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# A Review of Different Medical Image Registration Techniques

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***Abstract—This paper gives a review of different techniques for rigid and non-rigid registration of medical image before and at the time of surgery. Registration of preoperative MR images and Ultrasound images are used for the purpose of accuracy in detecting the tumour. Image-guided neurosurgery (IGNS) systems can be used to track surgical tools with respect to the pre-operative magnetic resonance (MR) images, movement of brain tissue during surgery invalidates the image-to-patient mapping and thus reduces the effectiveness of using pre-operative images for intra-operative surgical guidance. The movement of brain is caused by biochemical and physical 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 tumour image. The US and MRI images registered are compared tat which techniques reduces the mean target registration error.***
***Index Terms—Image Guided Neurosurgery (IGNS), Intraoperative Ultrasound, Non-Rigid Registration, Image Segmentation and RaPTOR.***

## I. INTRODUCTION

The success of the surgical resection of brain tumors depends to a large extent on the complete removal of the tumour. The proximity 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 challenging. 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 enable the surgeon to accurately localize the trajectories 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 magnitude, which leads to a bivariate extension of the CR. Secondly, we incorporate a robust intensity-based distance measure in order to prevent 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 MR images and patient's head. The US probe is tracked with a position sensor, which provides the transformation of the US images to the patient space. The US and MR 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. A critical part of an image-based registration technique is the similarity metric, which should be maximized to align the images. Popular similarity metrics include mutual information (MI), correlation ratio, correlation coefficient (CC) and sum of squared differences (SSD). A mutual information is that it samples the entire image to establish the statistical relationship. To compute RaPTOR over many small patches and sum the results in a short time.

### *A. RaPTOR*

Our approach is similar to that of in that we also perform nonparametric estimation, with the difference that we compute CR locally to achieve resistance to the large spatial intensity inhomogeneity in the US images. To this end, we perform binning of the X values instead of computing E<Y|X> for iso-sets of X. We use this property in by deriving the derivative of the cost function analytically and

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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.

*B. Patch - Based Correlation Ratio*

CR assumes pixel correlations consistent across the image

US intensities vary in a spatially dependent manner

Calculate CR independently for several small patches selected throughout the volume

$$RaPTOR(X,Y) = \frac{1}{N_p}\sum_{i=1}^{N_p}(1-\eta(Y|X:\Omega_i) \text{ .......... (1)}$$

## II. BLOCK DIAGRAM OF RaPTOR

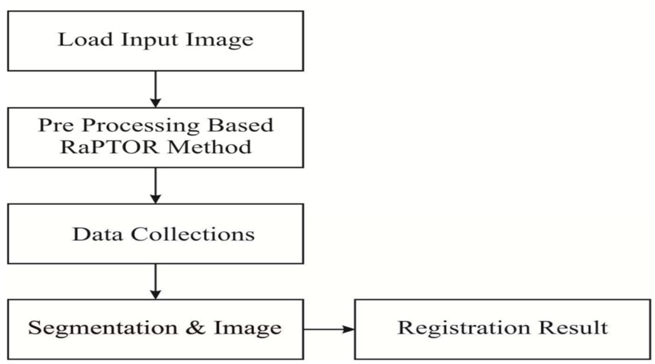


Fig. 1 Block Diagram of RaPTOR Phase Correlation Pixel-to-Pixel Image Coregistration

The Input image should first be roughly oriented to the Reference image by standard routines of image shift, rotation and scale change before the robust phase correlation based motion flow estimation and image co-registration. The image rotation and minor scale change may introduce geometric errors as the results of interpolation and re-sampling. However, this type of errors will be largely eliminated by the later steps of the pixel to - pixel image co-registration based on the precise measurements of the shift between every corresponding pixel.

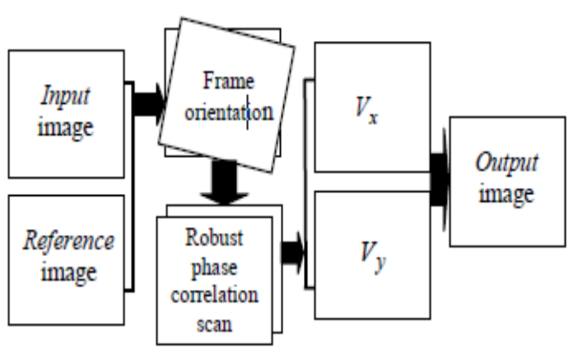


Fig. 2 Basic Scheme of Robust Phase Correlation based Pixel to-Pixel Image Co-registration

## III. IMAGE SEGMENTATION

After performing the top-hat transformation, the aim is to extract the registering preoperative MR to post resection US cluster part. For

 

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that segmentation algorithm is applied on the image. There are two different goals for the segmentation of registering preoperative MR to post resection US. One is to obtain the locations of cautious areas to aid radiologists for diagnose. The other is to classify the abnormalities of the breast into benign or malignant.
The clustering is used for segmentation. In the clustering algorithm at first define the number of clusters. Then cluster center are selected randomly. The distance between the each pixel to each cluster centers are estimated. The distance is of simple Euclidean function. The grouping is done by diminishing the Euclidean distance between data and the corresponding cluster centroid.

The image segmentation flow will performs in an order of image sequence of optic flow estimator, model estimator and region classifier will reaches the final segmentation. The feedbacks are region splitter and region generator. According to this flow we can performs the segmented image.

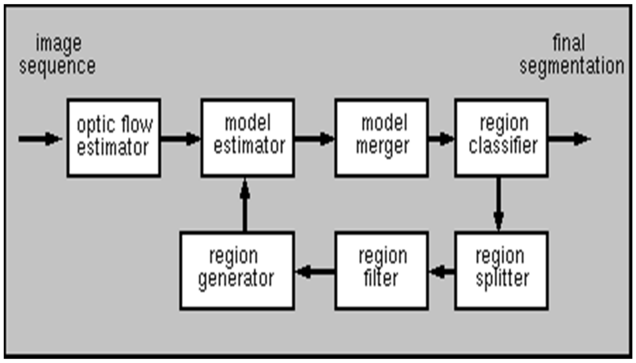


Fig. 3 Image Segmentation

It automatically populate with pixel wise object background segmentations. At each stage this propagation process expands into the images which are easiest to segment at that point in time. After segmentation the images are registered and measures the volume of changes in image.

*A. Flow Chart of Image Segmentation*

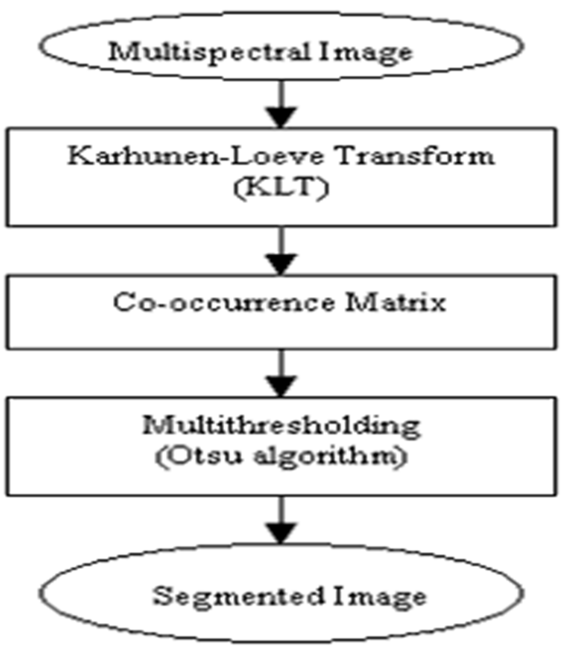


Fig. 4 Flow chart of Image Segmentation

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## IV. ARTIFICIAL NEURAL NETWORKS (ANN)

Neural network have received much attention for their successful application in pattern recognition. Once a neural network has been configured, it forms an appropriate internal feature extractors and classifiers based on training examples. Neural networks consist of a set of interconnected neurons which operates together to perform a particular task. Each neuron is associated with its weight. In training phase, network uses training set to update weights of its neuron in order to reduce network error. After the training phase, trained network is used for classification. An ANN is created by combining artificial neurons into a structure containing three layers. The first layer consists of neurons that are responsible for a face image sample.

The second layer is a hidden layer which allows an ANN to perform the error reduction necessary to successfully achieve the desired output.

The final layer is the output layer wherein the number of neurons in this layer is determined by the size of the set of desired outputs, with each possible output being represented by a separate neuron.

### *A. Feed Forward Neural Network*

A feed forward neural network is an artificial neural network where connections between the units do not form a cycle. This is different from recurrent neural networks. The feed forward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network.

### *B. Training Process*

Any network must be trained in order to perform a particular task. In training process, training data set is presented to the network and network's weights are updated in order to minimize errors in the output of the network. Back propagation neural network uses back propagation algorithm for training the network. The principal advantages of Back propagation are simplicity and reasonable speed.

### *C. Neural Network*

The Back Propagation Neural Network is used for classifying the gender. There are seven input such as distance from eyebrow to eye (D1), distance from eye to nose (D2), distance from nose to mouth (D3), distance from eye to mouth (D4), distance from left eye to right eye (D5), width of nose (D6), width of mouth (D7), four hidden layers and one output such as male or female. The network architecture is described below.

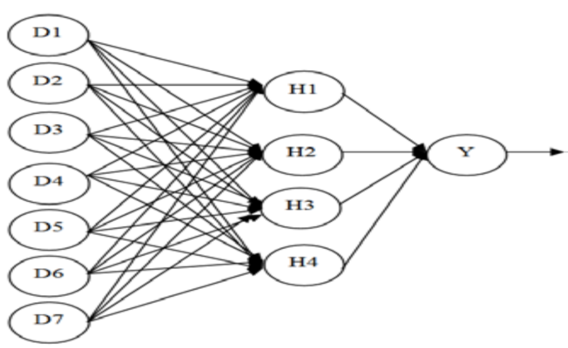


Fig. 5 Architecture of Neural Network

| | RaPTOR | ANN | NMI |
|---|---|---|---|
| Target Registration Error | 18 | 13 | 15 |

Table. 1 Comparison of Different Image Registration Techniques to reduce m-TREE

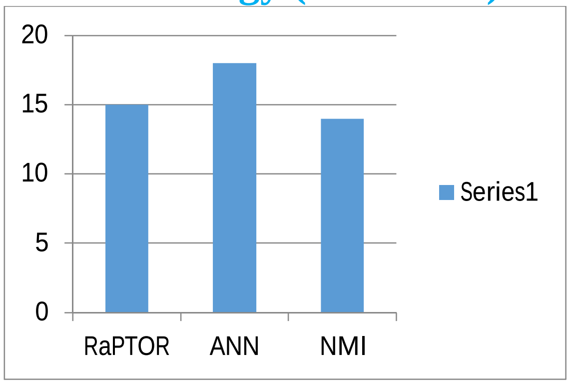


Fig. 6 Comparison graph using different techniques

*D. Normalized Mutual Information*

The normalized mutual information of two images is a combination of the entropy values of the images, both separately and jointly. One interpretation of entropy is as a measure of dispersion of a probability distribution. A distribution with only a few large probabilities has a low entropy value; the maximum entropy value is reached for a uniform distribution. The entropy of an image can be computed by estimating the probability distribution of the image intensities.

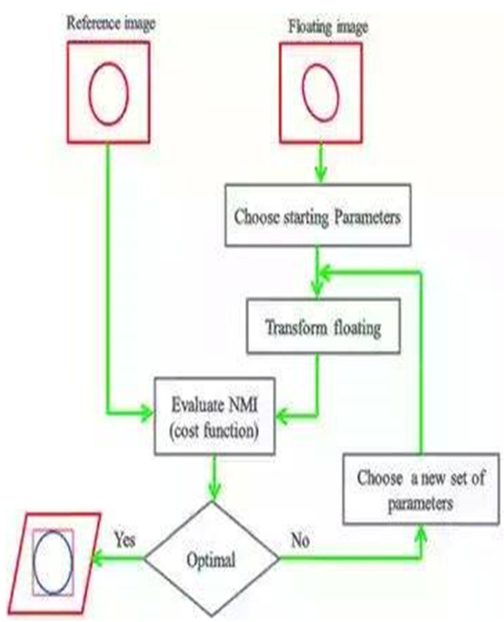


Fig. 7 Flowchart for Normalized Mutual Information

## V. CONCLUSION

A comparative study of all the registration techniques implemented is done and the results are evaluated. The contrast of brain tumors is often low in the US images and therefore fusion of the MR can improve tumor visualization. Accurate registration of MR and post resection US can potentially reduce the presence of residual tumors. Hence integrate RaPTOR with our neuro navigation system IBIS, and to assess its robustness, accuracy and potential improvement on the outcome of the surgery. Our implementation of the bivariate CR using Powell's optimization method was successful in rigidly registering a number of US/MR volume pairs from phantom and clinical data. Adaptation of normalized mutual information measures, by incorporating spatial information. The measure with gradient information has good performance for normalized mutual information. Thus the US, MR images are registered and the mean target registration error are reduced by using different algorithms. Different methods have different advantages and disadvantages based on computational time required and the use of other parameters.

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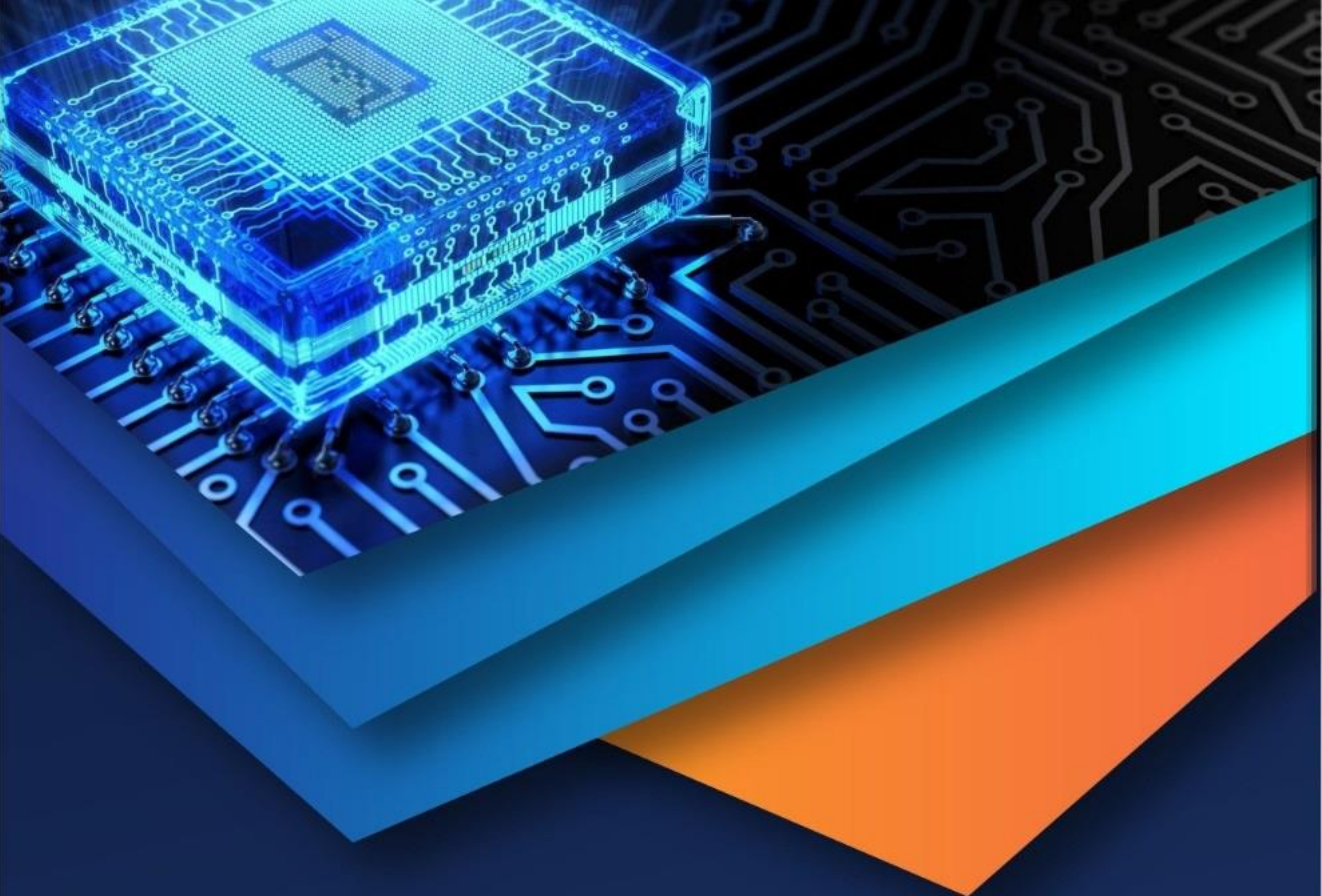


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