Performance Analysis of Medical Image Fusion Using Multimodal Graph Cut Algorithm

S.Anbumozhi, P. S.Manoharan

Abstract— **Image fusion plays a vital role in medical field to diagnose the disorders. It is the process of integrating multiple images of the same scene into a single fused image to reduce uncertainty and minimizing redundancy while extracting all the useful information from the source images. The resulting image will be more informative than the source images. In this paper, the multimodal graph cut technique based on discrete wavelet transform is used to fuse the spine MRI and CT images, in order to diagnose the disorders in spine images. The fused image is validated using the quantitative measures such as PSNR, MSE and fusion latency. Experimental results obtained from fusion process prove that the use of the graph cut based image fusion approach shows better performance while compared with conventional fusion methodologies.**

Index Terms—**Fuzzy reasoning, Fuzzy rules, Image fusion, Low power.**

I. INTRODUCTION

A fusion process is a combination of salient information in order to synthesize an image with more information than individual image and synthesized image is more suitable for visual perception. We use the term image fusion to denote a process by which multiple images or information from multiple images is combined. These images may be obtained from different types of sensors. With the availability of the multisensor data in many fields, such as remote sensing, medical imaging or machine vision, image fusion has emerged as a promising and important research area. In other words, Image fusion is a process of combining multiple input images of the same scene into a single fused image, which preserves full content information and also retaining the important features from each of the original images. The fused image should have more useful information content compared to the individual image. As far as the knowledge of the author, none of the image fusion method has been reported which deals with multi focus and multimodal images simultaneously.

In the case of spinal disorder and spinal injury, MR images of the spine depict useful soft-tissue details including the spinal discs, nerves, cerebral spinal fluid, and spinal cord. CT images clearly represent the bony structures, especially the bone cortex, allowing the assessment of damaged joints.

Radiologists mostly prefer both MR and CT images side by side, when both images are available. This provides them all the available image information, but its accessibility is limited to visual correlation between the two images. Both CT and MR images can be employed as it is difficult to determine whether narrowing of a spinal canal is caused by a tissue or bone. Both the CT and MR modalities provide complementary information. In order to properly visualize the related bone and soft tissue structures, the images must be mentally aligned and fused together.

Image fusion is a tool to combine multimodal images by using image processing techniques. Image fusion leads to more accurate data and increased utility. In addition, it has been stated that fused data provides for robust operational performance such as increased confidence, reduced ambiguity, improved reliability and improved classification. Image fusion is a procedure that aims at the integration of disparate and complementary data to enhance the information present in the source images as well as to increase the reliability of the interpretation. This process leads to more accurate data interpretation and utility.

So in this paper we propose a novel image fusion algorithm for medical images based on Graph cuts which also overcomes the limitations of different approaches.

II. RELATED WORK

A novel CT/MR spine image fusion algorithm based on graph cuts has been proposed in [1]. In that algorithm,both soft tissue and bony detail can be assessed on a single fused image. They worked on the three terms: (a) squared error, which encourages the solution to be similar to the MR input, with a preference to strong MR edges; (b) squared error, which encourages the solution to be similar to the CT input, with a preference to strong CT edges and (c) a prior, which favors smooth solutions by encouraging neighboring pixels to have similar fused-image values. Their fusion algorithmwas evaluatedfor about 40 pairs of CT/MR images acquired from 20 patients, which demonstrate a very competitive performance in comparisons to the existing methods.

Shen et al. [2] proposed a medical image fusion algorithm employing cross-scale fusion rule for multi-scale decomposition based fusion of volumetric medical images. This method was designed for joint analysis of medical data from various imaging modalities and also for efficient color image fusion. An optimal set of coefficients from the multi-scale representations of the source image is effectively determined using neighborhood information. Experiment results show that the fusion method produces better results compared to other existing techniques.

Reference [3] presented a multi-region graph cut image partitioning via kernel mapping of the image data. The image data is transformed implicitly by a kernel function

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so that the piecewise constant model of the graph cut formulation becomes applicable. Their method gives an effective alternative for complex modeling of original image data while taking advantage of the computational benefits of graph cuts. A quantitative and comparative performance assessment was carried out over a large number of experiments using synthetic grey level data as well as natural images from the Berkeley database and their results were evaluated.

Reference [4] proposed an image fusion algorithm based on Wavelet Transform was proposed. It includes multi resolution analysis ability in Wavelet Transform. The method applies pixel-based algorithm for approximations involving fusion based on taking the maximum valued pixels from approximations of source images. Based on the maximum pixel values, a binary decision map is formulated. Then inverse wavelet transform is applied to reconstruct the resultant fused image and display the result. The wavelet sharpened images have a very good spectral quality.

In [5], a fusion algorithm based on atlas-based segmentation was proposed. The atlas-robust-fuzzy c-means approach combined prior anatomical knowledge by means of a rigidly registered probabilistic disc atlas with fuzzy clustering techniques incorporating smoothness constraints. Moreover, this approach could be exploited in computer-assisted spine surgery. The simulation results showed that the dice similarity indices of this method to be 91.6% for normal and 87.2% for degenerated discs.

Boykov et al. presented two algorithms based on graph cut method in [6] that efficiently finds a local minimum with respect to two types of large moves, namely expansion moves and swap moves. These moves simultaneously change the labels of arbitrarily large sets of pixels. This expansion algorithm finds a labeling within a known factor of the global minimum, while the swap algorithm handles more general energy functions. Experimental results showed that this method achieved 98% accuracy over real data with its corresponding ground truth images.

III. Proposed Fusion Algorithm

Fig. 1 shows the block diagram of the proposed fusion algorithm. It consists of a preprocessing block, wavelet decomposition block, Graph cut fusion, Inverse wavelet block and finally, fused image is obtained.

A. Pre-Processing of Images

Preprocessing is a process to remove the noises from the input images. It is also used to convert the heterogeneous image into homogeneous image. Anisotropic diffusion filter is used here for the purpose of preprocessing. MRI and CT images are prone to be affected by noise in digital imaging which can occur during image transmission and digitization. In the resultant image the neighboring pixels represent additional samples of the same value as the reference pixel, i.e. they represent the same feature. At edges, this is clearly not true, and blurring of features results. In this paper, we have used Anisotropic diffusion filtering to perform de-noising and image smoothing. Here, the neighboring pixels are ranked according to brightness (intensity) and the median value becomes the new value for the central pixel. Anisotropic diffusion filters can do an excellent job of rejecting certain types of noise, in particular, shot or impulse noise in which some individual pixels have extreme values.

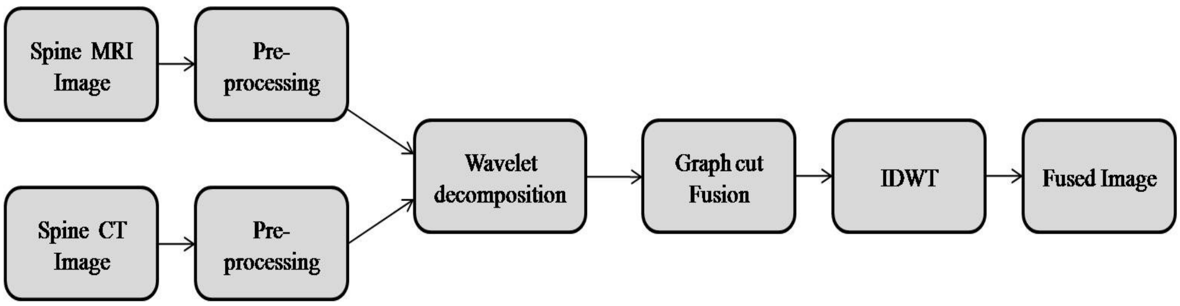

Fig. 1: Block diagram of proposed fusion methodology

B. Wavelet Decomposition

Image fusion using wavelet scheme decomposes the source images I_1 and I_2 into approximation and detailed coefficients at required level using DWT. The approximation and detailed coefficients of both images are combined using fusion rule. Based on the maximum valued pixels between the approximations, a binary decision map is generated gives the decision rule for fusion of approximation coefficients in the two source images I_1 and I_2.

C. Graph-Cut Fusion Algorithm

Multi Label Formulation.The proposed image fusion is stated as the following multilabel optimization problem:

$$\gamma^* = \min E(\gamma) \text{with} E(\gamma) = D_T(\gamma) + cS(\gamma) \quad (1)$$

where, $\gamma$is a labeling function by which each point in image domain φ is assigned to a label l, defining the intensity of fused image at that point.

$$\gamma : p \in \varphi \rightarrow \gamma(p) \in L \quad (2)$$

Ldenotes a closed finite set of integers. The Data term $D_T$is defined as,

$$D_T(\gamma) = \sum_{p \in \varphi} D_{Tp}\big(\gamma(p)\big)$$
$$= \sum_{l \in L} \quad \sum_{p \in R_l} [W_1(l - e_1(p))^2 + W_2(l - e_2(p))^2] \quad (3)$$

where, $e_1 : \varphi \to R$ and $e_2 : \varphi \to R$ represents the input images, and $R_l$is the label l region. W_1 and W_2 are weights defined as follows:

$$W_1 = \frac{|\nabla e_1| * K}{(|\nabla e_1| * K) + (|\nabla e_2| * K)} \text{and} W_2 = \frac{|\nabla e_2| * K}{(|\nabla e_1| * K) + (|\nabla e_2| * K)} \quad (4)$$

K denotes the kernel function. W_1 and W_2 determine the solution toward strong edges in e_1 and e_2, respectively.

S is the Smoothness term which provides smooth solutions by making the neighboring pixels to have similar fused-image values,

$$S(\gamma) = \sum_{(p,q) \in P} s(\gamma(p), \gamma(q)) \quad (5)$$

where, P is a set of all pairs of pixels p and q in a local neighborhood of p and $s(\gamma(p), \gamma(q))$ is defined as follows:

$$s(\gamma(p), \gamma(q)) = \min(c, |l_p - l_q|) \quad (6)$$

where$c$ is a positive constant.

Alpha-Blending Reformulation.The number of labels needed to express the output image must be equal to the number of all possible pixel values. This causes a high computational load in the case of images with large dynamic ranges, as is common in medical imaging. Therefore, in order to reduce the number of labels, the data term is reformulated as a transparency labeling,

$$e_\alpha = \alpha e_1 + (1 - \alpha) e_2 \quad (7)$$

where$e_\alpha$denotes the output fused image.

Based on (7), the data term in (3) is reformulated as follows:

$$D_T(\gamma) = \sum_{p \in \varphi} D_{Tp}(\gamma(p)) = \sum_{l \in L_\alpha} \sum_{p \in R_l} [W_1 (e_\alpha(p, l) - e_1(p))^2 + W_2 (e_\alpha(p, l) - e_2(p))^2] \quad (8)$$

where,

$$e_\alpha(p, l) = \frac{1}{N_l} e_1(p) + \left(1 - \frac{1}{N_l}\right) e_2(p); \quad l \in L_\alpha \quad (9)$$

with$L_\alpha$being a reduced set of non-negative integer labels $\{0, 1, 2, \ldots, N_l\}$, parameterized by the user specified number of labels N_l.

Graph-Cut Optimization.The problem in proposed method is similar to efficient graph-cut optimization [6]. Exactly one label is given to each pixel in the image, with associated data and smoothness costs assigned to the links in the graph. Let $G = \{V, E_w\}$ be a weighted graph, where, V contains a set of nodes for each pixel in φ and for each label in L. There is an edge $e_{\{p,q\}}$between each pair of nodes p, q. A cut $C \in E_w$is a set of edges separating the label nodes from each other. A cut $C$with the lowest cost is the minimum-cut problem. The cost of this minimum cut$|C|$ is equal to the sum of the edge weights of$C$. For effective computation of minimum-cost cuts, it is necessary to properly set the weights of the graph.

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 be 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 function.

D. *Inverse DWT*

The fused image I could beobtained by taking the inverse discrete wavelet transform (IDWT) as:

$$I = \frac{\mathrm{DWT}\{I_1\} + \mathrm{DWT}\{I_2\}}{2} \quad (10)$$

The fusion rule used here simply averages the approximation coefficients and picks thedetailed coefficient in each sub band with the largest magnitude.

Also, additional weights may be selected along with the DWT of the images. The fusedimage can be obtained by taking the inverse discrete wavelet transform (IDWT) as:

$$I = \frac{W_1 * DWT\{I_1\} + W_2 * DWT\{I_2\}}{W_1 + W_2} \quad (11)$$

IV. SIMULATION AND RESULTS

There are several different algorithms for image fusion. Recent spectral scanners can assemble several hundred of spectral bands which can be both visualized and processed individually, or which can be fused into a single image, depending on the image analysis task. In this section, the input images are fused using Graph cut approach. Fig. 2 illustrates the CT and MRI images and their corresponding fused images using our proposed fusion method.

A. *Mean Square Error*

The mean square error (MSE) measures the amount of change per pixel due to processing. The MSE between a reference image R and the fused image I is given by,

$$\mathrm{MSE} = \frac{1}{mn} \sum_0^{m-1} \sum_0^{n-1} \|R(i,j) - I(i,j)\|^2 \quad (12)$$

where 'm' represents width of the fused image and 'n' represents height of the fused image.

B. *Peak Signal to Noise Ratio*

Peak signal to noise ratio (PSNR) can be calculated by using the formula,

$$\mathrm{PSNR} = 20 \log_{10} \frac{\mathrm{MAX}_f}{\sqrt{\mathrm{MSE}}} \quad (13)$$

where *MSE* denotes the mean square error and MAX_frefers to the number of gray levels in the image.

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Fig. 2: Simulation results of fusion technique. (a)-(c) CT images of spine, (d)-(f) MR images of spine, and (g)-(i) Final fused images of spine

The performance of proposed fusion method has been evaluated and the parameters explained above (PSNR and MSE) have been evaluated and tabulated in Table I. The PSNR and MSE values are evaluated for certain sets of images as below.

Table I: Performance evaluation of proposed fusion method

Image Set	PSNR	MSE
Image Set1	60.35	62.45
Image Set2	62.39	49.37
Image Set3	64.63	38.15
Average	62.45	49.99

Table II and Table III shows the comparison of proposed technique with other existing methodologies in terms of PSNR, MSE and latency.

Table II: Performance comparison of proposed method in terms of PSNR and MSE

Methodology	PSNR	MSE
Proposed work	62.45	49.99
Srinivasa*et al*. (2012) [15]	24.6348	-
Srinivasa*et al*. (2012) [16]	13.7226	52.5301
Li *et al*. (2012) [11]	29.54	32.56
Rabbani *et al*. (2009) [14]	22.16	37.19

Table III: Performance comparison of proposed method in terms of latency

Methodology	Processing Time (s)
Proposed work	0.49
Michopoulou*et al*. (2009) [5]	0.6

The graphical plot of performance comparisons are illustrated in Fig. 3and Fig. 4.

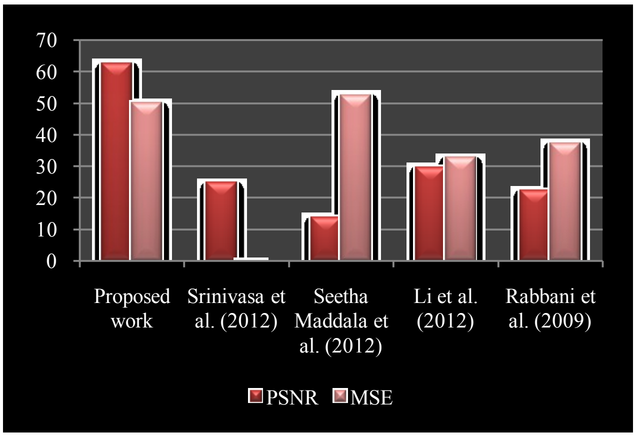

Fig. 3: Graphical illustration of performance comparison in terms of PSNR and MSE

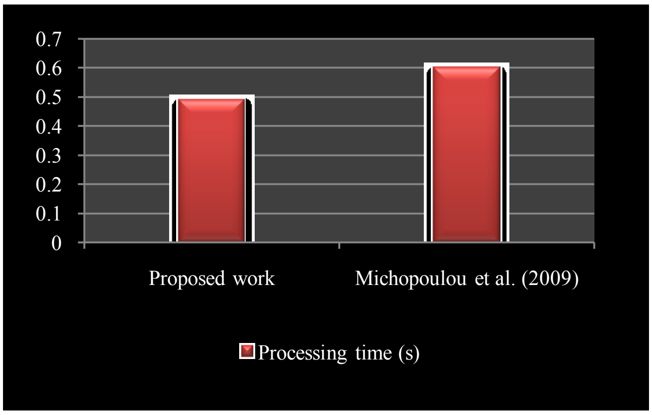

Fig. 4: Graphical illustration of performance comparison in terms of latency

V. Conclusion

Medical image fusion combines different modality of medical images to produce a high quality fused image with spatial and spectral information. The fused image with more information improved the performance of image analysis algorithms used in different medical diagnosis applications. In this paper, the multi modal graph cut technique based on discrete wavelet transform is used to fuse the spine MRI and CT images, in order to diagnose the disorders in spine images. The proposed method in this paper has achieved PSNR 62.45 and fusion latency of 0.49sec.Future work also includes the iterative combination of fuzzy logic and iterative neuro fuzzy logic to fuse the medical images.

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