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Enhanced Monomodal Image Registration Process With Cuckoo Search Algorithm

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Abstract. Medical image registration is one of the processes involved in medical image analysis. During the process, an image will be computed and transform it for mapping the reference image to the target image to analyze the similarity merits as to help in diagnosis the situation in the medical field. However, the accuracy of the image registration is in question, might be improved if we can make use some optimization during the image registration process. In this research, we propose an enhancement of image registration algorithms based on monomodal registration by incorporating Cuckoo Search (CS) method for Lévy flight generation while simultaneously modifying and optimizing it to work on MRI image scanners, specifically to detect brain cancer. The performance of the proposed monomodal registration with CS algorithm was compared with basic traditional monomodal registration. The experimental results were validated by measuring the Normalized Mutual Information (NMI) and CPU run-time for all cases investigated. Our results show that the proposed monomodal registration with CS algorithm achieved the best 2% improved in NMI results and 42% reduced in CPU run-time. The method evolved to be more promising and computationally efficient for medical image registration.

1. Introduction

Medical imaging is the process of creating optical exposition of the inner body for diagnostic and treatment purposes within digital health. To diagnose and treat disease is indeed need to disclose inner structures unseen by the bones and skin. X-ray radiography and magnetic resonance imaging (MRI) is some part of it, which are clinical and critical to be used in the medical field and it often perceives to appoint the set of techniques that noninvasively produce images of the inner aspect of the body [1]. Medical image computation is a field at the junction of computer science, data science, physics, mathematics, and medicine. For solving problems of medical images and their use for biomedical research and clinical care we need this too builds computational and mathematical methods. Extracting as much information of knowledge from medical images is the main aim for this area [2]. They are several categories regarding medical image computation, namely, image segmentation, image registration, and image visualization [1].

Image registration is the process of transforming a set of data into one coordinate system, which the data can be a different setting such as different viewpoints, depth, or sensors. It is necessary to do image registration to compare the obtained data from this different measurement or the same measurement [2]. Medical image registration plays an important role in medical image analysis. For instance, Computer-Aided Diagnosis (CAD), surgical planning and navigation [1]. It helps by way of improving the quality of the images and providing more information. All the required information in diagnosis may not be able to be provided by an image obtained from a single modality like MRI, CT, *etc*. To provide a method for registering the images from the individual modality that the registration results is an image that gives more information without any loss of the input data and any sacking or artefacts. The images might be in contrasting coordinate systems and have to be aligned correctly for efficient registration [1].

Based on brain images, many possible registration tasks can be defined. This includes all types of mono-modal, multimodal, model and patient registration of a plethora of image modalities in various

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diagnostic and interventionist settings. Sample of brain image can be seen in Figure 1 which show a cross-section of the brain. Registration of brain images, possibly along with the fact that the brain can be considered as a rigid body in many applications compared to many thoracic, abdominal, pelvic or spinal images. The reason that little attempt has been made to resolve the registration problem perhaps due to the thus-induced complexity [3]. Thus, this makes for a prevalence of papers concerned.

Optimization is a good process, which can bring improvement for medical image registration. Cuckoo Search (CS) algorithm is one of the optimization methods that have the potential to improve the accuracy in medical image registration. In the previous study, researchers have shown that the CS algorithm which is used in industrial inspection during manufacturing parts obtained faster convergence compared to other techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). In another study, we found that CS converge faster with fewer iterations to achieve global optima rather than PSO and GA [4]. Similarly, CS algorithm has been applied in medical image segmentation to detect breast cancer [5].

2. Methodology

2.1 Medical Image Registration Process

Medical image registration process fundamentally consists of four bases as shown below:

i. Feature space: A process to extract the feature that will be used for mapping.
ii. Search space: A process to determine the degree of transformations that will brings alignment between the reference image and the target image.
iii. Similarity measure: A process to find the similarity merits of the references image and the target image.
iv. Search strategy: A process to optimize or compute the optimal transformation.

Monomodal Registration is a technique that basically runs all these fundamental processes of image registration. This method using a single modality. In this research, we focus on the search strategy phase because the parameter value is not an optimal. Thus, affect the final outcome of the original monomodal registration. Therefore, we proposed a CS algorithm for finding the optimal value of the parameter of the search strategy.

2.2 Optimization Methods and Cuckoo Search (CS) Algorithm

Optimization is a good process on adjusting inputs or characteristics of modalities, mathematical processes or experiments to find the minimum and maximum outputs. Various method has been developed to solving an optimization problem. Some of those methods are inspired by natural processes that usually commence with an initial set of variables before evolving to obtain the global minimum or maximum of the objective function [6].

Enhancing optimization procedure using the CS algorithm in medical image registration for better search range result which can affect the performance of the process. CS algorithm is very useful to be used in nonlinear problems and multi-objective optimization.

The process flow of the CS algorithm can be considered as a meta-heuristic optimization algorithm which had evolved due to the captivating reproduction policy of certain cuckoo species developed by Yang and Deb (2010) [7]. This algorithm is nature-inspired from the cuckoo birds which lay eggs on other bird's nests and even remove its original host eggs to increase the probability of their eggs to hatch.

The CS algorithm begins its initial iteration with a randomly generated solution set specifically gathered by Eq. (2.1). Once the host species discovers the cuckoo's egg in its nests, the host will abandon the nest or throw away that eggs. This can be performed in the algorithm by replacing $\mathrm{p_a}$ of the total number of nest *s* with the new total.

$$x_{i,j} = x_j^{min} + rand(0,1)(x_j^{max} - x_j^{min}) \tag{2.1}$$

A novel solution is developed using the idea of Lévy flight that is formulated by Eq. (2.2)

$$x_i(t+1) = x_i(t) + a \oplus Levy(\lambda) \tag{2.2}$$

where Œ ± is the step size. Lévy flight simulates random walks wherein the step sizes follow Lévy distribution as

$$Levy(\lambda) = t^{-\lambda}; 1 < \lambda \leq 3 \tag{2.3}$$

The nonlinear relationship of the variance of Lévy flight as given in Eq. (2.1) assists in investigating huge unknown search spaces more efficiently compared with those models with a linear relationship.

$$\sigma^2(t) \sim t^{2-\beta}; 1 \leq \beta \leq 2 \tag{2.4}$$

This iterative process remains until it reaches the global optima to preferably avoid the problem of being detected in the local optima, which usually arises in the PSO algorithm.

2.3 Performance Measures

2.3.1 Mutual Information with Cuckoo Search Algorithm

In this part, we analyze the performance of the optimization using the CS algorithm for better search range result and period for the process. The performance of enhancing the Mutual Information (MI) method on CPU will analyze whether it delivers great performance using MI methods. Accuracy is another question concerning in computed registration. Such measures are often requiring as concerns of clinical needs. Apart from a thus-obtained reference accuracy, accuracy variability measure is also required since it cannot be executed locally in a clinical example. Therefore, it needs to be supplied with reliability bound but neither do such measures easily transfer to particular clinical cases. Formula to analyse MI is as follow:

$$I(x;y) = h(x) + h(y) - h(x;y) \tag{2.5}$$

Normalized Mutual Information (NMI) shown to be independent of the amount of overlap between images, as MI is sensitive to the overlap of two images. The adoption of MI to measure the similarity between images should concern of two sensitive factors: (a) the accuracy of spatial registration between the images; and (b) any image interpolation that may have been applied to spatially transform the images before computing the MI. It is a desirable characteristic of MI to have a sensitivity to misalignment between images as a utility in image registration applications. However, sensitivity to interpolation operations is a confounding effect that restricts the accuracy of MI and should be reduced. When spatial registration between images is either at or close to the optimum point, variations in MI due to interpolation effects can dominate those due to registration errors, thus restricting the accuracy of spatial registration. As for the validation, there will be accuracy measure and sensitivity measure. The formula for NMI can be written as:

$$z = sqrt(\left(\frac{MI}{Hx}\right) * \left(\frac{MI}{Hy}\right)) \tag{2.6}$$

$$z = \max(0, z) \tag{2.7}$$

2.3.2 CPU Run-Time

It is recommended that *timeit* or tic toc is used to measure the performance of the code. These functions return the wall clock time. Unlike tic toc, *timeit* function calls your code several times, and, eventually, assuming the costs for the first time.

Cputime function measures the amount of CPU time that is currently running in all threads. This measure is different from the wall clock *timeit* or returns tic / toc, and can be confusing. For example, the CPU time for the pause function is typically small, but the wall-clock time accounts for the actual time that MATLAB execution is paused. Therefore, the wall-clock time might be longer. If your function uses four processing cores equally, the CPU time could be approximately four times higher than the wall-clock time.

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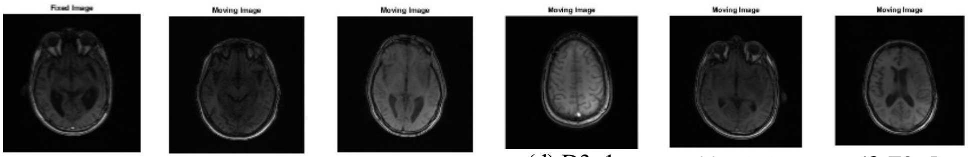
3. Results and Discussion

The results of the image registration of brain images scanned using an MRI will be discussed in this sub-section. Image A3_1 is a fixed image that acts as a reference image to compare with other five images which are, B1_3, C3_4, D3_1, E1_2, and F2_5 that will be registered on this registration process. All these images are shown in Figure 1.



(a) A3_1 (b) B1_3 (c) C3_4 (d) D3_1 (e) E1_2 (f) F2_5

Figure 1. Sample image used in experiments

Performance metric values of monomodal registration with CS algorithm has been evaluated and compared with the monomodal registration without CS algorithm. The study was conducted using MATLAB R2017a running on Intel Core ™ i5 CPU with 2.2 GHz and 8 GB of RAM.

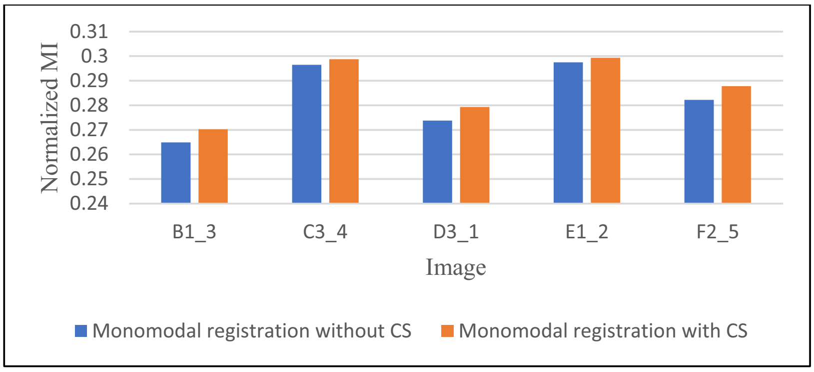


Figure 2. Normalized Mutual Information results

Figure 2 shows the Normalized Mutual Information results. We can see that monomodal registration with CS algorithm obtained better Normalized Mutual Information results compared to monomodal registration without CS. For moving image B1_3, D3_1 and F2_5, the percentage improvement is about 2%. Whilst, the rest obtained about 1% improvement.

Next, Figure 3 depicted the result of CPU run-time for monomodal registration with CS versus monomodal registration without CS, which is a lower value is better. It is shown that monomodal registration with CS reduced CPU run-time. The moving image C3_4 achieved the highest time reduced percentage, i.e., 43% when monomodal registration with CS was run. The rest has between 30% to 39% reduced in CPU run-time.

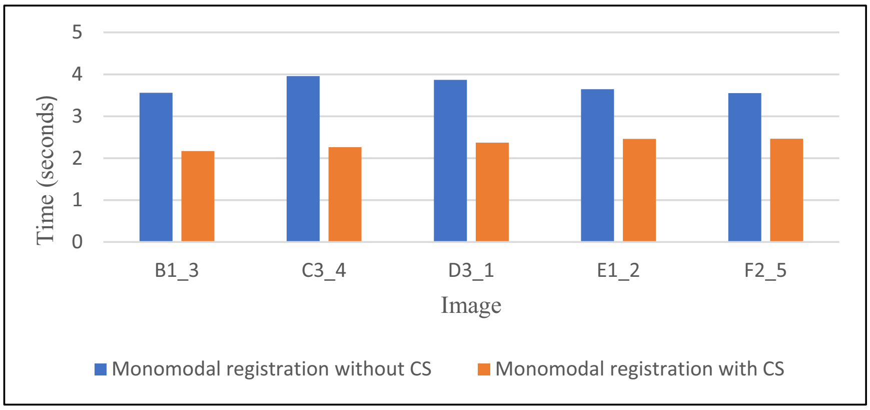


Figure 3. Performance measures bases on CPU run-time

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4. Conclusions

The medical image registration (*i.e.*, monomodal registration) with the CS algorithm has yield better performances compared to the method without CS algorithm. The experimental results were confirmed by measuring the Normalized Mutual Information and CPU run-time for MRI brain images. Thus, it shows that the proposed method evolved to be more promising and computationally efficient for medical image registration. We could extend this work on other MRI image for further evaluations.

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