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A New Approach to Efficient Medical Image Fusion

Urba Ziyauddin Siddiqui [1], P.R Thorat[2]

PG Student, EC Department, Savitribai Phule Women's Engineering College, Aurangabad, Maharashtra, India [1]

Professor, EC Department, Savitribai Phule Women's Engineering College, Aurangabad, Maharashtra, India [2]

Abstract: Image fusion is a process of blending the complementary as well as the common features of a set of images, to generate a resultant image with superior information content in terms of subjective as well as objective analysis point of view. The ultimate aim of medical image fusion can be broadly defined as the combination of visual information contained in any number of input medical images into a single fused image without introducing distortion or information loss. This paper gives a the most efficient method to serve the fusion purpose. The objective of this proposed method is to develop a novel image fusion algorithm and its applications in biomedical field such as in image-guided surgery and radiotherapy with efficient and true diagnosis.

Keywords: Computerized tomography Scan(CT), Magnetic resonance imaging(MRI), Positron emission tomography(PET), Discrete wavelet(DWT), Stationary wavelet(SWT), Dual-tree complex wavelet(DTCWT), Contourlet (CT), Principal Component Analyses(PCA), Pulse coupled neural network(PCNN), Nonsubsampled Contourlet (NSCT), Shearlet transform(SHLT).

I. INTRODUCTION

Multi-modal medical image fusion has emerged as a promising new research area in recent years. Using medical images from multiple modalities increases robustness and enhances accuracy in biomedical research and clinical diagnosis. However, the greater number of sources of medical images used in clinics leads to the problem of information overload. In the past two decades, research attention has focused on techniques for incorporating the overwhelming amount of medical data from different acquisition methods without cancelling out the benefits of additional information. The ultimate aim of medical image fusion can be broadly defined as the combination of visual information contained in any number of input medical images into a single fused image without introducing distortion or information loss. In practice, this is almost impossible, so the next best option of faithfully incorporating the most important information from the input is generally accepted as a suitable target. Thus far, considerable progress on medical image fusion techniques has been made, and various fusion algorithms have been developed. Medical image fusion can be performed at three broad levels: pixel level, feature level, and decision level [1].

A multi-modal imaging system is a medical imaging system that combines optical, radioactive and magnetic properties. This method of imaging is composed of positron emission topography, optical fluorescence and bioluminescence as well as magnetic resonance spectroscopy and single photon emission topography. Basically, multimodal imaging combines elements of MRI and PET scans as well as imaging tests with radioactive elements that illuminate imagery inside the body. Using different methods to study human tissue at the same time allows doctors to see multiple aspects of the same area. The goal of multi-modal imaging is to provide a complete picture of a specific tissue in the human body. The image should allow doctors to see anything present in that specific tissue: its size, its exact location and its metabolic activity. It should also allow doctors to analyse the metabolic activity of surrounding tissues. Thus, doctors can evaluate any abnormalities or changes in the function of those tissues as a result of a condition or a tumour or any other medical complication [2].

The fusion of data for medical imaging has become a central issue in such biomedical applications as image-guided surgery and radiotherapy. The multi-level local extrema (MLE) representation has been shown to have many advantages over conventional image representation methods. We propose a new fusion algorithm for multi-modal medical images based on MLE. Our method enables the decomposition of input images into coarse and detailed layers in the MLE schema, and utilizes local energy and contrast fusion rules for coefficient selection in the different layers. This preserves more detail in the source images and further improves the quality of the fused image. The final fused image is obtained from the superposition of selected coefficients in the coarse and detailed layers. We illustrate the performance of the proposed method using three groups of medical images from different sources as our experimental subjects.We also compare our method with other techniques using cumulative mutual information, the objective image fusion performance measure, spatial frequency, and a blind quality index. This method shows that it achieves a superior performance in both subjective and objective assessment criteria [3].

II. NECESSITY

This method helps to study human tissue at the same time allows doctors to see multiple aspects of the same area.

The goal of multi-modal imaging is to provide a complete picture of a specific tissue in the human body. The image should allow doctors to see anything present in that specific tissue: its size, its exact location and its metabolic activity. It should also allow doctors to analyze the metabolic activity of surrounding tissues. Thus, doctors can evaluate any abnormalities or changes in the function of those tissues as a result of a condition or a tumor or any other medical complication [3]. This can be used to analyze cancers and metastases of cancers around the human body, especially a type of brain cancer known as a glioma. These multi-modal scans are also used to analyze brain functions both in seemingly healthy individuals and in individuals who have suffered strokes.

Multi-modal imaging techniques allow scientists to view high-definition images of the virus starting from the point of infection and continuing through the process through which the virus uses a human body to replicate itself and destroy immune cells. Doctors can be hopeful that multi-modal imaging may detect disease in human tissue before it develops too far. Detecting cancer by this method, they hope, will be possible through the study of just a small number of abnormal cells, rather than the millions required by other methods. As this mode of imaging is also used to study neural function, it could theoretically be used to detect the earliest stages of Alzheimer's Disease as well[3].

III. LITERATURE SURVEY

A. Introduction

Image Fusion is used extensively in image processing systems. Various Image Fusion methods have been proposed in the literature to reduce blurring effects. Many of these methods are based on the post-processing idea. In other words, Image fusion enhances the quality of image by removing the noise and the blurriness of the image. Image fusion takes place at three different levels i.e. pixel, feature and decision. Its methods can be broadly classified into two that is special domain fusion and transform domain fusion. Averaging, Brovery method, Principal Component Analysis
(PCA), based methods are special domain methods. But special domain methods produce special distortion in the fused image .This problem can be solved by transform domain approach. The multi-resolution analysis has become a very useful tool for analyzing images. A brief summary of the literature is given below

B. History

Li, H et al. (1995) [6] has discussed the wavelet transform of the input images are appropriately combined, and the new image is obtained by taking the inverse wavelet transform of the fused wavelet coefficients. An area-based maximum selection rule and a consistency verification step are used for feature selection. A performance measure using specially generated test images is also suggested.

Y-T, K et al. (1997) [10] has discussed the Histogram equalization is widely used for contrast enhancement in a variety of applications due to its simple function and effectiveness. Examples include medical image processing and radar signal processing. One drawback of the histogram equalization can be found on the fact that the brightness of an image can be changed after the histogram equalization,

He, D et al. (2004) [5] explained that the The main objective of image fusion is to create a new image regrouping the complementary information of the original images. He present h a new and original method of fusion, capable of (1) Combining a high resolution image with a low resolution image with or without any spectral relationship existing between these two images; (2) Preserving the spectral aspect of the low resolution image while integrating the spatial information of the high resolution image. Compared to existing technologies reported in the literature the new proposed method is an innovative and unique technique in its own right.

We Qiang Wang et al. (2004) [5] has discussed that the Image fusion is becoming one of the hottest technique in image processing. Authors explained the typical hyper spectral image data set is fused using the same wavelet transform based image fusion technique, but applying differ-rent fusion structures. The differences among their fused images are analyzed.

Pei, Y et al. (2010) [10] explained an improved discrete wavelet framework based image fusion algorithm, after studying the principles and characteristics of the discrete wavelet framework. The improvement is the careful consideration of the high frequency subband image region characteristic.

Mohamed, M et al. (2011) [7] has define the Image fusion is a process which combines the data from two or more source images from the same scene to generate one single image containing more precise details of the scene than any of the source images. Among many image fusion methods like averaging, principle component analysis and various types of Pyramid Transforms, Discrete cosine transform, Discrete Wavelet Transform special frequency and ANN and they are the most common approaches. He Implement the technique by using Field Programmable Gate Arrays (FPGA). FPGA.

Patil, U et al. (2011) [9] has focused on image fusion algorithm using hierarchical PCA. Authors described that the Image fusion is a process of combining two or more images (which are registered) of the same scene to get the more informative image. Principal component analysis (PCA) is a well-known scheme for feature extraction and dimension reduction and is used for image fusion.

Aribi, W et al. (2012) [4] explained that the quality of the medical image can be evaluated by several subjective techniques. However, the objective technical assessments of the quality of medical imaging have been recently proposed. The fusion of information from different imaging modalities allows a more accurate analysis.

Prakash, C et al. (2012) [10] explained that the Image fusion is basically a process where multiple images (more than one) are combined to form a single resultant fused image. Firstly two registered are taken as input. Then the fusion techniques are applied onto the input images and

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Redundancy Discrete Wavelet Transform (RDWT) and the resultant fused image is analyzed with quantitative metrics namely Over all Cross Entropy(OCE),Peak Signal –to- Noise Ratio (PSNR), Signal to Noise Ratio(SNR),

Sruthy, S et al. (2013) [4] has discussed that the Image Fusion is the process of combining information of two or more images into a single image which can retain all important features of the all original images. Here the input to fusion involves set of images taken from different modalities of the same scene. Output is a better quality image; which depends on a particular application. The objective of fusion is to generate an image which describes a scene better or even higher than any single image with respect to some relevant properties providing an informative image. These fusion techniques are important in diagnosing and treating cancer in medical fields. This paper focuses on the development of an image fusion method using Dual Tree Complex Wavelet Transform. The results show the proposed algorithm has a better visual quality than the base methods. Also the quality of the fused image has been evaluated using a set of quality metrics.

IV. IMAGE FUSION

A. Introduction

Image fusion is a process of combining two or more images into an image. It can extract features from source images, and provide more information than one image can . In other words, image fusion is a technique to integrate information from multiple images. These images may come from one sensor or multiple sensors . Image fusion provides a useful tool to integrate multiple images into a composite image that is more suitable for the purposes of human visual perception and can help us to extract more features. The aim of image fusion is to integrate complementary and redundant information from multiple images to create a composite image that contains a better description of the scene. By integrating information, image fusion can reduce dimensionality [6] .

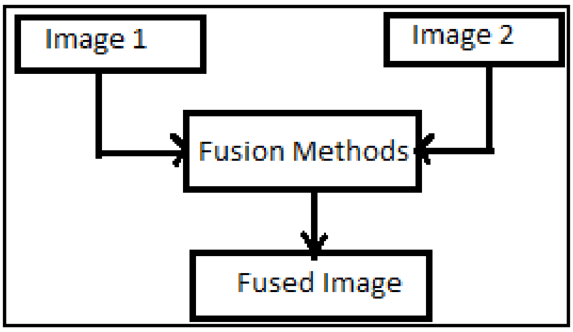

Fig.1. Image Fusion Process

In Medical application MRI-PET medical image fusion has important clinical significance. Medical image fusion is the important step after registration, which is an integrative display method of two images. The PET image shows the brain function with a low spatial resolution, MRI image shows the brain tissue anatomy and contains no functional information. Hence, a perfect fused image should contains both functional information and more spatial characteristics with no spatial & color distortion.

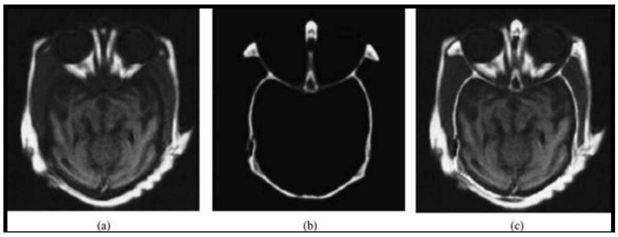

Fig.2.An example of image fusion in medical imaging.(a) MRI image;(b)CT image;(c)the fused image from(a)and (b)

When using the image fusion technique, some general requirements must be considered: The fusion algorithm should not discard any information contained in the source images. The fusion algorithm should not introduce any artifacts or inconsistencies that can distract or mislead a human observer or any subsequent image processing steps. The fusion algorithm must be reliable, robust and have, as much as possible, the capability to tolerate imperfections such as noise or misregistrations. The simplest method of fusing images is accomplished by computing their average generally. Through averaging, features from each source image are presented in the fused image; however, the contrast of the original features may be significantly reduced, especially for the details [6].

B. Block Diagram

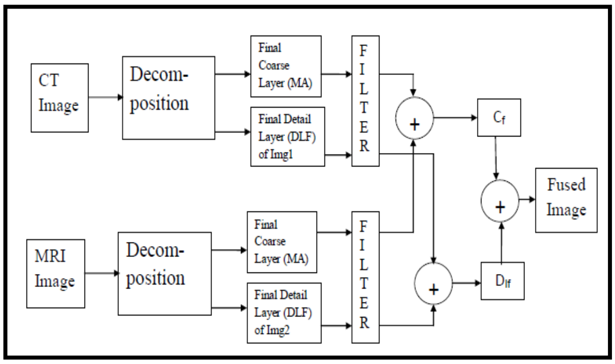

Fig3. Block Diagram of the proposed System

The above block diagrams consist of the input as multimodal images. We decompose an image into multi-layers of the same size as the original. We decompose an image into coarse and detailed layers. The proposed method utilizes the detailed layer, which reflects the regional pattern and edge information of the image, to guide the fusion process. This method uses a fast decomposition method. It is done with the help of an average filter. Pixel saliency and spatial consistency are joined together by using a weight construction method. Proposed system does not depend on optimization methods. It uses a guided filtering technique. Guide filter is a type of edge preserving filter which won't produce ringing artifacts. Also the computing time of guided filter is very less Guides filtering are also applied in this stage. The output of this stage is processed during reconstruction

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of images in the final stage. An average filter is used there to average the number of pixels in the source images. Then Fusion of Base and Detail layers are performed using guided filtering technique.

C. Working Principle

We propose a new fusion algorithm for multi-modal medical images based on MLE. Our method enables the decomposition of input images into coarse and detailed layers in the MLE schema, and utilizes local energy and contrast fusion rules for coefficient selection in the different layers. This preserves more detail in the source images and further improves the quality of the fused image. The final fused image is obtained from the superposition of selected coefficients in the coarse and detailed layers our proposed fusion method makes three contributions:

1. We propose a simple and effective image decomposition schema that separates one image into a series of coarse and detailed layers.
2. We develop a mesh-free approximation method to form the envelope of local extremes, which is shift-invariant.
3. We present the Blind Structural Similarity (BSSIM), a new image fusion quality metric that does not rely on a reference image [6].

D. Flowchart

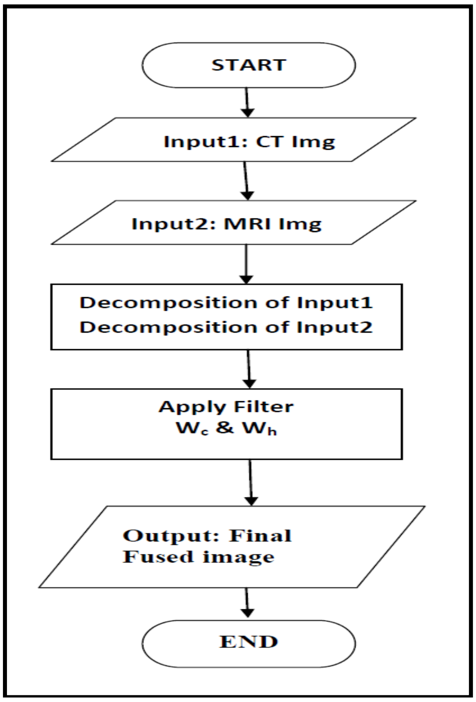

Fig.4. Flowchart of the Proposed System

The flowchart of the image fusion technique using multilevel local extrema is given as follows. The flow consists of several steps like acquisition of input images then dcomposition of images into detail and coarse layer. The reason for decomposing an image into coarse and detailed layers is to separate the texture and local edge information from the image. By averaging the local minima and maxima envelopes, we are likely to get very similar results to the convolution of the image with a Gaussian function. However, when the image itself is subtracted from the convolutional version, the residual image cannot capture all the texture information, which is still in the convolutional version of the image. Our decomposition schema can successfully separate texture from the original image. Guided filtering method is also applied known as edge preserving filtering. While using other kinds of filters the edges of output image looks blurred which will affect the quality. Guided filters are known for their edge preserving qualities. Guided filter takes less time to process an image. In most of the filters selection of filter size directly affects the processing time. So more the filter size more will be the time to produce fusion. Guided filtering can be used for both color and colorless images. In color images there will be red, green, and blue channels. In order to create fusion of color images these three channels must be filtered separately .The final fused image is the combination of the final coarse and detailed layers. In the fusion of medical images, a good result should preserve all the salient features from multi-modal images and introduce as few artifacts or inconsistencies as possible. The detailed layers generated from multi-level window sizes w can reveal the local properties of images better than existing image representation methods. Based on these attributes, it is natural to use this method to fuse medical images from different sources. We propose a novel medical image fusion algorithm that combines different levels of coarse and detailed layers from multi-source images using new fusion rules.

E. Algorithm

Input: Acquisition of medical images from two different equipments from CT scan and 2 from MRI scan

Output: Final Fused Image with more information than a single image

```
/* Acquisition of medical images from database
Get the CT image
Get the MRI image
Decompose both the images with decomposition   level=3
Apply filter Wc and Wh to coarse and detailed layers
respectively.
if EA>EB
        CF = MLA;
    Else if EA == EB
        CF = 0.5*(MLA+MLB);
    else
        CF=MLB;
 end
Cf is the final coarsed layer
 if SLA > SLB
        DF = DLA;
        Else if SLA == SLB
        DF = 0.5.*(DLA+DLB);
        else
        DF = DLB;
end
```

Df is the final detailed layer Combining the coarse and detail layers the final fused image is obtained

Display the final Fused Image i.e F = CF + DF

This creates a fused image that contains more information than a single source image, and is more suitable for human visual perception and object detection in clinical applications.

V. JUSTIFICATION

The evaluation standards are the mutual information between image A and fused image F, the mutual information between image B and fused image the cumulative mutual information, the objective image fusion performance measure the spatial frequency, and the proposed BSSIM. SF can be used to measure the overall clarity level of an image, where a larger SF value implies a better fusion result.

TABLE I EVALUATION OF RESULTS OF IMAGE FUSION USING DIFFERENT TECHNIQUES

Method	$MI_{AB,F}$	$Q_{AB,F}$	SF	BSSIM	NIQE
CP	3.4603	0.2961	12.9609	0.9929	30.1237
DWT	3.8704	0.7537	11.1020	0.9976	22.2551
GP	3.8859	0.7763	11.3601	0.9976	21.6689
SDW	3.8820	0.7918	11.6428	0.9975	24.7500
PCNN	3.9616	0.7974	9.6093	0.9969	23.3457
NSCT	3.7953	0.7136	14.4690	0.9934	25.0960
SHLT	3.7442	0.7461	9.9965	0.9954	23.3093
OUR	**3.9859**	**0.8695**	**16.1485**	**0.9987**	**21.3293**

In the practice of medical image fusion, the ideal reference fused image is very difficult to obtain. We propose a new fusion quality metric called BSSIM that does not require the reference image. The similarity between two images can be measured by the structural similarity (SSIM) index Natural Image Quality Evaluator (NIQE) evaluates image quality without knowledge of distortions or human opinions in advance. The higher the NIQE score, the lower the image quality. By definition, the best medical image fusion result should have the largest values of $MI_{AB;F}$; $Q_{AB;F}$, SF, and BSSIM and the smallest value of NIQE. From Table 1, we can see that the proposed method is dominant in terms of these indicators we can try to come up with the stated evaluation using this proposed method during implementation.

VI. APPLICATIONS

The fusion of data for medical imaging has become a central issue in such biomedical applications as image-guided surgery and radiotherapy and used to study human tissue at the same time allows doctors to see multiple aspects of the same area.

Multi-modal PET scans and MRIs are used to analyze cancers and metastases of cancers around the human body, especially a type of brain cancer known as a glioma. These multi-modal scans are also used to analyze brain functions both in seemingly healthy individuals and in individuals who have suffered strokes.

Multi-modal imaging techniques allow scientists to view high-definition images of the virus starting from the point of infection and continuing through the process through which the virus uses a human body to replicate itself and destroy immune cells. Doctors are hopeful that multi-modal imaging may detect disease in human tissue before it develops too far. Detecting cancer by this method, they hope, will be possible through the study of just a small number of abnormal cells, rather than the millions required by other methods. As this mode of imaging is also used to study neural function, it could theoretically be used to detect the earliest stages of Alzheimer's disease as well

VII. CONCLUSION

Multi-modal medical image fusion plays an important role in clinical applications, but current reference methods fail to meet the full range of requirements. Therefore, we proposed an MLE method for the purpose of medical image fusion. We used three groups of medical images to test the performance of the proposed schema against other methods. To estimate the performance of various methods, we used a range of measures, including BSSIM, a novel fusion quality evaluation metric that can be used in the case where no reference fused image exists. The experimental results showed that our proposed method outperformed the other methods. As our method is also efficient, we believe it is very suitable for medical image fusion. The proposed method assumes that input images were noise-free. Noise in the input image will affect the detailed layer, and so in future research, we will work to detect and reduce the effects of noise on the detailed layer, and develop a more robust medial image fusion schemes.

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