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Non-rigid multi-modal medical image registration by combining L-BFGS-B with cat swarm optimization

Feng Yang [a,b], Mingyue Ding [a], Xuming Zhang [a,*], Wenguang Hou [a], Cheng Zhong [b]

[a] Department of Biomedical Engineering, School of Life Science and Technology, Key Laboratory of Image Processing and Intelligent Control of Education Ministry of China, Huazhong University of Science and Technology, Wuhan, Hubei 430074, PR China
[b] School of Computer and Electronics and Information, Guangxi University, Nanning, Guangxi 530004, PR China

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ABSTRACT

Non-rigid multi-modal image registration plays an important role in medical image processing and analysis. Optimization is a key component of image registration. Mapped as a large-scale optimization problem, non-rigid image registration often requires global optimization methods because the functions defined by similarity metrics are generally non-convex and irregular. In this paper, a novel optimization method is proposed by combining the limited memory Broyden–Fletcher–Goldfarb–Shanno with boundaries (L-BFGS-B) with cat swarm optimization (CSO) for non-rigid multi-modal image registration using the normalized mutual information (NMI) measure and the free-form deformations (FFD) model. The proposed hybrid L-BFGS-B and CSO (HLCSO) method uses cooperative coevolving to tackle non-rigid image registration, and employs block grouping as the grouping strategy to capture the interdependency among variables. Moreover, to achieve faster convergence and higher accuracy of the final solution, the local optimization method L-BFGS-B and the roulette wheel method are introduced into the seeking mode and the tracing mode of the HLCSO, respectively. Extensive experiments on 3D CT, PET, T1, T2 and PD weighted MR images demonstrate that the proposed method outperforms the L-BFGS-B method and the CSO method in terms of registration accuracy, and it is provided with reasonable computational efficiency.

1. Introduction

With the development of medical imaging technology, various imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), ultrasound (US) and positron emission tomography (PET) are widely applied in clinical diagnosis and therapy. Generally, different imaging modalities provide a variety of non-overlapped and complementary information. For example, CT is effective for bony structures and dense tissue while MRI provides a good view of soft tissues. Therefore, multi-modal medical image registration is useful for relating clinically significant information from different images [16,29,35]. For example, it can be used to improve the computer-assisted diagnosis and image-guided interventions.

* Corresponding author.
E-mail address: xmboshi.zhang@gmail.com (X. Zhang).

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However, multi-modal image registration is highly challenging because of intensity variations and the possible non-rigid transformation between images [2,44]. Non-rigid registration procedures, capable to deal with more localized spatial changes, are therefore in the focus of current researches on image registration [1,19,43]. Aiming to non-rigid estimate the optimal non-rigid transformation, multi-modal image registration generally involves three main components: similarity metric, deformation model and optimization strategy.

Many similarity metrics have been proposed in the field of multi-modal image registration [13,20]. The well-known metrics such as Renyi entropy [46], Kullback-Leibler divergence [10], cross-cumulative residual entropy (CCRE) [6], mutual information (MI) [39] and normalized mutual information (NMI) [37] have been successfully used for multi-modal image registration. Among these metrics, the NMI has been investigated in-depth and widely applied. The NMI is relatively robust, in the sense that it usually attains its maximum at the correct alignment [11,17]. As regards the deformation model, the most popular one is relevant to interpolation and approximation theory including radial basis functions [45], elastic body splines [26] and free-form deformations (FFD) [28]. Among them, the FFD model has been used widely in the community of non-rigid registration because it is beneficial for modeling local transformations and fast computation [27]. However, the FFD model involves numerous parameters which need to be optimized. For example, for 3D images, a FFD defined by an $8 \times 8 \times 8$ mesh of control points yields a transformation with 1536 parameters. Therefore, the non-rigid image registration using the FFD model is a challenging large-scale optimization problem [17,18].

Numerous methods have been proposed to optimize the parameters of the deformation model in the non-rigid image registration. Local optimization methods, such as gradient descent, Newton's method and L-BFGS-B method are generally used in image registration [8,15,22]. Especially, the L-BFGS-B method, which approximates Newton's method and borrows the ideas from the trust region methods while keeping the L-BFGS update of the Hessian and line search algorithms, has been used to handle a large number of variables and constraints of registration, which is included in Insight Segmentation and Registration Toolkit (ITK) [12,31,33]. Local optimization methods can ensure a good registration results if the initial orientation is close to the transformation's ground truth. Otherwise, they are easy to be trapped in the local optima. Therefore, the global optimization is required.

Global optimization methods, such as graph cuts methods [4,34], evolutionary strategies (ESs) [14,24,30] and particle swarm optimization (PSO) [40] have been applied to tackle image registration problems. In graph cuts methods [4,34], the image registration problem is reformulated as a discrete labeling problem, which can be optimized by using the graph-cuts method via α-expansions. These methods can achieve lower registration errors for mono-modal images than the local optimization methods, but they involve high computational complexities. Klein et al. [14] executed the multi-modal medical image registration by using ESs, which is based on the principle of natural selection and consists of three phases: offspring generation, selection and recombination. Wachowiak et al. [40] proposed an approach to multi-modal medical image registration using PSO, which exploits the cooperative and social behaviors, such as fish schooling and birds flocking. The registration performance of Wachowiak's method is improved by the hybridization with crossover operators and constriction coefficients, but it only considers a rigid transformation, such as translation and rotation. In general, these global optimization methods are useful for performing a robust search in complex search spaces without requiring a good initial estimation of image registration. However, it is well known that classical ESs and PSO algorithms perform well on low dimensional problems, but their performance degrades on high dimensional ones [38].

In the case of function optimization, cat swarm optimization (CSO) is presented for solving global optimization problems by imitating two natural behaviors of the cat, i.e., looking around its environment for its next move and tracing the targets. The CSO refers to these two behaviors as the seeking and tracing modes [5]. The experimental results indicate that the CSO can improve the performance of PSO-type algorithms in finding the global best solutions [25,36,42]. However, the performance of the CSO deteriorates quickly as the dimensionality of the search space increases. If the CSO is directly applied to non-rigid image registration, it will be difficult to obtain satisfactory registration results.

In view of the good local search performance of the L-BFGS-B even for non-smooth optimization problems with large numbers of variables and the relatively good global search ability of the CSO, we have presented a novel optimization method in this paper by combining the L-BFGS-B with the CSO to address the non-rigid image registration problem. Inspired by the idea of cooperative coevolving PSO (CCPSO2) proposed by Liet al. [17], cooperative coevolving is introduced into the HLCSO to tackle the above large-scale optimization problem. Furthermore, in order to better capture the interdependency among variables, the HLCSO uses block grouping rather than just random grouping of CCPSO2 as the grouping strategy. Similar to the CSO, the HLCSO has the seeking mode and the tracing mode. However, in the HLCSO, in order to achieve faster convergence and better accuracy of the final solution, the local optimization method L-BFGS-B is introduced into the seeking mode and the roulette wheel method is introduced into the tracing mode. Extensive experiments on 3D CT, PET, T1, T2 and PD weighted MR images demonstrate the superiority of the proposed hybrid optimization method over the L-BFGS-B method and the CSO method in optimizing the parameters of the FFD model in the non-rigid image registration.

The rest of the paper is organized as follows. Section 2 presents the theories including the non-rigid image registration framework, the normalized mutual information, the free-form deformations and the cat swarm optimization. Section 3 presents the novel method HLCSO for non-rigid multi-modal image registration. Section 4 provides the experimental comparisons of registration accuracy and efficiency among our method, the CSO method and the L-BFGS-B method. Finally, the conclusion is given in Section 5.