ULTRASOUND AND COMPUTED TOMOGRAPHY CARDIAC IMAGE REGISTRATION

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Specially dedicated to my beloved family

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ABSTRACT

As the trend of the medical intervention moves towards becoming minimally invasive, the role of medical imaging has grown increasingly important. Medical images acquired from a variety of imaging modalities require image preprocessing, information extraction and data analysis algorithms in order for the potentially useful information to be delivered to clinicians so as to facilitate better diagnosis, treatment planning and surgical intervention. This thesis investigates the employment of an affine registration method to register the pre-operative Computed Tomography (CT) and intra-operative Ultrasound cardiac images. The main benefit of registering Ultrasound and CT cardiac images is to compensate the weaknesses and combine the advantages from both modalities. However, the multimodal registration is a complex and challenging task since there is no specific relationship between the intensity values of the corresponding pixels. Image preprocessing methods such as image denoising, edge detection and contour delineation are implemented to obtain the salient and significant features before the registration process. The features-based Scale Invariant Feature Transform (SIFT) method and homography transformation are then applied to find the transformation that aligns the floating image to the reference image. The registration results of three different patient datasets are assessed by the objective performance measures to ensure that the clinically meaningful result are obtained. Furthermore, the relationship between the pre-operative CT image and the transformed intra-operative Ultrasound image are evaluated using joint histogram, MI and NMI. Although the proposed framework falls slightly short of achieving the perfect compensation of cardiac movements and deformation, it can be legitimately implemented as an initialisation step for further studies in dynamic and deformable cardiac registration.

ABSTRAK

Dengan perubahan trend campur tangan perubatan yang semakin ke arah minimal, peranan pengimejan perubatan telah menjadi semakin penting. Imej-imej perubatan yang diperoleh daripada pelbagai kaedah pengimejan memerlukan pra pemprosesan, pengekstrakan maklumat dan algoritma analisa data bagi maklumat yang berguna agari dihantar kepada doktor untuk memudahkan diagnosis yang lebih baik, perancangan rawatan dan pembedahan. Tesis ini mengkaji pendekatan bagi kaedah pendaftaran secara affine untuk mendaftarkan Computed Tomography (CT) yang bersifat pra-pembedahan dan Ultrasound imej jantung yang bersifat sewaktu-pembedahan. Manfaat utama mendaftarkan imej Ultrasound dan CT jantung adalah untuk mengimbangi kelemahan dan menggabungkan kelebihan daripada kedua-dua kaedah. Walaubagaimanapun, pendaftaran pelbagai pengimejan adalah satu tugas yang kompleks dan mencabar kerana tidak ada hubungan tertentu antara nilai keamatan piksel sepadan. Kaedah pemprosesan imej seperti nyah-hingar, pengesanan titik hujung dan persempadanan kontur dilaksanakan untuk mendapatkan ciri-ciri utama dan penting sebelum proses pendaftaran. SIFT dan transformasi homografi kemudiannya digunakan untuk mencari transformasi yang menjajarkan imej terapung dengan imej rujukan. Keputusan pendaftaran tiga set data pesakit yang berbeza dinilai dengan ukuran objektif untuk memastikan keputusan klinikal yang sesuai diperolehi. Tambahan pula, hubungan antara imej pra-pembedahan CT dan imej sewaktu-pembedahan Ultrasound yang berubah dinilai menggunakan histogram bersama, MI dan NMI. Walaupun rangka kerja yang dicadangkan tidak mencukupi untuk mencapai pampasan yang sempurna pergerakan jantung dan ubah bentuk, ia boleh secara sah dilaksanakan sebagai langkah pengawalan untuk melanjutkan pelajaran dinamik dan pendaftaran jantung ubah bentuk.

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LIST OF SYMBOLS

θ	-	Angle
*	-	Convolution Operator
$\oplus$	-	Dilation Operator
$\ominus$	-	Erosion Operator
$\circ$	-	Opening Operator
$\bullet$	-	Closing Operator
∞	-	Infinity
μ	-	Attenuation Coefficient
σ	-	Standard Deviation

LIST OF ABBREVIATIONS

2D	-	2 Dimensional
3D	-	3 Dimensional
4D	-	4 Dimensional
CAT	-	Computerized Axial Tomography
CC	-	Correlation Coefficient
CDF	-	Cumulative Distribution Function
CLAHE	-	Contrast Limited Adaptive Histogram Equalization
CT	-	Computed Tomography
CVDs	-	Cardiovascular diseases
DICOM	-	Digital Imaging and Communications in Medicine
DLT	-	Direct Linear Transform
DOF	-	Degree of Freedom
DoG	-	Difference of Gaussian
ECG	-	Electrocardiogram
GVF	-	Gradient Vector Flow
HU	-	Hounsfield Units
ICP	-	Iterative Closest Point
MAE	-	Mean Absolute Error
MI	-	Mutual Information
MRI	-	Magnetic Resonance Imaging
MRN	-	Patient’s Medical Record
MSE	-	Mean Square Error
MWP	-	Multimodality Workplace
NCC	-	Normalized Cross Correlation
NMI	-	Normalized Mutual Information

PDE	-	Partial Differential Equation
PET	-	Positron Emission Tomography
PSNR	-	Peak Signal to Noise Ratio
RANSAC	-	RANdom SAmple Consensus
SAD	-	Sum of Absolute Differences
SIFT	-	Scale Invariant Feature Transform
SPECT	-	Single-Photon Emission Computerized Tomography
SRAD	-	Speckle Reducing Anisotropic Diffusion
SSD	-	Sum of Squared Differences
SSIM	-	Structural Similarity Index Metric
TEE	-	Transesophageal Echocardiography
TRE	-	Target Registration Error
VFC	-	Vector Field Convolution

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Cardiovascular diseases (CVDs) are diseases of the heart and blood vessel, including coronary heart disease, cerebrovascular disease, peripheral arterial disease, rheumatic heart disease and congenital heart disease [1]. They are also known as heart and circulatory disease. The most common cause of CVDs is atherosclerosis, which is the build-up of plaques on the inner walls of the arteries that limits or blocks the blood supply to the heart or brain. This can lead to serious health problems such as heart attack, heart failure, stroke or even death. According to the report “Heart disease and stroke statistic–2015 update” published by American Heart Association [1], CVDs remain the leading global cause of death with 17.3 million deaths each year. The number is expected to exceed 23.6 million by 2030, and 80% of CVD deaths occurred in low-income and middle-income countries [1]. The estimated global cost of direct and indirect loss, including healthcare expenditure and loss of productivity was 863 billion in 2010 and is expected to rise to $1.04 trillion in 2030 [2]. Therefore, it is essential to have effective and low cost healthcare services available for the general population, thus able to contribute to more saving of lives.

1.2 Research Background

Medical imaging is experiencing a significant growth and becoming an integral part in modern healthcare, due to the rapid development of computing power and the improvements in imaging technologies over the past few decades. Medical imaging has been extensively used for the purpose of diagnosis, disease monitoring, treatment planning, and surgical intervention. There are several medical imaging devices that are widely available, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Ultrasound, Single-Photon Emission Computerized Tomography (SPECT), X-ray, and more. The images acquired from these devices display the anatomical structure and functional information about a human organ. They are usually raw in nature and require subsequent preprocessing, information extraction and data analysis in order for the potentially useful information to be benefitted. In this regard, quantitative evaluation and assessment of medical images, using computer-aided imaging techniques, has enabled the clinicians in reaching an unbiased and more objective decision within a short span of time [3, 4].

Furthermore, the role of medical imaging has expanded beyond the visualization of anatomical structure and functional information of the organ, as it continues to develop into advanced clinical tools such as image-guided intervention [5, 6]. Image-guided intervention is the procedure that uses sophisticated imaging technology and computer-assisted systems to provide the information required by the clinicians to visualize and locate the surgical areas precisely [6]. It has become an essential medical procedure for cardiovascular diseases due to its minimally invasive characteristics, which is capable of performing the intervention by inserting catheters into the heart rather than opening up the heart. The advantages of minimally invasive intervention are numerous, including smaller incisions, lower risk of bleeding, lower risk of infection and shorter recovery time compared to open surgery [7].

However, minimally invasive intervention is not without its limitations; notably it has less or no direct open visual inspection with the surgical target and tool. Hence, the process of extracting, registering and combining the information acquired from medical images are required in providing a detailed road map that can lead to a successful image guided intervention [6]. It is known that different medical imaging modalities brings different complementary and advantageous information for different clinical applications. Each modality has different clinical domains and a range of applicability [8]. For example, CT acquires images of anatomical structures of the organ with high spatial resolution and high contrast between bones and tissues. MRI meanwhile, is mainly used for the imaging of soft tissues. PET and SPECT provide functional and metabolic information which allows the detection of a tumor and highlight its activities. On the other hand, Ultrasound imaging offers a non-invasive solution and real-time capability in guiding intervention. Based on all the above, it is clearly not possible for a single imaging modality aforementioned to comprehensively derive all details required to facilitate a proper diagnosis, treatment planning and intervention. Therefore, image fusion technique is used as solution to combine all information under one modality. A pre-requisite of fusion is a procedure known as image registration.

1.3 Problem Statement

Image registration technique is used to establish the correspondence or spatial mapping between sets of image data. It has a wide variety of applications in the field of remote sensing, computer vision, robotics and medical image processing. In medical imaging, the registration process aim to discover the transformation that spatially and geometrically aligns two or more images that are acquired from the same or different subjects, from the same or different modalities, at the same or different viewpoint and at a same or different time [9, 10]. It enables the establishment of the correspondence between the target image and the reference image by mapping the correlated point or feature in one coordinate space into another coordinate space. The choice of modalities reflects real world situations. The high temporal resolution, non-invasive and real-time intra-operative Ultrasound image is registered with high spatial resolution pre-operative CT image in order to explore the possibility of implementing the real-time Ultrasound and CT cardiac image guided intervention system.

Nevertheless, multi-modal image registration is a unique, complex and challenging task in the medical imaging field. The reasons for this is described as follows: different imaging modalities use different principles and parameters in their acquisition process. Hence, different imaging modality devices tend to produce the images with different characteristics and different physical representations, even for the same target organ [11]. In other words, the correlation between the images of different imaging modalities are relatively low. Thus, the contrast in image properties, viewing size, angle and position between the respective imaging modalities may become the obstacles.

Another issue is a forced compromise between spatial resolution and temporal resolution of an image. The medical image with high spatial resolution usually does not have good temporal resolution and vice versa. Registration of Ultrasound and CT images ensures compensation of the spatial and temporal difference, and the information acquired from both modalities can be integrated [12,13]. This in turn can greatly assist the clinician in locating targeted regions and making objective decisions during the intervention. Besides that, due to no specific or unknown relationship between the intensity values of the corresponding pixels of intra-operative Ultrasound image and pre-operative CT image acquired from the patient in the operating room, registration becomes much more difficult process [14]. In addition, there is still no standard procedure or fully automated registration method available to handle various clinical applications. Thus, multimodal cardiac image registration remains as an open and challenging research area.

1.4 Research Objectives

The research proposed in this thesis is part of a larger research framework that aims to implement real-time Ultrasound and Computed Tomography cardiac image-guided intervention system. It has been the central aim of collaborative research efforts at the IJN-UTM Cardiovascular Engineering Centre, Universiti Teknologi Malaysia. The overview and workflow of the proposed system are shown in Figure 1.1. The red-dotted box is the main focus of this thesis.

Based on the problem statement, the objectives of this research are stated as follows:

i. To preprocess and extract the salient features from the intra-operative Ultrasound cardiac image and pre-operative CT cardiac image, respectively.

ii. To register the intra-operative Ultrasound cardiac image and pre-operative CT cardiac image via a feature-based registration method.

iii. To assess and evaluate the performance of the proposed Ultrasound-CT image registration framework using an intensity-based similarity measure.

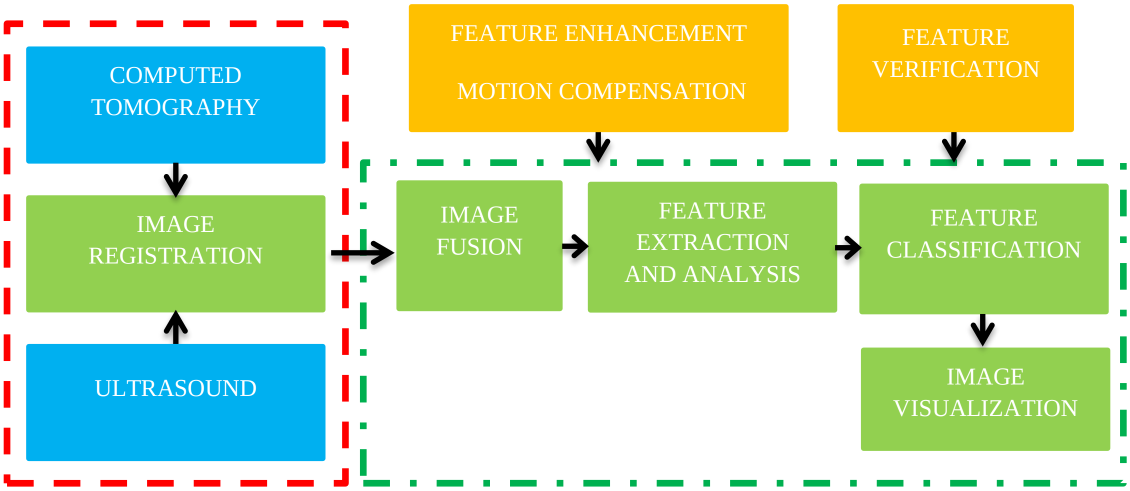

Figure 1.1: Overview and workflow of the real-time Ultrasound and CT cardiac image-guided intervention system proposed by IJN-UTM Cardiovascular Engineering Centre

1.5 Research Scopes

Several scopes have been outlined for this research:

i. Two-dimensional (2D) Ultrasound and CT cardiac images are used.

ii. Three randomly selected patient datasets are acquired from IJN and used throughout this research.

iii. Includes only four different basic Ultrasound cardiac views: apical two chamber view, apical four chamber view, parasternal long axis view and parasternal short axis view at the papillary muscle level. A total of 24 images are therefore used in this thesis.

iv. Affine transformation which is invariant to translation, rotation, shearing and scaling, are considered.

v. Pre-registered or manually registered Ultrasound datasets constructed by the IJN medical practitioner, are used as the reference image in determining the geometrical transformation that maps and aligns the Ultrasound and CT cardiac images.

1.6 Structure of Thesis

This thesis consists of five chapters and is organized as follows: Chapter One presents the introduction of the research study. This chapter includes an introduction, research background, problem statements, research objectives, research scope and structure of the thesis. Chapter Two describes the anatomical structure of the heart. The basic physic of the Ultrasound and CT imaging modalities also discussed in this chapter. Next, the literature review related to the medical image registration methods is studied, thus pointing out their strengths and limitations respectively. Chapter Three highlights the detail of the proposed methodology and techniques used for the registration framework. It consists of four main stages: preprocessing stage, feature extraction stage, registration stage and similarity measure stage. Chapter Four presents and discusses the experimental findings obtained using patient datasets for each stage. Lastly, Chapter Five summarizes and concludes the thesis along with the recommendations for future work.

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