Multimodal Medical Image Sensor Fusion And Segmentation Non-Subsampled Contourlet Transform Domains And Clustering

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Abstract: Multimodality medical image fusion is being done to reduce the redundancy by augmenting the essential information from the input images acquired using different medical imaging sensors. The main aim is to yield a single fused image, which might be more informative for an efficient clinical analysis. This paper describes about the multimodal image fusion framework using the non-sub sampled contourlet transform (NSCT) domain for the images acquired using two distinct medical imaging modalities (i.e., Magnetic resonance imaging and computed tomography scan). The major advantage of using NSCT is to improve upon the shift variance, directionality, and phase information in the finally fused image. The first stage employs a NSCT domain for fusion and then second stage is segmenting tumour part by applying fuzzy c-means clustering if the fused image is abnormal. A quantitative analysis of fused images is carried out using dedicated fusion metrics. The fusion responses of the proposed approach are also compared with other state-of-the-art fusion approaches; depicting the superiority of the obtained fusion results.

Keywords—Image fusion, non-sampled countourlet transform, medical imaging, fusion rule

I. INTRODUCTION

The image fusion is the process of combining two or more images to form a single fused image which can provide more consistent and accurate information [1]. It is useful for human visual and machine perception or further analysis and image processing tasks. The image fusion plays an important part in medical imaging, machine vision, remote sensing, microscopic imaging and military applications. Over the last few decades, medical imaging plays an important part in a large number of healthcare applications including diagnosis, treatment, etc. The main objective of multimodal medical image fusion is to capture the most interrelated information from input images into a single output image which is useful in clinical applications.

The different modalities of medical images contain complementary information of human organs and tissues which help the physicians to diagnose the diseases. The multimodality medical images such as Computed Tomography (CT), Magnetic Resonance Angiography (MRA), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), USG, Single-Photon Emission Computed Tomography (SPECT) images, X-rays, etc. can provide limited information. These multimodality medical images cannot provide complete and accurate information [2]. For example, MRI, CT, USG, MRA images are the structural medical images which offer high resolution images with anatomical information, while PET, SPECT and functional MRI (fMRI) images are functional medical images which provide low-spatial resolution images with functional information. Hence, anatomical and functional medical images can be combined to obtain more useful information about the same object. It helps in diagnosing diseases exactly and reduces storage cost by storing the single fused image instead of multiple-input images. The efficiency of this method is carried out by fusion experiments on different multimodality medical image pairs.

In this paper, the CT and MRI images of brain are fused together using NSCT. Then the features are extracted from the fused image. It is then classified and the tumour part is segmented by means of fuzzy c-means clustering.

Both qualitative and quantitative image analysis reveals that the proposed framework provides a better fusion results compared to the conventional image fusion techniques. In this paper the comparison of existing and proposed method by quantitative analysis are also done.

II. EXISTING METHOD

A. Image Averaging

Image averaging is a digital image processing technique that is often engaged to enhance medical images that have been degraded by random noise. The algorithm operates by figuring an average or arithmetic mean of the intensity values for each pixel position in a set of captured images from the same field. Each degraded image has a stable signal component and a random noise component. In the
averaging process, the signal component of the image remains the same, but the noise component differs from one image frame to another. As the noise is random, it tends to cancel during the summation. When the averaged image is computed, the image signal component has a stronger influence over the summation than does the noise component. The result is an enhanced signal component and the noise component is very likely to be minimised by a factor approximately equal to the square root of the number of images averaged[8]. The contrast information is lost by using this method.

B. Principal Component Analysis

Principal Components Analysis (PCA) is a mathematical formulation applied in the reduction of data dimensions. Thus, the PCA technique allows the identification of standards in data and their expression in such a way that their similarities and differences are emphasized. Once patterns are found, without much loss of information it can be compressed and its dimensions can be reduced[7]. The PCA formulation can also be used as a digital image compression algorithm with a low level of loss. It transforms number of correlated variable to uncorrelated variable[8]. In the PCA approach, the information contained in a set of data is stored in a computational structure with reduced dimensions based on the integral projection of the data set onto a subspace generated by a system of orthogonal axes.The resultant fused image has spectral degradation by this method[8].

III. PROPOSED METHOD

The multimodal images ,MRI and CT images of brain are fused by using the NSCT transform is proposed and the tumour part of brain is detected at very early stage with the help of clustering process and segmentation. NSCT provides better edges and texture region than other transforms. It also provides better computational complexity and fast implementation. It also provides better subband decomposition.NSCT decomposition is to compute the multi scale and different direction components of the discrete images[3]. It involves the two stages such as non-sub sampled pyramid (NSP) and non-sub sample directional filter bank (NSDFB) to extract the texture, contours and detailed coefficients.

A. Non-Subsampled Contourlet Transform (NSCT)

The NSCT is based on the theory of Contourlet Transform (CT) achieves better results in image processing in geometric transformations. The CT is a shift variant as it contains both down-samplers and up-samplers in the Laplacian Pyramid (LP) as well as Directional Filter Bank (DFB) stages[6]. NSCT is a shift invariant, multi-scale and multi-directional transform as it has a very vibrant implementation. It is obtained by using Non-subsampled Pyramid Filter Bank (NSP or NSPFB) and the Non-subsampled Directional Filter Bank (NSDFB).

B. Non-Subsampled Pyramid Filter Bank

The multiscale property is being ensured by the non-subsampled pyramid filter bank by means of two-channel non-subsampled filter bank. At each decomposition level, one low-frequency image and one high-frequency image could be produced[2]. In the succeeding NSP decomposition level, the low-frequency components are decomposed iteratively to capture the singularities in the image. As a result, NSP can result in L + 1 sub-images, which consists of one low frequency image and L high frequency images where L denotes the number of decomposition levels. The sub-images have the same size as the source image.

C. Non-Subsampled Directional Filter Bank

The Non-subsampled Directional Filter Bank is a two-channel NSDFB that is being constructed by combining the directional fan filter banks. The NSDFB ensures the NSCT with the multi-direction property and provides more directional detail information. NSDFB is being achieved by eliminating the downsamplers and upsamplers in each two-channel filter bank in DFB tree structure and upsampling filters accordingly[13].

NSDFB permits the direction decomposition with k levels in each of the high-frequency subbands from NSPFB and produces 2 k directional subbands with the same size as that of source images[10]. Therefore, the NSDFB provides the NSCT with multidirectional performance and gives more specific directional detail information to get more accurate results. Therefore, NSCT provides better frequency selectivity and an important property of the shift-invariance on account of non-subsampled operation.

![Fig: 1 block diagram of fusion process](image-url)
A new image fusion framework for multimodal medical images, which relies on the NSCT decomposes the images into sub bands. The sub band images of two source images obtained from NSCT are utilized for morphological process to get the enhanced information to diagnose the brain diseases. Here, the pixel level fusion method is implemented based on Gabor-filter bank and gradient detection for coefficient selection. The low frequency sub bands of two source images were fused by Gabor coefficients selection. It is helpful to discriminate and characterize the texture of an image through frequency and orientation representation. It uses the Gaussian kernel function modulated by sinusoidal wave to estimate the filter coefficients for convolving with an image. The high-frequency coefficients always contain edge and texture features and the high frequency sub bands were fused by Gradient measurement to select desired coefficients. Finally, fused frequency sub bands are inverse transformed to reconstruct the fused image.

Gray level co-occurrence matrix (GLCM) is being proved as a trendy statistical method of extracting the textural features from images [14]. It is a statistical method of examining texture that considers the spatial relationship of pixels in the gray level co-occurrence matrix. After creating GLCM, using graycomatrix, several statistics were derived from them using graycoprops. These statistics provide information about the texture of an image. The important features are energy, entropy, correlation, contrast and homogeneity.

Classification of the fused image is done by neural network. Neural network is one of the techniques which can be used for image recognition. It is used to train the images and then classify the image into abnormal or normal which is based on the GLCM algorithm. Fuzzy c-means clustering process is done to find whether the fused image is abnormal and the tumor part is segmented from the abnormal image of brain otherwise it shows normal. Parameters were evaluated between input and fused image for abnormal cases where tumor is detected.

IV. RESULTS

The CT and MRI image of brain are fused by NSCT method. The fused images which are detected as abnormal are clustered and One of the images is chosen from the clustered image. Then it is segmented to detect the tumour part of the brain.

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![Fig: 2 Decomposition of NSCT framework](image1.png)

![Fig: 2 Decomposition of NSCT framework](image2.png)

![Fig: 3 CT & MRI of human brain and fused image using NSCT](image3.png)

![Fig: 4 Dialog box showing abnormal image](image4.png)

![Fig 5: Clustered images](image5.png)

![Fig 6: Segmented image detecting the tumor part](image6.png)

![Fig: 7 CT & MRI of human head and fused image using NSCT](image7.png)

![Fig: 8 Dialog box showing abnormal image](image8.png)
Fig 9: Clustered images

Fig 10: Segmented image

Fig 11: Fusion using (a) image averaging method (b) PCA method (c) NSCT for normal images of human brain.

Fig 12: Fusion using (a) image averaging method (b) PCA method (c) NSCT for normal images of human brain.

EXISTING METHOD:
1. IMAGE AVERAGING METHOD
2. PRINCIPAL COMPONENT ANALYSIS

PROPOSED METHOD:
NON-SUBSAMPLED CONTOURLET TRANSFORM

Fig 13: Fusion using (a) image averaging method (b) PCA method (c) NSCT for abnormal images of human brain.

Fig 14: Fusion using (a) image averaging method (b) PCA method (c) NSCT for abnormal images of human head.
It is clear that the fused images for the existing methods is not clear and hence the NSCT method is better than the other methods. The resultant image for existing method is not at all informative and is not helpful for clinical analysis. The edge and contrast informations are lost in the existing method. Spatial distortion is high hence the image is not clear in the existing methods. A better resolution and high contrast fused image is obtained by the proposed method. This image could be useful for clinical analysis and the stage of the disease could be detected easily. The fused image which does not have any tumor or any affect are classified and displayed in the dialog box as normal. Hence, quantitative analysis is done for all the images. The various images of CT & MRI of brain are fused and the fused images are compared with the existing methods like Image Averaging Method and Principal Component Analysis. The fused image obtained contains information about bones and tissues, which cannot be seen in the separate CT & MRI image. From the fused image with NSCT domain and clustering method one can detect the tumor part affected in brain easily.

V. PERFORMANCE METRICS

An image fusing process requires all valid and useful pattern information from the source images to be preserved, while at the same time it should not introduce artifacts that could interfere with subsequent analyses. The performance of image fusion is evaluated by considering some of the performance metrics.

A. Correlation coefficient

The closeness between two images can be qualified in terms of the correlation function the correlation coefficient ranges from -1 to 1. A correlation coefficient value of +1 indicates that the two images are highly correlated i.e. very close to one another a correlation coefficient of -1 indicates that the two images are exactly opposite to each other.

\[ r = \frac{\sum A_{mn} - \bar{A} \sum B_{mn} - \bar{B}}{\sqrt{\left(\sum A_{mn} - \bar{A}\right)^2 \left(\sum B_{mn} - \bar{B}\right)^2}} \]

B. RMSE

Root mean square error provides the standard error of fused images and expresses the spatial and spectral distortion contained in the fused image. It is very popular even through the individual band variance.

\[ \text{RMSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [R(i,j) - F(i,j)]^2 \]

Smaller value of RMSE indicates better fusion.

C. PSNR

Peak signal to noise ratio commonly used as the quality of reconstruction of fused image and indicate how many useful information content of images. The value of reconstruction of fused image, the value of PSNR must be high for less noise in image. PSNR value should be high when the fused and reference images are similar.

\[ \text{PSNR} = 10 \log_{10} \left[ \frac{255^2}{\frac{1}{M \times N} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (f(m,n) - g(m,n))^2} \right] \]

D. Entropy

Entropy could effectively reflect the amount of information in certain image. The larger the value is better fusion results are obtained. greater the entropy of the fused images is more abundant information include in it and the greater the quality of the fusion.

\[ E_N = \sum_{i=0}^{L-1} p_F(i) \log_2 p_F(i) \]

Where \( p_F \) is the normalized histogram of the fused image to be evaluated. Here \( L \) is the maximum gray level for a pixel in the image.

E. Spatial frequency

Spatial frequency information in the resolution image (that represent image edges) should be transferred to the fused images.

\[ SF = \sqrt{RF^2 + CF^2} \]

Where \( RF \) is the row frequency and \( CF \) is the column frequency.

\[ RF = \sqrt{\frac{1}{M(N-1)} \sum_{i=0}^{M-1} \sum_{j=0}^{N-2} (F(i,j+1) - F(i,j))^2} \]

\[ CF = \sqrt{\frac{1}{N(M-1)} \sum_{i=0}^{N-2} \sum_{j=0}^{M-1} (F(i+1,j+1) - F(i,j))^2} \]

The various fusion metrics which has been described above were compared with two existing method: Image Averaging method Principle component Analysis method with NSCT transform for quantitative analysis.
VI. COMPARISON OF PERFORMANCE METRICS

<table>
<thead>
<tr>
<th>PARAMETERS</th>
<th>PROPOSED METHOD</th>
<th>EXISTING METHOD 1</th>
<th>EXISTING METHOD 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation coeff.</td>
<td>0.954</td>
<td>0.964</td>
<td>0.4562</td>
</tr>
<tr>
<td>RMSE</td>
<td>3.5069</td>
<td>9.2198</td>
<td>14.2806</td>
</tr>
<tr>
<td>PSNR</td>
<td>42.6816</td>
<td>38.4840</td>
<td>36.5833</td>
</tr>
<tr>
<td>Entropy</td>
<td>5.7708</td>
<td>3.3826</td>
<td>1.9418</td>
</tr>
<tr>
<td>Variance seg.</td>
<td>5.4256±103</td>
<td>2.2306±103</td>
<td>2.3454±103</td>
</tr>
<tr>
<td>Std. deviation seg.</td>
<td>73.6587</td>
<td>48.1731</td>
<td>48.4296</td>
</tr>
<tr>
<td>Spatial frequency</td>
<td>80.0386</td>
<td>32.5807</td>
<td>56.4644</td>
</tr>
<tr>
<td>Gradient</td>
<td>7.4744</td>
<td>1.9208</td>
<td>3.9107</td>
</tr>
</tbody>
</table>

Here PSNR, entropy, gradient, spatial frequency and standard deviation are high and RMSE value is low in proposed method when compared to existing method. Hence, it gives better fusion result compared to other fusion method. The indices used in this framework measure the amount of information present in the fused image, contrast of the fused image, average intensity of the fused image, edge information present in the fused image. Compared with the proposed method, the fused image from all the two methods, contains information about bones and tissues, which cannot be seen in the separate CT, MRI images. Result of the proposed method is better than the other methods. The result of the principal component analysis method gives least values for all the indices because the information of bones and tissues are blurred. Obtained the results of nsct based method is good when compared to PCA based methods. Image averaging methods suffer from the problem of contrast reduction. The proposed method results in high clarity, high information content and low contrast reduction. Hence, it is clear from the subjective analysis that the proposed method is more effective in fusing multimodality medical images and superior than other state-of-the-art medical image fusion techniques.

VII. CONCLUSION

Multimodal medical image fusion method is proposed based on Non-Subsampled Contourlet Transform (NSCT), which consists of three steps. In the first step, the medical images to be fused are decomposed into low and high frequency components by Non-Subsample Contourlet Transform. Next two different fusion rules are utilised for fusing the low frequency and high frequency bands which preserve more information in the fused image along with improved quality. The fused images obtained by the proposed method are more informative and have higher contrast than the existing method images which is helpful in visualization and interpretation. The fused image contains both soft tissue and bone information. The fused images obtained by the proposed method are more informative and have higher contrast than the input medical images which is helpful in visualization and interpretation. The fused images obtained by the proposed method have higher quantitative results than the methods of image averaging and principal component analysis.

REFERENCES


