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Parallel Registration of Multi-modal Medical Image Triples Having Unknown Inter-image Geometry

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***Abstract*— A method is proposed to register three multi-modal medical data, where none of the images are superimposed. Contrary to previously presented solutions that perform more simultaneous registrations after one-by-one, present method registers all images in parallel. The method minimizes the registration error by seeking the optimum of a vector including rigid transformation parameters of both reslice images. To measure the similarity among all three images, a higher dimensional extended normalized mutual information have been adopted. Comparison with simultaneous methods have been performed on brain and femoral multi-modal image triples. Based on the comparative results, presented parallel method significantly outperforms the simultaneous methods in both translation and rotation registration error minimizations. On the contrary, the simultaneous methods need less computational time to converge.**

I. INTRODUCTION

Automated algorithms built on mutual information [1],[2] have been successfully adopted and widely used in medical fusion applications. Most of these solutions focus on dual modality registration, although registering three images becomes necessary in some certain cases. When the registration of more than two images is desired, the method to superimpose all of them depends on the manner of their inter-image geometry [3]. In case of images having known inter-image geometry, all of them except one are superimposed, hence one unknown transformation need to be determined. Several methods have been proposed for these cases. Andersson and Thurfjell [4] registered two PET transmission and emission scans to two differently weighted MRI images by an extended joint histogram. Boes and Meyer [5] registered three MRI brain slices by an extended mutual information similarity measurement. Studholme et. al [6] registered a PET image to an MRI by including the segmentation of the MRI as a third image. In recent studies pulmonary [7] - as well as cardiac [8] image triples have been superimposed by an extended normalized mutual information.

When the inter-image geometry of the images is unknown, none of them are superimposed, hence more than one transformations need to be found. Most of the related studies choose a master reference image from the whole and register all other images to the chosen one simultaneously [9], [10], [11], [12], [13]. A hybrid solution performs a dual registration between two of the images first, then registers the third one to the previously superimposed ones by an extended similarity measurement [14].

The drawback of simultaneous methods appears when different multi-modality images are registered, since the choice of the master reference image might bring uncertainties to the accuracy of the registrations [8]. On the other hand if simultaneous depending registrations are performed, inheritance of registration errors may occur.

To avoid the difficulties mentioned above, a role selection invariant method is proposed in this paper, which performs the parallel registration of two images to a third one by only one optimization procedure and one extended normalized mutual information similarity measurement.

II. MATERIALS AND METHODS

A. Parallel method

1) Image normalization: All image triples of the given study have been re-sampled in the first step to have a (1 x 1 x 1) mm voxel size, then the images were cropped to have equal size in all directions. Finally the gray values were down sampled between 0 and 255 to speed up further joint histogram related calculations [15].

2) Similarity measurement: The extended normalized mutual information [8],[7] have been adopted to measure the similarity among all three images during the optimal transformations search. The equation of the extended NMI was defined by (1).

$$-\frac{H(A)+H(B)+H(C)}{H(A,B,C)} \tag{1}$$

where $H(A)$, $H(B)$ and $H(C)$ is the Shannon entropy [16] of images A, B and C respectively defined by (2). $H(A,B,C)$ is the joint Shannon entropy of images A, B and C defined by (3).

$$H(I) = -\sum_{i \in I} p(i) \log p(i) \tag{2}$$

where $p(i)$ is the probability of value i in image I.

$$H(A,B,C) = -\sum_{i \in A} \sum_{j \in B} \sum_{k \in C} p(i,j,k) \log p(i,j,k) \tag{3}$$

where $p(i,j,k)$ is the joint probability of values (i,j,k) in images A, B and C respectively.

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3) Optimization procedure: The Downhill-Simplex method [17] has been adopted to minimize the cost function defined by (1). This method optimizes all functional parameters in parallel and has been successfully applied in several studies focusing on mutual information based multi-modal registrations [3]. Before the optimization started, one image from the three were chosen as reference, while the other two were both reslice images that had to be superimposed to the reference one.

The method optimized two rigid transformations in parallel, hence the search was done on a 12 length vector. During the search the first 6 and the last 6 parameters were chosen as the transformation values of the first and second reslice images respectively. After every parameter generation released by the Downhill-Simplex method, the reslice images were transformed by their corresponding transformation values. The similarity among all three images was measured by (1) which was minimized to converge to the optimal transformations.

B. Comparison with simultaneous and hybrid methods

In order to compare the parallel method to previously proposed ones, the chosen reslice images were both superimposed to the reference one by performing a simultaneous and a hybrid method as well.

1) Similarity measurements: The measurement for the simultaneous registrations and for the first registration of the hybrid method was the dual normalized mutual information [18] defined by (4). The second extended measurement for the hybrid method was calculated as defined by (5).

$$-\frac{H(A)+H(B)}{H(A,B)} \tag{4}$$

$$-(-H(A,B)+H(C)-H(A,B,C)) \tag{5}$$

where $H(A)$ and $H(B)$ is the Shannon entropy of images A, and B respectively, defined by (2). $H(A,B)$ is the joint Shannon entropy of images A and B defined by (6).

$$H(A,B) = -\sum_{i \in A} \sum_{j \in B} p(i,j) \log p(i,j) \tag{6}$$

where $p(i,j)$ is the joint probability of values (i,j) in images A and B respectively.

2) Optimization procedure: Since in simultaneous and hybrid cases only one reslice image was transformed during the the given transformation search, a 6 parameter length vector was optimized by using Downhill-Simplex method.

C. Implementation

Our transformations have been implemented to directly operate with the video card based on CUDA SDK [19]. The histogram as well as the entropy calculations were performed by the CPU.

D. Patient data

Two patient triples – femoral MRI/CT/SPECT and brain MRI/PET/SPECT – with unknown inter-image geometry have been collected (see Fig. 1 and Fig. 2). All images have been obtained at different time by different cameras, hence none of them were superimposed. Both image groups had advantageous properties by the means of the necessary transformations, namely that all could be characterized by rigid transformations. Femoral images represented only one of the legs having rigid misalignments, while brain images included only the brain itself which is naturally a rigid organ. The resolution and voxel size of the collected data are represented in Table I and Table II.

TABLE I
FEMORAL MRI/CT/SPECT RESOLUTION AND VOXEL SIZE

Modality	Axial resolution	Voxel size
MRI	512 x 416	0.78 x 0.78 x 5.20
CT	512 x 512	0.86 x 0.86 x 1.00
SPECT	128 x 128	4.80 x 4.80 x 4.80

TABLE II
BRAIN MRI/PET/SPECT RESOLUTION AND VOXEL SIZE

Modality	Axial resolution	Voxel size
MRI	256 x 256	1.00 x 1.00 x 1.00
PET	128 x 128	2.57 x 2.57 x 3.38
SPECT	128 x 128	2.90 x 2.90 x 2.90

E. Validation

Registration of the two image groups was performed by all methods to compare them by the means of translation - rotation errors and the number of iterations to converge to the optimum. The validation of every individual transformation was performed manually by a medical physician.

The result of the given method was visualized in a triple modality fusion window (see Fig. 1 and Fig. 2). Correction

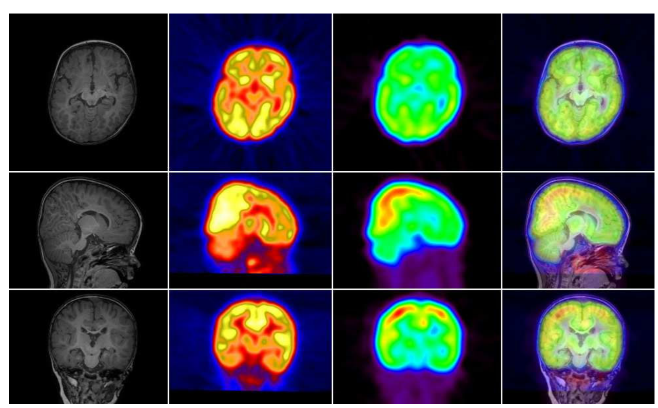

Fig. 1. Triple fusion of the brain MRI/PET/SPECT study superimposed by the parallel registration method.

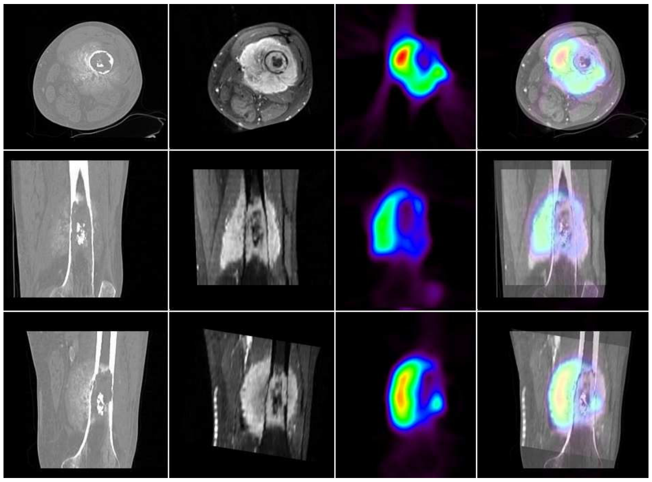

Fig. 2. Triple fusion of the femoral CT/MRI/SPECT study superimposed by the parallel registration method.

of the automatically determined transformations for both reslice images was provided for the medical physician. The possible manual modifications of all transformation parameters for both reslice images were recorded. The registration error of a method was considered to be the sum of the registration errors of both reslice images. The number of iterations as well as the runtime to converge to the optimal transformations was recorded for all methods.

III. RESULTS

The parallel method significantly outperformed both simultaneous and hybrid methods in the registration error parameters (see Table III and Table IV). There were no significant differences in the number of iterations, although the parallel method needed slightly more iterations. Since the parallel method performed two transformations in one iteration, it needed double time to converge to the optimum (see Table V and Table VI) The simultaneous method generated relatively higher misalignments in both groups. The hybrid method inherited these misalignments and produced a higher registration errors, since it depended on an initial dual transformation. The mentioned misalignments were significantly high in Z direction, since one of the images had a relatively higher voxel size in both groups in this direction (see Table I and Table II).

TABLE III

FEMORAL MRI/CT/SPECT REGISTRATION ERRORS

Method	x	y	z	α	β	γ
Simultaneous	2.66	3.47	7.32	4.15	4.19	18.91
Hybrid	3.18	4.12	8.56	5.62	4.23	17.84
Parallel	2.98	1.34	4.17	4.01	3.98	4.38

Where (x, y, z) and (α, β, γ) are translation and rotation errors respectively.

TABLE IV

BRAIN MRI/PET/SPECT REGISTRATION ERRORS

Method	x	y	z	α	β	γ
Simultaneous	3.14	2.97	5.67	2.96	3.65	4.49
Hybrid	4.32	4.56	7.48	3.38	5.92	6.76
Parallel	3.38	3.42	3.65	2.23	3.76	3.27

Where (x, y, z) and (α, β, γ) are translation and rotation errors respectively.

TABLE V

FEMORAL MRI/CT/SPECT REGISTRATION ITERATIONS AND RUNTIME

Method	Iterations	Runtime (sec)
Simultaneous	184	98
Hybrid	176	93
Parallel	204	217

TABLE VI

BRAIN MRI/PET/SPECT REGISTRATION ITERATIONS AND RUNTIME

Method	Iterations	Runtime (sec)
Simultaneous	147	112
Hybrid	156	118
Parallel	174	265

IV. CONCLUSIONS AND FUTURE WORKS

Since only one optimization procedure minimized an extended measurement among all three images in the parallel method, a global optimum among the images could be achieved. Simultaneous and hybrid methods both represented decreasing accuracy in those transformation parameters that were associated with high voxel sizes (Table I and Table II). It indicates the fact that these solutions have an increased sensitivity of interpolation distortions originated from non-uniform voxel sizes comparing them to the parallel method. On the contrary, they need approximately half the time the parallel method needs, since the last one performs two transformations in one iteration. Considering that the parallel method significantly outperforms previous solutions, it is advised to be the subject of further investigations operating with more than two unknown inter-image geometry images.

As the next step of our research, the parallel method will be modified to operate with non-linear transformations in order to superimpose medical image triples having non-linear misalignments. A large number of multi-modal medical image triples will be collected for more precise evaluations.

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