IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-5, May 2019 E-ISSN: 2347-2693

Implementation and Performance Analysis of Pixel based and Wavelet based Image Fusion

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DOI: https://doi.org/10.26438/ijcse/v7i5.392399 | Available online at: www.ijcseonline.org

Accepted: 11/May/2019, Published: 31/May/2019

Abstract – Medical image fusion has been used to derive useful information from multimodal medical image data. Multimodal image fusion is to integrate images from different modalities (like MRI with PET, CT with PET, and MRI with CT) to enhance the contrast of an image, and amount of data in an image. In this present work, two-level discrete wavelet-based image fusion has been chosen. The two-level discrete wavelet-based image fusion is compared both subjectively and objectively by using suitable quality metrics with the other image fusion techniques. On the basis of experimental results, it shows that the two-level discrete wavelet-based image fusion shows better quality of an image as compared to other techniques of image fusion.

Keywords — multimodal image fusion, wavelet-based image fusion, pixel-based image fusion**.**

I. INTRODUCTION

Over the last few decades, medical imaging is playing an increasingly critical and vital role in a large number of healthcare applications such as diagnosis, treatment, research, and education. To provide the support to the physicians various modalities of medical image have become available, reflecting different information of human organs and tissues, and possessing their respective application ranges [1]. Some of the major modalities in clinical practice include structural medical images like magnetic resonance imaging (MRI), computed tomography (CT), ultrasonography (USG), magnetic resonance angiography (MRA) etc. which provide high resolution images with non-functional information. The functional medical images such as position emission tomography (PET), single-photon emission computed tomography (SPECT), and functional MRI (fMRI) etc. provide low-spatial resolution images with functional information [2]. It is practically impossible to capture all the details from one imaging modality that would ensure clinical accuracy, and robustness of the analysis and resulting diagnosis. Therefore, combining non-functional and functional medical images provide much more useful information through image fusion become the focus of imaging research.

The goal of image fusion (IF) is to integrate complementary information from all frames into one image containing information, the quality of which cannot be achieved otherwise. Here, the term "better quality" means less blur, less noise, less geometric distortion, and higher spatial resolution.

Image fusion has been used in many application areas like remote sensing and in astronomy, medical imaging, military, security, and surveillance areas. In remote sensing and in astronomy, multi-sensor fusion is applied to achieve high spatial and spectral resolution [3]. Numerous fusion applications have appeared in medical imaging like computed tomography (CT), magnetic resonance imaging (MRI), and position emission tomography (PET). Several applications use multi-sensor fusion for visible, and infrared images appeared in military, security, and surveillance areas. In the case of multi-view fusion, a set of images of the same scene taken by the same sensor but from different view-points is fused to obtain a single image with higher resolution [4]. The multi-temporal approach recognizes the same scene acquired at different times to find, and evaluate changes in the scene. Image fusion increases reliability, decreases uncertainty, and storage cost by a single informative image than storing multiple images. Image fusion can be broadly classified into two groups: (i) pixel-based image fusion, and (ii) wavelet-based image fusion.

Pixel-based image fusion methods work by combining the pixel values of two or more images to be fused. One of the simplest of these image fusion methods just takes the pixel-by-pixel intensity average of the source. Pixel-based image fusion methods are affected by blurring which has a direct effect on contrast of the image [5]. The input images for the pixel-based image fusion must be the same scene, and of an equal size.

Wavelet-based image fusion decomposes the image into Low-High (LH), High-Low (HL), High-High (HH) spatial frequency bands at different scales, and Low-Low (LL) band at coarsest scale. The LL band contains the average image information whereas the other bands contain directional information due to spatial orientation. Higher absolute values of wavelet coefficients in the high bands correspond to salient features such as edges or lines [6].

II. PRESENT WORK

The fusion on multimodal imaging for a given clinical application is very important. A perfect fused image should contain both more functional information, and more spatial characteristics with no spatial, and color distortion. There are number of approaches presented for fusing multimodal image information. These approaches are:

A. *Discrete wavelet-based image fusion*

The discrete wavelet transform (DWT) is a tool that separates data into sub-bands, and then operates each component/sub-band with resolution matched to its scale. It reduces the computation time, and resources required for wavelet transform. Each sub-band provides different information about the image. The low-low (LL) sub-band is a coarse approximation of the images, and removes all high frequency information. The low-high (LH) sub-band removes high frequency information along the rows, and emphasizes high frequency information along the columns. The result is an image in which vertical edges are emphasized. The high-low (HL) sub-band emphasizes horizontal edges, and high-high (HH) sub-band emphasizes diagonal edges as shown in Figure 1.1.

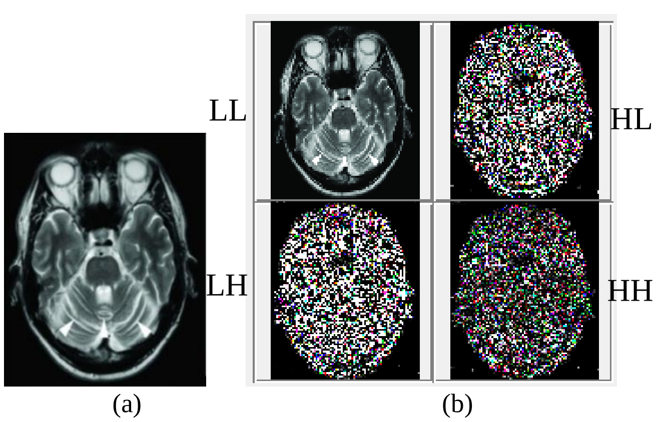


Figure 1.1: (a) Original image, (b) One-level DWT image based on approximate image detail (LL), horizontal details (HL), vertical details (LH), and diagonal details (HH)

As shown in Figure 1.1, each sub-band is handled individually. So, the main condition for successful fusion is that "all" visible information in the input images should also appear visible in the fused image. The main requirement of the fusion process then, is to identify the most significant features in the input images, and to transfer them without loss into the fused image. The discrete wavelet transform achieves this fusion using two-level DWT and multi-level DWT.

The two-level DWT are extension from the one-level discrete wavelet transform. To compute the discrete wavelet transform of the image at the next level, the process is applied again to the LL sub-band as shown in Figure 1.2.

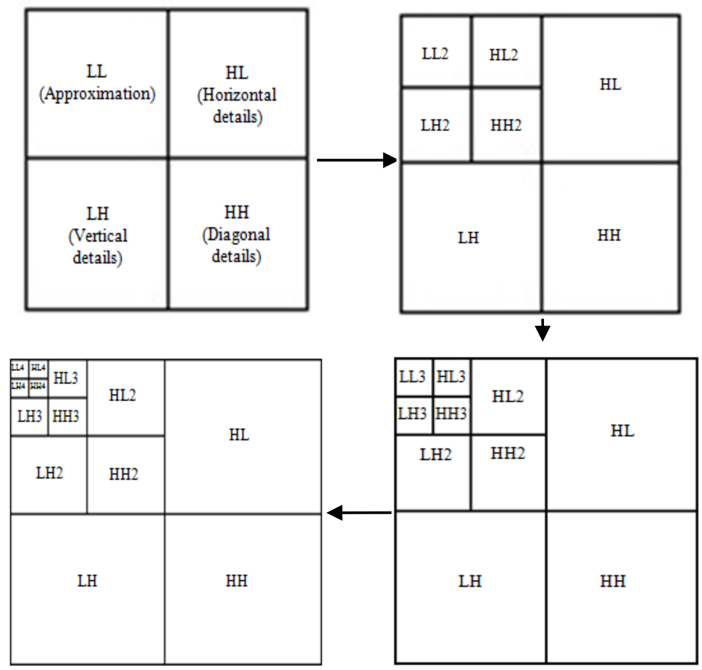


Figure 1.2: Different decomposition levels of discrete wavelet transform of LL sub-band

In each level of the wavelet decomposition, four images are created from the original NxN pixel image. The size of these new images is reduced to $1/4^{th}$ of the original size. The LH image is a result of applying the low-pass filter in horizontal direction, and high-pass filter in vertical direction, and contains horizontal edge features. The LL image is considered a reduced version of the original as it retains most details of original image whereas HL contains vertical edge features. The HH contains only high frequency information therefore it is typically noisy. Thereafter, the wavelet-based image fusion methods work by combining the sub-bands of the two multimodality input images as per the following steps:

Step I: Read the set of multimodal images (i.e. two images of different modality of same size).

Step II: Perform single-level wavelet decomposition on both images to get approximation information (LL), horizontal details (HL), vertical details (LH), and diagonal details (HH) of the image.

Step III: Perform single-level wavelet decomposition on approximation information (LL) of Step II to get second-level approximation information (LL2), horizontal details (HL2), vertical details (LH2), and diagonal details (HH2).

Step IV: Apply the fusion rule on each detail of second-level decomposition as follows:

a. Calculate the average values of horizontal details (HL2), and diagonal details (HH2) from both decomposed images respectively.
b. Choose the maximum values of approximation information (LL2) and vertical details (LH2) by comparing the coefficient of both decomposed images respectively.

Step V: Reconstruct the approximation image (LL) by inverse wavelet transform using second-level approximation information (LL2), horizontal details (HL2), vertical details (LH2), and diagonal details (HH2).

Step VI: Apply the fusion rule on details of first-level decomposition as follows:

a. Calculate the average values of horizontal details (HL), and diagonal details (HH) from both decomposed images respectively.
b. Choose the maximum values of vertical details (LH) by comparing the coefficient of both decomposed images.

Step VII: Reconstruct the image by inverse wavelet transform using modified details achieved from Step V, and Step VI.

Step VIII: Display the final fused image.

B. Pixel-based image fusion

Pixel-based image fusion generally deal with pixel level information directly usually works on spatial domain. Spatial image fusion methods work by combining the pixel values of the two or more images to be fused in a linear way as shown in Figure 1.3.

Pixel-based image fusion methods are affected by blurring effect which directly affect on the contrast of the image. Pixel-based image fusion method is generally a time consuming as it requires number of computations. The main disadvantage of pixel-based approach is that it does not guarantee to have a clear object from the set of images. This is due to variations in focus on the images with different level of intensity.

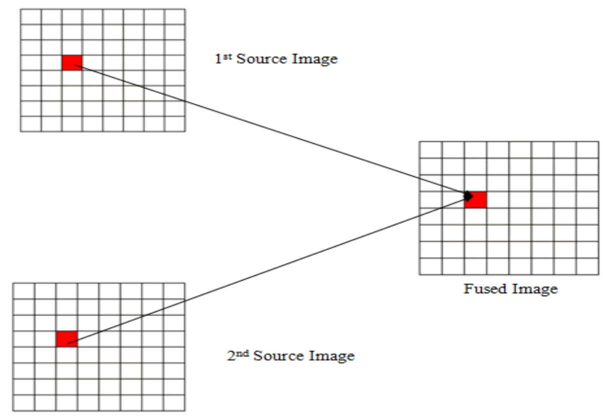


Figure 1.3: Pixel-based Image Fusion

Following are the steps for generating pixel-based fused image:

Step I: Read the set of multimodal images (i.e. two images of different modality of same size).

Step II: Identify rows and columns of both the input images to get the intensity value of each pixel in an image.

Step III: Traverse each row and column of both the images to get a particular pixel intensity value.

Step IV: Now calculate average of the intensity values of both pixels as:

$$c(r,c) = \frac{a(r,c) + b(r,c)}{2}$$

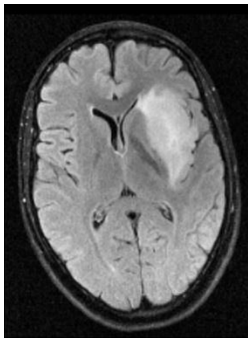
Where, *a* is first input image, *b* is second input image, *r* is a row of an image, *c* is a column of an image, and *c* is the resultant image containing each pixel intensity value.

Step V: The calculated average value from step IV is considered as new intensity value for final fused image.

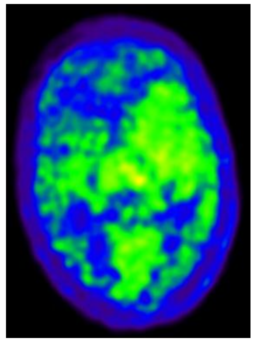
Step VI: Display the final fused image that contains the average of all the intensity values of both images.

III. RESULTS AND DISCUSSION

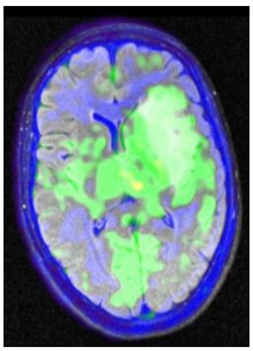
The work is based on two algorithms i.e. (i) pixel-based image fusion, and (ii) wavelet-based image fusion. Wavelet-based image fusion technique has four different levels of decomposition named as 1-Level DWT, 2-Level DWT, 3-Level DWT, and 4-Level DWT. So, first challenge is to identify the best method among four levels of wavelet-based image fusion based on qualitative (visual) analysis, and then the best level of wavelet-based image fusion method is compared with pixel-based image fusion technique to identify the best fused image for human perception. For analysis medical images are used, and fusion combinations taken into account are MRI with PET, MRI with CT, and CT with PET.



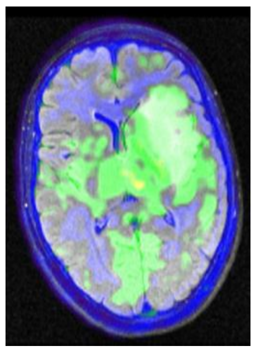
(a)



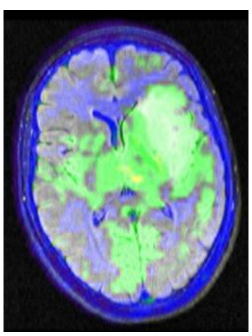
(b)



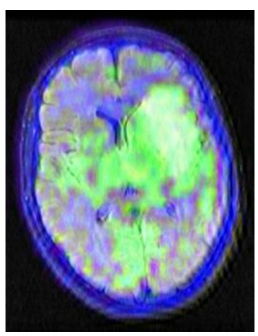
(c)



(d)



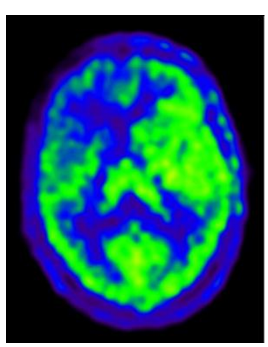
(e)



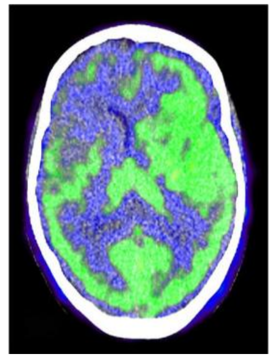
(f)

Figure 1.4: (a) Input image MRI, (b) Input image PET, (c) one-level wavelet-based image fusion, (d) two-level wavelet-based image fusion, (e) three-level wavelet-based image fusion, and (f) four-level wavelet-based image fusion.

(a)



(b)



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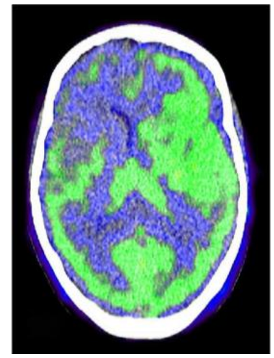
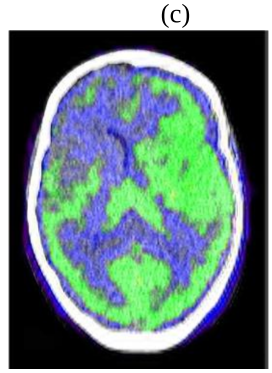
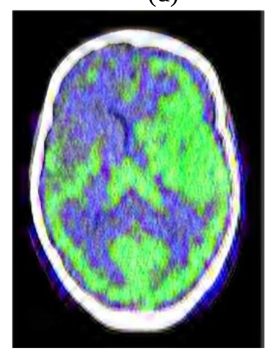


(d)



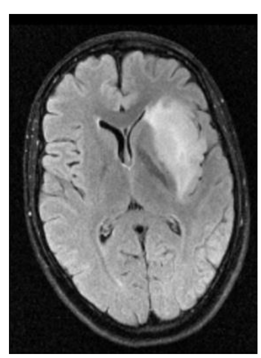
(e)



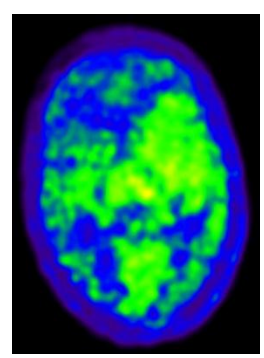
(f)

Figure 1.5: (a) Input image CT, (b) Input image PET, (c) one-level wavelet-based image fusion, (d) two-level wavelet-based image fusion, (e) three-level wavelet-based image fusion, and (f) four-level wavelet-based image fusion.

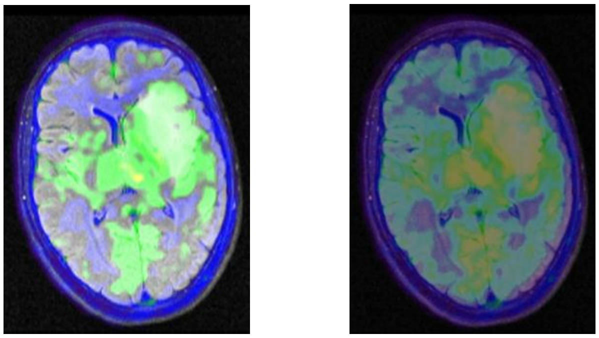
Through the qualitative analysis it is clear that 2-level discrete wavelet-based image fusion method generates good result as compared to 1-level DWT, 3-level DWT, and 4-level DWT in terms of noise reduction, image contrast, image quality, and information that it contains. The best wavelet level i.e. 2-level DWT image fusion method is now compared with pixel-based image fusion method on same set of test images.



(a)

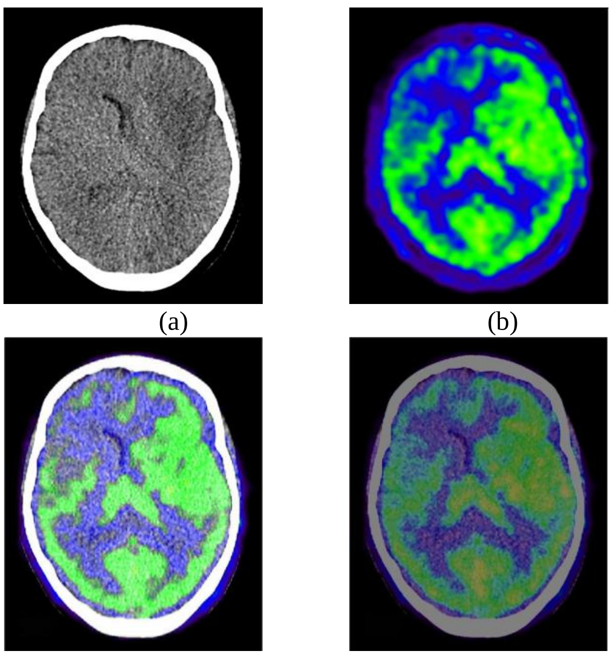


(b)



(c) (d)

Figure 1.6: (a) Input image MRI, (b) Input image PET, (c) two-level wavelet-based image fusion, (d) pixel-based image fusion



(a) (b)

(c) (d)

Figure 1.7: (a) Input image CT, (b) Input image PET, (c) two-level wavelet-based image fusion, (d) pixel-based image fusion.

Through the qualitative analysis it is clear that two-level discrete wavelet-based image fusion method generates good result as compared to pixel-based image fusion method in terms of noise reduction, image contrast, image quality, and information that it contains.

A quantitative analysis is carried out on 15 set of test images. The range of peak signal to noise ratio (PSNR), entropy, and standard deviation (SD) is not defined, but higher values of these are always considered good. The range of structural similarity index measure (SSIM) is between -1 to 1, and higher value of SSIM is always considered good.

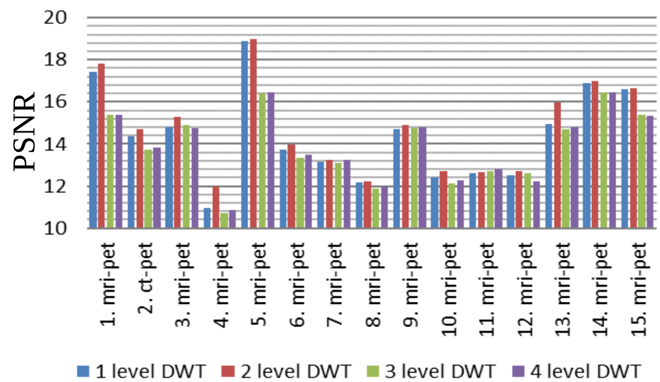


Figure 1.8: Comparison of 1-level DWT, 2-level DWT, 3-level DWT, and 4-level DWT image fusion method in terms of peak signal to noise ratio

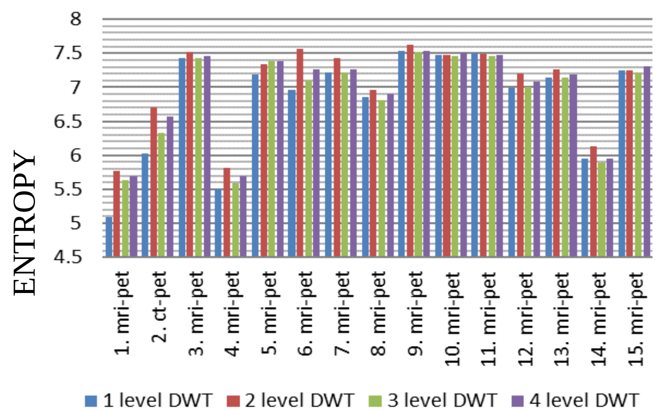


Figure 1.9: Comparison of 1-level DWT, 2-level DWT, 3-level DWT, and 4-level DWT image fusion method in terms of entropy

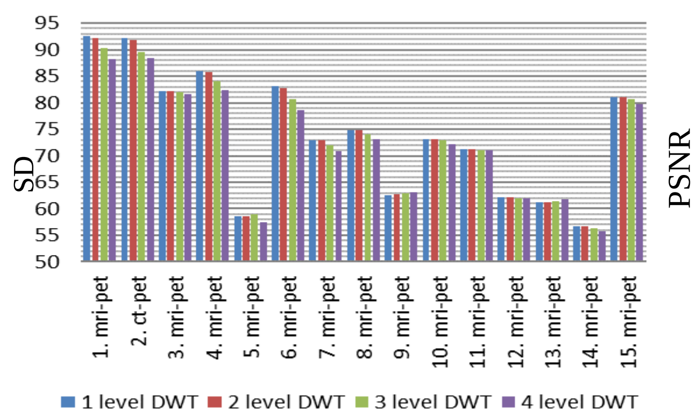


Figure 1.10: Comparison of 1-level DWT, 2-level DWT, 3-level DWT, and 4-level DWT image fusion method in terms of standard deviation

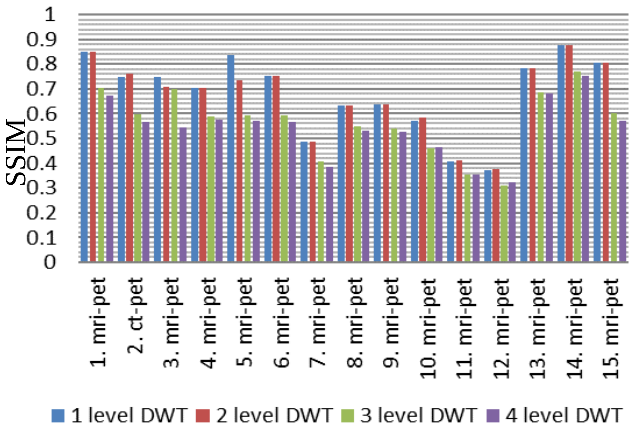


Figure 1.11: Comparison of 1-level DWT, 2-level DWT, 3-level DWT, and 4-level DWT image fusion method in terms of structural similarity index measure

From quantitative analysis, it is clear that 2-level DWT image fusion method is good technique for multi-modal image fusion. Now, the quantitative analysis is performed on 2-level DWT image fusion, and pixel-based image fusion technique on same set of test images.

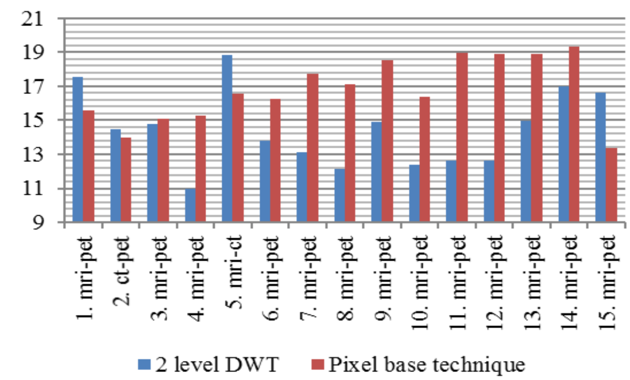


Figure 1.12: Comparison of 2-level wavelet and pixel-based image fusion method based on peak signal to noise ratio

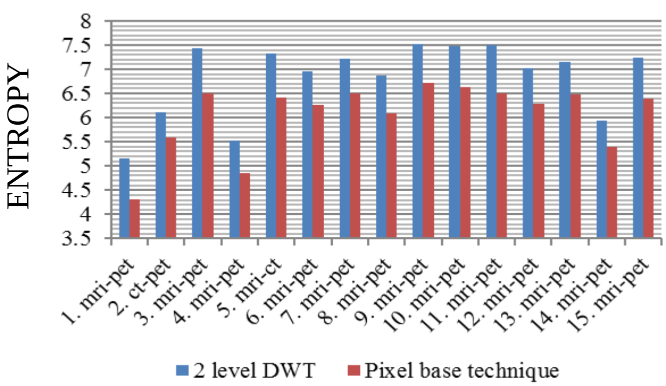


Figure 1.13: Comparison of 2-level wavelet and pixel-based image fusion method based on entropy

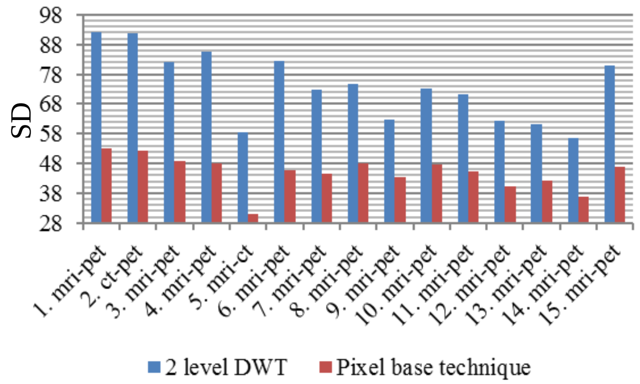


Figure 1.14: Comparison of 2-level wavelet and pixel-based image fusion method based on standard deviation

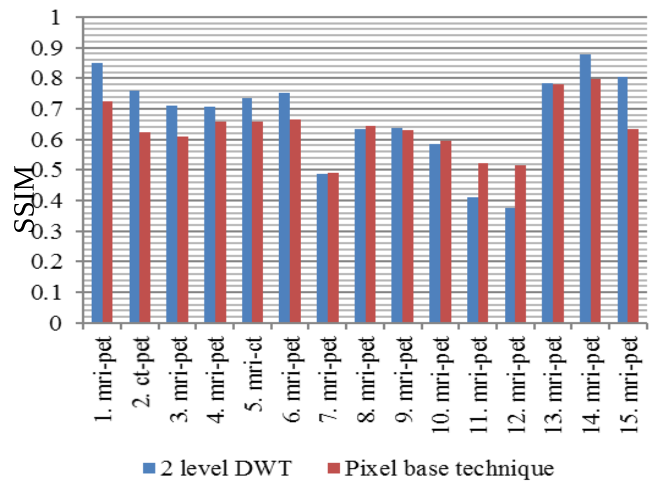


Figure 1.15: Comparison of 2-level wavelet and pixel-based image fusion method based on structural similarity index measure

From the obtained metrics values it is clear that 2-level discrete wavelet-based image fusion method produces good result as compared to pixel-based image fusion method in terms of noise reduction, image quality, image contrast, and information that it contains.

IV. CONCLUSIONS

Multimodal image fusion is to integrate images from different modalities (like MRI with PET, CT with PET, and MRI with CT) to enhance the contrast of an image, and amount of data in an image. In this present work, two-level discrete wavelet-based image fusion has been chosen. Although there are many image fusion techniques which enhances the amount of data in the image, but the two-level discrete wavelet-based image fusion enhances the contrast, and amount of data in an image to a great extent. The two-level discrete wavelet-based image fusion is compared both subjectively and objectively by using suitable quality metrics with the other image fusion techniques. On the basis of experimental results, it shows that the two-level discrete wavelet-based image fusion shows better quality of an image as compared to other techniques of image fusion. The obtained images are visually pleasing, artifact free, and natural looking. A desirable feature of the two-level discrete wavelet-based image fusion is that it does not introduce flickering, poor contrast, and noise.

V. FUTURE SCOPE

For the future work, 2-level discrete wavelet-based image fusion can be applied on other types of image fusion such as multi-view image fusion, multi-temporal image fusion, multi-focus image fusion, and spatial and spectral image fusion, and may also be used for image restoration.

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