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AN OPTIMIZED IMAGE FUSION TECHNIQUE FOR NEUROSURGERY

L.Siva Yamini[1], M.Bindusree[2], B.Harichandana[3], S.Ayeshasidikha[4]

[1]Assistant Professor, Department of ECE, AITS, Rajampet, Andhra Pradesh, India

[2, 3, 4]Student, Department of ECE, AITS, Rajampet, Andhra Pradesh, India

Abstract:

Medical image fusion is the process of registering and combining multiple images from single or multiple imaging modalities to improve the imaging quality and reduce randomness and redundancy. Image fusion increases the clinical applicability of medical images for diagnosis and assessment of medical problems in neurosurgery. Multi-modal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images for neurosurgery. The two stages of any classical image fusion method are image registration and fusion of relevant features from the registered images. The registration of the images requires a method to correct the spatial misalignment between the different image data sets. The problem of registration becomes complicated in the presence of inter-image noise, missing features and outliers in the images. Previously the problems are rectified by using so many segmentation algorithms, but they are not optimized. So in this work a dynamic optimized image fusion technique is proposed where ultrasound (US) and MR images are fused and get a more accurate and very less error probability images which act as a guide in surgery process.

Keywords — **Modalities, Redundancy, Multi-modal, Fusion, Registration, Neurosurgery**

I. INTRODUCTION

Medical imaging is the technique where it process and creates a visual representations of interior parts of human body which are hidden by the skin and bones for clinical analysis and medical intervention [1]. Today, in medical field imaging draws an additional attention for clinical examination and disease diagnosis because of increased requirements. Present neurosurgery especially for brain tumors or nerves in spinal cord excision has perceived a spectacular change in the use of image information over the past decennium.

Medical images produced by different imaging modalities like MRI, CT and Ultrasound provides data as assortment of balancing information concerning the internal structure of human body. Though, single imaging modality does not provide a high resolution image for diagnosis of disease and visualization in neurosurgery [2]. So to enhance the diagnostic accuracy the image fusion is considered where it integrates more than one imaging techniques and produces fused images which are more appropriate for abet the doctors in diagnosis. [Y].

Among all the imaging modalities US (ultrasound) and MRI has acquired noteworthy impetus in neurosurgery. But, due to having their limitations the registration problem gets intricate in existence of multimodality noise.

In this paper a vibrant optimized image fusion technique is presented where ultrasound (US) and MR images are merged to get more precise images which act as a guide to doctors in neurosurgery process.

II. LITERATURE SURVEY

In 2006, R.Thillaikkarasi *et.al* [3] proposed a novel algorithm based on E-Raptor which acts as guide for neurosurgery. In this work authors considered the US & MRI brain images for fusion. Also in their work local binary patterns & gray level co-occurrence methods as feature extraction and SVM as classification method are considered for detection of tumors or malignant in surgery.

Hassan Rivaz, et al. [4] proposed a RaPTOR algorithm along with stochastic gradient optimization algorithm for non-rigid registration of challenging data sets of MR and US images.

Frank Lindseth *et al* [5] proposed a Multi-Modal Volume Visualizer for image fusion. This method fuses intraoperative 3D ultrasound and preoperative MRI for improvement of quality of the surgical procedures

III. METHODOLOGY

The structure of the proposed surgery system based on optimization involves several steps is as shown in Fig.1.

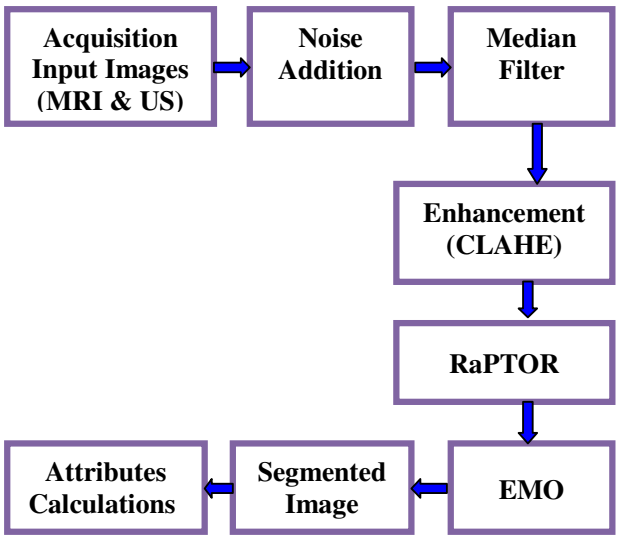

Fig:1. Proposed Block Diagram.

At first the MRI and US images are read from the data base and given as input for processing stage.

A. *Pre-processing*

Image preprocessing can increase the reliability of an optimal inspection. Several filter operations are carried out which intensify the image details.

Noise Addition

Normally small amount of noise is present in any image, if the noise is removed directly then there is a chance the clarity of the image is reduced [6]. So to reduce the noise, initially enhances the levels of noise in the image by adding external salt & pepper noise [7]. The noise is added in the input image because the less amount of noise is also removed by adding the noise.

Median Filtering

Image enhancement operations can also work with the values of the image pixels in the neighborhood and the corresponding values of a sub image that has the same dimensions as the neighborhood. The sub image is called a filter.

Median filtering is a nonlinear process useful in dropping impulsive or salt and pepper noise which occurs due to random errors. It is also reduces the random noise and conserves edges in an image[8]. This filter is a simple sliding window spatial filter that replaces the center value in the window with the average of all the pixel values in the window.

Enhancement

It increases the contrast or brightness of an image for better visual perception by enhancing the reduced noise image. In this work the enhancement is carried out by contrast limited histogram equalization (CLAHE)[9]. If AHE (Adaptive Histogram Equalization) performs in particular region of image whose intensity range is low then noise present in that particular region gets increased and generates artifacts[10]. To reduce such artifacts a modified version of AHE called Contrast Limited AHE is used. CLAHE increases the contrast levels as a function of slope of the CDF function.

RaPTOR

This algorithm transforms the Low dynamic range images which has low range of illumination in to high dynamic range images. It approximates equivalent metrics in petite patches and averages the results over a lot of patches[11]. Finally, it executes precise registration of MR and US images whose intensities are only related in very local scales.

IV. OPTIMIZATION

EMO is a global optimization algorithm that mimics the electromagnetism law of physics[12]. It is a population-based method which has an attraction-repulsion mechanism to evolve the members of the population guided by their objective function values. The main idea of EMO is

to move a particle through the space following the force exerted by the rest of the population

The algorithm takes random samples from a feasible search space which depends on the image histogram[13]. Such samples build each particle in the EMO context. The quality of each particle is evaluated considering the objective function employed by the Otsu's or Kapur's method

Step 1: Read the image I and if it RGB separate it into R I , G I and B I . If the I is gray scalestore it into Gr I . c □ 1,2,3 for RGB images or c □1for gray scale images.

Step 2: Obtain histograms: for RGB images R h , G h , B h and for gray scale images Gr h .

Step 3: Calculate the probability distribution using and the histograms.

Step 4: Initialize the EMO parameters: max Iter, local Iter, □ , k and N .

Step 5: Initialize a population ct**S** of N random particles with k dimensions.

Step 6: Compute the values c i . Evaluate c **S** in the objective function Otsu f or Kapur fdepending on the thresholding method.

Step 7: Compute the charge of each particle and compute the total force vector.

Step 8: Move the entire population c t **S** along the total force vector

Step 9: Apply the local search to the moved population and select the best elements of this search based on their objective function values.

Step 10: The t index is increased in 1, If max t □ Iteror if the stop criteria is satisfied the algorithm finishes the iteration process and jump to step 11. Otherwise jump to step 7.

Step 11: Select the particle that has the best c B t x objective function value using Otsu f or Kapur f).

Step 12: Apply the thresholds values contained in c Bt x to the image I

V. SIMULATION RESULTS

In this project, the MRI & Ultra Sound images are fused and cuckoo search optimization technique is used to produce an image that helps the neuro-surgeons in detecting the brain tumour. For the generation of the final optimised image, the MRI and Ultrasound images are subjected to some operations. The Output of each operation is as follows.

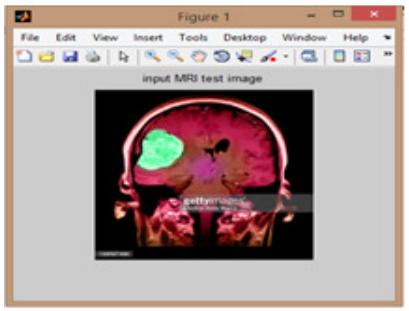

Fig:2. Input MR Image

Fig:3. Input Ultrasound Image

Figure 2 & 3. Shows the MRI and Ultrasound brain input images of a person. The MRI & CT image may contain small amounts of noise in it. It is difficult to remove those small amounts of noise as the clarity of the image decreases due to removal of small amounts of noise. So the images are further processed.

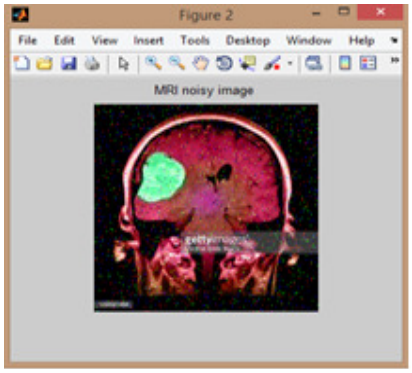

Fig:4. Noisy MR Image

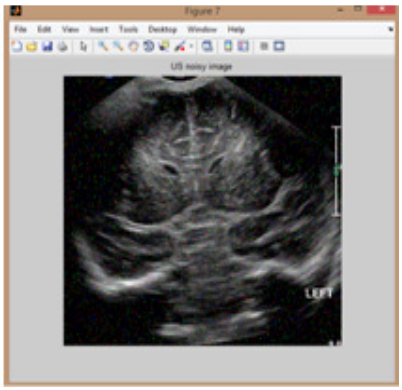

Fig:5. Noisy ultrasound Image

Figure 4 & 5. Shows noisy MRI and Ultrasound images. It is difficult to remove the small amounts of noise. Salt & pepper noise is added to the images in order to enhance the noise levels in the images.

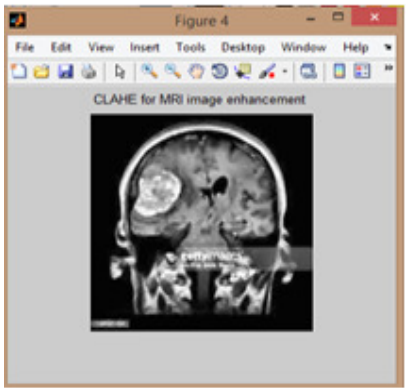

Fig:6.CLAHE enhanced MRI image

Fig:7.CLAHE enhanced US image

Figure 6 & 7. Shows enhanced MRI and US images. CLAHE is applied on the noise removed images to increase the contrast levels of the image. Increase in contrast levels results in the better clarity of the images.

Fig.8. Patched MRI image.

Fig.9. Patched US image.

Figure 8 & 9 shows the patched MRI and US images. The enhanced MRI and US image is divided into patches after 30 iterartions.RaPTOR is used to calcute the correlation ratio of the patches of the MRI image and the Ultrasound image.

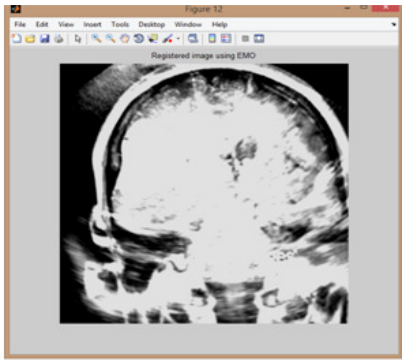

Fig:10.Registration of MRI & Ultra Sound image using EMO

Figure 10 shows the registered image of MRI & Ultra Sound image using EMO.EMO registers the

MRI & Ultra Sound image to generate a new image. EMO optimization technique is used for proper detection of the tumour[10]. The stastical parameters is shown in Table I. which shows the precession is achieved high valve (92.74) and accuracy (52)

Table I: Stastical Parameters

PARAMETERS	EMO
Precision	92.7470
BER	4.38
Sensitivity	37
FPR	31
PSNR	1.9211
Accuracy	52

VI. CONCLUSION

The field of medical diagnostics and monitoring using medical images faces several technological, scientific and societal challenges. The technological advancements in imaging technologies have resulted in improved imaging accuracies[11]. The ability of image fusion techniques to quantitatively and qualitatively improve the quality of imaging features makes multi model approaches efficient and accurate relative to uni-model approaches.

In this paper, a new idea is implemented where the ultrasound (US) and MR images are fused and then registered by Robust Patch based correlation Ratio algorithm along with EMO technique to obtain clear images with more accurate and very less error probability also gives a better understanding to doctors while doing neurosurgery.

REFERENCES

1. *M. Letteboer, P. Willems, M. Viergever, and W. Niessen, "Brain shift estimation in image-guided neurosurgery using 3-d ultrasound," IEEE Trans Med. Imag., vol. 52, pp. 267–276, 2005.*
2. *Reinertsen, A. Jakola, P. Friderichsen, F. Lindseth, O. Solheim, T. Selbekk, and G. Unsgård, "A new system for 3d ultrasound-guided placement of cerebral ventricle catheters," International journal of computer assisted radiology and surgery, vol. 7, no. 1, pp. 151–157,2012.*
3. *R.Thillaikkarasi, J.Arunmozhi, "Image-Guided Neurosurgery by Using E- Raptor Technique" International Journal of Engineering Science and Computing, Volume 6 Issue No. 5 , May 2016, ISSN 2321 3361.*
4. *Hassan Rivaz, Sean Jy-Shyang Chen , D. Louis Collins "Automatic Deformable MR-Ultrasound Registration for Image-Guided Neurosurgery" IEEE TRANS. MEDICAL IMAGING 1,pG:1-15.*
5. *Frank Lindseth et.al " Multimodal Image Fusion in Ultrasound-Based Neuronavigation: Improving Overview and Interpretation by Integrating Preoperative MRI with Intraoperative 3D Ultrasound" Computer Aided Surgery, Volume :8, Pg.No:49–69 ,2003.*
6. *D. De Nigris, D. L. Collins, and T. Arbel, "Multi-modal image registration based on gradient orientations of minimal uncertainty," IEEE Trans. Medical Imag, vol. 31, no. 12, pp. 2343–2354, 2012.*
7. *Nabavi, P. Black, and et al., "Serial intraoperative magnetic resonance imaging of brain shift," Neurosurgery, vol. 48, no. 4, pp. 787–798, 2001.*
8. *Roche, G. Malandain, N. Ayache, and S. Prima, "Towards a better comprehension of similarity measures used in medical image registration," in Medical Image Computing and Computer-Assisted Intervention. Springer, 1999, pp. 555–566.*
9. *W. Wells, P. Viola, H. Atsumid, S. Nakajimae, and R. Kikinis, "Multimodal volume registration maximization of mutual information," Med Imag Anal, vol. 1, no. 1, pp. 35–51, 1996.*
10. *F. Maes, A. Collignon, D. Vandermeulen, M. G, and P. Suetens, "Multimodality image registration by maximization of mutual information," IEEE Trans. Medical Imag, vol. 16, no. 2, pp. 187–198, 1997.*
11. *J. Pluim, J. Maintz, and M. Viergever, "Mutual-information-based registration\ of medical images: a survey," IEEE Trans. Medical Imag., vol. 22, no. 8, pp. 986–1004, 2003.*
12. *A.Roche, G. Malandain, X. Pennec, and N. Ayache, "The correlation ratio as a new similarity measure for multimodal image registration," Medical Image Computing Computer Assisted Intervention (MICCAI), pp. 1115–1124, 1998.*
13. *S. Klein, U. van der Heide, I. Lips, M. van Vulpen, M. Staring, and J. Pluim, "Automatic segmentation of the prostate in 3D MR images by atlas matching using localized mutual information," Med. Phys., vol. 35, no. 4, pp. 1407–1417, 2008.*