

OPTIMIZED MONOMODAL IMAGE REGISTRATION USING CUCKOO  
SEARCH ALGORITHM

MUHAMMAD SYAFIQ BIN MD ROSLAN

UNIVERSITI TEKNOLOGI MALAYSIA

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MUHAMMAD SYAFIQ BIN MD ROSLAN

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## ABSTRACT

Medical image registration, which is employed in analyzing the similarity merits in helping the diagnosis is an important part of the medical image analysis. The process involves combining two or more images in order to provide more information. Therefore, there is a need for a method that can produce an image as a registration result that can produce more information without any loss of the input information and without any redundancy. The accuracy and computation time of the existing picture registration approach are now in question, although they could be improved if an optimization methodology is applied. Hence, this research proposed an enhancement of the image registration process focusing on monomodal registration by incorporating an optimization method called Cuckoo Search (CS) algorithm with Lévy flight generation. This method was used to find the optimum parameter value (Gradient Magnitude Tolerance, Minimum Step Length, Maximum Step Length) and it was tested to brain, breast and kidney cancer that are captured on Magnetic Resonance Imaging (MRI) image. The performance of the proposed method was then compared with standard monomodal registration. For all the cases investigated, the experimental results were validated by measuring the following: Mutual Information (MI), Normalized Mutual Information (NMI), Mean Square Error (MSE), Coefficient Correlation (CC) and Central Processing Unit run-time. The results of the study illustrated that the proposed method achieved the best 2% improvement in MI, NMI, MSE, CC results. In addition, the proposed method reduced about 40% in Central Processing Unit run-time as compared to the benchmarks methods. This indicates that the proposed method has the potential to provide faster and better medical image registration results.

## ABSTRAK

Pendaftaran Imej Perubatan yang digunakan dalam menganalisis kelebihan kesamaan untuk membantu dalam diagnosis adalah merupakan bahagian penting dalam analisis imej perubatan. Prosesnya melibatkan penggabungan dua atau lebih gambar untuk memberikan lebih banyak maklumat. Oleh itu, terdapat keperluan untuk kaedah yang dapat menghasilkan gambar sebagai hasil pendaftaran imej yang memberikan lebih banyak maklumat tanpa kehilangan maklumat input dan tanpa kelebihan. Pada zaman sekarang, ketepatan dan kepantasan pengiraan merupakan cara yang ada dalam pendaftaran gambar dipersoalkan dan ketepatan dan kepantasan pengiraan ini mungkin akan ditingkatkan jika teknik pengoptimuman diterapkan. Oleh itu, penyelidikan ini mencadangkan peningkatan Pendaftaran Imej Perubatan yang berfokus kepada Pendaftaran Imej Monomodal dengan memasukkan kaedah pengoptimuman yang disebut algoritma Carian Cuckoo (CS) dengan generasi penerbangan Lévy. Kaedah ini digunakan untuk mencari nilai parameter optimum *Gradient Magnitude Tolerance*, *Minimum Step Length*, *Maximum Step Length* dan diuji ke otak, payudara dan buah pinggang yang ditangkap pada gambar Pengimejan Resonan Magnetik (MRI). Prestasi kaedah yang dicadangkan kemudiannya dibandingkan dengan piawai Pendaftaran Imej Monomodal. Untuk semua kes yang disiasat, hasil eksperimen disahkan dengan mengukur perkara berikut: *Mutual Information (MI)*, *Normalized Mutual Information (NMI)*, *Mean Square Error (MSE)*, *Coefficient Correlation (CC)* dan masa berjalan Unit Pemprosesan Pusat. Dapatan kajian mendapati bahawa kaedah yang dicadangkan mencapai peningkatan 2% terbaik dalam hasil *MI*, *NMI*, *MSE*, *CC*. Tambahan pula didapati masa berjalan Unit Pemprosesan Pusat berkurangan sebanyak 40% berbanding dengan kaedah penanda aras. Dapat dinyatakan bahawa kaedah yang dicadangkan berpotensi memberikan hasil pendaftaran gambar perubatan yang lebih cepat dan lebih baik.

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## LIST OF ABBREVIATIONS

CT	-	Computed Tomography
MRI	-	Magnetic Resonance Imaging
PSO	-	Particle Swarm Optimization
CS	-	Cuckoo Search
IT	-	Information Technology
WDO	-	Wind Driven Optimization
DPSO	-	Darwinian Particle Swarm Optimization
NRC	-	National Cancer Registry of Malaysia
ICD-10	-	International Statistical Classification of Diseases and Related Health Problem 10 <sup>th</sup> Revision
DRG	-	Diagnosis Related Group
IE	-	Image Engineering
SRG	-	Seeded Region Growing
GAs	-	Genetic Algorithm
CIA	-	Cancer Imaging Archive

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# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

Giving them the ability for enabling the formation of non-image function photoreaction and to process visual information, the human eye and brain are the most precious creation a human could own as it allows the function of the visual system. The process of creating visual representations of the interior body for clinical analysis and medical intervention is known as a technique in medical imaging, as well to show the visual representation of the function of some organs or tissues. To diagnose and treat disease is indeed needed to reveal internal structures hidden by the bones and skin. X-ray radiography, magnetic resonance imaging is some part of it, which are clinical and critical to be used in the medical field. Besides, it is often perceived to appoint the set of techniques that noninvasively produce images of the internal aspect of the body.

Medical image computation is a field at the junction of computer science, data science, physics, mathematics, and medicine. For solving problems, pertaining to medical images and their use for biomedical research and clinical care, this field need this to build computational and mathematical methods. Extracting as much information of knowledge from medical images is the main aim for this area. Focusing not on their acquisition but computational analysis. There are several categories that are image segmentation, image registration and image visualization.

Medical image registration plays an important role in medical image analysis, for instance, computer-aided diagnosis (CAD), surgical planning and navigation (Shi, Liu, Zhang, Xie, & Wang, 2012). It is also a prerequisite for all imaging applications that compare datasets across subjects, imaging modalities or time (A.W. Toga, 2009). Registration also enables structural analysis such as counting the number of tumours,

diagnosing based on characteristics of the image to the patient. The development of CAD systems based on image registration has shown its efficiency to improve diagnostic accuracy in cancer and therapeutic planning.

In addition, medical image registration is the process of combining two or more images for providing more information. The aim is to provide a method for registration of the images from the individual modalities in such a way that the registration results is an image that gives more information without any loss of the input information and without any redundancy or artefacts. The images might be in different coordinate systems and must be aligned properly for efficient registration, in the registration of medical images obtained from different modalities. The alignment of the input images before proceeding with the fusion is called image registration. The results on the images display the performance of the fusion algorithms in comparison with the registration (Mohammed, 2016).

There are two techniques in image registration which are intensity-based image registration and feature-based image registration. Intensity-based image registration using correlation metrics to compare intensity patterns on the image. Feature-based image registration using image features like lines, points and contour to find correspondence points.

It is important to note that existing medical image registration is yet to be near ideal. The challenge perceived is finding a good similarity measure. This measure needs to be maximized to obtain the best alignment between two images. Another obstacle is the optimization method by which to identify transformation function parameters. Computational efficiency (performance) and accuracy in the alignments of images are difficult in medical image registration (Alam, 2016).

Monomodal image registration focuses on the process of mapping points from one image to corresponding points in another image that has the same modality. The essence of this algorithm is by incorporation of images from the same source to be aligned. The proposed optimized monomodal image registration yields promising methods for registration on selected brain, breast, and kidney images.

This research proposed an optimized medical image registration using Cuckoo Search (CS) Algorithm, incorporating Levy flight in CS. The proposed method will help to get rid of local minima and improve global search capability. This study is a progressive effort to revamp and boost up the existing system in the hope that the outcome of the study can improve medical image registration in better diagnostic of the images.

## **1.2 Problem Background**

The role of computers in medical image display and analysis continues to be one of the most computationally demanding tasks. A more efficient implementation is necessary, as most of the registration methods are expensive, and many methods of medical data are rapidly increasing. In addition, detecting cancer using CT / MRI scan images is a challenging task because there is no colour information in the images and the neighbouring organs tend to be separated by smooth edges with varying intensities. As volumetric imaging such as CT/MRI/Mammogram to digital histology has become invaluable to modern medicine. Registration is fundamental for personalized medicine has become more complex. As in the medical field, the detection of tumours for a patient is where it is a very critical procedure (Kumar & Shaik, 2016)

Image registration is the process of transforming a set of data into one coordinate system, in which the data can be a different setting such as different viewpoints, depth, or sensors. It is necessary to do image registration in order to compare the obtained data from this different measurement or the same measurement (Markelj, Tomazevic, Likar, & Pernus, 2012). Medical image registration allows visualization of the structure of interest and matching the necessary information for analysing the image.

Monomodal image registration is a method that is usually used for medical image registration which mapping two images collected from the same modalities or sensors. The intensity-based image registration technique basically finding differences in intensity patterns in the selected image through correlation metrics. This technique



requires registering entire images or sub-images and if the sub-images are registered, centres of corresponding sub-images are treated as corresponding feature points (Goshtasby, 2005). Intensity-based image registration is the registration of an image based on scalar values lie in the image pixels or voxels is considered. Lack of human supervision in this method may also produce inaccurate registrations results.

Efficiency and accuracy are obstacles that exist in this spectacular area. Effect of blur, noise and organ movement is not consistent as it is natural acts in medical images. For similarity measure in example Mutual Information, it automatically estimates the similarity between the images, however, in high volume images the corresponding point greatly varies which result in the differences in intensities (Alam, 2016). The reason that little attempt has been made to solve the registration problem perhaps the thus-induced complexity is. Even more surprising, since it claims that serially acquired MR images (with and without a contrast agent) of a freely suspended breast imaged using a breast coil, display only rigid motion if any at all (Maintz & Viergever, 1998). The time complexity is quite high which affect the efficiency of registration while using PSO (Bai, Shao, Qiu, Du, & Hao, 2012).

In monomodal image registration, there are some similarity measure parameters that are essential for producing good image registration results. The parameters are Gradient Magnitude Tolerance, Minimum Step Length, Maximum Step Length. It is important to optimize this parameter as some parameters if not optimized correctly will cause image registration to become plateau and resulting in bad image registration. Some parameters also will be resulting slow computing time in image registration if not optimized. This corresponding to the problem which results in low or not good image registration in intensities (Alam, 2016).

The previous work has been done by incorporating a soft-computing approach such as Particle Swarm Optimization (PSO) to optimize the parameter in monomodal image registration. The problem of early convergence in the PSO algorithm often causes the search process to be trapped in a local optimum (Raju and Rao, 2013). This problem often occurs when the diversity of the swarm decrease, and the swarm cannot escape from the local optimum.

Thus, the introduction of the CS algorithm has the potential to overcome the PSO problem as it satisfies the global convergence requirements and support the local and global search capabilities. Moreover, the convergence rate of CS, to some extent, is not sensitive to the parameter used. This means that the fine adjustment of algorithm dependent parameters is not needed for any given problem (Adnan et al, 2013). In addition, the extended problem from original CS is on the highly random search leading to a strong leaping (Wang et al, 2015). The easy jump from one region to another makes the search to another causing a reckless search around each bird nest consequently denies the full use of information nearby the bird's nest. Therefore, flight generation using Lévy flight can be proposed in solving this situation. The more efficient search takes place in the search space.

Optimization is a good process, which can bring improvement for medical image registration and example for optimization processes such as CS Algorithm. Purposing to improve the accuracy in medical image registration, which make an uncertain answer for accuracy, CS Algorithm might be beneficial. CS in image registration is an interesting algorithm that might have potential in the medical image registration process, and it shows some potential in the freeform surface inspection case study (Li & Li, 2015). There is room for improvement for optimizing strategies.

Some performance measures that can be used to evaluate the performance of the image registration are Mutual Information, Normalized Mutual Information, Mean Square Error and Correlation Coefficient. This research aim to show an improvement in the image registration process by implementing an appropriate optimization method compared to the standard approach.

The problem statement of this research is,

*“How to obtain optimum value for similarity measure parameter in image registration?”*

Two fundamental questions need to be answered through this research:

- i. Does CS algorithm optimization can be implemented in image registration?
- ii. Does the algorithm affect the performance of image registration?

### **1.3 Objective**

The main objectives of the research are:

- i. To examine the standard monomodal image registration technique for benchmark performance.
- ii. To optimize parameter value in monomodal registration technique using Cuckoo Search Algorithm.
- iii. To evaluate the Similarity Indexes of the registered image using proposed monomodal registration with Cuckoo Search Algorithm.

### **1.4 Scope**

The scopes of this research area are as follow:

- i. Only selected images of brain, breast and kidney cancers from MRI will be used during the experimental phase.
- ii. All MRI scan images are gathered from [http:// www.cancerimagingarchive.net/](http://www.cancerimagingarchive.net/).
- iii. Using Normalized Mutual Information, Mean Squared Error, Correlation Coefficient and CPU Running Time as the benchmark.
- iv. Using Basic Monomodal Registration and PSO Monomodal Registration as the benchmark.

### **1.5 Research Contribution**

As information technology (IT) is rapidly developing and has grown tremendously, organisations should take the opportunity to gain more benefits and advantages from it. Hence, this research contributes to the field of study is as follows:

- i. The experiment yielded promising results, which should encourage other researchers in the field of computer vision, remote sensing and image processing applications that are needed.
- ii. An efficient optimization algorithm designed was equivalent to mimic the evolution of a self-organizing system.
- iii. It creates a path to the development of many meta-heuristic approaches for implementing optimization algorithms to solve complex image registration problems.

## **1.6 Thesis Organization**

The arrangement of the thesis is as follow:

- i. Chapter 1: Introduction  
This chapter gives the preface to the background of the research problems and justification of the proposed optimized monomodal image registration technique for medical images registration. The research aims and objectives are defined.
- ii. Literature Review  
This chapter reviews the literature on topics related to the research. Among the topics discussed is the concept of image registration and its use in a cancer case study. Optimization algorithms focusing on CS algorithms are described in this chapter. Image Registration measurements are being discussed where all possible methods are present, and reasons for the selected method are justified.
- iii. Methodology  
In this chapter, a brief explanation about steps, techniques, strategies and experimental setup in carrying out the whole research is presented. Database descriptions and how data preparation was conducted are described. The overall research design was presented in a schematic way. In addition, formulas for the experiment are explained.
- iv. Proposed Methodology

In this chapter, a simple explanation about the proposed methodology. The flow and how this research carried out the experiment.

v. **Results and Discussion**

The results of image registration of brain, breasts and kidney images scanned using MRI will be discussed in this chapter. The analysis is presented in the table are well explained. Discussion about the experiment and results were highlighted.

vi. **Conclusion**

The contribution of the research is well explained in this chapter. Suggestions for the future will also propose besides inspiring other researchers to further exploring the topics.

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