ENHANCED PHASE CONGRUENCY FEATURE-BASED IMAGE REGISTRATION FOR MULTIMODAL REMOTE SENSING IMAGERY

MOHAMMAD AWWAD MOHAMMAD ALNAGDAWI

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Faculty of Engineering
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DEDICATION

To my late father, who taught me that the best thing I can do is spend my life following my passion, and the good conduct is the most beautiful thing I can wear.

To my mother, who implant in myself that is the pure heart full of love and honesty is a big blessing.

To my wife, that helps me to rediscover myself

To my friends who have supported me in all means… really thank you

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ABSTRACT

Multimodal image registration is an essential image processing task in remote sensing. Basically, multimodal image registration searches for optimal alignment between images captured by different sensors for the same scene to provide better visualization and more informative images. Manual image registration is a tedious task and requires more effort, hence developing an automated image registration is very crucial to provide a faster and reliable solution. However, image registration faces many challenges from the nature of remote sensing image, the environment, and the technical shortcoming of the current methods that cause three issues, namely intensive processing power, local intensity variation, and rotational distortion. Since not all image details are significant, relying on the salient features will be more efficient in terms of processing power. Thus, the feature-based registration method was adopted as an efficient method to avoid intensive processing. The proposed method resolves rotation distortion issue using Oriented FAST and Rotated BRIEF (ORB) to produce invariant rotation features. However, since it is not intensity invariant, it cannot support multimodal data. To overcome the intensity variations issue, Phase Congruence (PC) was integrated with ORB to introduce ORB-PC feature extraction to generate feature invariance to rotation distortion and local intensity variation. However, the solution is not complete since the ORB-PC matching rate is below the expectation. Enhanced ORB-PC was proposed to solve the matching issue by modifying the feature descriptor. While better feature matches were achieved, a high number of outliers from multimodal data makes the common outlier removal methods unsuccessful. Therefore, the Normalized Barycentric Coordinate System (NBCS) outlier removal was utilized to find precise matches even with a high number of outliers. The experiments were conducted to verify the registration qualitatively and quantitatively. The qualitative experiment shows the proposed method has a broader and better features distribution, while the quantitative evaluation indicates improved performance in terms of registration accuracy by 18% compared to the related works.

ABSTRAK

Pengimejan gambar multimodal adalah tugas pemprosesan imej yang penting dalam penginderaan jauh. Pada dasarnya, pengimejan gambar multimodal mencari penjajaran optimum antara gambar yang diambil oleh sensor yang berbeza bagi pemandangan yang sama untuk memberikan visualisasi yang lebih baik dan lebih bermaklumat. Pengimejan gambar secara manual adalah tugas yang rumit dan memerlukan lebih banyak usaha, oleh itu membangunkan pengimejan gambar automatik adalah sangat penting untuk memberikan penyelesaian yang lebih cepat dan boleh dipercayai. Walau bagaimanapun, petngimejan gambar menghadapi banyak cabaran dari segi sifat imej penginderaan jauh, persekitaran, dan kekurangan kaedah teknikal semasa yang menyebabkan tiga isu, iaitu daya pemprosesan intensif, variasi intensiti tempatan, dan herotan putaran. Oleh kerana tidak semua butiran gambar adalah penting, kebergantungan pada ciri-ciri penting akan lebih efisien dari segi daya pemprosesan. Oleh itu, kaedah pengimejan berdasarkan ciri diguna pakai kerana ini merupakan kaedah yang efisien untuk mengelakkan pemprosesan intensif. Kaedah yang dicadangkan bagi menyelesaikan masalah putaran ialah *Oriented FAST* dan *Rotated BRIEF* (ORB) untuk menghasilkan ciri putaran invarian. Namun, kerana ia bukan invariasi intensiti, ia tidak dapat menyokong data multimodal. Untuk mengatasi masalah variasi intensiti, *Phase Congruence* (PC) digabung dengan ORB untuk memperkenalkan pengekstrakan ciri ORB-PC bagi menghasilkan ciri invarian kepada herotan putaran dan variasi intensiti tempatan. Namun, penyelesaiannya tidak lengkap kerana kadar pemadanan ORB-PC berada di bawah jangkaan. ORB-PC yang dipertingkatkan dicadangkan untuk menyelesaikan masalah pemadanan dengan mengubah cirinya. Walaupun pemadanan ciri yang lebih baik dicapai, sebilangan besar penyimpangan data multimodal menjadikan kaedah penghapusan *outlier* umum tidak berjaya. Oleh itu, kaedah penghapusan *outlier Normalized Barycentric Coordinate System* (NBCS) digunakan kerana ia dapat mencari padanan yang lebih tepat walaupun dengan jumlah *outlier* yang tinggi. Kajian secara kualitatif dan kuantitatif dijalankan untuk mengesahkan pengimejan. Kajian kualitatif menunjukkan kaedah yang dicadangkan mempunyai taburan ciri yang lebih luas dan lebih baik, sementara penilaian kuantitatif menunjukkan peningkatan prestasi dari segi ketepatan pendaftaran sebanyak 18% berbanding hasil kajian lain yang berkaitan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ORB	Oriented FAST and Rotated BRIEF
FAST	Features from Accelerated Segment Test
BRIEF	Binary Robust Independent Elementary Features
NBCS	Normalized Barycentric Coordinate System
PC	Phase Congruency
RIFT	Radiation-Invariant Feature Transform
MIM	Maximum Index Map
HOG	Histograms of Oriented Gradient
HOPC	Histogram of Orientated Phase Congruency
NM	Number of matches

CHAPTER 1
INTRODUCTION

1.1 Overview

Image registration is a subsection of the image processing field intend to find optimal alignments between images that carry different information for the same scene. In the image registration, transformation is only done for one image, which is called floating, moving, or target image, while the second image remains constant and is known as the fixed or reference image.

Correct registrations are related to distortion complexity between images, therefore, accurate registration sometime requires a different Degree of Freedom (DoF) parameters based on search space, rigid or non-rigid transformation model. Non-rigid transformation is complex, so it needs to adjust many parameters. Nevertheless, non-rigid usually used with medical images because it is more suitable for the flexible nature of the human body. On the other hand, rigid transformation is less complex, therefore, it needs fewer DoF parameters compared to non-rigid. Accordingly, rigid transformation is used in this study because it provides enough transformation space necessary to register remote sensing images in most cases (Pluim, Maintz and Viergever, 2003; Le Moigne, Netanyahu and Eastman, 2011; Wang *et al.*, 2015; Rundo *et al.*, 2016).

Image registration has many applications in medical imaging, remote sensing, industry, and machine vision (Goshtasby, 2005; El-Gamal, Elmogy and Atwan, 2016). For instance, decision-makers may be required to use an old historical optical image with a newly acquired SAR image as an optical image may not be available. The effective of SAR sensors are able to see through clouds and take images at night that could be the only option during a catastrophic event. However, images obtained from SAR sensors have very different characteristics from the optical sensor images. Registering those images is not an easy task because of the representation difference, such as intensity variation and noise. Such differences must be resolved by a registration method before using these images in various applications such as change detection, image fusion, and 3D visualization. Hence, image transformation model has a strong relation to registration processing complexity, being either rigid or non-rigid (Zitová and Flusser, 2003; Mani and Arivazhagan, 2013).

There are many approaches for image registration of remote sensing, such as multimodal and multi-temporal, each of which serves a certain purpose. Multimodal images are captured by different devices and provide different information for the same scene. Registering multimodal images make the output image more informative that can be visualized better than an individual image. Therefore, there are many studies that try to find a solution to correctly align images using multimodal image registration methods. While multi-temporal registration can be used to monitor developments in a specific area or estimate the damage after a natural disaster over a period of time. Image registration is required to align images before the change detection model finds changes between the images. In general, accurate registration has a high impact on image fusion and change detection (Brown, 1992; Dawn, Saxena and Sharma, 2010; Xu *et al.*, 2016). Therefore, proposing a new solution for the issues related to multimodal image registration can improve the accuracy of the related application.

Multimodal image registration methods have four approaches, intensity-based, hybrid, coarse-to-fine, and features-based. The intensity-based method computes the optimal registration by finding the highest degree of similarity between the images at the pixel level (El-Gamal, Elmogy and Atwan, 2016). Hybrid methods integrate intensity-based, feature-based, or other methods to accomplish registration tasks (Murphy *et al.*, 2016). Coarse-to-fine find near to optimal solution in the first phase then uses a more accurate method for optimal registration in the second phase (Gong *et al.*, 2014). Usually, the fine phase is more computationally expensive than the coarse phase because it adopts intensity-base methods. Feature-based is the most computational efficient approach because it uses salient image features for registration (Li, Hu and Ai, 2018).

1.2 Problem Background

Image registration solves the spatial distortion between the images before image fusion and analysis are carried out. Any small amount of distortion between the images has a negative impact on the results; thus, many solutions were proposed to overcome this issue. Interestingly, the first use of this method was for remote sensing at the beginning of the 1970s (Goshtasby, 2012). Later, multimodal image registration began to be used in the medical field (Goshtasby, 2012).

The beginning of image registration was based on correlation coefficients (Svedlow, Mcgillem and Anuta, 1978), until the breakthrough in image registration method introduced a multimodal image registration method called mutual information. Viola (1995) introduced mutual information in (Viola and WELLS III, 1997). Since then, mutual information has been used as an essential method for similarity measure in multimodal image registration. In addition, many MI-based methods were proposed such as, normalized mutual information (NMI) (Studholme, Hill and Hawkes, 1999), the regional mutual information (Studholme *et al.*, 2006), the localized mutual information (Klein *et al.*, 2008), the conditional mutual information (Loeckx *et al.*, 2010), and symmetric form of mutual information, so-called Jeffery's divergence (Xu *et al.*, 2016). Because intensity-based method need a lot of processing powers so the feature-based method start raising as a less expensive (Woo, Stone and Prince, 2015) but an accurate solution.

Feature-based multimodal registration mainly focuses on improving feature extraction and matching. Feature extraction utilizes image structures to extract salient features for the registration process (Li, Hu and Ai, 2018). Well-known feature extraction methods, such as Scale-invariant feature transform (SIFT), has been adopted for multimodal image registration to poor results as these methods were designed for monomodal images. In related works (Mukherjee, Velez-Reyes and Roysam, 2009; Schwind *et al.*, 2010), it was proven that directly using SIFT in multimodal may wrongly represent the features due to local intensity variations. Therefore, certain improvements to multimodal images are necessary.

New feature-based image registration methods have been developed to support local intensity variation in multimodal images. Hasan, Pickering and Jia, (2012a) proposed a modified SIFT feature extraction for multimodal images that used edge detection based on image gradient. Uniform Robust SIFT (UR-SIFT) is a strategy for an entropy-based high-quality SIFT feature extraction method that creates a uniform distribution that is then filtered for mismatches to get more accurate results (Sedaghat, Mokhtarzade and Ebadi, 2011). Adaptive Binning Scale-Invariant Feature Transform (AB-SIFT) computes local feature descriptors using an adaptive binning gradient histogram, which makes it more robust against local geometric distortions (Sedaghat and Ebadi, 2015). These feature-based methods generally use gradient information to identify and describe features. However, they are highly susceptible to local intensity variations. In other words, the robust features mean they are not affected by local intensity variation or spatial distortion.

Gradient-based feature methods cannot provide good results with multimodal images as these methods are affected by local intensity variations as well as other intensity changes, such as illumination and noise (Ma *et al.*, 2018). These effects are common in multimodal images, so gradient-based feature methods produce unstable and imprecise features (Ma *et al.*, 2018). The main issue is that the feature extraction method may have the wrong feature descriptions. Thus, there are insufficient correct matches, which decreases feature position accuracy. Therefore, a new method is needed to solve this issue.

Extracted features using the gradient-based feature are not efficient for multimodal images. A method based on the frequency domain, called Phase Congruency (PC), was introduced to image registration to improve feature consistency in multimodal data (Kovesi, 2003). PC has great advantages in feature extraction and detection for multimodal images as it is not affected by illumination and contrast variations while being robust to handle the speckled noise that appears in radio images such as SAR (Dellinger *et al.*, 2015; Ma *et al.*, 2018)

Synthetic Aperture Radar - Scale-Invariant Feature Transform (SAR-SIFT) operators improved SIFT feature extraction when registering noisy SAR images

(Dellinger *et al.*, 2015). However, it cannot be applied directly to a multimodal image. To address this issue, Ma *et al.,* 2018 (Ma *et al.*, 2018) introduced phase congruency (PC) for SAR-SIFT. PC-SAR-SIFT successfully integrated PC into SAR-SIFT operators to support multimodal images. Outliers were removed using spatial constraints such as position and orientation. Consequently, PC shows good results for multimodal images and assists feature extraction methods in getting more robust features with different modalities. The PC also increases the correct matching rate, which improves registration accuracy.

Radiation-Invariant Feature Transform (RIFT) adopts a Maximum Index Map (MIM) for feature extraction. MIM is created using PC convolution sequences, according to log-Gabor. MIM has significant advantages with an intensity variation robustness that is computationally inexpensive (Li, Hu and Ai, 2018).

The particular problems of feature-based image registration lie within two main factors; local intensity variation from different pattern representations over modalities and spatial distortion from external environmental factors (Ghaffari and Fatemizadeh, 2014; Xu *et al.*, 2016). Local intensity variation has gained much attention from scientists, and many solutions have been proposed to deal with it. Similar to local intensity variation, the effect of spatial distortion is significant and always exists between registered images. Therefore, scientists proposed solutions to solve different types of distortion, such as horizontal, vertical, and scale. However, rotation distortion does not gain the same attention from the research community as other kinds of spatial distortion (Xu *et al.*, 2016; Ye *et al.*, 2017). Also, rotation distortion has limited feature extraction methods to deal with, therefore, rotation distortion is still an open challenge (Wei *et al.*, 2013).

Figure 1.1 presents the gap discovery scenario for image registration in change detection and image fusion for multimodal remote sensing. The gap implies by limitations of existing studies and challenges facing registration methods. The limitation of the existing studies is required to discover the gap and the motivation to address it. A reliable image registration method should also be able to cope with multimodal limitations, which are intensity variations and rotation distortions. In other words, the reliable registration method provides similar results even with a different dataset as it has limited affected by data variation.

Finally, the desired solution is characterized to resolve the gap with satisfactory results. The solution should be rotation and intensity invariant, so accurate registration can be found efficiently.

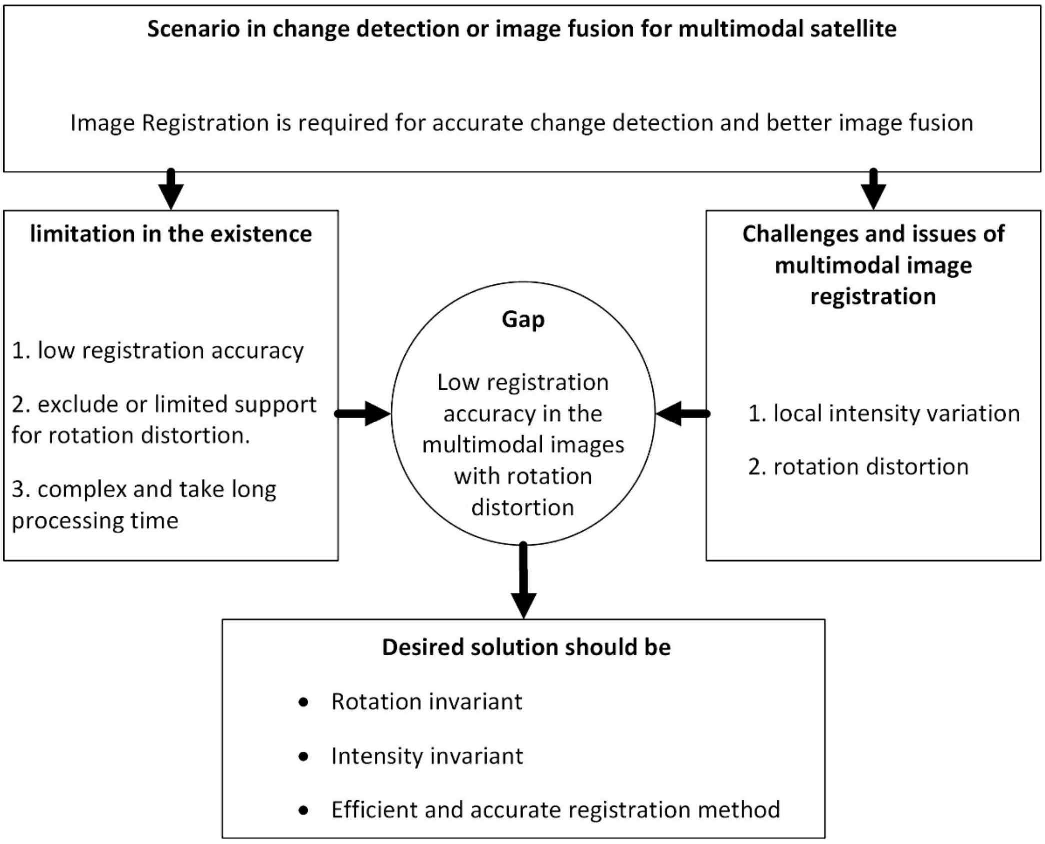

Figure 1.1 Research Problem Scenario

1.3 Problem Statement

Multimodal image registration is a method behind many essential remote sensing applications, such as image fusion and change detection (Ye and Shan, 2014). This method is capable of providing better and more informative visualization of an image, which can help remote sensing analysis. Due to the complementary information content of remote sensing images from different sensors, it is necessary to integrate these images for analyses, such as land cover change detection. Image registration brings images captured by different sensors into a single spatial domain. Image registration needs further research to enhance accuracy. However, current methods have a limited capability to registrar images when rotation distortion is present.

The multimodal image registration community has proposed many methods to solve image registration issues, such as intensity variation or rotation distortion. These methods can be categorized as intensity-based, feature-based, and others. Feature-based methods use the matched features between images to calculate transformation parameters for the floating image. Calculations for feature-based image registration requires feature detection, feature description, and feature matching methods that can deal with intensity and pattern variations in multimodal images. However, the reason behind choosing feature-based over other approaches is explained in Chapter 2 in detail.

Feature detection for monomodal images can be used to detect corners, which are a preferable feature (Li, Hu and Ai, 2018), as discussed later in this thesis. However, feature descriptions that work effectively for monomodal images cannot be applied directly to multimodal images because the feature description will not be matched with their corresponding features due to different representations in each image. In this thesis, Phase Congruency (PC) was adopted for multimodal image registration to make the features more relevant.

Remote sensing rotation distortion is an inevitable issue for image registration. Existing methods can deal with horizontal and vertical distortion, but rotation still needs further research. Methods such as Radiation-Invariant Feature Transform (RIFT) (Li, Hu and Ai, 2018) and SIFT-based methods (Hasan *et al.*, 2010; Hasan, Pickering and Jia, 2012b; Dellinger *et al.*, 2015; Ma *et al.*, 2017, 2018) still need improvements in terms of registration accuracy. Therefore, developing rotation-invariant features is inevitable because it can help in finding more matches and improving registration accuracy. To solve this issue, this study adopts Oriented FAST and Rotated BRIEF (ORB) (Rublee, Rabaud and Konolige, 2011) because it extracts rotation-invariant features efficiently. However, ORB cannot deal with multimodal data as it is designed for monomodal images. Thus, this study integrated ORB with PC to support intensity invariance.

Based on the above issues, the main research question is:

> How to build an efficient and accurate image registration method that can find optimal alignments between two imperfect multimodal remote sensing images according to rigid transformations?

Thus, the following issues need to be addressed:

(a) Could the proposed method extract intensity invariant and rotation invariant features from multimodal images?

(b) Could the proposed method improve matching rate accuracy between the extracted features?

(c) Could the matching process find correct correspondences and avoid outliers to enhance registration accuracy?

1.4 Research Goal

The main goal of this research is to develop a feature-based registration method for multimodal remote sensing images that achieves more accurate registration by extracting robust correspondence features using the proposed method in the presence of local intensity variations and rotation distortions.

1.5 Study Objectives

To accomplish the research goal, this study addressed the following objectives:

(a) To propose an integration between the ORB feature extraction method and Phase Congruency (ORB-PC) to minimize local intensity variation effects.

(b) To improve the feature matching rate by introducing the enhanced ORB-PC (EORB-PC) feature extraction through the adoption of the BRIEF feature description method to resolve misrepresented features issue.

(c) To enhance registration accuracy by integrating the EORB-PC feature extraction method with Normalized Barycentric Coordinate System (NBCS) feature matching so more correct matches can be found.

1.6 Research Scope

This research presents a feature-based registration method for remote sensing images. The scope of this research covers the following:

(a) The type of variation between the images is local intensity variation.

(b) This study mainly focuses on rigid transformations for multimodal remote sensing images, specifically, rotation distortions.

(c) In this study, all experiments were conducted with remote sensing datasets in different locations.

This work also adopts a rigid transformation for remote sensing images similar to (Xu *et al.*, 2016; Li, Hu and Ai, 2018).

1.7 Study Significance

Multimodal image registration problems are present in many fields and play a vital role in common remote sensing applications, such as image fusion and change detection (Hasan, Pickering and Jia, 2012b; El-Gamal, Elmogy and Atwan, 2016). Manual registration is a time-consuming and tedious process that is not suitable for real-life applications, therefore, developing an automatic image registration is essential.

The goal of developing a fully automated image registration method was to overcome the challenges facing existing registration methods, such as intensity invariance or spatial distortion. To achieve this goal, feature-based registration methods have been developed with reliable intensity invariance features and robust matching methods. Existing image registration studies have shown improved accuracy and decreased error rates. However, these results are inconclusive because sometimes rotation distortion was not taken into account even though it may be present in naturally collected remote sensing images (Wu *et al.*, 2015). In this case, testing images with different degrees of rotation is necessary to confirm the effectiveness of these methods for actual scenarios.

Nonetheless, the significance of this study is not exclusive to multimodal image registration, but it will also contribute to knowledge development.

1.8 Thesis Structure and Organization

This thesis consists of seven chapters as follows:

- Chapter 1

This chapter presents the research gap and the steps used to resolve it with well-established objectives. The research aim, scope, and significance are explained and summarized in Table 1.1 Each objective achieved part of the solution to get a better image registration method. The contributions of each objective enhanced the results of the next step and became an essential part of its improvement. Also, the benchmarks used to qualitatively and quantitatively validate the results of each objective were explained in the same table.

- Chapter 2

This chapter provides an overview of related studies on multimodal image registration and defines the common problem that motivated this study. The chapter also describes the most important image registration components and why particular research objectives were included or excluded.

- Chapter 3

This chapter describes the research methods and strategies used to achieve the study objectives. It also explains the datasets and measures used to validate the proposed method.

- Chapter 4

This chapter, titled 'Oriented FAST and Rotated BRIEF with Phase Congruency Feature Extraction for Local Intensity Invariant', gives a detailed explanation of the proposed feature extraction that improves feature extraction accuracy in terms of intensity variation and rotation distortion.

- Chapter 5

This chapter Enhances ORB-PC feature extraction by modifying the ORB feature descriptor to simplify the features by resolving features misrepresentation, thus increase the matching rate. The enhancement was discussed in detail, and many features samples before and after the modification are demonstrated. Finally, the method tested and compared with the related works.

- Chapter 6

EORB-PC feature extraction and NBCS has been integrated to form ORB-PC image registration. EORB-PC feature extraction can provide reliable features that are required to calculate the registration. Invalid feature matches are high with multimodal images, so NBCS feature matching is adopted because it can find the correct matches even with high outliers rate efficiently. The proposed registration method has been evaluated qualitatively and quantitatively in a variety of real experiments.

- Chapter 7

This chapter contains the thesis conclusion and the main study contributions. This chapter draws general conclusions from the results, summarizes important findings, and presents the research contributions. Several recommendations for addressing the limitations of the proposed methods are explained to provide potential future research directions.

Table 1.1 Summary table

	Objective	Findings	Contribution	Benchmark	Validation method
1	To propose an integration between the ORB feature extraction method and Phase Congruency (ORB-PC) to minimize local intensity variation effects.	- Handle local intensity variation by introducing Phase Congruency (PC) to ORB. - Minimize rotation distortion effect by ORB	- ORB-PC feature extraction method	- ORB	- Number of matches (NM) - RMSE
2	To improve the feature matching rate by introducing the enhanced ORB-PC (EORB-PC) feature extraction through the adoption of the BRIEF feature description method to resolve misrepresented features issue.	- Increase the number of matches and matching rate by adopting BRIEF for feature description	- EORB-PC feature extraction method	- ORB - ORB-PC	- NM - RMSE
3	To enhance registration accuracy by integrating the EORB-PC feature extraction method with Normalized Barycentric Coordinate System (NBCS) feature matching so more correct matches can be found.	- Enhance the matching accuracy of EORP-PC features using NBCS.	- EORB-PC + NBCS image registration method	- ORB - RIFT	- Qualitative - RMSE - NCM

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