

Medical Image Fusion based on Non-subsampled Contourlet Transform

Diksha Patel¹, Dr. Uday Panwar²

Electronics & Communication, Sagar Institute of Research & Technology Bhopal [MP], India

Dikshapatel1814@gmail.com¹

Abstract: Image processing plays a prominent role in various medical applications like image guided surgery, study of disease progression, medical diagnostics and radiotherapy. The extraction of clinically useful and significant information from medical images is very crucial in all these applications. The medical images provide unique information about the organs inside the body. However, the information derived from a single modality medical image is limited and hardly meets the requirements of an accurate clinical diagnosis. To address this, multimodal medical image fusion emerged as a promising solution to provide information about an organ from different perspectives. This research work proposes an improved fusion technique for medical images using Non-subsampled Contourlet Transform (NSCT) and Neural Network (NN). The proposed approach is based on two processes, namely, image enhancement and image fusion to obtain more information on the fused image. Experimental results show that the application of proposed fusion has higher Peak Signal to Noise Ratio (PSNR) values with good visual perception. Comparing with other fusion methods, the proposed method has higher average gradient lower discrepancy and less Mean Square Error (MSE). Therefore the method proposed exhibits better image quality and proved to be advantageous.

Keywords: PSNR, NSCT, MSE, NN.

1. INTRODUCTION

The requirement of image fusion for medical imaging is increased significantly because of limitations of cameras, lack of transparency, eminence and inappropriate image capturing [1]. This thesis is focused to improve the features of these kinds of captured medical images by designing an efficient new image fusion method. Medical image fusion methods are needed for improving clinical diagnosis [2]. Medical images are classified as low resolution and high resolution or classified according to physical process and sensor device. It is also used to produce multimodality image like Magnetic Resonance Images (MRI) and Computed Tomography (CT) images of the brain. MRI provides more useful information of soft tissue for human body whereas CT provides more useful information for hard tissue. Positron Emission Tomography (PET) contains functional information and produces low resolution images. Single Photon Emission

Computed Tomography (SPECT) provides visceral metabolism and blood circulation images [3].

Medical Image Fusion techniques are applied on these images to produce more information for clinical diagnosis of diseases [4]. An Example of the multi-modal images is given in the Fig 1.

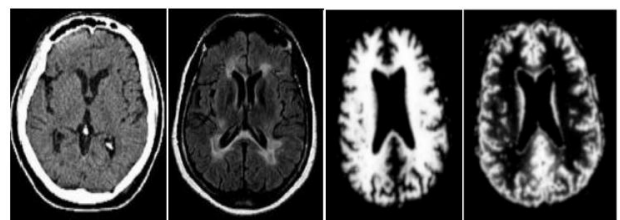


Figure 1: Multi-modal Images Examples

Medical image fusion was developed on the basis of information fusion and image fusion. It is a process of

combining a set of images of the same scene into one composite image without any artifacts or noise. The goal of this technique is to merge desired and required information from several images to generate a new fused image as final fused output image. This final fused output image should restrain more precise information of the scene than any of the other image. These images should be more suitable for human visual and machine perception [5]. Image fusion process extracts all the useful information to minimize redundancy & reduce uncertainty from the source images.

Magnetic resonance imaging (MRI):- In 1977, for diagnosing cancer, Dr. Raymond Damadian, made the MRI imaging modality available for the medical community. For recording the images a strong field of magnetism is employed absorbing this, discrete patterns are emitted by different human organisms. It is worth noting that there is no ionizing radiation.



Figure 2: MRI imaging scanner

The time length of the procedure and the noisy equipment sound are the concerns with MRI scan. In additions there is a practical difficulty of staying without any physical movement. An illustration with possible MRI is provided in Fig. 2.

2. IMAGE FUSION

Following are few general requirements of image fusion:- The fusion procedure must not reject any information available in the source images. The fusion techniques should not have any noise which may mislead a human and machine vision processing steps. The fusion method should be clear, transparent, reliable, strong, have as much as desired information and the ability to abide imperfections such as artifacts [6]. Medical image fusion is the technique to develop the image content by fusing images taken from

different machines like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT).

Form last so many years research are going on different method of biomedical image fusion as it plays an important role in clinical applications and provide accurate information to diagnose diseases .The medical images are taken from different sensors at different time and at different view point .Before the images to be fused it should be properly aligned and should have equal size which can be achieved from image registration techniques. Multimodal medical images provide complementary information like the structural image with higher spatial resolution provides more anatomy information while the functional image contains functional information of tissues. So when they are fused better image with greater accuracy is resulted Ex: CT scan of brain contains bony information while PET or MRI scan provides the soft tissue information. Thus resulted fused image contains both the information, the quality metric of several approaches such as pixel-based fusion, Laplacian Pyramid based fusion, and DWT based fusion. After fusion to properly analyze, segmentation algorithm is adopted to separate out the affected area. Usually bio-medical images like CT, MRI, and PET are used to diagnose brain tumor and cancer. This scheme can also be applied to any fracture in bones, ulcer and stones in the body [7, 8].

An important research issue in medical image processing, specifically in information computation, is fusion of multimodal information. Medical images from different modalities often provide complementary information. Several diagnostic cases require integration of complementary information for better analysis. Fusion of multimodal medical images can provide a single composite image that is dependable for improved analysis and diagnosis.

3. PROPOSED METHODOLOGY

Medical images are widely being used for identification and analysis of human body parts. Diagnosis and treatment of illness want that specific facts to be acquire from different modalities. Generally these methods are used to acquire hidden information about the injurious or corrupted internal body parts. An image fusion method plays an important role to extract further useful information from scanned images. In this paper it is suggested to improve the contrast before fusing the images. This enhances the features quality of the medical images. Fusing the contrast enhanced images improves the information content by the images as shown in the Fig 3.

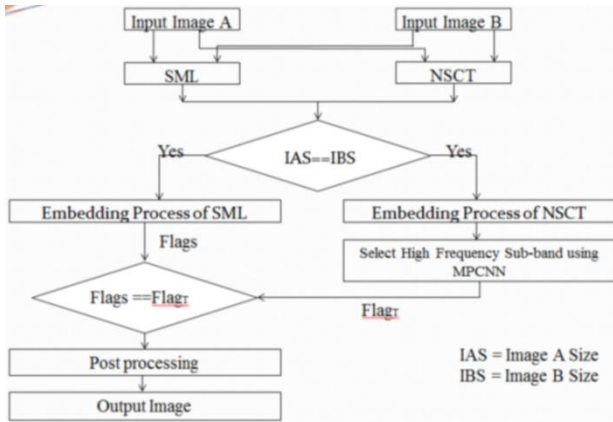


Figure 3: flow Chart of Proposed Methodology

Image fusion is a method of combining the features of two images (medical) to produce a single fused image, fused image have better features as shown in Fig 3. It is strictly required to avoid any lose of information after the fusion process, this makes the fusion task tedious and entropy analysis becomes essential. In case of medical images the features are captured from multi sensors modalities, therefore medical image fusion has become a great choice for researcher to work.

Neural Network (NN):-

Artificial neural networks (ANN) [4] have been motivated by the biological neural system comprising of a number of interconnected neurons. The input data, which can be a multidimensional vector, is fed to an input layer that is further joined to a series of hidden layers. Basing upon the information received from previous layers, these hidden layers create activations that encode information about vital features contained in the input data and formulate decisions. The network undergoes the process of learning that is enabled by varying the strength of weighted connections (or weights) between neurons in the diverse layers. An ANN with one hidden layer can be observed in the fig. 4.

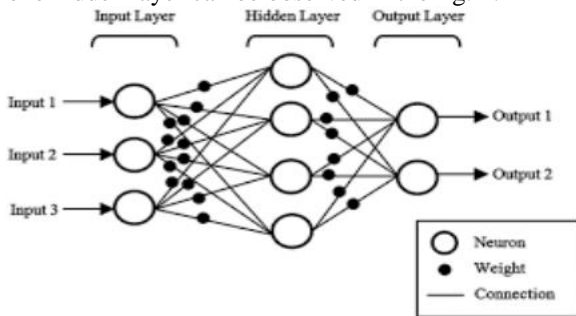


Figure 4: Neural Network

Supervised Learning: In supervised learning [5, 6], the network is fed with the input data along with the ground truth labels while the desired output is available to progress the learning process by performing weight updating in the network. During training, the final classification error is reduced based on these ground truth labels. Examples of supervised learning consist of regression and classification tasks.

Unsupervised Learning: The training process in unsupervised learning does not consist of any ground truth labels. The neural network enhances by minimizing or increasing the cost function connected with the learning process. An example of unsupervised learning is clustering which divides the whole dataset into dissimilar groups according to some unfamiliar pattern. Another example is self-organizing maps characteristically used for dimensionality reduction [7].

Semi-supervised Learning: Semi-supervised learning make use of huge amount of unlabeled data collectively with little amount of labeled data for training a network. Lately, such an arrangement of supervised and unsupervised learning was planned for deep neural networks, well-known as the Ladder Networks trained to concurrently diminish the amount of supervised and unsupervised loss functions [8]

4. SIMULATION RESULT

This section presents some of experimental results generated by fusion based method for multi-modal sample medical images using NSCT and NN fusion. This method is tested on the wide input medical images database of the multi modal images taken from different body parts through different scanning techniques Viz. CT scan, MRI etc. as shown in Fig. 5. The method uses variety of medical images from inner parts of body and also been tested open the images restored from different papers. This method is an hybrid combination of DC coefficient scaling enhancement and the wavelet based Gradient fusion for improving the information content of the multi modal images and to enhance the their visual quality.

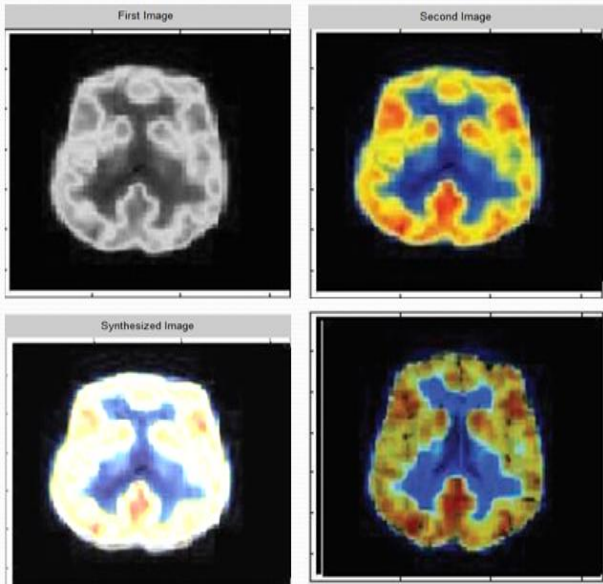


Figure 5: Fused image of MRI and PET normal Image

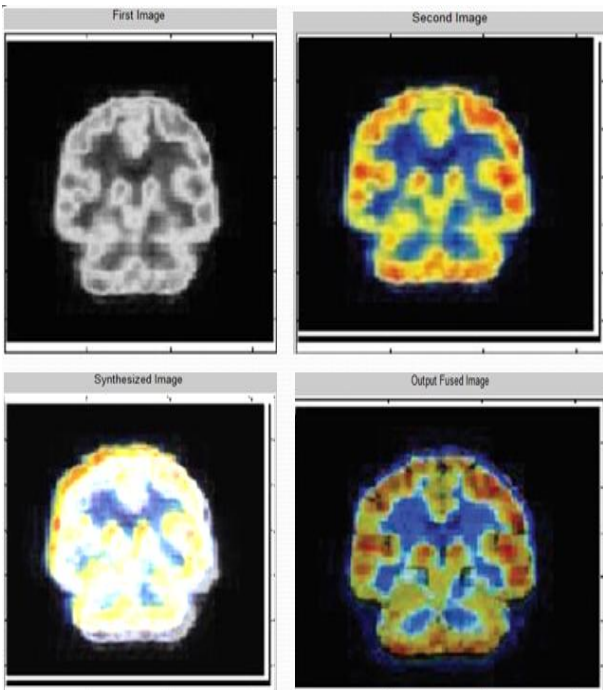


Figure 6: Fused image of MRI and PET normal Coronal images

Table 1: Performance Measure Based on Mean Square Error of the Output Fused Image

Method	Database-I	Database-II	Database-III	Average
DWT	0.0190	0.0183	0.0192	0.01883
CT	0.0213	0.0198	0.0212	0.0207
Hybrid	0.0072	0.0171	0.0047	0.00963

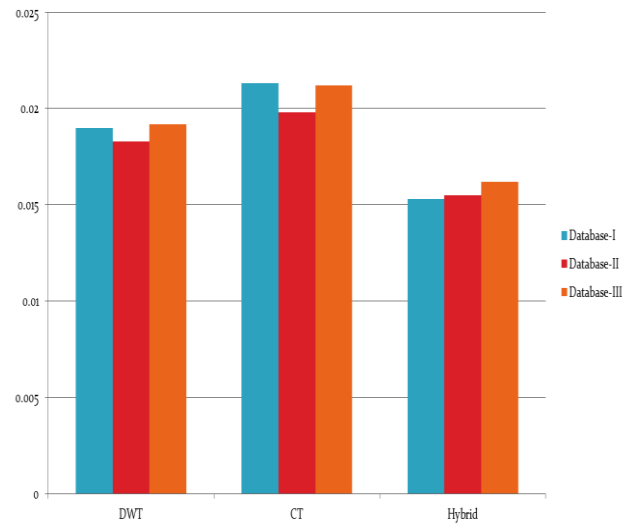


Figure 7: Bar Graph of the MSE for different technique

Table 2: Performance Measure Based on Peak Signal to Noise Ratio of The Output Fused Image

S. No.	Method	Database-I	Database-II	Database-III	Average
1	DWT	64.783 dB	63.983 dB	74.993 dB	67.919
2	CT	73.662 dB	68.962 dB	82.602 dB	75.075
3.	Hybrid	82.442 dB	73.859 dB	90.075 dB	82.125
					75.039

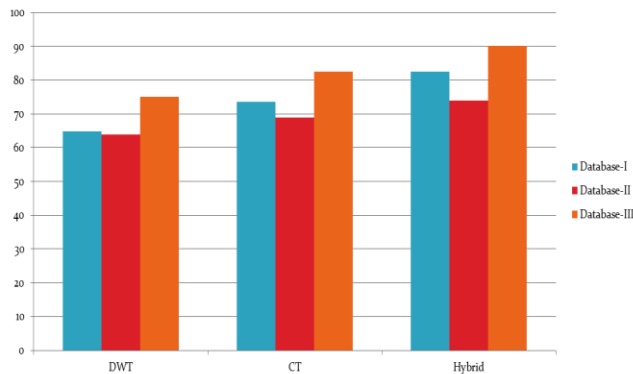


Figure 8: Bar Graph of the PSNR for different technique

5. CONCLUSION

Current research has developed to implement an adaptive multi modal medical image fusion method which merges the images using NSCT and NN then improves entropy further using the pixel level fusion rules to improve the quality of fused image. This fusion method is primarily based on discrete wavelet transform (DWT) decomposition method. This wavelet decomposition is used due to their multi-resolution characteristic. In this method captured multimodal images are first enhanced by using the standard DC coefficient scaling method in LAB Colour space. Images are decomposed into LL, LH, HL and HH sub-images by using DWT. Then NSCT and NN based fusion rules are used to fuse the coefficients of the LL sub-image of the sub band images of the both original images. It is found from performance comparison that this research not only performs better in case of PSNR and MSE but also gives approximate constant index. This method also performs better in terms of the PSNR and for most of images Pixel level maxima gives the more entropy.

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