A hybrid method for Non-rigid registration of Intra-operative Ultrasound Images with pre-operative MR images

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Abstract— **In recent years intra-operative ultrasound images have been used for many procedures in neurosurgery. The registration of intra-operative ultrasound images with preoperative magnetic resonance images is still a challenging problem. In this study a new hybrid method based on residual complexity is proposed for this problem.**

A new two stages method based on the matching echogenic structures such as sulci is achieved by optimizing the residual complexity (RC) value with quantized coefficients between the ultrasound image and the probabilistic map of MR image. The proposed method is a compromise between feature-based and intensity-based approaches. The evaluation is performed on both a brain phantom and patient data set.

The results of the phantom data set confirmed that the proposed method outperforms the accuracy of conventional RC by 39%. Also the mean of fiducial registration errors reached to 1.45, 1.94 mm when the method was applied on phantom and clinical data set, respectively.

This hybrid method based on RC enables non-rigid multi-modal image registration in a computational time compatible with clinical use as well as being accurate.

I. Introduction

In recent years intra-operative ultrasound due to its advantages such as being non-ionized, inexpensive, real time, portable and operating room equipment compatibility has been used for many procedures such as biopsy, tumor localization and determining the tumor or the tissue margin in many patients who undergo neurosurgery [1-6].

One of the most important applications of intra-operative US imaging is calculating and compensating brain shift which invalidates the pre-operative image (MR) coordination. There are increasing concerns about US-MR image registration accuracy which has a direct impact on the final target registration (TRE) and still not a satisfactory solution for this problem [5, 7-10]. In addition to the different nature of two image modalities which is lead to each image contains features that are not necessarily visible in the other modality, the limited field of view of ultrasound images compared to the pre-operative images (MRI) and its lower image quality are appearing as two main problems in US-MR image registration. Also severe reverberation in the images makes it difficult to interpret information about anatomic structures and lesions located deeper in the brain [11].

Heretofore many registration algorithms in two basic categories intensity-based registration and features-based registration have been proposed for intra-operative ultrasound and pre-operative MR image registration [8, 12-15]. The most important approach in the feature-based registration methods is using the anatomical landmarks; these methods segment the anatomical structures such as tumors, sulci, surfaces or blood vessels which are available in both images to register two image modalities [9, 14, 16-20]. In the most of feature-based methods accuracy of registration depends on segmentation method, especially segmentation of noisy ultrasound images. In the intensity based registration methods objective functions such as mutual information, correlation ratio, sum square differences were used commonly. It is notable that due to different nature of these two imaging modalities these well-known objective functions are known to fail [21]. In 2013 Wein proposed an effective solution based on Linear Correlation of Linear Combination (LC2) for intra-operative US and pre-operative MR images during surgery. Their algorithm is evaluated on 14 clinical neurosurgical patients with an average Fiducial Registration Error (FRE) of 2.52 mm for the rigid transformation [21]. Most of intensity based methods are suffering from complexity of computational time which is not suitable during surgery.

Consequently, few hybrid methods which are using intensity and features of images simultaneously were introduced recently. In [22] Coupé introduced a new hybrid objective function based on the matching of cerebral hyper-echogenic structures such as the cerebral flax, sulci, and the lesions by maximizing correlation value. Their study carried out on real intra-operative data and they reported an acceptable accuracy compared to the expert results. There was a drawback which their method was proposed for rigid registration whiles the brain deformation after opening Dura is non-rigid problem. Overall, in different phantom studies the registration accuracy between intra-operative ultrasound and pre-operative MR images has been achieved between 1.5 mm and 3 mm and the mean of accuracy for real data was achieved about 5 mm in different studies [22].

Determining a proper objective function is one of the main challenges in image registration particularly in multimodal cases with non0rigid deformations. In this paper, we focused on proposing a hybrid method which adapts well in matching intra-operative US images with MR images based on their proper structures. It is recommended to utilize features such as sulci, blood vessels, lesions and tumor boundaries which are usually distributed in most surgical

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978-1-4244-7929-0/14/$26.00 ©2014 IEEE

regions of interest (ROI) and appeared easily in both modalities. On the other hand, scale and resolution differentiation between MR and US images imposes us with using intensity based methods.

We proposed a new two stages algorithm based on the matching of the echogenic structures such as sulci is achieved by optimizing the residual complexity (RC) value with quantized coefficients between the US image and the probabilistic map of MR image. The proposed method is thus a compromise between features and intensity-based approaches. The RC similarity measure was proposed for mono-modal image registration in 2010 [26]. In this paper we have improved the RC criteria to enable multi-modal image registration.

II. Method and Materials

A. Data

To evaluate and compare our algorithm with others, our experiments were carried out on two types of dataset. The first one was based on using available online database containing pre-operative T1-weighted MRI and pre-resection US Images of Brain with tumor from 3 patients. These data provided by Montreal Neurological Institute (MNI BITE) contained initial transformations and corresponding landmarks for each US-MRI pair [27]. In the second experiment, we performed the method on the PVA-C brain simulated phantom dataset which is described in our previous work [19, 28]. Examples of real data and phantom data were shown in Fig. 1, Fig. 2, respectively.

Fig.1 The examples of patient 2 data, (a) the pre-operative MRI, (b) corresponded pre-resection US image

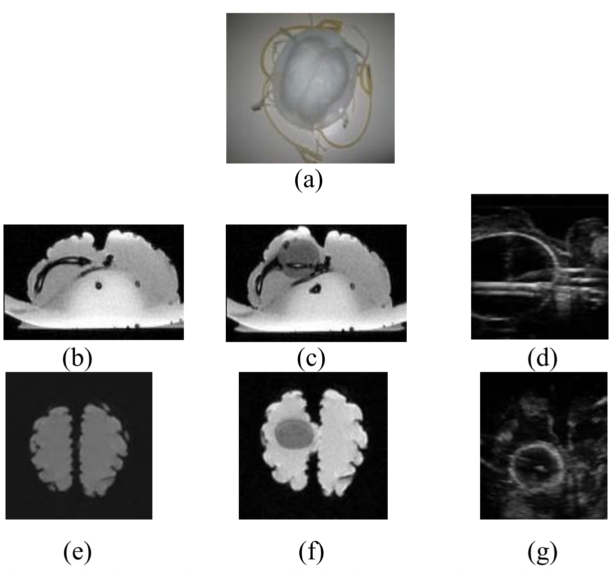

Fig.2 (a) the simulated phantom of brain, (b), (e) MRI images before deformation in different view, (c), (f) Corresponding MRI images after deformation, (d), (g) corresponding US images after deformation.

B. Processing of the pre-operative MR Data

Since the skull structure in MR images does not appear in the area of the craniotomy and produce unusable information in MR-US registration, skull removing in MRI is necessary prior to any procedure. For this, we used robust Skull stripping algorithm based on 2D region growing [29].

C. First Stage: Extraction of Features

Most of intensity based methods use all of the image information to register images which is time consuming procedures especially during the surgery. In contrary to these intensity-based method, the proposed hybrid method uses the pixels that including echogenic features such as sulci, boundary of tumors and lesions to capture overall curvatures of the image for multi-modal registration. Echogenic features contain structures that reflect high-frequency sound waves subsequently can be imaged by ultrasound techniques. In fact, the registration procedure is maximizing the probability of pixel A = (x, y) in both modalities included echogenic demanded structures as below:

$$\hat{T} = \arg\max \sum p(A \in F_{US}, T(A) \in F_{MR}) \tag{1}$$

Where$(A \in F_{US})$, $P(T(A) \in F_{MR})$ are probabilities for pixel 'A' and its transformed $(T(A))$ contained demanded features in the US and MR images, respectively. Considering independency of two modalities:

$$p(A \in F_{US}, T(A) \in F_{MR}) = p(A \in F_{US}).P(T(A) \in F_{MR}) \tag{2}$$

To extract echogenic structures in pre-operative T1-weighted MR images of the brain, the curvature-based MLvv operator which was used for the first time in [31] is applied to detect these structures in MR images. Since the US images are correlated to both MRI intensity values and its gradient magnitude, derivative-based operator is the suitable choice for extraction of curvature shapes in MR images. The MLvv as a mean of Lvv operator which is the combination of first and second derivative of the image intensity function in the v direction is less sensitive to flat areas with low gradients.

$$v=\begin{pmatrix} l_y \\ -l_x \end{pmatrix} \tag{3}$$
$$Lvv=\frac{1}{\|v^2\|}(v.\nabla)^2 L$$

The positive values of MLvv operator are used to detect sulci and convex bounding hull of the brain [32]. It is notable that due to the fact that the MLvv operator is a derivative based operator, using de-nosing filters before applying MLvv is indispensible. In Fig. 3 the example of a skull removing MR image of a patient is shown after, considering positive value of MLvv on de-noised image [22].

D. Second Stage: Residual Complexity (RC)

In this study, the new hybrid method based on Residual Complexity (RC) is proposed for non-rigid multimodal image registration. RC is a novel intensity-based similarity measure, which is presented for mono-modal registration of the images with non-stationary slow-varying intensity distortions. This method considers intensity information and intensity correction field simultaneously. The RC method estimates the transformation (T_{RC}) and correction field (S) to maximize a posterior probability which is equivalent to minimization of the following objective function with considering regularization term:

$$E(S,T_{RC}) = \|I - T_{RC}(J) - S\|^2 + B\|PS\|^2 \qquad (4)$$

Where B and P are related to an adaptive regularization term defined for the intensity correction field 'S'. The registration problem is then solved for intensity correction field and eliminates it from $E(S,T_{RC})$, after simplify:

$$E(T_{RC}) = r^T(\boldsymbol{Q}^T L \boldsymbol{Q})r \qquad (5)$$

Where r is residual of images, the Q and L comes from the eigenvectors and eigenvalues of square, symmetric, and positive semi definite matrix $P^T P$. The Q is a form of basis functions which is considered Discrete Cosine Transform (DCT) coefficients in RC. This method is optimized when the residual of the images achieves its minimum complexity or in the other word the residual image could be sparsely represented using only a few basis functions. In DCT coefficients, most of the information tends to be concentrated in a few low-frequency components and low complexity corresponds to a small number of nonzero coefficients. In order to achieve more sparseness in DCT coefficients, it should be quantized. So we accept DCT coefficients with quantization in RC similarity measure. A demanded form of function Q is chosen without considering the eigenvalues absorbed in L. L is then estimated in our optimization procedures. The minimum value in equation 5 is a zero matrix which is not a desired solution. To solve this problem the regularization term on L was added to $E(T_{RC})$ function to prevent revealing all zeros matrix as a minimum of function.

$$E(L,T) = (\boldsymbol{Q}^T r)^T L(\boldsymbol{Q}^T r) + \alpha R(L), \qquad 0 \le l_i \le 1 \qquad (6)$$

Where α is the trade-off parameter. By describing regularization term on L as follow, the optimum eigenvalues are bounded in [0, 1]. This R(L) term guarantees positivity for the regularized solution. Thus $E(L,T)$ is as below which $\boldsymbol{Q}^T$ is quantized coefficient of DCT.

$$E(L,T) = \sum_{n=1}^{N} \frac{\log(Q_n^T r)^2}{\alpha+1} \qquad (7)$$

Finally, Recovery index (RI) was calculated to show how much of deformation was recovered by applying the registration algorithm [9].

$$RI = \frac{FRE_{before} - FRE_{after}}{FRE_{before}} \qquad (8)$$

III. RESULTS

All of our experiments were carried out on real data and data of the simulated phantom of brain. We considered the average Euclidean distance of the landmarks in all of data as Fiducial Registration Error (FRE).

In the case of multi-modal image registration, the RC method was failed without extraction of echogenic structures in the MR images. Indeed the residual image that is used in RC and QRC is the difference between US and the MR images on which the MLvv operator applied. Subtracting echogenic structures in two modalities is a meaningful difference. As it is shown in Table.1, to evaluate the performance of QRC, at first the algorithm was tested on the phantom data with 5 level of deformation and compared with the result of RC algorithm. About 30 data were selected in each deformation level.

The calculated RI of RC and QRC for data of phantom are shown in Fig. 3. As the mean of the calculated RI for RC and QRC are appeared about 46% and 77%, respectively. This means 39% improvement of QRC over RC. It was found that the performance of RC for phantom data with low deformation is better than data with large deformation but QRC has an acceptable and fix performance for all amounts of deformations.

The proposed method obtained success rates of 98%, 96%, 95%, 95% and 94% for deformations 5, 10, 15, 20 and 25 ml for phantom data with a mean of 2.5mm threshold criteria based on reports of recent studies [22, 33].

To compare our framework to other publications the results of our algorithm for all 3 patient data sets were compared into result of deformable registration in [21] in Table. 2. The result of this Table confirms that our method had no significant differences in terms of accuracy of registration. But the average of achieved computational time is about 160 seconds. Even though the proposed algorithm was not simulated on such powerful system that they used, the achieved run time reveal this algorithm is 38% faster than the reported time in [21].

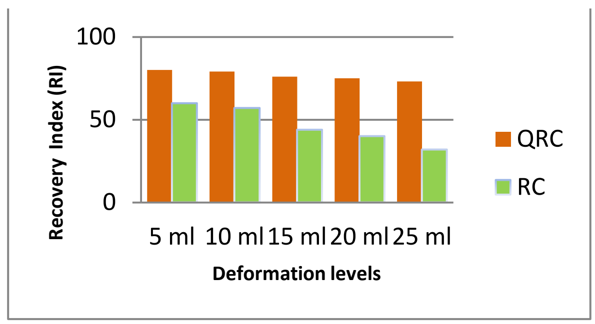

Fig. 3 Recovery index calculated of RC and QRC for 5 levels of deformation on simulated phantom of brain.

Table 1. Evaluation of RC and QRC on the phantom data with considering 5 level of deformation

Mean ±STD (mm)	RC method		QRC method	
	Initial	FRE	Initial	FRE
5 ml	1.4 ± 0.2	0.56±0.2	1.4 ± 0.2	0.28±0.27
10 ml	3.2± 0.3	1.37±0.4	3.2± 0.3	0.67±0.2
15 ml	7.6±0.1	4.25±0.6	7.6±0.1	1.82±0.4
20 ml	13.3±0.1	7.98 ±0.2	13.3±0.1	3.22±0.2
25 ml	20.9±0.2	14.2 ±0.1	20.9±0.2	5.64±0.2

Table 2. Evaluation of RC and QRC on the phantom data with considering 5 level of deformation

FRE (mm)	QRC method	Proposed method in[21]
Patient 1	1.63	1.64
Patient 2	1.92	1.91
Patient 3	2.27	2.26
Mean ±STD (mm)	1.94 ±0.31	1.93 ±0.32

IV. CONCLUSION

We have introduced an algorithm based on residual complexity similarity measure, which could be applied in multi-modal non-rigid registration. The proposed hybrid method enables registration US and T1 weighted MRI data in a computational time compatible with clinical use. Our experiments were performed on both real intra-operative data and simulated phantom of brain data. In order to achieve meaningful differences in the residual image of two different modality images, echogenic structures, which can be imaged by ultrasound techniques as they reflect high-frequency sound waves, were extracted in T1 weighted MR images by positive values of MLvv operator. Compared to the proposed method by Coupe; both methods use the echogenic structures in MRI and have the advantage of not requiring segmentation of the US image which is time consuming producers during the surgery. In contrast to their method which had two drawbacks of applying only for rigid registration and needing manual segmentation , our proposed algorithm is used for non-rigid registration without any manual segmentation in pre-operative MR images with improvement in performance. The evaluation results on the phantom data set indicate that the novel registration algorithm outlined in this paper compared to [33] which is using vessels as features in both modalities and have 93% mean of success rate , is achieved the average success rate 95.6% with 2.5mm threshold criteria. The validation of results in the same data of 3 patients compared to [21] indicates that we do not have any significant changes in term of accuracy but it is faster than proposed method in [21].

Finally using intra-operative ultrasound can be useful in cases where preoperative MRI information is invalidated such as brain shift. The Hybrid MR–ultrasound image registration technique proposed here could be used in neurosurgical procedure, as long as the craniotomy size is large enough to fit the head of the ultrasound probe (about 3 cm).

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