A Novel Architecture of Medical Image Fusion Based on YCbCr-DWT Transform

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Abstract: *Image fusion is one of the most modern, accurate and useful diagnostic techniques in medical imaging. Mainly, image fusion tries to offer a method for solving the problem that no system is able to integrate functional and anatomical information. Multiple image fusion of brain is very important for clinical applications. Positron Emission Tomography (PET) image indicates the brain function and Single-Photon Emission Computerized Tomography (SPECT) indicates local performance in the internal organs like heart and brain imaging. Both of these images are multi-spectral images and have a low spatial resolution. The Magnetic Resonance Imaging (MRI) image shows the brain tissue anatomy and contains no functional information. A good fusion scheme should preserve the spectral characteristics of the source multispectral image as well as the high spatial resolution characteristics of the source panchromatic image. There are many methods for image fusion but each of them has certain limitations. The studies have shown that YCbCr preserves spatial information and Discrete Wavelet Transforms (DWT) preserves spectral information without distortion. The proposed method contains the advantages of both methods and it preserves spatial and spectral information without distortion. Visual and statistical analyses show that the results of our algorithm considerably enhance the fusion quality in connection with: discrepancy, average gradient and Mutual information; compared to fusion methods including, Hue-Intensity-Saturation (HIS), YCbCr, Brovey, Laplacian-pyramid, Contourlet and DWT.*

Keywords: *YCbCr, DWT, PET, SPECT, image fusion.*

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1. Introduction

The importance of medical images for diagnosis can be increased by combining images of different medical system. New technology in patient care has an important role by compression of the time between diagnosis and treatment. In recent years, medical imaging widely applied into the clinical therapy and treatment planning. Therefore, there is a great number of medical imaging. Generally, medical imaging is divided into functional and anatomical systems. Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) provide high spatial resolution images with anatomical information. Single-Photon Emission Computerized Tomography (SPECT) and Positron Emission Tomography (PET) provide functional information with lows patial resolution. A single image can’t provide clinical needs, s of used of anatomical and functional images provide much more useful and necessary information [5]. Medical image fusion is useful for physicians to extract features that may not be normally visible in different images. Image fusion not only helps in diagnosis, but also reduces the storage cost by storage one fused image instead of several images. Fused of anatomical and functional images provide much more advantage. Positron Emission Tomography- Computed Tomography (PET-CT) is used in diagnosis of lung cancer, Magnetic Resonance Imaging- Positron Emission Tomography (MRI-PET) and (Magnetic Resonance Imaging-Single-Photon Emission Computerized Tomography) MRI-SPETC are used in the determination of brain tumor and Single-Photon Emission Computerized Tomography-Positron Emission Tomography (SPECT-PET) is applied in abdominal studies and Ultrasound Image-MRI is used for observation of vascular blood.Process of fusion can be represented in different levels of information. Common categories are the distinction between pixels, feature and decision level [1, 4]. Medical image fusion usually employs the pixel level fusion techniques. The advantage of pixel level fusion is that the fused image uses the original information. In addition, the algorithms are rather easy to implement and time efficient. The combination of medical images is used to extract useful information from multiple medical images. The purpose of image fusion at the pixel level fusion is to represent visual information present in input images, in a single fused image without the introduction of distortion or loss of information [12, 19, 22, 23]. The purpose of this classification is to recognize different degrees of detail, complexity and accuracy. Many algorithms have been developed that are generally classified into four main categories: Substitution methods such as principal component analysis, Average weighted, color mixed RGB and intensity hue saturation [14, 21]. Mathematical combination which normalizes multi spectral bands are used for Red-Green-Blue (RGB) display such as Brovey transform. Optimization techniques such as neural networks and Bayesian[4, 5].Transform domain such as multi resolution decomposition which introduces spatial features from the high-resolution images into the multispectral images, such as, Laplacian Pyramid, wavelet, Curve let transform, Contour let transform and Non-sampled contour let transform [8, 9, 16].

Each of methods is efficient for combining the certain images and they have applied limitations.

The multi resolution fusion techniques have been considered widely in the recent studies because of their advantages over the other fusion techniques. A major group of these methods as the most used in researches is discrete wave let transform. Substitution methods have also been used in the practical applications. Most of the researches in the field of medical image fusion are done by using these methods and advantage of these methods is low computational cost.

In the process of fusion, it is desirable that original spectral information in the PET (or SPETCT) images and spatial characteristics in the MRI images are preserved, this means that only the spatial information existing in MRI data introduced into the PET (or SPECT) [5]. All the above methods have advantages and disadvantages. In this article we used YCbCr (kind of color space)-Discrete Wavelet Transforms (DWT) Transform to combined two functional and anatomical images. By studying of the strong and weak points of the mentioned methods, we represent this method to improve weak points of them. Multi-scale decomposition methods such as DWT preserve spectral information but they have spatial distortion. Substitution methods such as YCbCr preserve spatial information but they have spectral distortion. In this paper to improve the weak points of the YCbCr fusion technique and DWT technique, a combined approach is considered. This means that the proposed method has all the advantages of both methods, on the other hand the weak points of these methods are minimized.

The contents of our method are organized as follows:

- Describing the DWT fusion method.
- Explaining the YCbCr fusion method and its ability and imperfection.
- Proposing the use of a model based on integrated YCbCr and DWT to improve the fusion performance.
- Using four databases for performance evaluation, compared to IHS model, YCbCr model, Brovey, Laplacian-pyramids, Contour let and DWT methods. These methods are commonly used to evaluate the new methods.
- Analyzing the proposed method by mutual information (entropy), discrepancy, and average gradient criteria.

Sections 2 and 3 discuss the DWT and YCbCr methods, respectively. In section 4, we present the proposed integrated model. The experimental results and discussions are described in section 5. Concluding statements are discussed in section 6.

2. Image Fusion by using Discrete Wavelet Transforms (DWT)

Wavelet transform is a mathematical tool that can detect local characteristics in the signal process. Also, it is used for decomposition of two-dimensional digital signal such as image into the multi-scale levels with different resolution. The basic content and theory of multi resolution wavelet analysis is originated from Mallat [9, 24]. Wavelet is a common method that is used in multi resolution analysis and it is useful linear evolution in the signal processing. Wavelet is used to separate the datasets into different frequency components and then showing them in common scales [20]. In the real world time series are discrete, thus the DWT is selected to decompose and reconstruct the time series. Wavelet series expansion of the function $f(x)=L^2(R)$ depends on wavelet $\psi(x)$ and scaling function $\emptyset(X)$ is defined as follows [17]:

$$f(x)=\sum_{k} c_{j_0}(k)\phi_{j_0,k}(x)+\sum_{j=j_0}^{\infty}\sum_{k} d_j(k)\psi_{j,k}(x) \tag{1}$$

Where $j_0$isanoptionalstartingscale and $c_{j0}(k)$ is typically called approximation or scaling coefficients, $d_j(k)$ is called details or wavelet coefficients, Expansion coefficients are calculated according to Equation (2):

$$\begin{aligned} c_{j_0}(k)&=\left\langle f(x),\phi_{j_0,k}(x)\right\rangle=\int f(x),\phi_{j_0,k}(x)dx \\ c_{j_0}(k)&=\left\langle f(x),\psi_{j,k}(x)\right\rangle=\int f(x),\psi_{j,k}(x)dx \end{aligned} \tag{2}$$

There are different forms for calculation of DWT fusion algorithm. One of the most widely used algorithms is the pyramidal algorithm of (Mallat and Hwang, 1992) [18], although it is low anisotropic characteristics cause to problems in fused images with a high content of borders being not horizontal, vertical or diagonal, it leads to high quality Spectral of image [6].Image fusion algorithm based on DWT has improved the multispectral and panchromatic image fusion. Panchromatic image and each band of multi-spectral image are decomposed in a coarse resolution for providing orthogonal wavelet, which consists of approximate image with low-frequency and a set of high frequency images.The fused image is obtained by performing inverse DWT using approximate image of each band of multi-spectral image and details of panchromatic image.

3. YCbCr Fusion Method

YCbCr is a family of color spaces that used as a part of the color image pipeline in digital video and photography systems. YCbCr model converts multi-spectral image with red, green and blue RGB channels into component Y, Cb and Cr; which Y is the luminance component, Cb and C rare the blue-difference and red difference chromatic components respectively. Y is independent of color in the YCbCr color space, so it can be used to solve the problem of luminance changes. The difference between YCbCr and RGB is that the YCbCr represents color as brightness and two color difference signals, while RGB represents the colors red, green and blue [11]. We selected the YCbCr color space because it preserves detailed information of luminance component better than any other color spaces [13]. This transformation can be used to fuse multi sensor images. This process will lead to a fused image. This model is based on the following Equation.

$$\begin{bmatrix} Y \\ C_b \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1140 \\ -0.1687 & -0.3313 & 0.5000 \\ 0.5000 & -0.4187 & -0.0813 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3}$$

The inverse transform is:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.0000 & 0.5870 & 1.4020 \\ 1.0000 & -0.3441 & -0.7141 \\ 1.0000 & 1.7720 & 0.0000 \end{bmatrix} \begin{bmatrix} Y \\ C_b \\ Cr \end{bmatrix} \tag{4}$$

4. Proposed Fusion Method

In this paper we used YCbCr-DWT Transform to combined two functional (PET, SPECT) and anatomical (MRI) images. By studying of the strong and weak points of the Wavelet transform and YCbCr methods, we represent this method to improve weak points of them. Multi-scale decomposition methods such as DWT preserve spectral information but they have spatial distortion. Substitution methods such as YCbCr preserve spatial information but they have spectral distortion. Also YCbCr fusion method produces an image with high spatial intensity. However, there is a low correlation between PET (or SPECT) intensity image and MRI; and spectral distortion is created. Table 1 shows this subject. In the other hand, DWT image fusion usually can preserve more spectral information than other fusion methods. However, spatial details in results of wavelet fusion are different from MRI image, which represents spatial distortion into results. To improve YCbCr method and DWT techniques, and to overcome the weaknesses of these two methods, an integrated fusion method is presented in this paper (YCbCr-DWT Transform). It uses the YCbCr transform to integrate the low-resolution multispectral color information with the high-resolution panchromatic spatial detail in formation to achieve a smooth integration of color and spatial features. However, the wavelet transform is used to generate the new Y component, which the new component has high correlation with the old Y component image and contains spatial details of the original panchromatic image.

As shown in Figure 1, the detailed steps of this integrated fusion method are:

1. The PET image is transformed into YCbCr components; The PET image should be aligned to the MRI image in advance.
2. Histogram matching is applied to match the histogram of the MRI image with the PET (or SPECT)-Y component.
3. Decomposition of new panchromatic image and Y component of PET (or SPECT) image into wavelet coefficients(three levels of analysis are applied). The pixelsize of the Ycomponent of PET (or SPECT) image is the same size of panchromatic image.
4. Substitution the estimated coefficient of Ycomponent (LL^Y) with estimation coefficient of new panchromatic image.
5. Final fusion result obtain by applying the Inverse Discrete Wavelet Transform (IDWT) on new coefficients in order to achieve new image, which contains thesame spatial detail of the original MRI and has the same intensity distribution to the original PET (or SPECT).

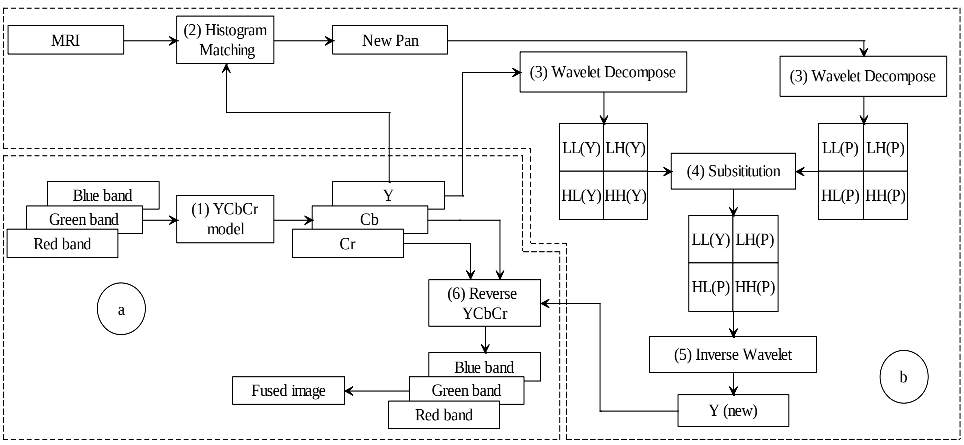
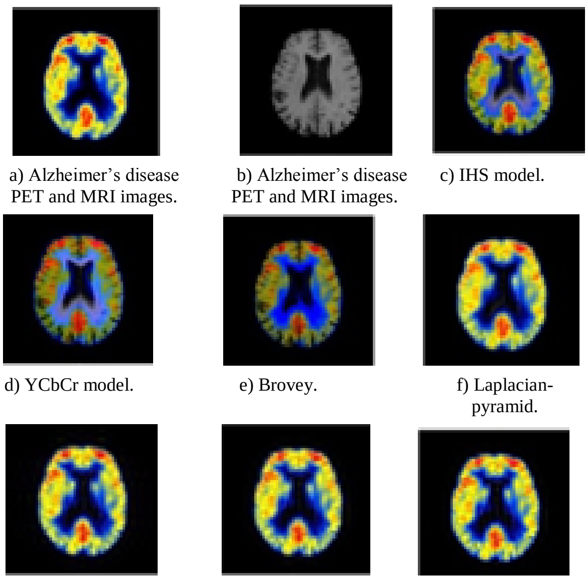


Figure 1. Diagram of fused image by the proposed method.

5. Results and discussion

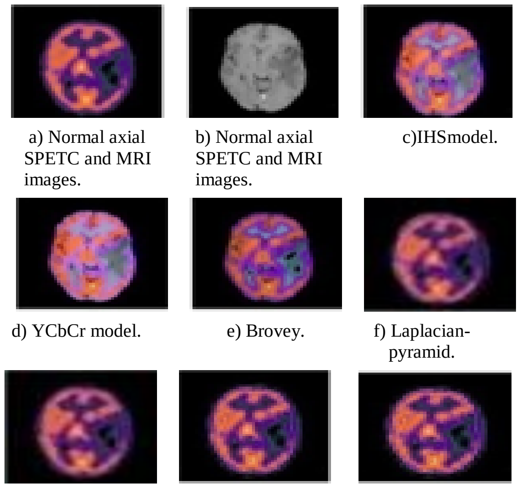
In recent years, a number of computational measures have been presented for assessment of the fused image quality. Metrics that accurately relate to human observer performance are of great value but are very difficult to design and, thus, are not yet available at present. In order to objectively compare different image fusion algorithms, what we also need the availability of multi-spectral or multi-sensor data sets that can be used to test existing and new algorithms. Test images are 256×256. We assume PET (or SPECT) images are shown in pseudo-color, and contain three spectral bands (red, green, blue).

MRI provides appropriate spatial resolution with no color information content. The color PET (or SPECT) images were registered to the corresponding MRI images. If the images are not registered, we can register them with different techniques [7, 10]. The brain images are classified into three groups (normal axial, normal coronal and Alzeimer's disease dataset images). We used 4 datasets (dataset 1: SPECT and MRI image, dataset 2: Alzeimer's disease MRI and PET, dataset 3: normal axial MRI and PET, dataset4: normal coronal MRI and PET). Hue- Intensity-Saturation (IHS) transform, YCbCr transform, Brovey, Laplacian-pyramid, Contourlet and DWT and the proposed method were employed to fuse the image datasets [2, 3]. Some original images and fused images are shown in Figures 2 and 3.



a) Alzheimer's disease PET and MRI images. b) Alzheimer's disease PET and MRI images. c) IHS model.
d) YCbCr model. e) Brovey. f) Laplacian-pyramid.
g) Contourlet. h) DWT. i) proposed method.

Figure 2. Alzheimer's disease PET and MRI images fusion.



a) Normal axial SPETC and MRI images. b) Normal axial SPETC and MRI images. c)IHSmodel.
d) YCbCr model. e) Brovey. f) Laplacian-pyramid.
g) Contourlet. h) DWT. i) proposed method.

Figure 3. Normal axial SPETC and MRI images fusion.

In this paper, three evaluation criteria (Discrepancy, Average gradient, Mutual information) are used for quantitative assessment of the fusion performance.

Discrepancy of the fused image in each spectral band is measured by D_k [15].

$$D_k = \frac{1}{P.Q}\sum_{x=1}^{P}\sum_{y=1}^{Q}\left| f_k(x,y) - f_{2k}(x,y) \right| \quad k=R,G,B \tag{5}$$

Where $f_K(x,y)$ and $f_{2K}(x,y)$ are the pixel values of fused image and original image at position (x,y); in this paper P=256, and Q=256.A tiny discrepancy means the fusion is acceptable.

Discrepancy of the spatial quality of fused image is computed by using the average gradient [15].

$$Avg_k = \frac{\sum_{x=1}^{P-1}\sum_{y=1}^{Q-1}\sqrt{\left(\frac{\partial f_k(x,y)}{\partial x}\right)^2 + \left(\frac{\partial f_k(x,y)}{\partial y}\right)^2}}{\sqrt{2\times((P-1).(Q-1))}} \quad k=R,G,B \tag{6}$$

Where $f_K(x,y)$ is pixel values of fused image at position (x,y). The average gradient reflects the clarity of the fused image. This technique can be used to measure the fused image spatial resolution. For example, the larger average gradient indicates higher spatial resolution.

Mutual Information (MI) is the basic concepts of information theory to compute the statistical dependence between two random variables. MI has been applied in many areas such as information fusion and images registration [15].

According to random probability distributions, $P_A(a)$ and $P_B(b)$, and m variables of A and B with marginal probability distribution, $P_B(b)$ and $P_A(a)$, with marginal joint probability distribution P_{AB}, MI will be as Equation (7).

$$MI(a,b) = \sum_{a,b} P_{AB}(a,b)\log\frac{P_{AB}(a,b)}{P_A(a)\,P_B(b)} \tag{7}$$

Table 1 shows the spectral discrepancies between images obtained by different algorithms and multi-spectral source image (SPECT or PET).

Table 1. The spectral discrepancies between the fused images and the multispetral image.

Fusion method	Mean $D_{k=R,G,B}$ Dataset1	Mean $D_{k=R,G,B}$ Dataset2	Mean $D_{k=R,G,B}$ Dataset3	Mean $D_{k=R,G,B}$ Dataset4
IHS	16.842	14.260	12.763	13.512
YCbCr	21.790	20.121	15.931	17.646
Brovey	13.678	18.374	9.986	10.129
Laplacian P	7.752	9.637	9.427	11.688
Contourlet	7.186	9.009	8.904	11.004
DWT	7.012	9.024	8.621	10.917
Our Method	7.347	6.249	7.190	8.874

This Table shows our method had the lowest discrepancy except in dataset 1that DWT was better.

Table 2 shows our method had the most average gradient from other different algorithms. According to the results of both tables, it can be said that color information distortion in the proposed method is minimized and spatial details are close to MRI reference image and also spectral bands off used images in YCbCr are drastically changed, which means that the spectral characteristics of this method have been distorted and this is a significant problem see Figures 2 and 3).

Table 2.The average gradients of the fused image.

Fusion method	Mean $Avg_{k=R,G,B}$ dataset1	Mean $Avg_{k=R,G,B}$ dataset2	Mean $Avg_{k=R,G,B}$ dataset3	Mean $Avg_{k=R,G,B}$ dataset4
IHS	3.826	4.389	4.754	6.159
YCbCr	4.265	4.245	4.887	6.326
Brovey	3.921	3.498	4.372	5.705
Laplacian P	3.757	4.024	4.160	5.429
Contourlet	4.212	4.413	4.625	5.852
DWT	4.098	4.238	4.485	5.664
Our Method	4.721	5.288	5.318	6.820

Table 3 illustrates that the mutual information obtained by the proposed method is highest in PET and SPECT data. The proposed method and other multi scale methods preserve spectral information well.

Table 3. The fusion methods Spectral performance measure based on entropy and mutual information.

Fusion Method	Spectral MI Dataset1	Spectral MI Dataset2	Spectral MI Dataset3	Spectral MI Dataset4
IHS	0.810	0.591	0.640	0.665
YCbCr	0.754	0.515	0.594	0.611
Brovey	0.793	0.627	0.682	0.697
Laplacian P	1.003	0.651	0.725	0.682
Contourlet	1.173	0.701	0.789	0.742
DWT	1.149	0.689	0.783	0.732
Our Method	1.178	0.730	0.81	0.762

Table 4 illustrates spatial mutual information performance. In this table our method wasn't best result. As mentioned in the introduction part, methods like Brovey, YCbCr, and IHS preserve spatial information more than other methods that Table 4 confirms this issue, but in image fusion process, preserving spectral information is more important than preserving spatial information and for preserving spatial information should not lose the spatial information. We must create a balance between preserving of these two types of information till by increasing the amount of spectral information retention, spatial information preservation is also desirable.

Table 4. The fusion methods spatial performance measure based on entropy and mutual information.

Fusion Method	Spatial MI Dataset1	Spatial MI Dataset2	Spatial MI Dataset3	Spatial MI Dataset4
IHS	1.385	1.121	1.208	1.239
YCbCr	0.967	0.929	0.994	1.098
Brovey	1.349	1.300	1.190	1.197
Laplacian P	0.617	0.600	0.666	0.740
Contourlet	0.593	0.567	0.667	0.734
DWT	0.597	0.575	0.665	0.736
Our Method	0.589	0.580	0.652	0.717

Table 5 illustrates the mutual information, which includes spectral and spatial images performance evaluation. According to this table, the results IHS, YCbCr and Brovey are affected by input images, this means that when input image changes from SPECT to PET, their weaknesses apparent, while DWT, Laplacian-pyramid, Contourlet and proposed method do not have this problem. The proposed method is compared with other methods have desirable results in all datasets. According to the results of fused images evaluation and presentation of the tables, the average of the datasets is given in Table 6.

Table 5. The overallfusion performance measure based on entropy and mutual information.

Fusion method	MI Dataset1	MI Dataset2	MI Dataset3	MI Dataset4
IHS	0.403	0.217	0.238	0.259
YCbCr	0.603	0.222	0.311	0.267
Brovey	0.399	0.152	0.322	0.344
Laplacian P	0.730	0.615	0.683	0.641
Contourlet	0.763	0.606	0.703	0.736
DWT	0.759	0.608	0.700	0.729
Our Method	0.761	0.624	0.699	0.731

Table 6. Performance evaluation ofimagefusionbased onaverage.

Fusion method	Mean D_k	Mean Avg_k	Spectral MI mean	Spatial MI mean	MI mean
IHS	14.344	4.782	0.676	1.238	0.279
YCbCr	18.872	4.931	0.618	0.997	0.351
Brovey	13.042	4.374	0.700	1.259	0.304
Laplacian P	9.626	4.342	0765	0.656	0.667
Contourlet	9.026	4.776	0.851	0.640	0.702
DWT	8.893	4.621	0.838	0.644	0.699
Our Method	7.415	5.537	0.871	0.635	0.704

In totally the proposed method have minimum amount in evaluation of the discrepancy, in evaluation of fused image performance by average gradient, the spectral fusion performance and the overall fusion performance based on the entropy and mutual information have highest value, which these results are ideal. Also the proposed method has good spatial performance based on entropy and mutual informational though YCbCr, IHS, Brovey obtained high values in this evaluation, because our method considers balance between preserving of spatial and spectral information, it means that YCbCr, IHS, Brovey methods preserve spatial information and lose spectral information and they could not balance between spatial and spectral information.

6. Conclusions

In this paper, we proposed a new method for PET (or SPECT) and MRI images fusion. We assume PET (or SPECT) images are shown in pseudo-color, and as result, they were accepted as colored images. PET (or SPECT) images have desired spectrums and low spatial resolution, while MRI has suitable spatial resolution with no color information content.

Algorithms and fusion results of YCbCr fusion and the DWT fusion technique are reviewed to find the weak points of both fusion techniques and use their potencies. DWT image fusion method preserves more spectral features than YCbCr technique, but it preserves less spatial information content. The proposed method preserves the spatial and spectral information concurrently and reduces spectral bands distortion and spatial details are the same as original MRI.

Reference

[1] Amini N., Fatemizadeh E., and Behnam H., "MRI and PET Image Fusion by Using Curvelet Transform," *Journal of Advances in Computer Research*, vol. 5, no. 4, pp. 23-30, 2014.

[2] Amini N., Fatemizadeh E., and Behnam H., "MRI-PET Image Fusion Based on NSCT Transform Using Local Energy and Local Variance Fusion Rules," *Journal of Medical Engineering and Technology*, vol. 38, no. 4, pp. 211-219, 2014.

[3] Amolins K., Zhang Y., and Dare P., "Wavelet Based Image Fusion Techniques-An Introduction, Review And Comparison," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 62, no. 4, pp. 249-263, 2007.

[4] Chaia Y., Li H., and Zhang X., "Multifocus Image Fusion Based On Features Contrast of Multiscale Products in Non-Subsampled Contourlet Transform Domain," *Optik-International Journal for Light and Electron Optics*, vol. 123, no. 7, pp. 569-581, 2012.

[5] Daneshvar S. and Ghassemian H., "MRI and PET Image Fusion by Combining IHS and Retina-Inspired Models," *Information Fusion*, vol. 11, no. 2, pp. 114-123, 2010.

[6] Daneshvar S. and Ghassemian H., "MRI and PET Images Fusion Based on Human Retina Model," *Journal of Zhejiang University SCIENCE A*, vol. 8, no. 10, pp. 1624-1632, 2007.

[7] Eldad H., Heldmann S., and Modersitzki J., "A Computational Framework for Image-Based Constrained Registration," *Linear Algebra and its Applications*, vol. 431, no. 3-4, pp. 459-470, 2009.

[8] Eltoukhy M., Faye I., and Samir B., "Breast Cancer Diagnosis in Digital Mammogram Using Multiscale Curvelet Transform," *Computerized Medical Imaging and Graphics*, vol. 34, no. 4, pp. 269-276, 2010.

[9] Huang S., "Wavelet for Image Fusion," *Graduate Institute of Communication Engineering and Department of Electrical Engineering*, National Taiwan University, pp.1-29, 2010.

[10] Gharabaghi S., daneshvar S., and Sedaaghi M., "Retinal Image Registration Using Geometrical Features," *Digit Imaging*, vol. 26, no. 2, pp. 248-258, 2012.

[11] Iraji M. and Yavari A., "Skin Color Segmentation in Fuzzy YCbCr Color Space with the Mamdani Inference," *American Journal of Scientific Research*, pp. 131-137, 2011.

[12] Jiang J., Trundle P., and Ren J., "Medical Image Analysis with Artificial Neural Networks," *Computerized Medical Imaging and Graphics*, vol. 34, no. 8, pp. 617-631, 2010.

[13] Kang B., Jeon C., Han D., and Ko H., "Adaptive Height-Modified Histogram Equalization and Chroma Correction in Ycbcr Color Space For Fast Backlight Image Compensation," *Image and Vision Computing*, vol. 29, no. 8, pp. 557-568, 2011.

[14] Koutsias N., Karteris M., and Chuvieco E., "The Use of Intensity-Hue-Saturation Transformation of Landsat-5 Thematic Mapper Data for Burned Land Mapping," *Journal PE and RS, Photogrammetric Engineering and Remote Sensing*, vol. 66, no. 7, pp. 829-839, 2000.

[15] Kumar Y., "Comparison of Fusion Techniques Applied to Preclinical Images: Fast Discrete Curvelet Transform Using Wrapping Technique and Wavelet Transform," *Journal of Theoretical and Applied Information Technology*, vol. 5, no. 6, pp. 668-673, 2009.

[16] Li S., Yang B., and Hu J., "Performance Comparison of Different Multi-Resolution Transforms for Image Fusion," *Information Fusion*, vol. 12, no. 2, pp. 74-84, 2011.

[17] Mallat S., "A Theory for Multiresolution Signal Decomposition: the Wavelet Representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*. vol. 11, no. 7, pp. 674-693, 1989.

[18] Mallat S. and Hwang W., "Singularity Detection and Processing with Wavelets," *IEEE Transactions on Information Theory*, vol. 38, no. 2, pp. 617-642, 1992.

[19] Madhusudhanarao T., Setty S., and Srinivas Y., "Model Based Approach for Content Based Image Retrievals Based on Fusion and Relevancy Methodology," *The International Arab Journal of Information Technology*, vol. 12, no. 6, pp. 519-523, 2015.

[20] Pajares G. and Cruz J., "A Wavelet-Based Image Fusion Tutorial," *Pattern Recognition*, vol. 37, no. 9, pp. 1855-1872, 2004.

[21] Tu T., Su S., Shyu H., and Huang P., "A New Look at IHS-Like Image Fusion Methods," *Information Fusion*, vol. 2, no. 3, pp. 177-186, 2001.

[22] Wang Z., Ma Y., Cheng F., and Yang L., "Review of Pulse-Coupled Neural Networks," *Image and Vision Computing*, vol. 28, no. 1, pp. 5-13, 2010.

[23] Yang S., Wang M., Jiao L., Wu R., and Wang Z., "Image Fusion Based on A New Contourlet Packet," *Information Fusion*, vol. 11, no. 2, pp. 78-84, 2010.

[24] Zhang Y. and Hong G., "An IHS and Wavelet Integrated Approach to Improve Pan-Sharpening Visual Quality of Natural Colour IKONOS and Quickbird Images," *Information Fusion*, vol. 6, no. 3, pp. 225-234, 2005.

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