Medical Image Fusion Using Combination of PCA and Wavelet Analysis

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Abstract—Medical image fusion for merging of complementary diagnostic content has been carried out in this paper using Principal Component Analysis (PCA) and Wavelets. The proposed fusion approach involves sub-band decomposition using 2D-Discrete Wavelet Transform (DWT) in order to preserve both spectral and spatial information. Further, PCA is applied on the decomposed coefficients to maximize the spatial resolution. An optimal variant of the daubechies wavelet family has been selected experimentally for better fusion results. Simulation results demonstrate an improvement in visual quality of the fused image in comparison to other state-of-art fusion approaches.

Index Terms—CT-Scan, Daubechies, Entropy, PCA, Wavelets.

I. INTRODUCTION

Medical imaging technique helps to create visual representations of the internal structure of human body for clinical analysis. The complementary nature of medical imaging sensors of different modalities, (X-ray, Magnetic Resonance Imaging (MRI), Computed Tomography (CT)) has brought a great need of image fusion for the retrieval of relevant information from medical images. ‘Medical Image Fusion’ is the process of combining and merging complementary information into a single image from two or more source images to maximize the information content of images and minimize the distortion and artifacts in the resulting image [1]. The significance of fusion process is important for multimodal images as single modal medical images provides only specific information; thus it is not feasible to get all the requisite information from image generated by single modality [2]-[3]. To elaborate further, CT helps in accessing the extent of disease; yet it is limited in soft-tissue contrast, needed for differentiating tumors from scar tissues. On the other hand, MRI scores over CT in terms of soft tissue discrimination. This is necessary because the soft tissue contrast allows better visualization of tumors. This highlights the need towards the development of multimodality medical imaging sensors for extracting clinical information to explore the possibility of data reduction along with better visual representation. In the past decades, several fusion algorithms varying from the traditional fusion algorithms like simple averaging and weighted averaging, maximum and minimum selection rule [4] have been proposed. With the advancement of research in this field, algorithms such as Intensity–Hue–Saturation (IHS) [5] and Brovey transform (BT) [6] have been used to fuse medical images. In the recent years multi-resolution approaches using Mallat [7], the à trous [8] transforms, contourlet [9]-[10] have been proposed for image fusion. Fusion approaches employing wavelets analysis include transforms such as SWT [11], LWT [12], MWT [12], RDWT [13], and complex wavelet [4]. B. Yang et al. [14] implemented the pixel level decomposition on weighted average fusion rule. Though the algorithm was simple to implement yet the fused image did not justify the presence of the objects from the set of images used. V. S. Petrovic et al. [15] proposed a ‘fuse then decompose’ technique which represented input image in the form of gradient maps at each resolution level. Although, it has been observed that the said approach by authors did not yield satisfactory performance but in turn increased the computational complexity due to the involvement of gradient maps. D. A. Godse in their work [16] selected maximum pixel intensity approach along with wavelet to perform fusion. The said combination produced a focused image but the image suffered with blurring and reduced contrast. On the other hand, work of A. Deng et al. [17] emphasized only on the DWT. The output image reduced the noise content but it contained high spatial distortion, which did not solve the purpose of image fusion. Although, PCA coupled with DWT provides better spatial information. S. K. Sadhasivam in their work [18] applied PCA along with the selection of maximum pixel intensity to perform fusion. The method yielded an image with less structural similarity with the source images along with low contrast and luminescence. The above discussion incurred the desire to improve the quality of the fused image by removing the redundant information from the images. The reason behind choosing the wavelet based approach in comparison to other approaches is that they are localized in time and frequency and can be defined with specific time span. Hence, the wavelets preserve time and frequency information, thereby yielding a suitable approach for medical image fusion. Further, these fused images are also processed with denoising [19]-[20], contrast [21]-[30] and edge enhancement [31]-[33] techniques to improve upon the visualization of diagnostic information. The proposed work therefore presents a combination of wavelet transform and PCA as an improvement to the aforementioned
limitations. The obtained results have been evaluated using entropy, fusion factor (FF) and standard deviation as fusion metrics; yielding satisfactory performance. The rest of the paper is organized as follows: The proposed fusion approach is discussed in section II. Section III presents experimental results and finally the paper is concluded in section IV.

II. PROPOSED FUSION APPROACH

Modalities like CT and MRI generally contain solitary information i.e. either demonstration of disease extent or the details of soft tissues. Thus, this section discusses the application of PCA fusion rule in wavelet domain as an approach to combine the complementary information from both the images into a single one for precise diagnosis. Wavelets preserves time and frequency content of the images to be fused. Since, a long time many other transforms like Fourier transform were used to obtain good spatial and spectral information. While, the basic advantage of wavelet transform over the other transforms is that it contains the temporal information of the images; i.e. it captures both the location and frequency that makes it suitable for the fusion purposes. Moreover, by using wavelet transform we can easily detect the local features involved in the signal process. Wavelets are oscillatory function with finite duration having zero average value. The irregularity and good localization are the properties that provide a good platform for the analysis of signal with discontinuities [34].

A. Proposed Fusion Algorithm

The first step in the proposed fusion approach involves the pre-processing of the MRI and CT-scan images, i.e. the conversion of image from RGB scale to Gray scale (RGB components of the image are converted into Gray scale components). The next step is to decompose the source images using wavelet transform. The wavelet transform decomposes the image into frequency bands namely a lower-frequency band and other higher-frequency bands. Wavelets can be described as the combination of the two scaling functions i.e. f(t), also known as father wavelet and the wavelet function or mother wavelet ψ(t) [35]. Mother wavelet goes through several alterations and scaling to give synonymous wavelet families as in Eq. (1).

\[ \psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{t-b}{a} \right) \text{ for } (a, b \in R), a > 0 \quad (1) \]

where: \( \psi(t) \) represents mother wavelet function, while, \( a \) & \( b \) are the scale and translation parameters respectively, given by Eq. (2).

\[ a = a^j_0, b = ma^j_0b_0, \text{ for } (j, m \in Z) \quad (2) \]

Thus, the wavelet family can be represented by Eq. (3).

\[ \psi_{j,m}(t) = a^{-j/2}_0 \psi \left( a^{-j/2}_0 t - mb_0 \right) \text{ for } (j, m \in Z) \quad (3) \]

Once the source images are decomposed using wavelet transform, the approximation and detailed coefficients are obtained; PCA is applied as a fusion rule to selectively combine the appropriate wavelet coefficients of input images [36]. PCA serves to transform/project the features from the original domain to a new domain (PCA domain) where they are arranged in order of their variance. Fusion in PCA domain is achieved by only retaining those features that hold a pregnant amount of information. This can be achieved by retaining only those components which have a larger variance. The steps involved in the proposed PCA algorithm are outlined in fig. 1. The next step involves, the reconstruction of the processed coefficients (after PCA fusion rule) using inverse wavelet transform to generate the fused image.

BEGIN

Step 1 : Input: Wavelet coefficients (of both MRI & CT).
Step 2 : Compute: Column vectors from wavelet coefficients.
Step 3 : Compute: Covariance matrix using these vectors.
Step 4 : Process: Diagonal elements of the covariance vector.
Step 5 : Compute: Eigen vectors and Eigen values of covariance matrix.
Step 6 : Compute: Column vector corresponding to large Eigen value (by dividing each element with the mean of Eigen vector).
Step 7 : Compute: Multiplication of normalized Eigen vector values by each term of wavelet coefficient matrix.
Step 8 : Process: Repeat the above steps for all the approximation and detailed coefficients.
Step 11 : Output: Fused image.

END

Fig. 1: Proposed Fusion Algorithm.

B. Objective Evaluation of Proposed Fusion Approach

Once the fusion process is completed; the final step requires the objective evaluation of the proposed approach using the appropriate fusion metrics. The final step of the proposed approach is its objective evaluation; which requires usage of HVS based image quality assessment (IQA) approaches [37]-[43]. In the present work, the performance evaluation is carried out using Entropy (E), Fusion Factor (FF) and Standard Deviation (SD) as fusion metrics [4].

1) Entropy

Entropy of an image is the measure of the information content in the fused image. Higher values of entropy indicate that the fused image contains more information than the other fused images having lower value of entropy. Entropy is given by Eq. (4).

\[ H = - \sum p(x) \log p(x) \]

where \( p(x) \) is the probability of occurrence of gray level \( x \) in the image.

The obtained results have been evaluated using entropy, fusion factor (FF) and standard deviation as fusion metrics; yielding satisfactory performance. The rest of the paper is organized as follows: The proposed fusion approach is discussed in section II. Section III presents experimental results and finally the paper is concluded in section IV.
\[ E = - \sum_{L=0}^{L-1} P_l \log_2 P_l \]  \hspace{1cm} (4)

where: \( L \) represents no. of gray level, \( P_l \) is the ratio between the no. of pixels with gray values \( l \) and total no. of pixels.

2) Fusion Factor

For two input images A, B and the fused image F, fusion factor is given by Eq. (5).

\[ \text{FF} = I_{AF} + I_{BF} \]  \hspace{1cm} (5)

where: \( I_{AF} \) and \( I_{BF} \) are mutual information between source images and the fused image. Higher values of fusion factor [4] indicate better fusion results.

3) Standard Deviation

Standard deviation of \( m \times n \) image is given by Eq. (6).

\[ SD = \left( \frac{1}{m \times n} \sum_{l=1}^{m} \sum_{n=1}^{n} (f(l, m) - \mu)^2 \right)^{1/2} \]  \hspace{1cm} (6)

where: \( f(l, m) \) & \( \mu \) represents the pixel and the mean values of fused image respectively. Higher values of standard deviation indicate high quality of fused image.

III. RESULTS AND DISCUSSIONS

Simulations in the present work have been performed on images of two different modalities (CT and MRI). This section deals with the qualitative and quantitative analysis of the fused image obtained from the proposed approach. The two input images (CT & MRI) after pre-processing are subjected to sub-band decomposition using daubechies family. Experiments have been performed on different variants of daubechies family and an appropriate wavelet ‘db2’ has been selected. The experimental results of the selection criteria has been represented by fig. 2 and table I.

<table>
<thead>
<tr>
<th>Variant of Daubechies Family</th>
<th>E</th>
<th>FF</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>db2</td>
<td>5.4073</td>
<td>6.2791</td>
<td>76.5860</td>
</tr>
<tr>
<td>db5</td>
<td>5.4883</td>
<td>3.7467</td>
<td>76.5228</td>
</tr>
<tr>
<td>db8</td>
<td>5.5446</td>
<td>3.7347</td>
<td>76.4175</td>
</tr>
<tr>
<td>db10</td>
<td>5.5791</td>
<td>3.6984</td>
<td>76.3696</td>
</tr>
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</table>

The selection of ‘db2’ is made clear from the above analysis as it not only provides high values of fusion metrics but also relevant from the visual point of view. The results of fused images obtained using the proposed approach are given in Fig. 3; while, the quantitative analysis of the same has been shown in table II. Fusion results in Fig. 3 for Set 1 & Set 2 show that the fused image has a better visual characteristic from the diagnostic point of view. CT-scan images give information about the shape of the tumor which is helpful in determining the extent of disease; whereas MRI image gives soft tissue details. It can be clearly seen that fused image contains complementary information of both the images; i.e. soft tissue details as well as the shape of the tumor. This is further supported by high values of fusion metrics (FF, E and SD). High values of entropy and standard deviation depicts the increased information content and a good quality of fused image; demonstrating the effectiveness of the proposed fusion approach.
The present approach has been compared with the DTCWT based fusion approach in work of R. Singh et al. [44] and sparse representation approaches like Simultaneous Orthogonal Matching Pursuit (SOMP) and Orthogonal Matching Pursuit (OMP) [45] for Medical image fusion. The obtained result shows the effectiveness of the proposed approach in visual representation as compared to DTCWT, SOMP and OMP approaches. The fused image obtained from the proposed approach represents that the information from the source images are preserved as compared to images obtained from other approaches; which can be clearly seen in Fig. 4. Moreover, the higher values of the fusion metric shown in table III validate, that the proposed fusion approach has better diagnostic utility than the other approaches.

Table II: Quantitative Analysis of Proposed Fusion Approach.

<table>
<thead>
<tr>
<th>Set No</th>
<th>E</th>
<th>FF</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.2687</td>
<td>5.6635</td>
<td>81.9457</td>
</tr>
<tr>
<td>2</td>
<td>5.4035</td>
<td>3.2746</td>
<td>76.0780</td>
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Table III: Performance Comparison of Fused Images.

<table>
<thead>
<tr>
<th>Fusion Approach</th>
<th>FF</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWT Avg – Max[44]</td>
<td>1.6390</td>
</tr>
<tr>
<td>DTCWT Avg – Max[44]</td>
<td>1.6582</td>
</tr>
<tr>
<td>DWT Max[44]</td>
<td>2.2713</td>
</tr>
<tr>
<td>OMP[45]</td>
<td>2.2964</td>
</tr>
<tr>
<td>SOMP[45]</td>
<td>2.2965</td>
</tr>
<tr>
<td>Proposed Approach</td>
<td><strong>2.8698</strong></td>
</tr>
</tbody>
</table>

IV. CONCLUSION

This paper presents an approach for medical image fusion employing PCA in wavelet domain. The time and frequency conservation property of wavelet and feature enhancement property of PCA makes this approach more suitable for medical image fusion. The fused image of the proposed fusion approach is more refined in representing spectral and spatial information, as well as the soft tissue details of tumor. Thus, it is providing the details of two different modalities in one single image, justifying the purpose of medical image fusion. Significant results relevant from a visual point of view, as well as high values of the fusion, have been obtained from the proposed fusion approach. Comparison results show a significant improvement in restoration of information and quality features in the obtained fused image; as depicted by high value of fusion factor, in comparison to other fused images. Hence, the proposed fusion approach is more precise and can be used more effectively for medical diagnosis than the other methods of fusion.

REFERENCES


