

FUZZY LOGIC BASED SPINE IMAGE FUSION

Ms.Sathiya Jeyaseeli.V*

Mr.Napolean.A**

Abstract—

Image Fusion is a method that integrates complementary details from multiple images such that the fused image is more informative and suitable for processing tasks. The different imaging modality of spine image fusion has been increased in the medical field for the purpose of getting more information regarding spine reordering and bone fracture. CT and MRI of the spinal cord provide complementary information of possible relevance for diagnostic and therapeutic decisions. This article investigates a novel CT/MRI spine image fusion based on Fuzzy Logic. This algorithm allows physicians to visually assess corresponding soft tissue and bony detail on a single image eliminating mental alignment and correlation needed when both CT and MRI images are required for diagnosis. The source medical images are first changed by DWT which decompose the images into four sub bands. Sixteen dissimilar fusion rules based on fuzzy logic are proposed. Fusion rules are used to fuse low frequency components and high frequency components individually. Finally, the fused image is obtained by the inverse DWT. The proposed work is carried out for CT and MRI images. This image fusion framework not only helps in diagnosing diseases, but it also reduces the storage cost by reducing storage to a single fused image instead of multiple-source images.

***Index Terms:* Image fusion, spine, fuzzy logic, multi modal,PSNR.**

* P. G Scholar, V.S.B Engineering College, Karur, Tamilnadu, India

** Assistant Professor, V.S.B Engineering College, Karur, Tamilnadu, India,

LINTRODUCTION

In the recent years, medical imaging has attracted increasing concentration due to its critical role in health care. However, different types of imaging techniques such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), etc., provide limited information where some information is common, and some are unique. For example, X-ray and computed tomography (CT) can provide dense structures like bones and implants with less distortion, but it cannot detect physiological changes. Similarly, normal and pathological soft tissue can be better visualized by MRI image whereas PET can be used to provide better information on blood flow and flood activity with low spatial resolution. As a result, the anatomical and functional medical images are needed to be combined for a compendious view. For this purpose, the multimodal medical image fusion has been identified as a promising solution which aims to integrating information from multiple modality images to obtain a more complete and accurate description of the same object. Multimodal medical image fusion not only helps in diagnosing diseases, but it also reduces the storage cost by reducing storage to a single fused image instead of multiple-source images.

So far, extensive work has been made on image fusion technique with various techniques dedicated to multimodal medical image fusion. These techniques have been categorized into three according to merging stage. These includes pixel level, feature level and decision level fusion where medical image fusion usually employs the pixel level fusion due to the advantage of containing the original measured quantities, easy implementation and computationally efficiency. The well-known pixel level fusion is based on principal component analysis (PCA), independent component analysis (ICA), contrast pyramid (CP), gradient pyramid (GP) filtering, etc. Since, the image features are sensitive to the human visual system exists in different scales. Therefore, these are not the highly suitable for medical image fusion. Recently, with the development of multiscale decomposition, wavelet transform has been identified ideal method for image fusion. However, it is argued that wavelet decomposition is good at isolated discontinuities, but not good at edges and textured region. Further, it captures limited directional information along vertical, horizontal and diagonal direction. These issues are rectified in a recent multiscale decomposition contourlet, and its non-sub sampled version. Afterwards they are fused using any of the transforms. It then generates fused image which is more accurate, all-

around and reliable. It can result in less data size, more efficient Target detection, and target identification and situation estimation for observers.

For medical image fusion, the fusion of images can often lead to additional clinical information not apparent in the separate images. Another advantage is that it can reduce the storage cost by storing just the single fused image instead of multi-source images. The fusion of multiple measurements can reduce noise and therefore eliminates their individual limitations. It is required that the fused image should preserve as closely as possible all relevant information obtained in the input images and the fusion process should not introduce any artifacts or inconsistencies, which can distract or mislead the medical professional, thereby a wrong diagnosis.

In the proposed work MRI and CT images are fused to obtain a more complete and accurate description of the same object. Image fusion algorithm consist of DWT and fuzzy logic. Discrete wavelet transform decompose the image into four sub bands. Fuzzy logic is used to detect the edge pixels and fuse its information to enhance the medical images. Sixteen fuzzy rules are constructed based on the fuzzy logic as a result the accuracy level of edge detection will be improved.

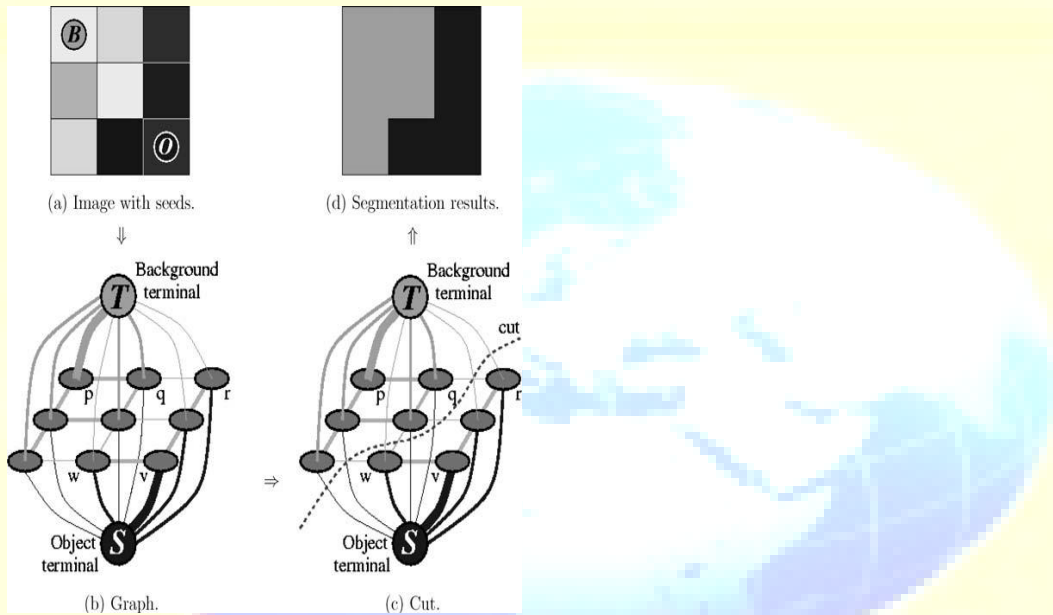


Fig .1 Images of bony spur formation: left - the CT image shows the osteophyte, but not the soft tissue ; middle - in the MR, the osteophyte is not identifiable; right - in the fused image, the osteophyte is clearly visible along with the surrounding soft tissue.

Graph Cut Method

Recent works have shown that the graph-based method can preserve the geometrical structure effectively in manifold learning [23]. An illustration of the multilabel graph-cut problem is provided in Fig. 3. Exactly one label is given to each pixel in the image, with associated data and smoothness costs assigned to the links in the graph. To formulate this optimization let $G = (V, E)$ be a weighted graph, with V a set of nodes and E a set of weighted edges. V contains a node

for each pixel in Ω and for each label in L_a . There is an edge $e\{p,q\}$ between every pair of nodes p, q . A cut $C \subset E$ is a set of edges that separates all the label nodes from each other, thereby, creating a subgraph for each label. The minimum-cut problem consists of finding a cut C with the lowest cost. The cost of this minimum cut, denoted $|C|$, equals the sum of the edge weights in C . By properly setting the weights of the graph, one can use a series of swap moves from combinatorial optimization to efficiently compute the minimum-cost cuts corresponding to a minimum of functional E



A swap move starts with a labeled graph and determines for a given pair of labels, p and q , whether each node having a value in p, q should 1) retain its current label or 2) be updated to the other label in the pair. Each swap is accomplished globally in an exact manner by finding the minimum cut on a binary graph consisting of only two labels. This can be extended to the multilabel case by iterating over the set of all possible pairs of labels. The minimum cut is selected at each stage, with the final labeling corresponding to a minimum of the energy functional. One can also use alpha-expansion moves to optimize energy functions of the form E . It is well-known that alpha-expansion moves guarantee a solution that is within a constant factor of the global optimum [26]. However, experimentally, it is well established that swap moves outperform alpha expansions.

II. IMAGE FUSION BASED FUZZY LOGIC

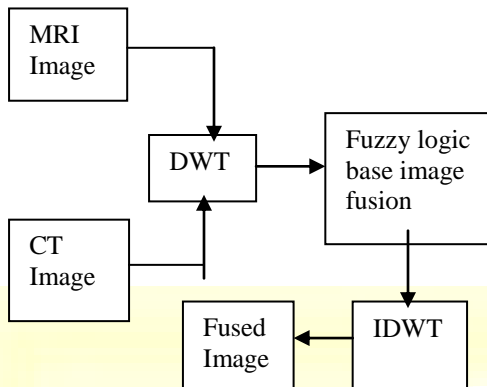


Fig 2.Fusion block diagram

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The process of fuzzy inference involves developing membership functions, fuzzy logic operators and if-then rules. Mamdani-type and Sugeno-type are the two types of Fuzzy Inference Systems that can be implemented in Fuzzy Logic. In this case, framing the fuzzy rules and implementing them for image segmentation are done by Mamdani type controller exclusively. The Fuzzy Logic provides a number of interactive tools that allow accessing many of the functions through a graphical user interface (GUI). Normal and pathological soft tissue can be better visualized by MRI image whereas CT can be used to provide better information on bony details. As a result, the multimodal medical image fusion integrates information from multiple modality images to obtain a more complete and accurate information which is useful for human or machine perception. Image processing requires high spatial and spectral resolution in a single image. The methodology has been designed with membership functions and other descriptions using fuzzy logic.

A. Discrete Wavelet Transform

As multi resolution analysis has become one of the most promising methods in image processing, the wavelet transform has become a very useful tool for image fusion. It has been found that wavelet-based fusion techniques outperform the standard fusion techniques in spatial and spectral quality, especially in minimizing color distortion. Schemes that combine the standard methods (HIS or PCA) with wavelet transforms produce superior results than either

standard methods or simple wavelet-based methods alone. However, the tradeoff is higher complexity and cost.

In this paper, we only introduce the discrete wavelet transform (DWT) based fusion schemes because DWT is the basic and simplest transform. The wavelet transform takes an approach that permits the window size to scale to the particular frequency components being analyzed. Wavelets are, generally speaking, functions that meet certain requirements. The name *wavelet* originates from the requirement of integrating to zero by oscillating about the x axis and being well localized. In fact, there are many kinds of wavelets. There are smooth wavelets, wavelets with simple mathematical expressions, wavelets that are associated with filters, etc. The reconstruction process from the DWT coefficients is called inverse DWT. Sub band coding is the process of splitting the frequency band of an image into various sub bands. The filters used in sub band coding are known as QMF (Quadrature mirror filter). Discrete wavelet transform is used to decompose the image data into various frequency sub bands.

B. Steps Involved In Designing The Methodology Using Fuzzy Logic:

Step1: The input value and the output value of the fuzzy system are assigned first and the range for the values for both input and output is chosen between 0 and 256.

Step2: The input and the output values of Fuzzy Inference System are mentioned with name such as input1, input2 & input3 and output1, output2 & output3 for mf1, mf2 and mf3 respectively.

Step3: Triangular membership functions are assigned (mf1,mf2, mf3).

Step4: The membership parameter values are chosen for the input values and output values.

Step5: The antecedent and the consequent part of the fuzzy logic along with the weight and connection part used in framing the fuzzy rule are assigned.

Step6: Based on fuzzy rules the clustering of the image is done and it is executed with three clusters namely clust1, clust2 and clust3. The values of the cluster are finally reshaped and stored in the variable values AA1, AA2 and AA3 respectively.

Step7: Using FOR loop command, iterative clustering is done over the image and stored in AA1, AA2 and AA3.

C. Fusion Fuzzy Rules: Fuzzy is a combination of rules and decisions. The accuracy level of edge detection in an image will be improved by using fuzzy logic. For 2*2 pixel block 16 Fuzzy rules are constructed. Let P1,P2,P3 and P4 be the pixels in the 2*2 sub block. Here P1, P2, P3 and P4 are the input variables. P4_OUT is the output variable. Check whether p4 is either black or white or edge based on input variables combinations. If the abrupt change in pixel P4 with respect to any P1,P2 and P3 then the pixel P4 is considered as edge pixel. Therefore, $2^4 = 16$ rules will be constructed.

Table 1 shows the fusion rules based on fuzzy logic. For example, the first rule if all the input variables have same membership function 'B' then the output obtained is also the same membership function-B. In the second rule three input variables have Black and P4 is assigned as white. In this case the output will be edge because there is an abrupt change in P4 with respect to other input variables. The membership function fully defines the fuzzy set. A membership function provides a measure of the degree of similarity of an element to a fuzzy set. There are different shapes of membership functions; triangular, trapezoidal, piecewise-linear, Gaussian, bell-shaped, etc. Median filters are known for their capability to remove impulse noise without damaging the edges. Median filter first identifies possible noisy pixels and then replaces them using the median filter or its variants, while leaving all other pixels unchanged. This filter is good at detecting noise even at a high noise level. In this paper, we use triangular membership function. The triangular membership functions are used both for the inputs and the output. The input and output ranges are assigned for fuzzy sets. Wavelets are finite duration oscillatory functions with zero average value. The irregularity and good localization properties make them better basis for analysis of signals with discontinuities.

Fuzzy Inputs				Fuzzy Output
P1	P2	P3	P4	P4_out
B	B	B	B	B
B	B	B	W	E
B	B	W	B	E
B	B	W	W	E
B	W	B	B	E

B	W	B	W	E
B	W	W	B	E
B	W	W	W	E
W	B	B	B	E
W	B	B	W	E
W	B	W	B	E
W	B	W	W	E
W	W	B	B	E
W	W	B	W	E
W	W	W	B	E
W	W	W	W	W

Table 1. Fusion fuzzy rules

Drawbacks in existing method are no optimum enhancement and time consuming process. So we propose a novel image fusion algorithm to enhance the details of the fused image, and can improve the visual effect with much less information distortion than its competitors.

III.SIMULATION RESULTS

In medicine, CT and MRI image both are tomography scanning images. They have different features. Image brightness are related to tissue density, brightness of bones is higher, and some soft tissue cannot be seen in CT images. MRI image, here image brightness related to amount of hydrogen atom in tissue, thus brightness of soft tissue is higher, and bones cannot be seen. There is complementary information in these images. We use three methods of fusion forenamed in medical images, and adopt the same fusion standards.

MRI and CT image is fed to the MATLAB. Preprocessing of an image is done to reduce the noise and to enhance the image for further processing. The purpose of these steps is basically to improve the image and the image quality to get more surety and ease in Diagnosis. Fuzzy tool box is chosen. Mamdani (image processing) and sugeno (signal processing) are the two types of fuzzy logic. Here we select mamdani since we process the image. Add four input variables for the fuzzy and the values are assigned to the input. Set the range and type for the same. Repeat the procedure for all the input variables. Set the range and type for output variable. The framed fusion rules are added to the fuzzy logic and it is exported to the file created in a path. Here the

file name is given as fuzzy edge detection .fis Program is coded using MATLAB then the final results are obtained.

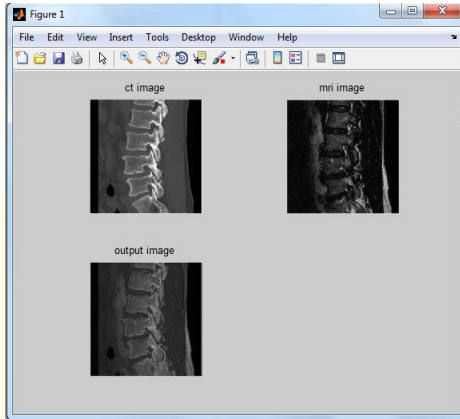


Fig. 3 Fuzzy Result

The fused image has more complete information which is useful for human or machine perception and also improves the performance of image analysis algorithms for medical applications.

$$PSNR = 10 \log_{10} \frac{R \cdot R}{MSE} \quad (2)$$

Where,

MSE – mean square error

R- the maximum fluctuation in the input image data type

Methodology	PSNR
Proposed Methodology	40.45
Graphcut Algorithm [2]	35.46

Table2.Comparison results

IV. CONCLUSION

In this paper, a novel image fusion framework is proposed for multi-modal medical images, which is based on fuzzy logic. For fusion, sixteen different rules are used by which more information can be preserved in the fused image with improved quality. The visual and statistical comparisons demonstrate that the proposed algorithm can enhance the details of the fused image,

and can improve the visual effect with much less information distortion than its competitors. The proposed work automatically fuses the multi-modal medical images for better diagnosis and improves the performance of image analysis algorithm for medical applications.

Proposed algorithm is implemented using MATLAB. This paper shows that proposed image fusion frame work performs well then the other image fusion technique through certain performance evaluation parameters. The experimental result proves that image fusion algorithm which is integrated with fuzzy rules increase the PSNR.

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