CUCKOO LÉVY FLIGHT WITH OTSU FOR IMAGE SEGMENTATION IN CANCER DETECTION

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Dedicated to my dad, mom and sisters. I hope that this will be the guidance for me to start a multi-billionaire company, in syaa Allah.

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ABSTRACT

Detecting cancer cells from computed tomography (CT), magnetic resonance imaging (MRI) or mammogram scan images is a challenging task as the images are black and white and the neighbouring organs tend to be separated by edges with smooth varying intensity. On top of that, medical images segmentation is challenging due to the presence of weakly correlated and ambiguous multiple regions of interest. A few bio-inspired algorithms were developed to efficiently generate optimum threshold values for the process of segmenting such images. Their exhaustive search nature makes them computationally expensive when extended to multilevel thresholding, thus, this research is keen to solve the optimum threshold problems. This research propose an enhancement of image segmentation algorithms based on Otsu's method by incorporating Cuckoo Search (CS) method for Lévy flight generation while simultaneously modifying and optimizing it to work on CT, MRI or mammogram image scanners, specifically to detect breast cancer. The performance of the proposed Otsu's method with CS algorithm was compared with other bio-inspired algorithms such as Otsu with Particle Swarm Optimization (PSO) and Otsu with Darwinian Particle Swarm Optimization (DPSO). The experimental results were validated by measuring the peak signal-to-noise ratio (PNSR), mean squared error (MSE), feature similarity index (FSIM) and CPU running time for all cases investigated. The proposed Otsu's method with CS algorithm experimental results achieved an average of 231.52 of MSE, 24.60 of PNSR, 0.93 of FSIM and 3.36 second of CPU running time. The method evolved to be more promising and computationally efficient for segmenting medical images. It is expected that the experiment results will benefit those in the areas of computer vision, remote sensing and image processing application.

ABSTRAK

Mengesan sel kanser melalui imej imbasan tomografi berkomputer (CT), pengimejan resonans magnetic (MRI) atau mammogram adalah satu tugas yang mencabar kerana imej berwarna hitam putih dan organ-organ berhampiran cenderung untuk terasing oleh imbasan garis pinggiran yang berintensiti berbeza. Di samping itu, proses pensegmenan imej perubatan menjadi agak sukar dengan kewujudan Kawasankawasan berhubung kait yang berkolerasi lemah dan kabur. Terdapat beberapa algoritma yang dibangunkan berasaskan konsep biologi untuk mencari nilai ambang yang optimum untuk proses pensegmenan imej yang efisyen. Sifat gelintaran habisan algoritma tersebut menyebabkan mereka mahal dari segi pengiraan apabila dilanjutkan kepada pencarian nilai ambang berbilang aras. Oleh itu, kajian ini sangat berminat untuk menyelesaikan masalah-masalah nilai ambang yang optimum. Kajian ini mencadangkan penambahbaikan algoritma pensegmenan imej melalui kaedah Otsu dengan menggabungkan teknik Cuckoo Search (CS) untuk penjanaan Lévy flight, pada masa yang sama mengubah suai dan mengoptimumkan algoritma tersebut untuk mengimbas imej imbasan CT, MRI atau mammogram, khusus untuk mengesan sel kanser payudara. Prestasi algoritma Otsu dengan CS yang dicadangkan ini dibandingkan dengan prestasi bio-algoritma lain, seperti Otsu dengan Particle Swarm Optimization (PSO) serta Otsu dengan Darwinian Particle Swarm Optimization (DPSO). Hasil kajian telah disahkan dengan mengukur nilai peak signal-to-noise ratio (PNSR), mean squared error (MSE), feature similarity index (FSIM) dan masa operasi algoritma di komputer unit pemprosesan pusat (CPU) bagi semua kes yang diselidiki. Hasil kajian menunjukkan algoritma Otsu dengan CS yang dicadangkan ini mendapat purata sebanyak 231.52 bagi MSE, 24.60 bagi PSNR, 0.93 bagi FSIM dan 3.36 saat bagi masa operasi CPU. Kaedah tersebut telah berevolusi menjadi lebih berpotensi dan efisyen dari segi pengiraan untuk melakukan pensegmenan imej perubatan. Keputusan kajian ini dijangkakan dapat memberi manfaat kepada mereka yang berada dalam bidang-bidang berkaitan seperti visi komputer, penderian jauh dan aplikasi pemprosesan imej.

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LIST OF ABBREVIATIONS

ASRs - Age Dependent Rates

CEA - Carcinoembryonic Antigens

CIA - Cancer Imaging Archive

CS - Cuckoo Search

CT - Computed Tomography

CumR - Cumulative Risk

DCIS - Ductal Carcinoma in Situ

DPSO - Darwinian Particle Swarm Optimization

DRG - Diagnosis Related Group

FSIM - Feature Similarity Index

GAs - Genetic Algorithm

GM - Gradient Image

GVF - Gradient Vector Flow

HVS - Human Visual System

ICD-10 - International Statistical Classification of Diseases and

Related Health Problem 10th Revision

IE - Image Engineering

IQA - Image Quality Assessment

IT - Information Technology

MRI - Magnetic Resonance Imaging

MS - Multiple Sclerosis

MSE - Mean Square Error

NPR - Normal Probability Rand

NRC - National Cancer Registry of Malaysia

PSAs - Prostatic Specific Antigens

PSNR - Peak Signal to Noise Ratio

PSO - Particle Swarm Optimization

ROI - Region of Interest

SRG - Seeded Region Growing

UsRG - Unseeded Region Growing

WDO - Wind Driven Optimization

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CHAPTER 1

INTRODUCTION

1.1 Introduction

An image can uphold important information that can be useful in understanding the conceptual condition within it (Yuheng and Hao, 2017). Historically, computer vision had tried to mimic the ability of eyes and brain to foresee image as it is regarded as a high-level image processing using a computer or malicious software to interpret the physical content of the image. In digital image technology, the rudimentary step in understanding the image itself is image segmentation. This technique is essential to facilitate the characterization and visualization of areas of interest in medical image segmentation (Patil and Deore, 2013).

The role of segmentation is pivotal in many tasks requiring image analysis. Medical image segmentation allows visualization of the structure of interest and removing unnecessary information. Segmentation also enables structural analysis such as counting the number of tumours, executing based on the characteristics of image-to-patient registration which is an important part of the image guided surgery. One of the medical related disease that require the use of image segmentation is cancer research. The development of computer-aided detection (CAD) system based on image segmentation has shown its efficacy to improve diagnostic accuracy in breast cancer and therapeutic planning.

Segmentation divides the digital image into its component objects or regions. it is categorized based on two properties of discontinuity and equation (Vala and Baxi, 2013). The process of dividing the image into different regions is aimed to closely relate objects in the image highlights. Segmentation can also be regarded as a process of grouping together pixels that have similar properties. Image segmentation algorithms have been developed to the point that they can provide segmentation that agrees substantially with human intuition. One of several segmentation algorithm that is commonly used in image segmentation is threshold segmentation method.

Threshold is a region-based segmentation algorithm focusing on establishment of clustering based on direct divides of image gray scale (Haralick et al, 1985). The essence of this algorithm is by incorporation of pixel with similar properties to form region. The proposed Otsu's with Cuckoo Search algorithm has evolved to be the most promising and computationally efficient method for segmenting breast mammogram images. The Otsu's method chooses the threshold to decline the intra class variance of the threshold black and white pixel and it will run directly on the gray level histogram of 256 x 256 pixel ranges (Meharunnisa et al, 2015).

It is important to note that the existing segmentation algorithm is yet to be near ideal. The challenges perceived from the presence of poor correlation and vague multiple region of interest. Their exhaustive search nature makes them computationally expensive when extended to a multilevel thresholding. Although previous study tried to come out with the optimum threshold by the optimization between the variance class, the inefficient formulation made the method a time consuming process (Otsu, 1979). In addition, threshold method only consider the gray information without considering the spatial information of the image, it is sensitive to noise and unevenness grayscale which led this system to the combination with other method.

In this research, we proposed an efficient image segmentation algorithm, called Otsu's with Cuckoo Search method, incorporating Lévy flights method for flight generation in Cuckoo Search (CS) algorithm. By incorporating Lévy flight in Cuckoo Search, it will help to get rid of local minima and improve global search capability are

ensured via this distribution in the basic Cuckoo Search. This study is a progressive effort to revamp and boost up the existing system in hope that the outcome of study can improve image target consequently help in better diagnostic of breast cancer cells.

1.2 Problem Background

The role of computers in the medical image display and analysis continues to be one of the most computationally demanding tasks. More efficient implementation is necessary, as most of the segmentation methods are expensive, and many methods of medical data is rapidly increasing. In addition, manually detecting cancer using CT/MRI/Mammogram scan images is a challenging task to radiologist 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, segmentation is fundamental for personalized medicine has become more complex (Baxter et al, 2018).

Thresholding is an important technique in image segmentation applications because it is simple and easy to code. The Otsu's method chooses the threshold to decline the intra-class variance of the threshold black and white pixel and it will run directly on the gray level histogram of 256 x 256 pixel ranges (Meharunnisa et al, 2015). But as reported by (Vala and Baxi, 2013), as the number in classes of an image increases, Otsu's intra-class variance takes too much time to be practical for multilevel threshold selection. Besides that, Otsu method assumes the histogram of the image is bi-modal which may break down when the two classes are very unequal. This will cause optimum threshold to be difficult to achieve thus affect in the segmentation accuracy.

Furthermore, a means of segmentation of medical images is to select the best threshold value to optimize the criteria for the use of entropy. However, they are computationally expensive when extended to multilevel thresholding depth as they seek optimal threshold to optimize the objective function (Oliva et al, 2014). Both Palani Thanaraj (2014) and Raja et al (2015) studies used particle swarm optimization (PSO) to find the optimal threshold value before the segmentation process is performed. As reported by Adnan et al (2013), using PSO in finding the optimal threshold requires large amount of memory, which can limit the implementation of the resource-rich based stations. Moreover, the iterative nature of PSO can forbid it from being used for high-speed real-time applications.

The introduction of cuckoo search (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. However, although it satisfied the global convergence requirements and support local and global search capabilities, CS analysis implies that the convergence rate of Cuckoo Search, 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). 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 local optimum.

In addition, the extend 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 deny the full use of information nearby the bird nest. Therefore, flight generation using Lévy flight can be proposed in solving this situation. More efficient search takes place in the search space in order to solve the optimum threshold issues in Otsu segmentation method thanks to the long jump to be made by the particle (Haklı and Harun, 2014).

1.3 Problem Statement

In present time, the image segmentation research theory is far from perfect and there are plenty of upgrade that need to be done. The objective of medical image segmentation is to extract meaningful objects. Digital image processing is the use of computer algorithms to perform image segmentation techniques, which is an important and challenging process of medical image processing.

In a study conducted by Otsu (1979), they had chosen the optimal thresholds by maximizing the between-class variance. However, inefficient formulation of between-class variance makes the method very time consuming. In addition, it is computationally expensive when extended to multilevel thresholding since they exhaustively search for the optimal threshold to optimize the objective functions. Research theory is far from perfect and there are plenty of upgrade that need to be done. Therefore, the aim of this research is to find the solution for the following statement:

"How to obtain the optimal threshold value in multilevel image segmentation?"

Two main research questions were addressed which in line with the aim of this study:

- i. How Lévy Flight can enhance Cuckoo Search to get optimum threshold value in multilevel image segmentation?
- ii. How is the image segmentation performance of hybrid Cuckoo Search-Lévy Flight compare to others optimization methods?

1.4 Objectives

The objectives of present study are;

1. To develop a hybrid Cuckoo Search with Otsu method by using the chosen breast cancer images in order to obtain the benchmark of performance.

- 2. To enhance the proposed hybrid image segmentation algorithm using Lévy Flight to improve random walk in original Cuckoo Search.
- 3. To evaluate the performance of proposed hybrid image segmentation algorithm in terms of accuracy compared to others standard approach.

1.5 Research Scope

The scope of the research focuses on:

- 1. CT/MRI/Mammogram image of breast cancers
- 2. All CT/MRI/Mammogram scan images are gathered from cancerimagingarchive.net.

1.6 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 as follows:

- 1. The experiment yielded promising results, which encourage other researchers in the field of computer vision, remote sensing and image processing applications.
- 2. An efficient optimization algorithm designed was equivalent to mimic the evolution of a self-organizing system.

- It paves a way to the development of many meta-heuristic approaches for implementing optimization algorithms to solve complex image segmentation problems.
- 4. Lévy Flight Generation implied two randomly distributed variables with the amount of time required to retrieve random numbers, which in this case is relatively low.

1.7 Thesis Organization

The arrangement of the thesis is as follows:

i. Chapter 1: Introduction

This chapter gives the preface to the background of the research problems and justification of the proposed new hybrid image segmentation technique for cancer detection. The research aim and objectives are defined.

ii. Chapter 2: Literature Review

This chapter reviews literature on topics related to the research. Among the topics discussed is explanation and description about cancer in Malaysia. Then, the concept of image segmentation is briefly discussed, the advantages and disadvantages of each techniques are explained and the performance benchmark of breast cancer image segmentation is presented. Optimization algorithm for image segmentation like Particle Swarm Optimization (PSO), Darwinian Particle Swarm Optimization (DPSO) and Cuckoo Search (CS) are described on this chapter. Besides that, image segmentation measurement are being discussed where all possible methods are presented and reasons of selected method are justified.

iii. Chapter 3: Methodology

In this chapter, a brief explanation about steps, techniques, strategies and experimental setup in carrying out the whole research are presented. Database descriptions and how the data preparation was conducted are described. The overall research design was presented in schematic way. In addition, formula for each optimization algorithm are explained.

iv. Chapter 4: Results

The results of the image segmentation of breast images scanned using a mammogram will be discussed in this chapter. Qualitative analysis of the results presented in each performance table are well explained. Discussion on Lévy flights that has improved all performance metrics where it helped in retrieving optimum threshold for the segmentation process are highlighted.

v. Chapter 5: Conclusion

The contributions of the research are well explained in this chapter. Suggestions for future will also be proposed besides inspiring other researchers to further explore the topics.

1.8 Summary

The background of the problem, objectives and scope of the research were discussed in this chapter. Since most of the environmental phenomena have image properties/weight, it is possible to incorporate high-level image processing knowledge on medical images like CT/MRI/Mammogram. The literature review related to this research will be described on the next chapter.

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