HHS Public Access

Author manuscript

Proc IEEE Int Conf Prog Inform Comput. Author manuscript; available in PMC 2016 December 28.

Published in final edited form as:

Proc IEEE Int Conf Prog Inform Comput. 2015 December ; 2015: 292–295. doi:10.1109/PIC.

2015.7489856

GPU-accelerated Block Matching Algorithm for Deformable Registration of Lung CT Images

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Abstract

Deformable registration (DR) is a key technology in the medical field. However, many of the existing DR methods are time-consuming and the registration accuracy needs to be improved, which prevents their clinical applications. In this study, we propose a parallel block matching algorithm for lung CT image registration, in which the sum of squared difference metric is modified as the cost function and the moving least squares approach is used to generate the full displacement field. The algorithm is implemented on Graphic Processing Unit (GPU) with the Compute Unified Device Architecture (CUDA). Results show that the proposed parallel block matching method achieves a fast runtime while maintaining an average registration error (standard deviation) of 1.08 (0.69) mm.

Keywords

Deformable registration; Graphic Processing Unit; block matching

I. Introduction

Image registration is a process of establishing the spatial correspondence between different images by estimating an optimal transformation. In general, image registration can be divided into two main categories: rigid registration (RR) and deformable registration (DR) [1]. RR only applies transformations of translation and rotation, while DR allows describing more complicated transformations including deformation and distortion. In the medical field, DR has become an increasingly powerful tool and a number of DR methods have been reported in literatures, such as feature based methods[2], intensity based algorithms[3–6], and physical models[7–9]. However, many of the existing registration methods are time-consuming and their registration accuracy needs to be improved for clinical application.

The block matching technique has been used in image registration because of its simplicity and robust performance. Unlike some other registration techniques, the block matching method registers images on a point by point basis, which is computationally expensive. Unless their runtimes are reduced to a few minutes, the block matching method cannot be clinically implemented for application. Therefore, it's of great significance to develop a fast and accurate block matching algorithm for medical image registration.

Graphics Processing Unit (GPU) provides a competitive parallel computing platform for image processing, which makes it possible to accelerate registration processing. In this study, we present a block matching algorithm for registration of lung CT images on GPU with Compute Unified Device Architecture (CUDA). The proposed GPU-accelerated block matching method makes full use of similarity in image intensity and takes intensity variation between images into account, which leads to high accuracy in deformable registration of lung CT images.

II. METHODS

A. Block matching algorithm

The block matching technique has been widely used for motion estimation in video compression. In block matching process, the current frame is often divided into a matrix of 'macro blocks' that is compared with corresponding block and its adjacent neighbors in the previous frame to estimates the motion of a macro block from one location to another in the previous frame[10]. As shown in Fig. 1, the reference image $I_0(x)$ and the target image $I_1(x)$ can be taken as two frames in video sequence. Here, a neighborhood centered at x represents the "matching window". Each matching window in the target image is compared with shifted regions of the same size from the reference image, and the shift resulting in minimum error is selected as the "best" displacement vector of x . Registration aims to determine the best displacement vector d for any position x in the reference image.

B. Registraion metric

To find the "best" match, there are various cost functions, such as the mean absolute difference (MAD), mean squared error (MSE), and sum of squared difference (SSD) [11]. The SSD metric is based on the assumption of constant intensity between images during registration, which is inappropriate to lung CT images because the respiratory motion causes

intensity variation in lung CT images at different breathing states. In our block matching method, we define the cost function f by modifying the SSD formulation as:

$$f = \sum_{x \in \Omega} [S(x) - \bar{S}]^2 \quad (1)$$

where $S(x) = I_0(x) - I_1(x+d)$ representing intensity difference between the point x and its corresponding point $x+d$, and $\bar{S}$ is the mean of S under the matching window Ω . In this way, the block matching method becomes a process to find the displacement vector d for each point x in the reference image by minimizing the cost function in Eq. (1).

C. GPU-accelerated algorithm implementation

Searching the best match is an independent process for each point in the reference image, which enable us to implement a GPU version of the parallel block matching algorithm with CUDA programming environment. GPU has many powerful multi-processors with low cost and wide availability [8]. Nowadays, GPU becomes flexible and programmable because of the development of CUDA that manages multi-threads in a hierarchical way. In CUDA, programs are expressed as kernels that run on a grid. A grid is made up of an array of blocks and each block is composed of a set of threads. Threads within a block can exchange data using shared memory, whereas threads in different blocks only communicate using global memory. Using GPU, thousands of threads woke at the same time and CUDA kernels can be executed in parallel.

Various search strategies have been used to perform the block matching motion estimation, of which the simplest and most popular is the full search method. The full search method has reasonable performance, but at a very high computational cost. To further reduce the block matching computational cost, we present a fast search approach by pre-defining a searching window (see gray area in Fig. 1) that is a given domain of displacement vector. In the searching window, each displacement vector leads to a value of the cost function and the minimum one corresponds to the best match. The accelerated block matching implementation on GPU is described as follows.

1. The image data is copied from CPU to the global memory of GPU and threads start reading data from global memory into the local registers.
2. For each point in the reference image, the related computation is performed on a GPU block, in which each thread calculates the cost function under the matching window that corresponds to each displacement vector in the searching window.
3. When calculations of multithreads have been completed, the calculated cost function values are compared in the shared memory, and the optimal displacement vector is accordingly determined by the minimum value for each point.
4. Optimal displacement vectors are written to the global memory and further copied back to CPU.

5. The displacement vectors are filtered using the least median of squares approach, a filter introduced in the literature[12], and the output is obtained as the registration result.

D. Full displacement field obtainment

Using block matching method, image registration aims to obtain the displacement field for each image pair. However, some point matches have been removed by the least median of squares approach during block matching algorithm implementation. To overcome this issue, spatial interpolation is then carried out to generate the full displacement field using the moving least squares (MLS) method [13] because of its ability to achieve accurate function approximations within the context of surface reconstruction from unorganized data.

Let (p_i, q_i) represent the i th filtered point matches consisting of p_i in the reference image and q_i in the target image. In the MLS method, a set of known point matches is used to determine an affine function $T_x(x)$ for the point x in the reference image by:

$$\min w_i(x) |T_x(p_i) - q_i|^2 \quad (2)$$

where $w_i(\cdot)$ is the weight, which is defined as a function of the Euclidean distance between x and p_i :

$$w_i(x) = b^{\frac{d(x, p_i)}{-a}}. \quad (3)$$

Here, the parameters a and b are predefined constants. The weight $w_i(\cdot)$ denotes the deformation influence from point p_i to point x . Substituting $w_i(x)$ into Eq. (2), the transformation T_x is solved for point x to compute the interpolation result. Using the MLS method, we can obtain the full displacement vector field between the reference and target images.

III. RESULTS

In this study, we propose a block matching algorithm and implement it with CUDA programming environment on a NVIDIA Tesla K20 GPU. The proposed algorithm has been applied to aligning five patients' lung CT images at end-inhale and end-exhale states with a runtime of 13.2 minutes on average, indicating fast implementation for clinical application.

Fig.2 illustrates the overlay of the end-inhale and end-exhale meshes prior to and after registration. The difference between the two meshes in Fig. 2 (a) becomes much subtle in Fig. 2 (b), which indicates that the proposed algorithm aligns CT images effectively.

To qualitatively evaluate the registration results, we measure the spatial error based on the use of a large number of landmark point pairs, which are vessel and bronchial bifurcations manually determined by experts. Fig.3 illustrates the error vectors of landmark point pairs in

lungs of one patient. We can see that the original error vectors have been substantially reduced after registration.

In addition, we calculate the registration errors of all five cases using the parallel block matching method (as shown in table). For each case, the 3D mean error is larger than 4.01mm before registration, but not over 1.33 mm after registration. Across all cases, the proposed block matching method achieves an overall 3D mean error (standard deviation) of 1.08 (0.69) mm, showing the promising ability of high accuracy.

IV. CONCLUSIONS

In this study, we have presented a GPU-accelerated block matching algorithm for registration of lung CT images, in which the large amount of computational workload is addressed by parallel computation of the algorithm utilizing GPU and CUDA programming. Results show that the proposed GPU-accelerated block matching algorithm achieves fast runtime and maintains accurate registration.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (No. 61501241), the Natural Science Foundation of Jiangsu Province (No. BK20150792), and the project funded by China Postdoctoral Science Foundation (No. 2015M570450).

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Fig. 1. The matching window (in green) and searching window (in gray) in block matching algorithm.

Fig.2. Surface mesh overlay between end-exhale (in blue) and end-inhale (in red) states: (a) prior to registration, and (b) after registration.

(a)

Fig.3.

The error vectors of landmark point pairs for case 1: (a) expert-determined displacement vectors, and (b) residual error for the proposed model.

Table 1

Spatial errors before and after the proposed DR using landmark point pairs.

P	Method	Spatial error (mm)							
		3D		LR		AP		SI	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	No DR	4.65	4.09	0.72	0.85	0.72	0.88	4.09	4.37
	DR	0.92	0.59	0.40	0.35	0.38	0.32	0.50	0.64
2	No DR	7.82	3.99	1.25	1.02	2.98	1.93	6.45	4.51
	DR	1.33	0.81	0.55	0.56	0.66	0.6	0.75	0.68
3	No DR	9.42	4.81	1.17	1.05	1.28	1.23	6.10	4.49
	DR	1.02	0.56	0.44	0.37	0.39	0.3	0.69	0.55
4	No DR	7.63	6.54	0.93	0.91	1.90	1.91	6.97	6.6
	DR	1.23	0.74	0.39	0.33	0.6	0.48	0.8	0.75
5	No DR	4.01	2.91	0.58	0.62	0.67	0.79	3.68	3.04
	DR	0.91	0.75	0.33	0.41	0.30	0.29	0.56	0.79
Average	No DR	6.71	4.47	0.93	0.89	1.51	1.35	5.46	4.60
	DR	1.08	0.69	0.42	0.40	0.47	0.4	0.66	0.68

P=Patient; LR=Left-right; AP=Anterior-posterior and SI=Superior-inferior.