,y+j)} (X_{i,j})}{I_2(x-i,y-j) | X_{i,j}^T \sum_{l \in [i-i,j],[j,j] \cap I_2(x+i,y+j)} (X_{i,j})} \quad (1.12)$$

$$\bar{R} = \frac{1}{N} \sum_{X_{i,j}} R(X_{i,j}) \quad (1.13)$$

where

$I_1(i,j)$ original image

$I_2(x+i,y+j)$ transformed image

$R$ intermediate ratio image

$\bar{R}$ mean value of the ratio of image intensities $N$ voxels voxels in the original image $I_1(i,j)$

$X_{i,j}^T$ voxels in the transformed image $I_2(x+i,y+j)$

$\Omega^T_{I_1(i,j) \cap I_2(x+i,y+j)}$ overlap domain
For each estimate of the registration transformation, a ratio image $R$ is calculated by dividing each voxel in $X$ by each voxel in transformed image. Uniformity $R$ is determined by calculating normalized standard deviation of $R$. The algorithm iteratively determines transformation $\tau$ that minimizes normalized standard deviation and maximizes uniformity. RIU ranges between 0 to 1. As RIU tends to 0 the deviations of errors is minimum and maximizes uniformity, when images tends to 1 it maximizes normalized standard deviation and minimizes uniformity.

1.6.2 Evaluation of Quality in Image Registration

Quality testing is done based on many metrics and accuracy and robustness is considered for testing as they are highly essential. Estimation of accuracy (Li 1991, Pan Zeng 1999) and robustness (John Doyle 1982, Nader Sadegh and Roberto Horowitz 1990, Tempo et al 1997) of registration algorithms is a substantial part of the registration process. The reason is that, without quantitative evaluation, no registration method can be accepted for practical utilization.

1.6.2.1 Accuracy

Accuracy influences the resulting medical image registration. To improve registration of an image, its subpixel accuracy of registration is essential. Proper evaluation of image registration requires the use of accuracy by finding its correlation coefficient (CC). Hence it is measured by computing the mean CC between the images. High CC increases the advantages of image registration.
1.6.2.2 Robustness

Robustness improves the registration quality. If the image registration is highly robust then its illumination variations, band limited noise, blurring, etc that causes image degradation in an image registration process is reduced. Robustness depends on the relationship between two images. Robustness of similarity measures depends on the particular images being registered. Robust similarity measure is computed by assigning binary weighting values to all the similarity measures. ‘1’ represents good similarity measure outcome and ‘0’ represent poor similarity measure outcome. So by considering the average of all these weighting values, robustness is obtained. 0.4 and less robustness measure specifies that the image is under noise and illumination changes etc, 0.5 indicates that the image possesses moderate robustness. But if the value is 0.6 or above, the registration algorithm is said to be highly robust and is highly noise tolerant and illumination invariant.

1.6.3 Simulation Tool

The algorithms proposed in this thesis are implemented in MATLAB. It is a high-level language and interactive environment that perform computationally intensive tasks that solves any problem, including technical computing problems, faster than with conventional programming languages for algorithm development, data visualization, data analysis, and numeric computation. MATLAB provides a number of features for documenting and sharing the essential work. MATLAB code can be integrated with other languages and applications.
1.7 APPLICATIONS OF IMAGE REGISTRATION

- Image registration contributes significantly, with an important role in various biomedical applications, such as medical image super resolution, medical image fusion, disease diagnosis, computer-assisted surgery as well as intrasubject, intersubject and intermodality analysis, registration with atlases, quantification and qualification of feature shapes and sizes, elastography, distortion compensation, motion detection and compensation.

- The result of image registration can be used as initial step for many remote sensing applications such as change detection, terrain reconstruction and image based sensor navigation.

- Image registration plays a vital role in astrophotography to align images taken in space.

- Image registration is applied in many fields including medical imaging, remote sensing (cartography updating), automatic target recognition, compiling, and analyzing images from satellites, quality control, computer vision, super-resolution, stereo reconstruction, motion analysis, video compression and coding, object tracking, image stabilization, segmentation, etc.

1.8 MOTIVATION FOR THE RESEARCH

Medical image registration has advanced at a fast pace during the last few years, creating new applications and opportunities. In addition, the number of clinical applications of image registration is increasing. Special attention has to be given in order to perform image registration efficiently. In the past, entropy based methods were used. The registration
solution is complicated as there may be misregistrations (Yang-Ming Zhu and Steven Cochoff 2002, Balasubramanian and Porkumaran 2005, Jiangang Liu and Jie Tian 2007). Brain image registration using transforms is automatic and has a number of interesting features that can simplify the clinical applications. A number of other image registration methods have been introduced, but registration using transforms remains the method that offers all the features and benefits given below.

- Global usage
- Monomodal and Multimodal image registration
- Axial, Frontal or Coronal and Sagittal image registration
- Ability to establish automatic image registration
- Ability to withstand interference from other sources like noise.
- Very accurate, efficient and robust image registration
- Negligible time consumption in comparison to other registration methods for similar use
- A simple and easy registration technique
- Competitively less computation complexity

Typically, solutions for image registration have existed as either a powerful, generic solution on brain images or as an application specific implementation in registration tools. Usage beyond application specific image registration solutions usually requires a significant investment and expertise in image processing systems.
Image registration has been adopted by engineers, scientists, doctors, etc., and is used widely. This registration technique can be easily intercepted, as other types of registration techniques. Image registration is essential to many applications with clinical usages. This technique can easily gain access in the medical applications. Complex image registration techniques if incorporated demand more memory, power consumption, time for registration and computation complexity, but most of the image registration techniques are not very complex. Many researchers are motivated to develop algorithms for improving the registration.

1.9 OBJECTIVES

As an image processing technology, image registration addresses all the traditional registration problems. The problem with image registration is that it has to align the original image and transformed image. In this thesis, images captured by imaging devices namely, Computed Tomography (CT), Magnetic Resonance Imaging (MRI)-T1 weighted, MRI-T2 weighted, etc, which are frontal, sagittal and / or axial images are used for monomodal and multimodal brain image registration.

The objective of this research is to

- Adopt fast computation techniques for the existing image registration algorithms to improve its image registration quality and speed.

- Use FWHT to improve image registration when compared to WT.

- Study the effect of Adaptive Polar Transform (APT) and Adaptive Monte Carlo (AMC) algorithms in the image registration process.
Apply AMC and WLAMC methods for image registration and study their performance.

Compare all the algorithms for various combinations of transformations based on MI, CC, CTR, NSSD and RIU metrics.

Analyze the algorithms with respect to accuracy and robustness of registration.

Apply Genetic Algorithm to obtain optimized transformation for FWHT Base 8 algorithm.

1.10 ORGANIZATION OF THE THESIS

The chapters of this thesis are organized as follows:

**Chapter 1** is an introduction for this thesis. This chapter discusses the introduction to medical image registration of brain images. It describes the image registration process. It also covers the classification and types of image registration. Image registration applications are also listed in this chapter. In addition to this, the overview of the image registration is outlined.

**Chapter 2** deals with the details of the first contribution made in this thesis. The fundamental concept of image registration using Walsh Transform (WT) is described in detail. This chapter discusses the image registration algorithm using Fast Walsh Hadamard Transform (FWHT) with its implementation details. The performance of the image registration algorithm using FWHT is compared with WT algorithm for both monomodal and multimodal images. Effectiveness of the algorithm is studied by determining the similarity measures.
Chapter 3 extends the existing image registration algorithm using Adaptive Polar Transform (APT) with modification. Applying Modified Gabor wavelet transform to the existing APT technique, similarity measures are determined and are compared for both monomodal and multimodal images.

Chapter 4 discusses the effectiveness of the image registration algorithm using (WLAMC) technique. Reliable, efficient and easily deployable brain image registration process that plays a vital role in providing image alignment services to the patients by applying WLAMC technique is described. Registration of CT and / or MR brain images using this technique is presented. The algorithm is analyzed for monomodal frontal, sagittal and / or axial brain images.

Chapter 5 specifies the enhancement of image registration using Genetic Algorithm (GA) technique. Selection of optimal value of Translation, Scaling, and Rotation parameters is done using GA to minimize the RIU of FWHT algorithm.

Chapter 6 summarizes the work in this dissertation and draws the conclusion and specifies the scope of future enhancements. Finally the references used in this research work and the publications made out of this research work are listed.