CHAPTER 1: INTRODUCTION

1.1 Background

Image Registration is defined as the process of establishing correspondences between two images. It is the process of aligning images so that corresponding features can easily be related and the best structural superimposition can be achieved. The term is also used to mean aligning images with a computer model or aligning features in an image with locations in physical space. The images might be acquired with different sensors (e.g., sensitive to different parts of the electromagnetic spectrum) or the same sensor at different times. The present differences between images are introduced due to different imaging conditions. 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 like in image fusion, change detection, and multichannel image restoration. Typically, registration is required in remote sensing (multispectral classification, environmental monitoring, change detection, image mosaicing, weather forecasting, creating super-resolution images, integrating information into geographic information systems (GIS)), in medicine (combining computer tomography (CT) and NMR data to obtain more complete information about the patient, monitoring tumor growth, treatment verification, comparison of the patient's data with anatomical atlases), in cartography (map updating), and in computer vision (target localization, automatic quality control), to name a few. In general, its applications can be divided into four main groups depending upon the manner of image acquisition:

Acquisition from different viewpoints (multi-view analysis): In this category images of the same scene are acquired from different viewpoints/angles. The aim is to gain a larger two dimensional view or a three dimensional representation of the scanned/acquired scene. Some examples are Computer vision-shape recovery (shape from stereo), Remote sensing-mosaicing of images of the surveyed area etc, some examples are shown in below figs. 1.1 and 1.2.

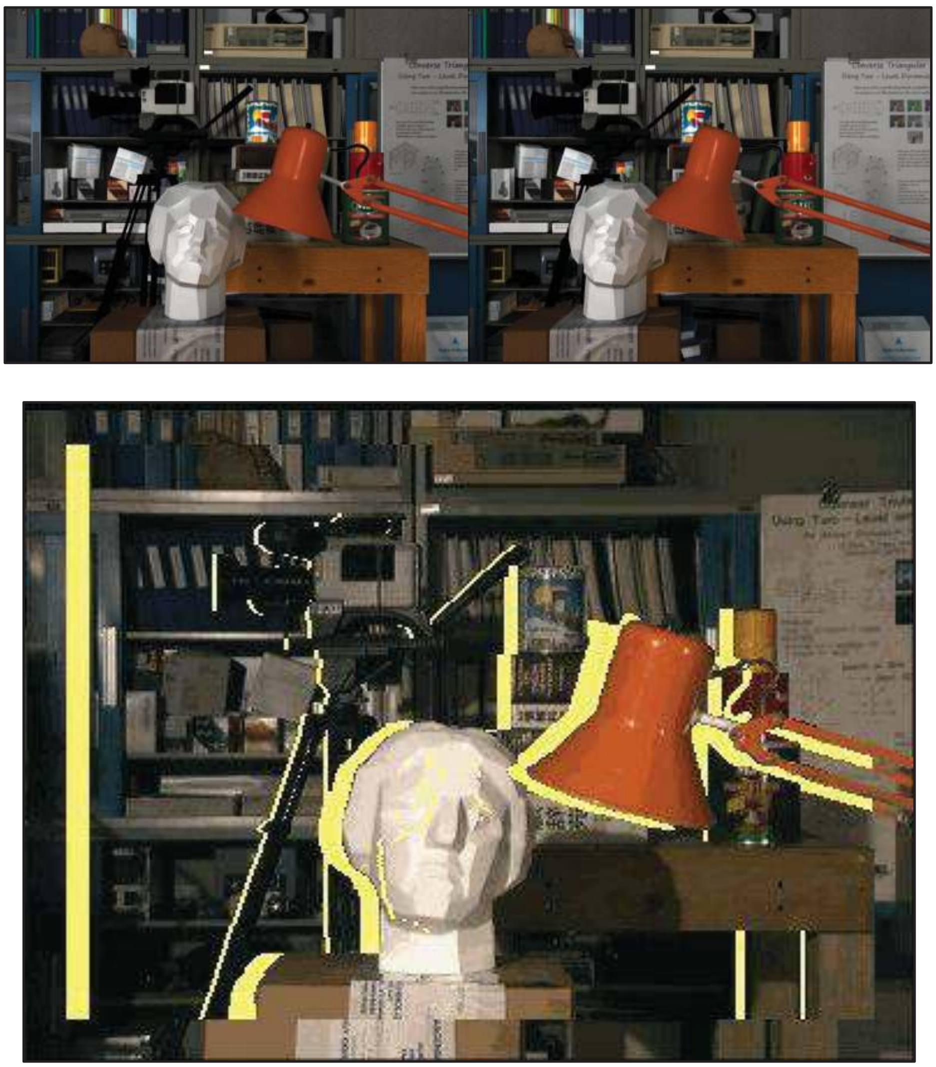

Figure 1.1: Multi-view capture of the same scene and its registered image showing the difference between two viewpoints.

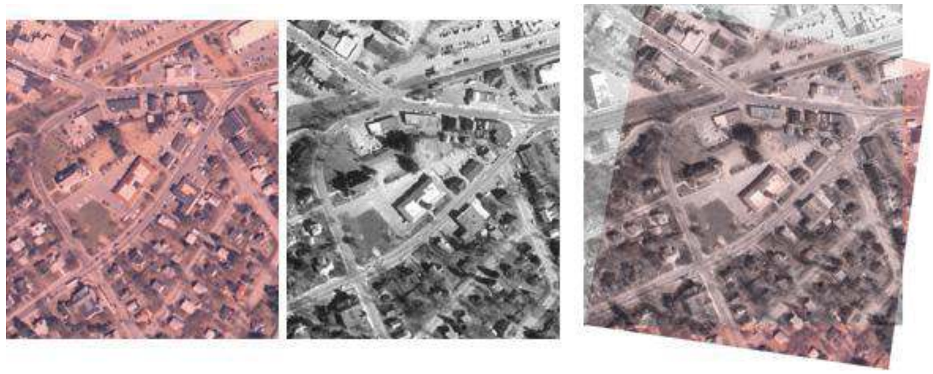

Figure 1.2: Another sample that can be taken as an example for multi-view image registration; first two are the aerial shots of a single scene at different angles, third is the registered image.

Images acquired at different timestamps (multi-temporal image analysis): In this categorization, images of the same scene are acquired at different times from the same viewing angle and same acquisition apparatus, often on regular basis and possibly under different conditions. The aim is to find and evaluate changes in the scene which seem to have happened between the consecutive image acquisitions. Some of the examples are Remote sensing-monitoring of global land usage, landscape planning. Computer vision-automatic change detection for security monitoring, motion tracking. Medical imaging based monitoring of the healing therapy, monitoring of the tumor evolution etc. Some examples are shown using figs. 1.3-1.5 below.

Figure 1.3: Temporal changes in a aerial scene where only a few parked trailers are left in a san diego, california trailer park over a period of 8 months

Figure 1.4: Temporal view of deforestation progress within a period of two years in Amazonian rain forests

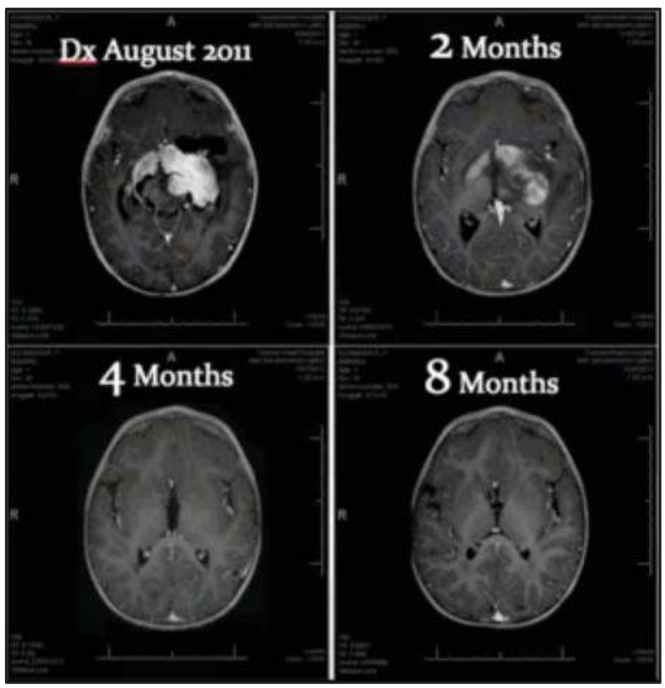

Figure 1.5: Brain tumour size reduction through several intervals in the 8 months time duration.

Images acquired using different sensors (multimodal analysis): when images of the same scene are acquired by different sensors while muting other variables such as time gap, viewing angle etc., and analyzed, it falls into the multimodal analysis category. The aim is to integrate the information obtained from different source streams to gain more complex and detailed scene representation. Examples of applications: Remote sensing-fusion of information from sensors with different characteristics like panchromatic images, offering better spatial resolution, color/multispectral images with better spectral resolution, or radar images independent of cloud cover and solar illumination. Medical imaging-combination of sensors recording the anatomical body structure like magnetic resonance image (MRI), ultrasound or CT with sensors monitoring functional and metabolic body activities like positron emission tomography (PET), single photon emission computed tomography (SPECT) or magnetic resonance spectroscopy (MRS). Results can be applied, for instance, in radiotherapy and nuclear medicine. Some examples are shown below in figs. 1.6 to 1.8.

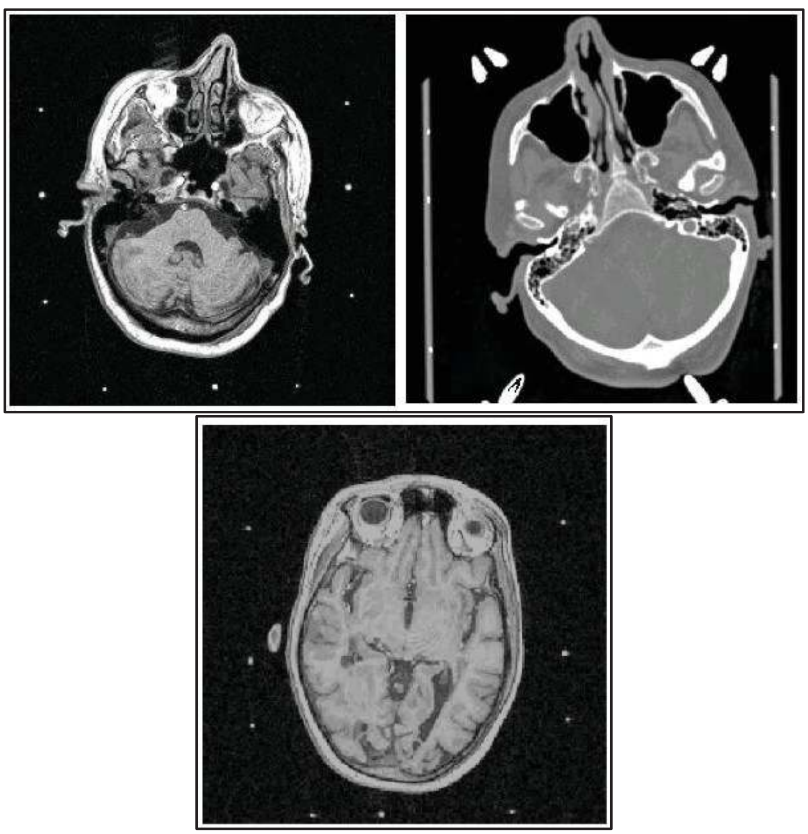

Figure 1.6: MRI image volume (showing soft tissues), CT image volume (shows bony structures) and fusion of both volumes to find the most optimal transformation.

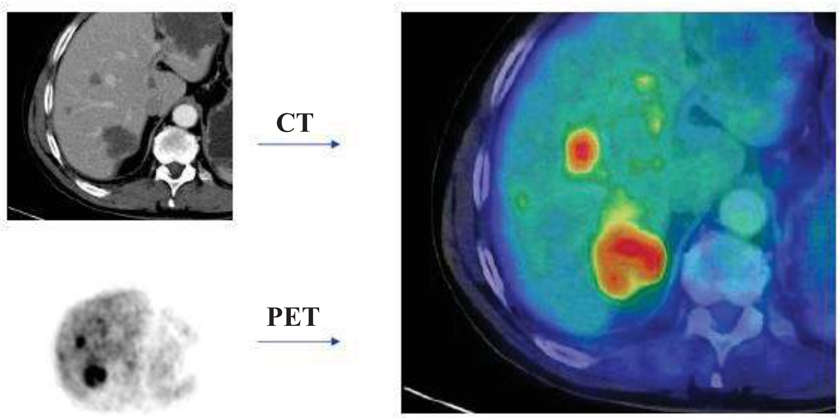

Figure 1.7: CT image volume, PET image volume and fusion of both volumes to find the best representation possible.

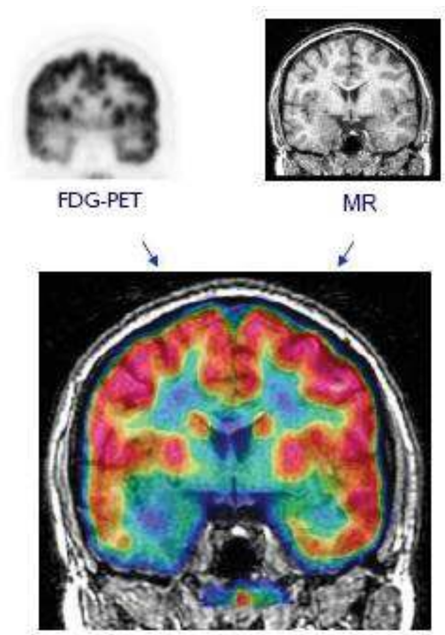

Figure 1.8: PET image volume, MR image volume and fusion of both volumes to find the best representation possible.

Scene to model registration: When images of a scene are registered with a computer generated model of that scene. This model can be a visual representation of the scene, for instance maps or digital elevation models (DEM) in GIS, another scene with similar content (for e.g. another patient), 'average' specimen, etc. The aim is to localize the acquired image in the scene/model and/or to compare them. Some examples are remote sensing-registration of aerial or satellite data into maps or other GIS layers. Creating Panoramas from the end to end stitching of acquired images. In computer vision, target template matching with real-time images, automatic quality inspections etc. are good examples. In case of medical imaging, comparison of the patient's image with digital anatomical atlases, specimen classification is an application. An example of image stitching is depicted below in fig. 1.9.

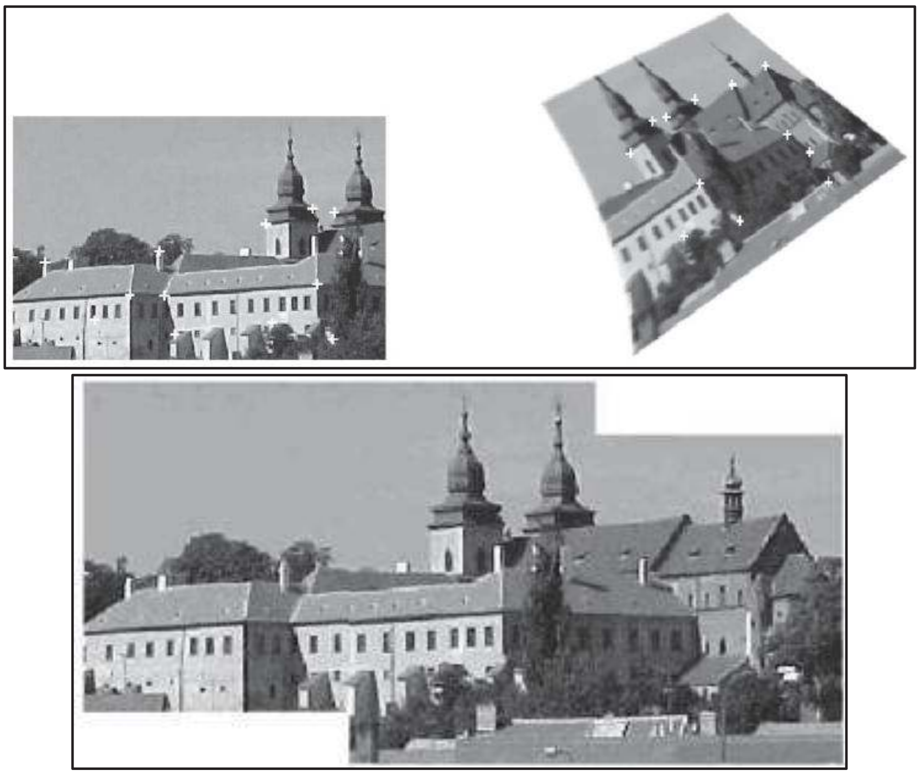

Figure 1.9: End to end stitching of two images at pre-designated points to create a panorama.

Though there can be more, usually there are two images involved in the process of image registration. One of them is called the moving image denoted by M or source image and is denoted by S, this image is to be registered against a fixed image indicated as F or a target image denoted by T. An example has been shown in fig. 1.10. Image registration can also be explained in terms of forward transform mapping i.e. mapping of points from the physical space of the fixed image into the physical space of the moving image. This is shown in the fig. 1.11 given below.

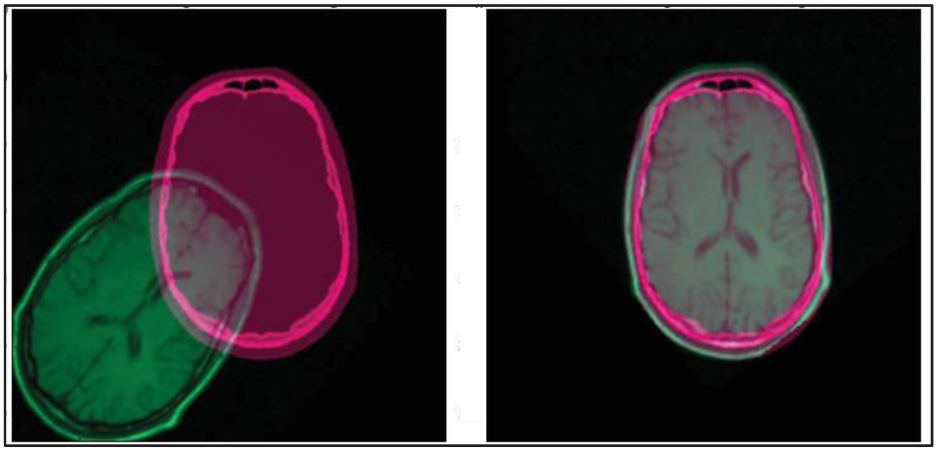

Figure 1.10: Source (S) is Green; Target (T) is Red and third is the registered image.

This implies that the Transform will accept as input points from the fixed image and it will compute the coordinates of the analogous points in the moving image. What tends to create confusion is the fact that when the Transform shifts a point on the positive X direction, the visual effect of this mapping, once the moving image is resampled, is equivalent to manually shifting the moving image along the negative X direction. In the same way, when the Transform applies a clock-wise rotation to the fixed image points, the visual effect of this mapping once the moving image has been resampled is equivalent to manually rotating the moving image counter-clock-wise. The reason why this direction of mapping has been chosen for implementation of registration framework widely is that this is the direction that better fits the fact that the moving image is expected to be resampled using the grid of the fixed image. The nature of the resampling process is such that an algorithm must go through every pixel of the fixed image and compute the intensity that should be assigned to this pixel from the mapping of the moving image. This computation involves taking the integral coordinates of the pixel in the image grid, usually called the "(i,j)" coordinates, mapping them into the physical space of the fixed image (transform T1 in fig. 1.11), mapping those physical coordinates into the physical space of the moving image (Transform to be optimized), then mapping the physical coordinates of the moving image in to the integral coordinates of the discrete grid of the moving image (transform T2 in the figure), where the value of the pixel intensity will be computed by interpolation.

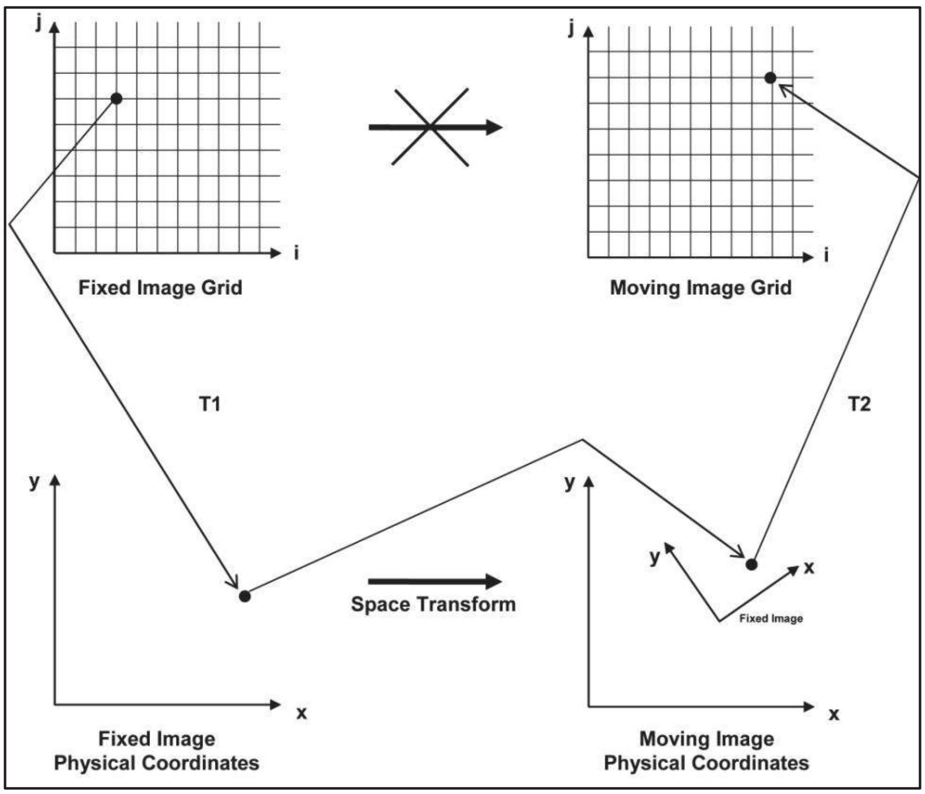

Figure 1.11: Different coordinate systems involved in the image registration process. Note that the transform being optimized is the one mapping from the physical space of the fixed image into the physical space of the moving image.

Registration of a moving image I_M (x, y) to a fixed image I_F (x, y) both of dimension D, is the problem of finding a displacement field **u(x)** that makes I_M (**x** + **u**(**x**)) spatially aligned to I_F (x). The obtained transformation is defined as:

$$T(\boldsymbol{x}) = \boldsymbol{x} + \boldsymbol{u(x)}$$

If the underlying transformation model allows local deformations, i.e. nonlinear displacement fields $\mathbf{u}(\mathbf{x})$, then it is called Deformable Image Registration (DIR).

1.2 Motivation

Many exciting potential applications of Deformable image registration (DIR) have been found in diagnostic medical imaging and radiation oncology. Automated propagation of physician-drawn contours to multiple image volumes, functional imaging, and 4D dose accumulation in thoracic radiotherapy are just a few examples. However, before such applications can be successfully and safely implemented, it is required that the DIR spatial accuracy performance be rigorously and objectively assessed. Objective evaluation of DIR is an active area of research. A framework for DIR evaluation is an essential utility for algorithm optimization, performing comparisons between algorithms, models, and implementations, acceptance testing prior to clinical implementation, and quality assurance of DIR on a routine basis. Based on many previously reported frameworks for DIR evaluation based on manual identification of large sets of prominent image features between image volume pairs it has been demonstrated that that considerable misrepresentation of DIR spatial accuracy performance characteristics can result from analyses based on inadequate landmark sample size and distribution.

Also, it has been shown that large feature point samples though slow down the registration process but more importantly facilitate thorough characterization of spatial accuracy performance in terms of clinically relevant parameters, such as relative spatial location or displacement magnitude. Analyses based on landmark samples that are not sufficient in size, or that are biased towards structures that are generally easier to identify risk misrepresentation of the actual spatial accuracy performance of an algorithm [dir-lab/motivation].

These considerations make objective comparison of published DIR spatial accuracies difficult to interpret and potentially misleading. Therefore, it seemed only appropriate and justified to investigate and make comparisons between various reported/published DIR models with the ones proposed in this work on the basis of common image database and error analysis metrics. Similar motivational issues are listed below point wise:

- Some of the hardest problems in deformable image registration are problems where large anatomical differences occur between image acquisitions.
- These would be large deformations due to images acquired in prone and supine positions and (dis)appearing structures between image acquisitions.
- To find the transformation that aligns the source best with the target image irrespective of the modality(ies) employed.
- By best alignment, the idea comes down to obtaining the optimum solution non-invasively in reasonable time.
- The tuning of the developed methods to specific problems (i.e. how to best combine different objectives such as similarity measure and transformation effort). This is one of the reasons why, despite significant progress, clinical implementation of such techniques has proven to be difficult.

Due to an uneven stress on a particular deformable image modality from the field of Radiotherapy, there are invariably scattered databases available from different modalities and of different anatomical parts of the body, which hinders a proper study on different modality investigations with the aim of a common disease diagnosis.

1.3 Objective of the Thesis

The objective of the proposed work in this thesis is to accurately register thoracic image pairs and image sequences for ten subjects at hand over a complete breathing cycle from full inhale to full exhale positions for all three anatomical positions i.e. Axial, Coronal and Sagittal. This is desired to be achieved by applying geometrical transformation based image registration methodologies on deformable image pairs as well as image sequences for all the test subjects through all three APs.

The objective of this work has been listed out in points below for clarity and precision:

- To develop a Deformable Registration model for Thoracic CT image sequences across multiple subjects (10 subject data has been taken as a sample)
- This model would help in accounting for the large anatomical differences happening in a subject over time.
- The deformation could be assessed and could be used as a prerequisite (correcting z-error) for radiotherapies etc.
- The same deformation can be used to put up a comparative study between multiple subjects in to assess the possible presence and extent of chronic pulmonary disorders etc. (a part of this study)

1.4 Contributions

Physical modeling based on geometric transforms can provide accurate results for medical image deformations, but its application in the field of deformable image registration is limited due to the difficulties in determining precise boundary conditions of the image mesh. In this work, three specific and different methodologies have been proposed to assess the deformation happening in thoracic region of ten subjects during a course of breathing i.e. from full inhale to full exhale with minimum image registration error. The methods have been proposed in a simplified way to gain better and more realistic deformed images without any a priori knowledge on the boundary conditions. The three methods which are also our primary contribution to the thesis are:

- A comprehensive literature review and comparative study of various classical as well as state-of-the art methods for deformable image registration under varying acquisition conditions. Further, design of new and efficient algorithms for registration of thoracic CT images.
- A common feature point set correspondence based application of the concept of least squares to assess the transformation required in the full inhale (moving image) with respect to the fixed image for them to get the best alignment. In turn, registering the moving image onto the fixed image as a result. The proposed method is compared against contemporary methods on the basis of an accuracy metric called the target registration error to establish relevance.
- A novel deformable image sequence registration methodology; a common feature point cloud is described between frames of the sequence. The position of those feature landmark points in every frame help in assessment of the deformation. The changing position of those common landmark points in all frames determine the flow (optical motion) and thus the deformation in the image, this helps in transformation required for the

moving image with respect to the reference image (fixed image). There has to be a reference frame out of the sequence pre-decided before determining the optical flow. Assessment of the flow would give clear movement of points across frames, it is depicting using trails/path the points leave behind while deformation. This would give a clearer picture into the motion of a human thorax during breathing from full inhale to full exhale phase non-invasively. Also, we can estimate the displacement of each of these landmark points having obtained their optical flow (velocity) with respect to the runtime of image sequence in question.

- An automatic deformable thoracic ct image registration using strain energy minimization. Medical images are broadly categorized as Elastic or deformable images; in this work the deformations in the elastic images are modeled after already established theories of elasticity by Navier-cauchy etc. An image pair is considered as a system, in case of perfect alignment of moving image with the fixed image the energy of this system is supposed to be at an optimum minimum. Strain energy minimization is the transformation applied to the moving image for that optimum alignment. Strain energy of the system at hand is minimized iteratively and checked using minimum intensity difference metric as validation to break the loop. Without using points or features, large image stacks can be registered using this method faster than point/feature based methods.

1.5 Organization of the Thesis

This thesis consists of six chapters. An outline of the thesis is as follows:

Chapter 1: here a brief introduction of the topic starting with basic background information has been presented, followed by the motivation and objectives of the thesis. Finally chapter concludes with a detailed list of contributions this thesis provides in the field of deformable image registration.

Chapter 2: concepts and theoretical background behind the topic of image registration as a whole and then deformable image registration specifically have been presented in this chapter. Starting with a basic introduction, it explains morphological classification of images and relevance of this information in the proposed works. Based on the morphological properties of images, a survey of deformable image registration methods based on geometric image deformation models has been presented. Small preludes of registration methodologies proposed in the thesis have been provided. Feature detectors/description methods used in the thesis are explained with proper justification for their use. Then the image database used in the proposed methods is discussed, database dimensions, its acquisition details, ethical issues that come along with medical image acquisition etc. Lastly, accuracy/similarity metrics employed to assess the proposed registration methodologies.

Chapter 3: this chapter presents a moving least squares approach for deformable image registration of thoracic ct images using common landmark point sets. It starts with a small introduction to the topic, followed by a background study, preparation for and description of the implementation of the methodology. This is followed by results and discussion and finally conclusion.

Chapter 4: a point correspondence path tracing and deformity estimation methodology for registration of thoracic ct image sequences from full inhale to full exhale positions has been proposed in this chapter. It starts with a small introduction to the topic, followed by a background study, preparation for and description of the implementation of the methodology. This is followed by results and discussion and finally conclusion.

Chapter 5: an automatic deformable thoracic ct image sequence registration using strain energy minimization has been coined in this chapter. It starts with a small introduction to the topic, followed by a background study, preparation for and description of the implementation of the methodology. This is followed by results and discussion and finally conclusion.

Chapter 6: it carries conclusions of the thesis and summarizes the main findings of this work. This chapter also proposes some possible future perspectives of the research work conducted so far.