



Image-Guided Neurosurgery by Using E- Raptor Technique

¹R.THILLAIKKARASI, Assistant Professor,
thillaiscet73@gmail.com

Department of ECE, Salem College of Engineering and Technology, Salem - 636 111.

²J.ARUNMOZHI, Post Graduate student, ME in Applied Electronics,

Department of ECE, Salem College of Engineering and Technology, Salem - 636 111.
jt.arunmozhi@gmail.com

ABSTRACT:-

An automatic and robust registration of pre-operative magnetic resonance imaging (MRI) for the rigid transformation and systematically study the accuracy, precision, and capture range of the algorithm, as well as and an intra-operative ultrasound (US) is essential to neurosurgery. It reformulate and extend an approach of a Linear Correlation of Linear Combination (LC2)-based similarity metric novel algorithm which allows for fully an automatic US-MRI registration in matter of seconds. It is invariant with respect to the unknown and locally varying relationship between US image intensities and MRI intensity gradient. The overall method based on both recovers global rigid alignment, as well as the parameters of a free-form-deformation (FFD) model. An algorithm is evaluated on 14 clinical neurosurgical cases with tumors and average landmark-based on error of 2.52mm its sensitivity to different choices of parameters.

1.INTRODUCTION

A modern neurosurgery heavily relies on both pre-operative and interventional medical imaging, in particular MRI and US. MRI provides a good visualization of tumors, a relatively large field of view and good reproducibility. Its use as intraoperative imaging modality is possible however with limited accessibility to the patient and high workflow complexity. On the other hand, US is inexpensive and easy to use, but imaging quality is reduced, fewer anatomical details are visible and, in general, US is operator-dependent and harder to interpret. Also, the field of view is limited and

direction dependent. The combination of both modalities would allow integrating high-, determine their tissue and boundary properties, and detect brain shift. contrast pre-operative MRI data into the interventional suite. Therefore, quick, robust and anautomatic alignment of MRI and US images is of high importance. In contrast to MRI, ultrasound provides real-time 2D images, which, when tracking the ultrasound transducer, can be interpreted in 3D space. This has been used in the past decades for brain examinations, for instance to localize tumors. Therefore, the basic and well known off-the-shelf registration approaches are known to fail, which includes registration using cost functions based on sum of squared distances, mutual information or correlation ratio. A method which uses a measure based on 3D gradient orientations in both US and MRI is presented in , however such an approach discards valuable MRI intensity information and hence requires either optimal data or close initialization. Many of the best existing approaches transform MRI and/or US intensities under application and organ-specific considerations, in order to make them easily comparable. This is done, for example, for liver vasculature in , with significant effort due to learning-based pre-processing. Similarly an US images may be generated using segmented structures from MRI. In light of the modality-specific considerations and most promising general strategy of robust US-MRI registration, without relying application-specific pre-processing or segmentation to compare US and MRI intensity and its gradient, as pioneered in



where a global polynomial intensity relationship is fitted during registration.

An over the last decade the development of image guided surgery techniques has been a major advance in minimally invasive neurosurgery. These techniques, carried out in operating rooms equipped with special purpose contrast between healthy and diseased tissue, imaging equipment, allow the neurosurgeon to acquire new images during surgery. These images, such as provided by intra operative ultrasound and intraoperative magnetic resonance imaging (IMRI), can provide improved and the ability to see past the surface of the exposed brain in order to better appreciate the deeper structures of the brain. Due to constraints of an operating room, intraoperative imaging typically results in images with lower signal to noise ratio is less flexibility in the choice of imaging modality than conventional imaging done outside the operating room. We have to developed an algorithm to allow the projection of preoperative images onto intraoperative images, allowing fusion of an images from multiple imaging modalities and with multiple contrast types.

The volumetric deformation of the brain found by solving for the displacement field that minimizes the energy described by Equation 1, after fixing displacements at the surface to match those generated by the active surface model. At each node of the finite element mesh, three variables representing the x, y and z displacements are to be determined. Each variable gives rise to one row and one column in global K matrix. The rows of the matrix are divided equally among the CPU available for computation and global matrix is assembled in parallel. Each CPU assembles the local Key matrix for each element in its sub domain. Each CPU has been equal number of rows to process but because the connectivity of the mesh is irregular, some CPU may be more work than other CPU. Following the assembly of the matrix, the boundary conditions determined the surface matching are applied. The global K matrix are adjusted such that rows associated with variables that are determined consist of a single non-zero entry of unit magnitude on the diagonal. The key insight is that, while location is an important in describing image content and the registration process, it is an ultimately incidental and it should thus be marginalized in an order to obtain the maximum posteriori (MAP) transform relating images. Marginalization provides a principle of leveraging local regional information registration contrast to omitting location information to maximizing a joint distribution over locations and

Second a novel mathematical link is established between Bayesian registration and mutual information (MI) similarity measure, motivating The alternating optimizations of the rigid pose and polynomial coefficients, as well as the fact of a global mapping, limit the convergence range. Higher-dimensional Mutual Information (α -MI) is theoretically suited for assess US-MRI alignment based on both intensity and gradient information. However, current approaches are neither practical in terms of an implementation effort nor computation time. Powerful tools for image registration is similarity measures which are invariant to local changes in local normalized cross-correlation (invariant wrt. Local brightness and contrast). In the similarity measure Linear Correlation of Linear Combination (LC2) is presented, whis exhibits local invariance to how much channels of information contribute to an ultrasound image.

the use of MI in a Bayesian setting and third new strategy is proposed for selecting informative local image regions for registration, based on MI of image intensity location within image regions. This strategy generalizes previous work advocating the selection of high-entropy image regions, by imposing the additional constraint that the intensity be informative with respect of an image location and remainder of this paper is organized as follow Section 2 outlines related work in the literature and Section 3 presents our Bayesian framework for location marginalization and informative region selection. Section 4 present an experiments are involving registration of an intra-operative US slices to pre-operative MR imagery in an image-guided neurosurgical (IGNS) application are challenging registration of scenario, location marginalization is shown in outperform standard registration. Furthermore, mutual information-based selection of image regions is shown to perform in both uniform sampling and entropy-based region selection. A challenge of marginalizing location is computing the integral over local regions experiments are here to recover global translation via enceinte numerical integration and computation time is linear in an image size and number of regions are used. Nescient marginalization with more complicated transforms could be addressed via coarse-to- τ ne methods or Monte Carlo integration, depending on the class of transforms are used. The MI-based feature selection criterion are currently evaluated at a τ -axed image window size, but could be used automatically to determine more elaborate descriptions of local region geometry, including



region size or shape in order to identify a wider variety of local image structures.

PROBLEM STATEMENT

The fusion of Magnetic Resonance Imaging (MRI) and Ultrasound (US) for targeted prostate biopsy can solve the diagnostic dilemma of patients with repeated negative prostate biopsies seen in the conventional Trans-Rectal UltraSound (TRUS) guided systematic biopsy. Recently 68Gallium labeled ligand Prostate Specific Membrane Antigen (68Ga-PSMA) Positron Emission Tomography (PET) was introduced that, in conjunction with MRI, provides combined molecular and structural information for the detection of Prostate Cancer (PCa) Hence, we developed an open source framework that combines the preoperative PET/MRI images with TRUS and to provides multimodal image guidance for targeted biopsy. In this paper, we present the technical challenges in the development of multimodal image guided prostate biopsy, especially in 3D TRUS acquisition and multimodal image registration. Further, we explain the steps to address these specific challenges and some unsolved problems.

PREPROCESSING

The preprocessing of an brain MR image is the first step in our proposed technique. The preprocessing of an image is to reduce the noise by a 3x3 median filter and to prepare the brain MR image for further processing. The purpose of these steps are basically to improve the image appearance and the image quality to get more surety and ease in detecting the tumor .

FEATURE EXTRACTION

The feature extraction stages are to analyze the objects from, Standard Variance, Median Intensity, Skewness the input image are to extract the most prominent features that are representative of the various classes of objects. The features are used as an input to classifiers that assign them to the class that they represent. The purpose of feature extraction is to reduce original data are measuring by certain properties, or features, that distinguish one input pattern from another pattern and the extracted feature should provide the characteristics of the input type to the classifier by considering the description of a relevant properties of an image into feature vectors. In this proposed methods are

interested to extract the features and Shape - circularity, irregularity, Area, Perimeter, Shape Index Intensity features – Mean, Variance, and Texture features – Contrast, Correlation, Entropy, Energy, Homogeneity, cluster shade, sum square variance of texture based tumor detection, segmentation and classification has been discussed to characterize the tumor surface variation are expected to be different from the non tumor region, which further increases the certainty of fine extraction.

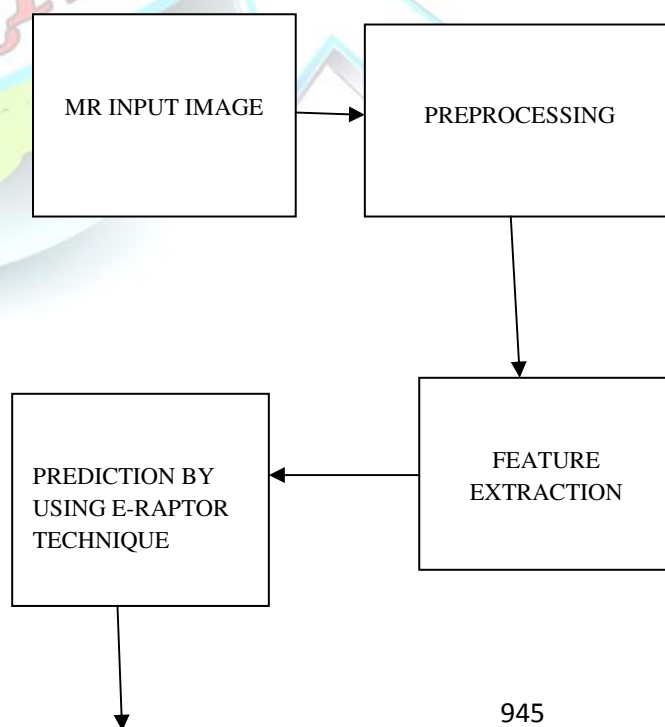
TARGET SEGMENTATION

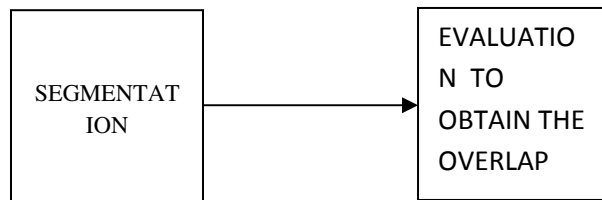
The brain MR image are next step of our proposed technique is to segment the brain tumor MR image. Segmentation is to separate the image foreground from its background and Segmenting an image also saves the processing time for further operations which has been to be applied to the image.

POST PROCESSING

After segmenting the MR brain images have a several post processing operations and applied an image to clearly locate the tumor part in the brain.

PROPOSED BLOCK DIAGRAM



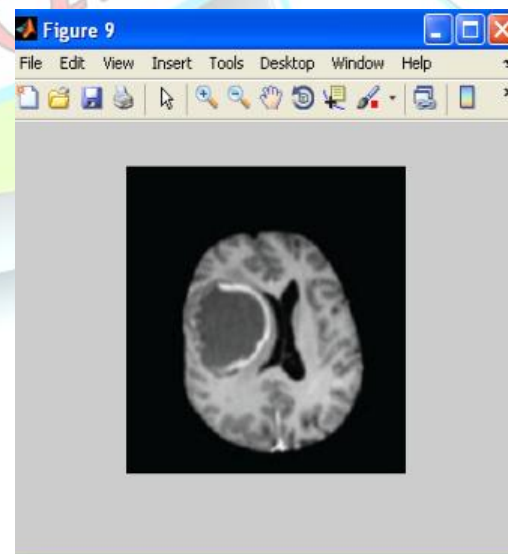
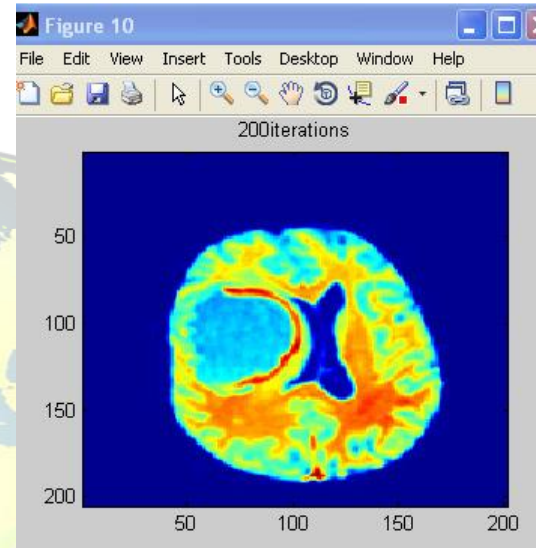


Starting from the MSB, each stage generates one bit of the resulting median value of the neighborhood being processed. We first describe the operation of an individual processing element and then explain the functioning of the entire linear systolic pipeline, which contains b processing elements.

II RESULTS

ENHANCED RAPTOR TECHNIQUE

Image gradient calculation is performed by an array of six parallel subtractors. These subtractors calculate the difference between the intensity of the voxel located in the center of the kernel against its six-connected neighbors. These values are then multiplied against their corresponding diffusion coefficients (supplied by the diffusion coefficient calculator) using an array of six parallel multipliers. The resulting filtered intensity is then obtained by adding the six results from the multipliers to the original center voxel intensity. After rounding and truncation, this result is then sent to the output buffer and is then further saved into output memory bank. The 3D median filtering design presented in this work is an extension of majority finding-based implementation proposed by Benkrid et al. That design was reported for a 2D realization and computed only one bit of the median value per clock cycle. All bits of the median value were obtained using a feedback loop and hence for b -bit images, this approach required b clock cycles to compute the resulting median value. The implementation presented in this dissertation extends that design to 3D and unrolls the feedback loop by using multiple processing stages. Moreover, our implementation exploits the regularity of this median finding algorithm with a systolic array architecture that allows a pipelined implementation and, therefore, can achieve a throughput of one median value per clock cycle. Thus, our implementation can achieve a voxel processing speed b times higher than the previously reported architecture. Our linear systolic array employs b identical processing stages for filtering a b -bit image. illustrates execution of this algorithm for a small example and can be used to gain further insights into its hardware implementation. Each processing stage of our systolic array implementation corresponds to one step of the algorithm execution.





CONCLUSION

To analyze the performance of the proposed algorithm to detect the surgery's, the images obtained using the proposed methodology is compared with its corresponding ground truth images. A new approach for the segmentation and classification of brain surgery is proposed. It helps the physician and radiologist for brain surgery detection and diagnosis for surgery local binary patterns and gray level co-occurrence features are extracted from brain images with brain images with malignant and normal brain images. the features are trained using SVM classifier in training mode. The same features are an extracted from test brain image and classified with trained patterns using SVM classifier in classification mode.

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