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AUTOMATIC DEFORMABLE MR-ULTRASOUND REGISTRATION FOR IMAGE-GUIDED NEUROSURGERY

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Abstract: *Registration of preoperative MR images and Ultrasound images are used for the purpose of accuracy in detecting the tumor. Image Guided Neurosurgery Systems (IGNS) can be used to track surgical tools with respect to the preoperative Magnetic Resonance (MR) images, brain tissue movement during surgery invalidates the image-to-patient mapping and thus reduces the effectiveness of using preoperative images for intraoperative surgical guidance. The movement of brain is caused by biochemical factors, and is referred to as brain shift. The various technique used for this purpose are RaPTOR, which is used to reduce the mean target registration errors from patients. The artificial neural network is used to set the data base about the patient's registered medical images. The Bivariate correlation ratio is used to correlate the images. The Gaussian blur normalized mutual information is used to allow automatic US-MRI registration in few seconds. Image segmentation is used to segment the tumor image. The US and MRI images registered are compared tat which techniques reduces the mean target registration error. RaPTOR calculate local correlation ratio (CR) values on small patches and adds the CR values to form a global cost function. It is therefore constant to large amounts of spatial intensity in homogeneity. We also propose a novel outlier suppression technique based on the direction of the RaPTOR gradients. RaPTOR is validated on tracked US images and MR of neurosurgery. Deformable registration of the US and MR images acquired respectively pre-operation and post-resection is of significant clinical significance, but challenging due to, among others, the large amount of missing correspondences among the two images. This work is also novel in that it performs automatic registration of this challenging dataset. for validating the results, we manually locate corresponding anatomical landmarks in the MR and US images of tumor resection in brain surgery.*

Keywords— *Brain surgery, IGNS, image guided neurosurgery, intra operative ultrasound, nonrigid registration, online database, validation database.*

I. INTRODUCTION

Medical image registration is the process of partially aligning images. It has been a widely investigated area in the past few decades, however remains demanding in particular for multimodal registration. Often, different modalities complement each other well, which is related to a huge range of clinical applications for improving diagnosis, treatment planning, screening, procedure.

The success of the surgical resection of brain tumors depends to a large extent on the complete removal of the tumor. The concurrence of many tumors to critical brain structures coupled with a poor visibility of brain tumors in the operating room renders complete removal of the tumor demanding. As a result, intraoperative tracked ultrasound has gained significant momentum in neurosurgery. The registration of intraoperative US with preoperative MR images has the potential to empower the surgeon to accurately localize the paths of instruments in the operative field, resulting in minimally invasive procedures. US is inexpensive and easy to use, provides real-time 2D images, which, when tracking the ultrasound transducer, can be interpreted in 3D space. Then correlate the US intensity with both the MR intensity and the MR gradient significance, which leads to a bivariate extension of the CR. Secondly, we incorporate a robust intensity-based distance measure in order to avoid the bivariate CR from being biased by various ultrasound artifacts. In image-guided neurosurgery, the preoperative MR images can be first converted to the patient space by selecting a few corresponding landmarks on the patient's head and MR images. The US probe is tracked with a position sensor, which provides the transformation of the US images to the patient space. The MR and US images, both in the patient space, should ideally be in correct alignment. Since brain tumors usually have a high contrast in the preoperative MR images, deformable registration of these images to post resection US can significantly reduce the extent and likelihood of residual tumor. Similarity metrics is a critical part of an image based registration technique. which should be maximized to align the images. popular similarity metrics exist Mutual Information (MI), Correlation Ratio, Correlation Coefficient (CC) and sum of squared differences (SSD). Mutual information is that it samples the entire image to establish the statistical relationship. To compute RaPTOR over many small patches and sum the output in a short time.

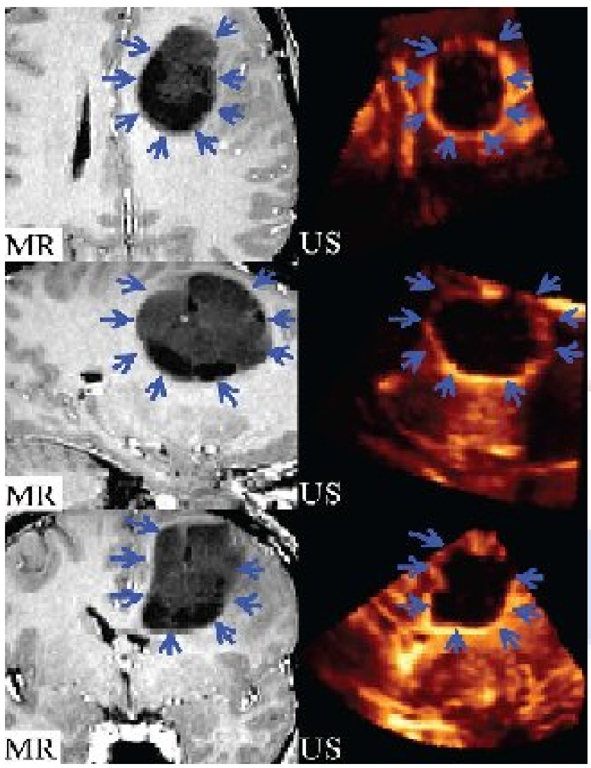


Figure.1. Tumor in the preoperative MR and the cavity in the post resection US images, pointed to by arrows. First to third row, respectively, show axial, sagittal, and coronal slices.

A) The contributions of this paper are as follows.

- *Proposing a CR-based measure that locally estimates the similarity metric from small patches.*
- *Deriving the analytic derivative of the similarity metric and performing efficient optimization*
- *Introducing a novel metric for outlier rejection.*

- *Registering preoperative MR to post resection US for the first time.*
- *Locating corresponding anatomical landmarks between Preoperative MR and post resection US for validation of the registration results, and providing these landmarks online. This is the first such database to the best of our knowledge.*

This paper is organized as follows. We first provide an overview of related work, followed by a more in -depth description of CR. We then provide RaPTOR details and derive its rise to perform efficient optimization. The outlier suppression based on RaPTOR gradient orientations is provided next, pursued by the description of the patient data experiments and validation results.

B) RaPTOR

Our approach is similar to that of in that we also perform non-parametric estimation, with the difference that we compute CR locally to achieve resistance to the large spatial intensity in homogeneity in the US images. To this end, we perform binning of the X values instead of computing E for iso-sets of X. We use this property in by deriving the derivative of the cost function analytically and performing efficient gradient-based optimization. In our histogram, each sample contributes to two closest bins j-1 and j linearly, according to its distance from the bin centers. We found this linear kernel to provide a good compromise between the running time and accuracy and robustness.

II. METHODS

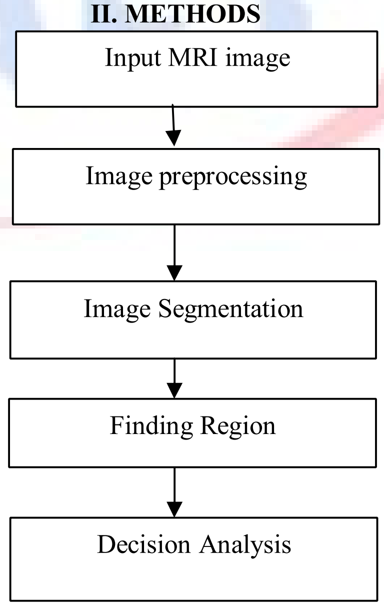


Figure 2: System flow of proposed System

2.1. Image preprocessing:

An MRI brain image is chosen from the database of brain images to be preprocessed. Soft brain tissues such as GM,CSF, and WM are surrounded by outward bone structure. The segmentation accuracy depends on the slice selection; standard process is followed to select a slice of the displayed brain image. Finally, the selected slice is converted into 2 dimensional image format using MATLAB code.

2.2 Image segmentation:

Segmentation subdivides an image into its fields of components or objects and an vital tool in medical image processing [1]. As an initial step segmentation can be used for compression and visualization. Through recognizing all pixels (for 2 dimensional image) or Voxels (for 3 dimensional image) belonging to an object, distribution of that particular object is achieved [2]. In medical imaging, segmentation is important for image measurement, feature extraction and image display [2, 3]. Distribution of the brain structure from magnetic resonance imaging (MRI) has accepted paramount importance as MRI distinguishes itself from other modalities also MRI can be applied in the volumetric analysis of brain tissues such as multiple Parkinson's disease, schizophrenia, sclerosis, epilepsy, cerebral atrophy, Alzheimer's disease etc [4].

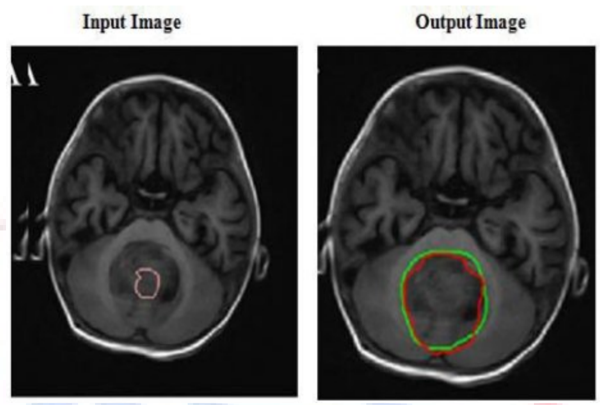
III. DISCUSSION AND RESULT

The registration of US and MR is challenging due to numerous reasons. In MR, the intensity of every voxel reflects the proton density modulated by the magnetic features of that tissue, and hence MR images tissue type. In contrast, US images the variations in the acoustic impedance of different tissue types, and therefore MR and US images intensities are widely different. In addition, spatial variations of the US image intensities are very high due to wave scattering and attenuation. We therefore used the RaPTOR algorithm for MR-US registration, which uses a local similarity metric based on statistical and information theoretic measures.

Our verification was based on real patient data using manually selected homologous landmarks. While the complexity of this data challenged our algorithms, there is an inherent ambiguity in manual landmark selection. In addition, although the landmarks cover most of the amounts and their number is large, some regions can be unrepresented in mTRE estimation. Therefore, qualitative study of the brain shift is an essential complement to the quantitative mTRE analysis.

Two factors are critical in determining the result of tumor resection surgery: the completeness of the resection while minimizing damage to healthy tissues. Accurate enrollment of the intra-operative US and pre-operative MR is significant in both fronts. It can aid the surgeon accurately recognize the safety zone, knowing that the intra- and post-resection scans enables identification of residual tumor. Among the three, the direct and group-wise methods give the smallest average mTRE values of respectively 2.9 mm and 2.8 mm. Another important factor is the robustness of the technique against large initial misalignments. The enrollment results of P11, which has the largest initial mTRE, show that the maximum TRE values of the group wise and direct methods are respectively 8.1 mm and 5.2 mm, showing that the group-wise method is significantly more robust.

RESULT:



MATLAB OUTPUT

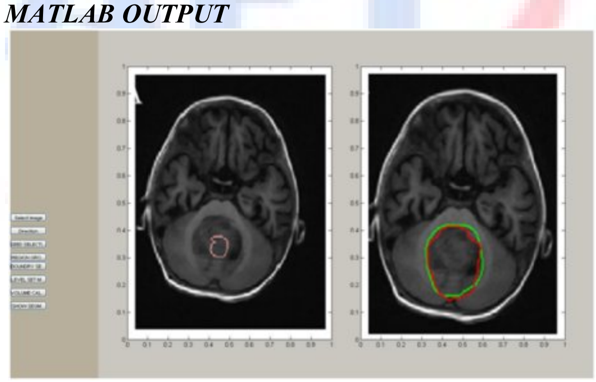


Figure 3: Output results

The deformable image registration techniques presented in this work significantly improves the alignment between MR and US images, which results in improved confidence in the neuron navigation system, and can potentially reduce surgical complications and time. In future work, we will analyze a larger series of patient data, and will study how often the enhanced image alignment leads to a change in the surgical plan. In addition, we will apply the methods developed in this work to other operations in the brain that are subject to brain shift.

IV. IMPLEMENTATION

This is a simple Matlab based design which depicts the various categories of images and their features extracted using Gabor filter. Figure 4 shows the image of a human brain having tumor's malady. As it can be viewed the image is not regular at the edges and after applying Gabor filter for extracting the features of the image the output is as shown in figure 5. Also the design indicates the figure 6 which is obtained by reading the healthy brain image of a healthy human being. The healthy human brain has no irregularity in its image mapping obtained from the digital scan of the brain. Figure 4 depicts the features of the healthy brain obtained after applying the Gabor filter. The difference between the two is quite clear as the two filtered images are not similar. When the difference between the two has been compared it is found that there is difference in the two when we compare on the basis of Euclidean distance.

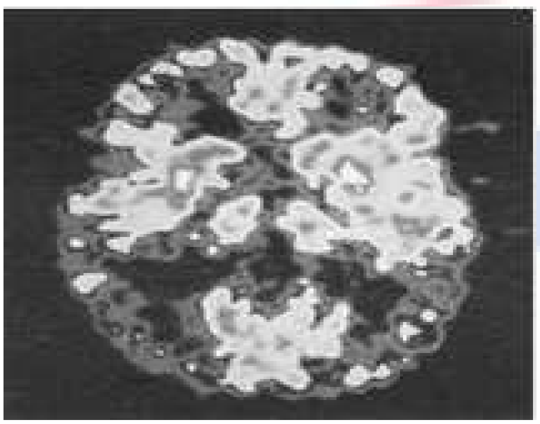


Figure 4:-Brain image having Alzheimer's disease

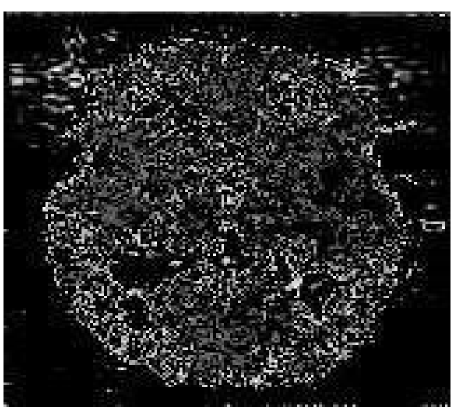


Figure 5: Gabor filter output for image with disease

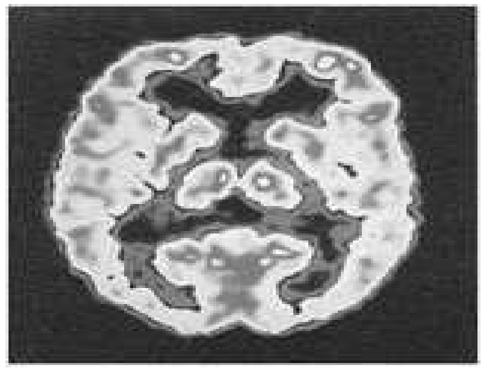


Figure 6: Digital scan of a human with healthy brain

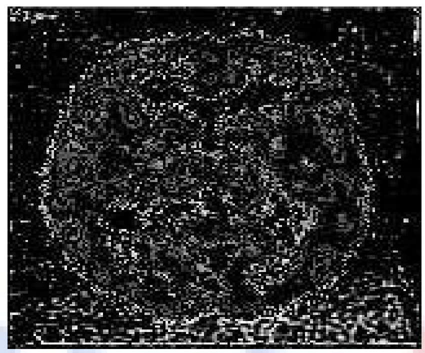


Figure 7: Gabor filter output for image with no disease

Figure 4 represents the gray equivalent of colored image having disease correspondingly we applied Gabor filter and we have obtained the image as shown in figure 5. Also we have obtained the gray scale and filtered images of healthy brain as depicted in figure 6 and figure 7.

IV. CONCLUSION

We presented RaPTOR, an algorithm for non rigid registration of challenging clinical images of preoperative MR and postoperative US. We analytically derived the derivatives of RaPTOR and optimized it using efficient stochastic gradient descent optimization. We also proposed a novel intuitive technique for minimizing the effect of outliers. We will provide our data available online, which we hope, speeds the translation of future registration techniques to the operating rooms Three sets of images are commonly available in IGNS: pre-operative MR, pre-resection US and post-resection US. We performed nonlinear enrollment of MR to pre-resection US, pre- to post-US, and MR to post-resection US. For the most challenging problem of MR to post resection US, we proposed 3 approaches: compositional, direct and group-wise. We showed that the group wise algorithm gives the best results, reducing the average mTRE over 13 patients from 5.9 mm to 2.8 mm, and the maximum TRE from 17.0 mm to 7.0 mm. The computational time of all of these non-rigid volumetric registration methods is less than 2 min on a single CPU core. hence, these methods are highly suit-able for integration within IGNS systems.

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