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An Efficient Framework for Image Matching∗

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Abstract

The goal of this paper is to present an efficient framework for non-rigid medical image matching. Previous non-rigid matching often produces unpredictable deformation field and unwanted stretching in the images. The as-rigid-as-possible nature of the Moving-LS technique thus makes it a new candidate by providing transformation that maintains the rigidity of structures for underlying physical reasons, while producing local deformations. In addition, it is very suitable for parallel computation, and the performance can be accelerated by multi-core processors through employment of multiple threads. The results demonstrate that the proposed matching method has good balance between accuracy and speed, and has potential in many medical applications.

Keywords: Medical image; Non-rigid matching

1. Introduction

Medical images are increasingly being used within healthcare for diagnosis, planning treatment, guiding treatment and monitoring disease progression. Within medical research they are used to investigate disease processes and understand normal development and ageing. In many of these studies, multiple images are acquired from subjects at different times, and often with different imaging modalities. In research studies, it is sometimes desirable to compare images obtained from patient cohorts rather than just single subjects imaged multiple times. Furthermore, the amount of data produced by each successive generation of imaging system is greater than the previous generation. This trend is set to continue with the introduction of multislice helical CT scanning and MR imaging systems with higher gradient strengths. There are, therefore, potential benefits in improving the way in which these images are compared and combined.

Image matching (also known as image registration) is an important technology aimed to align two or more images by finding a suitable transformation that relates the involved images. As a pre-step to compare and combine information taken from different images, image matching plays an important role in many medical applications, such as information fusion, 3D volume construction, atlas building and so on. For a mathematical treatment of this problem, image matching can be considered as an optimization problem which tries to maximize an objective energy function with respect to the transformation that measures the similarity between the two involved images under some regularization constraints.

Usually, image matching is classified as rigid or non-rigid based on the transformation function used [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]. Rigid matchings are those in which the distances between all points remain constant before and after the matching. This type of image matching is popular since it involves a rotation and translation alone to achieve the mapping between two images. Rigid matchings have the advantage of being simple and easy in the sense that it is possible to predict how the transformation will perform. The most common application for rigid matchings is to register images obtained from same subject over a short duration time.

Non-rigid matchings are those in which distance between all points do not necessarily remain constant after the matching. Unlike rigid matchings, non-rigid matchings involve more complex computations like local stretching and scaling to map the two images. Non-rigid matching in an active area of research in the field of medical image matching, as there exists no universal solution for the mapping problem, and one cannot decide on the best algorithm for all applications. Each algorithm works well under certain constraints and conditions but may not do so under a different set of conditions. The main drawback of non-rigid matching is the unpredictable nature of the deformation. It is not possible to exactly specify the mapping of each point in the source image to the target image. It is also possible that such matchings can cause certain regions, which should remain rigid for underlying physical reasons, to deform due to scaling or shearing.

To address these problems, this paper focuses on a new deformation method called the Moving Least Squares (Moving-LS) transformation. This technique is relatively recent and is better know for surface reconstruction [11] and in computer graphics for image deformation and morphing [12] but has not been previously applied to medical images previously. We will introduce this method in more detail, and then apply it for medical image matching. Finally, the performance is accelerated by multi-core processors through the use of multiple threads.

2. Moving-LS

2.1 *Feature of* Moving-LS

Unlike other deformation methods, for the Moving-LS method [12], a transformation function is obtained for each point in the image and is based on a weight function included in the least squares error function at each point of evaluation. This weight function ensures that the effect of a control point is seen most in the regions immediately surrounding it, while its effect is less prominent in far off regions.

In addition, the transformation matrix of the Moving-LS deformation can include affine, similarity and as-rigid-as-possible transformations. Affine transformations are those which preserve the parallel nature of lines in the image and also produce non-uniform scaling and skewing, Similarity transformations are a part of the affine transformations but with uniform scaling. As-rigid-as-possible transformations are those which are capable of producing local deformations while maintaining a global rigidity of the image.

Take the application of medical image matching, this paper focuses on the as-rigid-as-possible transformations.

2.2 As-Rigid-As-Possible Transformations

Given a set of control points on the source and target images, the Moving-LS technique computes the transformation $l_v(x)$ that best minimizes the least squares error

$$\sum_i |l_v(p_i) - q_i|^2 , \tag{1}$$

when p_i and q_i are the set of control points in the source and target images respectively. This transformation however produces a single affine transformation of the entire image as there is no control over the scaling or shearing in the image. A weighting function included to this least squares error fixes this problem and thus produces a different transformation function for each point of evaluation of the image

$$\sum_i w_i |l_v(p_i) - q_i|^2 . \tag{2}$$

The weighting function w_i of the form

$$w_i = \frac{1}{|p_i - v|^{2\alpha}} , \tag{3}$$

where v is the point of evaluation in the image and α is a parameter of the weighting function whose value decides if the weights computed are small or large. The weighting function w_i is dependent on the point of evaluation and thus produces a different transformation for each point of the image. Hence the method is called Moving Least Squares. We can see that as v approaches p_i, the weight approaches infinity and the transformation function interpolates.

The transformation function can be solved as a simple linear transformation matrix, M and a translation vector, T as

$$l_v(x) = xM + T . \tag{4}$$

The transformation matrix M can be modified to include affine, similarity and rigid transformations. To perform as-rigid-as-possible transformations, the matrix, M must be constrained to satisfy the condition for rigidity $M^T M = I$. The translation component can be easily computed by

$$T = q_* - p_* M , \tag{5}$$

where p_* and q_* are the weighted centroids of the control points given by

$$p_* = \frac{\sum_i w_i p_i}{\sum_i w_i} \text{ and } q_* = \frac{\sum_i w_i q_i}{\sum_i w_i} \tag{6}.$$

The transformation function can now be calculated as

$$l_v(x) = (x - p_*)M + q_* . \tag{7}$$

The least squares problem can be written as

$$\sum_i w_i |\hat{p}_i M - \hat{q}_i|^2 , \tag{8}$$

where $\hat{p}_i = p_i - p_*$ and $\hat{q}_i = q_i - q_*$.

The transformation matrix for the as-rigid-as-possible transformations can be obtained by eliminating the scaling constant. The solution is simple and closed form. It can be obtained easily by a slight modification of the similarity transformation for which the transformation matrix must satisfy the

condition $M_1^T M_2 = M_1 M_2^T = \lambda^2 I$, where λ is some constant and M_1 and M_2 are the columns of M and are vectors of size 2. M_1 and M_2 have the relationship $M_2 = M_1^\perp$ such that $(x,y)^\perp = (-y,x)$. For rigidity condition to be satisfied $M^T M = I$, the scaling constant needs to be removed. By using partial derivatives with respect to the free variables in M and substituting the values back into the error function the optimum transformation function is obtained as

$$M = \frac{1}{\mu_s} \sum_i w_i \begin{pmatrix} \hat{p}_i \\ -\hat{p}_i^\perp \end{pmatrix} \begin{pmatrix} \hat{q}_i & -\hat{q}_i^{\perp T} \end{pmatrix}, (9)$$

where $\mu_r = \sqrt{\left(\sum_i w_i \hat{q}_i \hat{p}_i^T \right)^2 + \left(\sum_i w_i \hat{q}_i \hat{p}_i^{\perp T} \right)^2}$ removes any scaling and thus produces an as rigid-

as-possible transformation. The detailed derivation for the as-rigid-as-possible transformations can be seen in [12].

3. Medical image matching

3.1 Operation framework and Experiments

The Moving-LS deformation is carried out by selecting control points on the source image, such as shown in Fig 1. (a, c). The points to which these control points must be mapped to in the target image are chosen as the deformed points, such as shown in Fig 1. (b, d). In addition, the 4 corner points of each image are automatically selected as deformation control points. This presents the deformation as a matching problem.
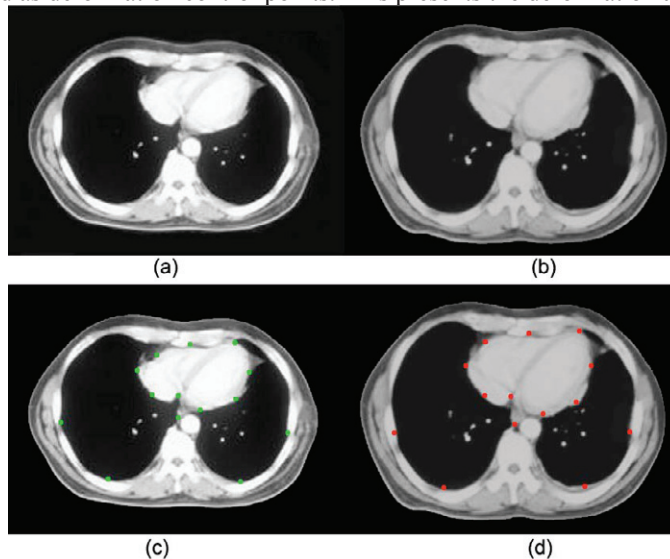

Fig. 1 Test data-set 1: (a) Source image. (b) Target image. (c) Select control points on the source image. (d) Select deformed points on the target image.
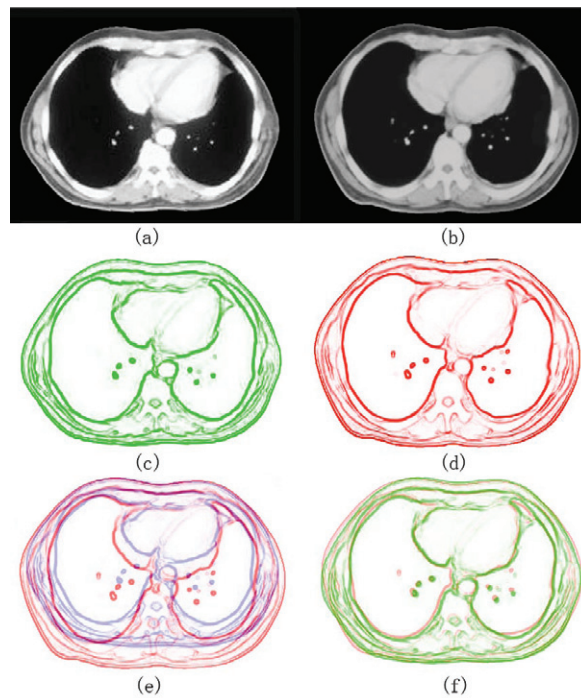
Fig. 2 Result of data 1: (a) Matching result image. (b) Target image. (c) Edge contour for the matching image. (d) Edge contour for the target image. (e) Source image blends with target image. (f) Matching image blends with target image.

We did the experiments using one human thoracic CT scan data, such as shown in Fig. 1 (a-b), and one rat lung CT scan, such as shown in Fig. 3 (a-b). The shape of lung is changed while other parts almost remain rigid. So we select control points mainly around the deformation objects.
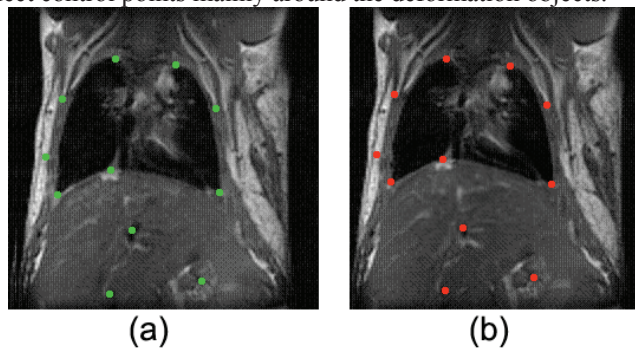

Fig. 3 Test data-set 2. (a) Select control points on the source image. (b) Select deformed points on the target image.
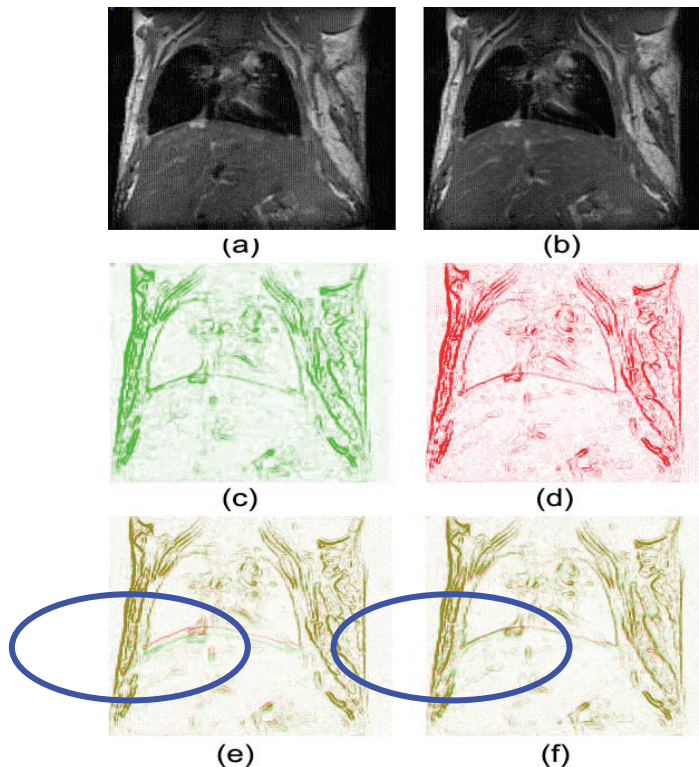
Fig. 4 Result of data 2: (a) Matching result image. (b) Target image. (c) Edge contour for the matching image. (d) Edge contour for the target image. (e) Source image blends with target image. (f) Matching image blends with target image.

After finish selection of control points, the matching result image is generated by deformation of the source image, such as shown in Fig 2. (a) and Fig 4. (a).

To have a better view of the matching result, we detect edge contour for the matching image, and target image, such as shown in Fig 2. (c-d), and Fig 4. (c-d), then blend the target image with the source image and matching image separately, such as shown in Fig 2. (e-f) and Fig 4. (e-f). We can see that so that the edge contour of the matching result image fits with the edge contour of the target image very well, especially the contour of the lung. Note that shape of lung is changed while other parts almost remain rigid.

For a common PC with Intel P4 processor 3.0 GHz and 4G RAM, the deformation time is about 1.8 s. This has a longer computation time than the most popular point-based non-rigid method e.g., the Thin-plate Spline (TPS) transformation [13]. This is because for the Moving-LS method, a transformation function is obtained for each point in the image, instead of a global transformation function. This problem can be addressed by the multi-core acceleration technology.

3.2 Multi-core Acceleration

To accelerate the matching performance, we further employ multi-core technology through the use of multiple threads. This is based on the observation that the Moving-LS method is very suitable for parallel computation. Because the calculation of each transformation function for each point in the image is performed independently.

Our implementation of multithreading is based on OpenMP, a method of parallelization whereby the master "thread" (a series of instructions executed consecutively) "forks" a specified number of slave

"threads" and a task is divided among them. The threads then run concurrently, with the runtime environment allocating threads to different processors. For a PC equipped with a Pentium Core 2 Quad processor running at 4×2.13 GHz, the multi-core implementation of the matching method is about 3.2 times faster.

4. Conclusion

This paper presents a new method for medical image matching by using the moving least squares transformation. Previous non-rigid matchings often produce unwanted stretching in the images and the unpredictable nature of the deformation field poses a major drawback which makes an algorithm with the ability to produce as-rigid-as-possible transformations attractive. The as-rigid-as-possible nature of the Moving-LS technique thus makes it a suitable candidate for non-rigid matchings as it provides a transformation that maintains the rigidity of structures that need to remain non-deformed, while producing local deformations. In addition, the performance is accelerated by multi-core processors through the use of multiple threads. The results demonstrate that the proposed medical image matching method has good balance between accuracy and speed, and has potential in many medical applications.

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