Transform Domain Analysis of Multimodal Medical Image Fusion

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Abstract. Fusion of multimodal medical images ensures the quality diagnosis in the field of medical sector. Fused image possess extra substance of data than input individual scanned images. The fusion process can be carried on different clinical scan images wherever more subjective data is required. In this work, we are supposed to discuss the subjective treatment of multiple transform techniques (Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Hadamard Transform (HT) & Discrete Wavelet Transform (DWT)) significance in fusion process. These coefficients are fused with the correlation of the spatial frequency (SF) and visibility (V) factor values. The resultant images are visually and qualitatively verified with standard execution estimates like Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Root Mean Square Error (RMSE).

1. Introduction

Acute disease recognition raised the need of medical image techniques like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT), etc. Medical image fusion divided into single-modal fusion and multimodal-fusion. Multimodal image fusion is the procedure to fuse different medical images in order to improvise better performance, high quality and visual enhancement by reducing redundancy in fused image. Fusion process can be done in spatial domain and transform domain. Spatial domain is based on the pixels and techniques are averaging, principal Component Analysis (PCA), Brovery method, I-H-S INTENSITY HUE SATURATION. Transform domain fusion is based on frequencies changes, popular transforms are Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Discrete Hadamard Transform (DHT), Discrete Wavelet Transform (DWT), Redundant Wavelet Transform (RWT), Contourlet Transform, Curvelet Transform and Singular Value Decomposition (SVD).

Fusion approaches classified in to 3 categories pixel-two images are fused by transforming into similar, decision -based on region interest- and feature-based on interpreted or labeled data. Muhammad Arif [1] Implemented new method for the medical images using curvelet transform for curve shapes and genetic algorithm for image features and approached detailed Image Enhancement for acute identification. Hadiakramhadi [2] proposed and promoted quality improvement in fused images with multimodal medical fusion technique discrete wavelet transform for (ct computerized tomography and MRI magnetic resonance imaging) by tested and analyzed metrics. Rajalingam [2]
implemented A Novel Neuro – Fuzzy Hybrid Multimodal Image Fusion technique by working with different medical images and produced high quality fusion image by reducing processing time for treatment diagnosis. Sridevi [4] implemented new Algorithm for the reconstruction of images as preprocessing stage, fuzzy sets called Yagers Intuitionistic Fuzzy Compliment Set and worked with several medical modalities (CT, MRI, PET etc) and promoted better contrast for visual recognition. Maruturi Haribabu [5] proposed Novel medical image fusion method with 2D Hartley Transform technique in HSV (Hue, Saturation, Value) color space and produce statistical measurements by Combining PET – MRI. Priyanka Sharma [6] presented the role and fundamentals of fusion in disease location and promoted redundancy in information of fusion in MRI – CT by applying Discrete Wavelet and Curvelet Transform fusion techniques. Sanjay Patsaria [7] presented review on modalities MRI, CT, IR, PET, SET based on organs (BRAIN, LIVER, HEAD, NECK, etc.), fusion in PIXEL, FEATURE, and DECISION levels fusion techniques DWT, DCT etc. Vaishnavi [8] proposed dual tree complex wavelet transform DTCW T method for fusing medical images MRI-PET to reduce redundancy by using complex valued filtering and promoted high quality fused image. RENICAN NIE [9] proposed a fusion framework based multisource information exchange and coding by using PCNN pulse complex coupled neural network for medical images CT, MRI, PET and approached better perception for the visual disease diagnosis. ANISH VIJAN [10] presented performance analysis on different medical modalities PET, MRI, CT with fusion techniques Discrete Wavelet Transform DWT, Principle Component Analysis PCT and Laplacian Pyramid Transform.

The rest of the paper coordinated in the method of proposed work and experimental results. At last the paper is finished up with conclusion.

2. Proposed method

This part of the paper discusses about the process of fusion with step by step explanation and shown in flow chart ‘figure 1’.

1. Consider two multimodal medical scan images of MRI and PET Images are input images of fusion process.
2. Initially RGB color model of PET image is transformed into HIS/HSV color model to extract intensity component (I) of an image by protecting color coordinates.
3. Further the intensity component of PET image and MRI image (Gray Image) are transformed into image coefficient information with the use of DFT, DCT, HT and DWT transform techniques.
4. Especially in DWT transform case the subbands are fused:
   a. The low frequency subband information of two images is fused using average method.
   b. The high frequency subband information of two images are undergoes fusion process with spatial frequency method or visibility factor.
5. For other transform coefficients are (DFT, DCT & HT) fused with spatial frequency method or visibility factor like DWT high frequency subbands.
6. Once the fusion is done apply inverse transform techniques to get the spatial domain information.
7. The resultant image is fused intensity component of two multimodal medical images, later the preserved color components (Saturation and Hue) of PET image is combined with the resultant intensity component.
8. The final resultant fused color image of multimodal images are obtained by converting HIS/HSV color model into RGB color model.
9. The resultant image is having more qualitative and quantitative information than the individual images.
10. The effectiveness of the proposed method is validated with the standard transform domain techniques of (DFT, DCT, HT) with basic performance measures.
2.1. Fusion rules

2.1.1. Spatial Frequency

The spatial frequency (SF), of an image coordinates are defined as:

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

Where RF and CF are the row frequency and column frequency respectively:

\[ CF = \frac{1}{MN} \sum_{i=1}^{N} \sum_{j=2}^{M} \left[ I(i, j) - I(i-1, j) \right] \]  

\[ RF = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=2}^{N} \left[ I(i, j) - I(i, j-1) \right] \]  

The neighbouring pixel coordinates are considered for CF and RF computation.

2.1.2. Visibility

The clarity of an image can be measured with visibility (V) factor. Here the \( \alpha = 0.6 \) to 0.7 and \( \mu \) is the mean value of the image.

\[ V_i = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} |LL_1(m, n) - \frac{\mu}{\mu^{\alpha+1}}|}{\sum_{m=1}^{M} \sum_{n=1}^{N} |LL_1(m, n)|} \]
3. Experimental Results

This experimental session discuss about the qualitative and quantitative analysis of the proposed work. The basic multi modal medical images are collected from [11]. These images are given as
input to the proposed process and the results were evaluated with performance measures of PSNR, RMSE, & MSE [12]. The resultant values are tabulated in the Table 1. The following Figure 2-5) show the resultant image starting from basic transform techniques to multi resolutional transform techniques. The results are plotted in graphical way also (Figure 6-7) for more visual analysis.

| Images | Methodology | Quality parameters |
|--------|-------------|--------------------|
|        |             | PSNR   | RMSE  | MSE   |
| Fig 1  | DFT+SF      | 62.9078 | 0.1825 | 0.0333 |
|        | DCT+SF      | 62.9078 | 0.1825 | 0.0333 |
|        | HT+SF       | 62.9085 | 0.1817 | 0.0312 |
|        | DWT+SF      | 62.9241 | 0.1603 | 0.0275 |
|        | DFT+SF      | 59.8625 | 0.2591 | 0.0671 |
| Fig 2  | DCT+SF      | 59.8629 | 0.2591 | 0.0671 |
|        | HT+SF       | 58.8524 | 0.2753 | 0.0724 |
|        | DWT+SF      | 60.1873 | 0.2496 | 0.0623 |
|        | DFT+VIS     | 60.4103 | 0.2432 | 0.0592 |
| Fig 3  | DCT+VIS     | 62.0785 | 0.2007 | 0.0403 |
|        | HT+VIS      | 58.9445 | 0.2875 | 0.0829 |
|        | DWT+VIS     | 62.9635 | 0.1813 | 0.0329 |
|        | DFT+VIS     | 57.3661 | 0.3453 | 0.1193 |
| Fig 4  | DCT+VIS     | 59.3876 | 0.2736 | 0.0749 |
|        | HT+VIS      | 56.4661 | 0.3830 | 0.1467 |
|        | DWT+VIS     | 60.3593 | 0.2447 | 0.0599 |

Table 1. Performance analysis of Proposed Work

Figure 2. (a) & (b) MRI and PET images, (c) reference image, (d) DFT+SF, (e) DCT+SF, (f) HT+SF, (g) DWT+SF
Figure 3. (a) & (b) MRI and PET images, (c) reference image, (d) DFT+SF, (e) DCT+SF, (f) HT+SF, (g) DWT+SF

Figure 4. (a) & (b) MRI and PET images, (c) reference image, (d) DFT+SF, (e) DCT+SF, (f) HT+SF, (g) DWT+SF
Figure 5. (a) & (b) MRI and PET images, (c) reference image, (d) DFT+VIS, (e) DCT+VIS, (f) HT+VIS, (g) DWT+VIS

Figure 6. The graphical representation of results with SF factor
Figure 7. The graphical representation of results with V

4. Conclusion
This work addressed about the fusion of multimodal medical images with multiple transform techniques. The transform techniques are considered with basic level to multi-resolutional level of techniques. The applied fusion methods are SF & V. The outcomes are compared with standard performance measures of PSNR, RMSE & MSE. By observing the experimental results section we can conclude that the multi resolutional transform technique is giving more accurate results in both fusion rules than the other standard transform methods. Further this can be verified with multi-level subband resolution and higher end of multi resolution techniques in future work.

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