Integration of Spatial and Transform Domain Technique for the Multimodal Medical Image Fusion

S. Sandhya, M. Senthil Kumar, B. Chidambararajan

ABSTRACT---In the area of medical image processing, multi-modality medical image-fusion plays a vital role as it is helpful in understanding the organs of human captured through different modalities like MRI, CT, PET and etc., In this paper, the proposed approach implements a hybrid fusion algorithm for the medical images obtained from multiple modalities using 2DPCA and curvelet transform. The hybrid fusion is useful in improving the quality of the medical images and it is greatly helpful in medical diagnosis and treatment. PCA is used to obtain the most important features from the images. It can be used for isolation or it can be combined with other image fusion methods. The proposed scheme applies 2DPCA a variation of PCA (Principal Component Analysis) which is a dimension-reduction method. In contrast to PCA, 2DPCA directly works on the two dimensional images without any vectorization. Curvelet transform is an image segmentation oriented technique which divides the input image into tiles on which ridgelet transform is applied to for the process of edge detection. The performance of the hybrid fusion algorithm is evaluated against the quality metrics and it is shown that the proposed scheme works better than the existing method.

Keywords: Medical Image Processing, Multi-modal medical image, MRI, PET, CT, PCA, 2DPCA, Curvelet Transform.

I. INTRODUCTION

Medical Image-Fusion is a technique of obtaining an image called as fused image which possess the quality information about the organ under study. The fused image is thus helpful in carrying out the diagnosis and analysis by the medical experts. Medical Image Fusion incorporates in itself the areas like image processing, pattern recognition, artificial intelligence and computer vision. The image fusion techniques are classified into categories like multi-modality image fusion, multi-focusing image fusion, multi-resolution and multi-exposure image fusion. Multi-modality image fusion in the field of medical imaging plays a major role as the inputs from different modals like MRI, PET, and CT are considered.

With the help of various modalities the detailed information about the organs of patients are captured further it is processed to perform the diagnosis and analysis effectively. The modalities which are used in the medical field can be classified as functional and structural modalities. The MRI and CT are structural based modalities which provide the anatomical information of the organ under inspection but not the functional information. In contrast the functional modalities like PET modality (Positron Emission Tomography) and SPECT modality gives the information like chemical composition, blood flow and metabolism of the organ under study. Thus in order to obtain high quality information about the organ, images is captured using either functional and structural modality or both and fused into a single quality image.

As the medical image fusion is a major element in the field of medical diagnosis and analysis, effective fusion technique has to be adopted for obtaining the fused image. From the literature on the medical image-fusion, it is observed that the techniques of medical image fusion shall be structured as dimension reduction, support vector machine, wavelet, morphological, fuzzy logic, neural-network and knowledge based techniques.

PCA is a dimension reduction based method and widely used concept in the medical image fusion environment. In PCA, important features are extracted from the images by applying mathematical transformation which can be processed either isolation or combination with further image fusion methods. The PCA technique is simple and effective, hence many variants of PCA have been proposed. One such variant is 2DPCA [11] which works on the 2D medical images.

In this proposed paper, a hybrid fusion based algorithm is given based on 2DPCA and Curvelet Transform for the multi-modal images. The images obtained from the MRI and PET is considered for evaluation. The Related Works, Proposed Work, Experimental results with Discussion and Conclusion are given in Section II, III, IV and V respectively.

II. RELATED WORKS

Qamar Nawaz, Xiao Bin et. al [11] proposed a new image fusion based on 2D-PCA for the medical images obtained from multi-modalities. In contrast to traditional PCA, 2DPCA technique directly considers the 2d matrices rather than 1D vectors. P. Mathiyalagan in [8] discussed the advantage of applying curvelet transform to the multi-modal medical images. Curvelet Transform is advantageous due to its usage in handling the curve discontinuities. It is based on ridgelet transform. The Curvelet Transform yields better performance in comparison with transform methods in the terms of signal to noise ratio. B.Rajalingam, Dr.R.Priya in [13] discussed the performance of image fusion results obtained from the methods like PCA, Image Fusion using Guided Filtering, DWT, Curvelet Transform and PCNN model and finally designed a

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S. Sandhya, Assistant Professor, SRM Valliammai Engineering College, Chennai, TN, India. (sanrsn@gmail.com)

Dr. M. Senthil Kumar, Associate Professor, SRM Valliammai Engineering College, Chennai, TN, India.. (msen1982@gmail.com)

Dr. B. Chidambararajan Professor/Principal, SRM Valliammai Engineering College, Chennai, TN, India.. (profbcr@yahoo.com)

hybrid multi-modal image fusion technique based on PCNN (Pulse-Coupled Neural Network) and Curvelet transform where the images are transformed using Curvelet Transform and finally fused using PCNN to obtain the high quality of the fused image. The concert of the hybrid technique were analysed against the existing techniques and it was shown that hybrid model yields better fusion results than the other fusion techniques. B.Rajalingam, Dr.R.Priya in [14] describes the hybrid multi-modality image fusion which combines of fuzzy logic with neural network for the improved performance and the superiority of the target image. In [5] JyotiAgarwalet. al derived a hybrid fusion of medical images using Wavelet and Curvelet Transform integrating the pixel level fusion rules to obtain the fused image. In this hybrid model, the input images are decomposed through low-pass filter and high-pass filter. Further it is subjected to decomposition into tiles using Curvelet Transform. In [1] S. Chavan, A. Pawar and S. Talbar discussed the performance of image fusion using the Rotated Wavelet Transform (RWT) which preserves the edge-related information about the images captured from different modalities. Qiang Cao, Baosheng Li and Liyuan Fan [12] combine the GPU accelerated nonsubsampledshearlet transform and 2DPCA for gaining the smoothness in the fused image by pixel distribution. Here the input images are fused together by applying nonsubsampledshearlet transform and 2DPCA for calculating the sub-bands by applying global and local replacement rule. In [9] the input images are MRI and PET respectively, the PET images are decomposed into HIS transform in which high activity area is transformed into low activity region. Then the target image is obtained by applying the transformation technique using DWT and inverse DWT. In [9] a Joint fusion method algorithm was proposed by combining OMP and PCA. From the source images the common and innovative images are extracted and then the sparse method for PCA is deployed for fusing the significant information. Finally the result of sparse PCA is fused by employing weighted average method along with significant features of the images considered for preserving the spatial information and edge information. RajashreeNambiar P et. al. in [15] discussed the image fusion of medical images using Curvelet transform where the registered input images are processed and a set of Curvelet-Coefficients are created. Then fusion rule i.e. PCA is applied for the better view of the fused images. MRI and CT images are considered as input and their performance results were shown. For the better medical diagnosis C.Karthikeyan and B. Ramadoss in [6] proposed a wavelet transform using the dual-tree complex (DTCWT) and SOM (Self-Organizing Map) for the image fusion. In [4] Jing-jingZonga and et.al.proposed the sparse representation of image patches for the medical images where the input images are segregated into confidential spots based on patch-geometrical route and the fusion rule for choose-max joined with the sparse coefficients. The fused image is finally restructured from the sparse-coefficients and its consistent sub-dictionary. RichaGautamet. al in [16] describes the method of union Laplacian in which numerous features are transferred accurately from the source to target image. In [10] the image-fusion of medical related images is done by using the method non-subsampled contourlet transform (NSCT) for decomposing the lowpasssubband images and highpasssubband images. In [2] Heba M. El-Hoseny et.al.given a model for hybrid fusion that integrates the Additive Wavelet and Dual-Tree Complex Wavelet Transform. Rangarajan P, UdhayaSuriya TS implements the DWT in [17] for the MRI and PET fusion images for the diagnosis of brain tumor.

III. PROPOSED SYSTEM

a. 2Dimensional Principal Component Analysis (2D PCA)

In 2D-PCA, 2D matrices are processed rather than ID vectors. Hence prior transformation is not required on the vectors rather the covariance matrix is calculated from the matrices extracted from the source images. The covariance matrix size of 2DPCA and the input images are equal and also retain the columns as well as rows information which can be calculated for principal components. 2D-PCA has the following pros when compared to PCA.

- Covariance matrix calculation is easy and accurate
- Corresponding eigenvectors requires less time.

Let A be a set of n, two dimensional input images of size axb. Calculate the mean value from the set A and normalize the images by removing the mean. Calculate the covariance matrix C from the images which removed mean. Then matrix is constructed from the eigen values and eigen vectors. Thus the principal components are calculated by the projection of source images onto eigen vectors.

b. Curvelet Transform

Curvelet Transform is an image segmentation based technique where the multi-modal input medical images are segmented into a number of coinciding tiles. Further edge detection is performed by applying ridgelet transform to the tiles. The Curvelet Transform works in 4 stages:

- ✓ Decomposing subband
- ✓ Smooth-Partitioning
- ✓ Re-normalization and
- ✓ Analysis of Ridgelet

In the first stage, the decomposed wavelet sub-bands are obtained from the input images and Curvelet sub-bands are made at various levels through the partial image reconstruction. In smooth partitioning stage, the image (decomposed) in each of the sub-band is processed as windowed into squares of appropriate scale. Further the square is reorganized as unit scale in renormalization stage. Finally ridgelet transform is applied where the curved edge details from the input images are obtained.

c. The Proposed Hybrid Fusion Model (Curvelet Transform and 2DPCA)

In the proposed scheme applies both the Curvelet Transform and 2DPCA techniques are applied to the multi-modality medical image. The input images are MRI and PET images. The structure of the proposed hybrid model is depicted in Figure 1.

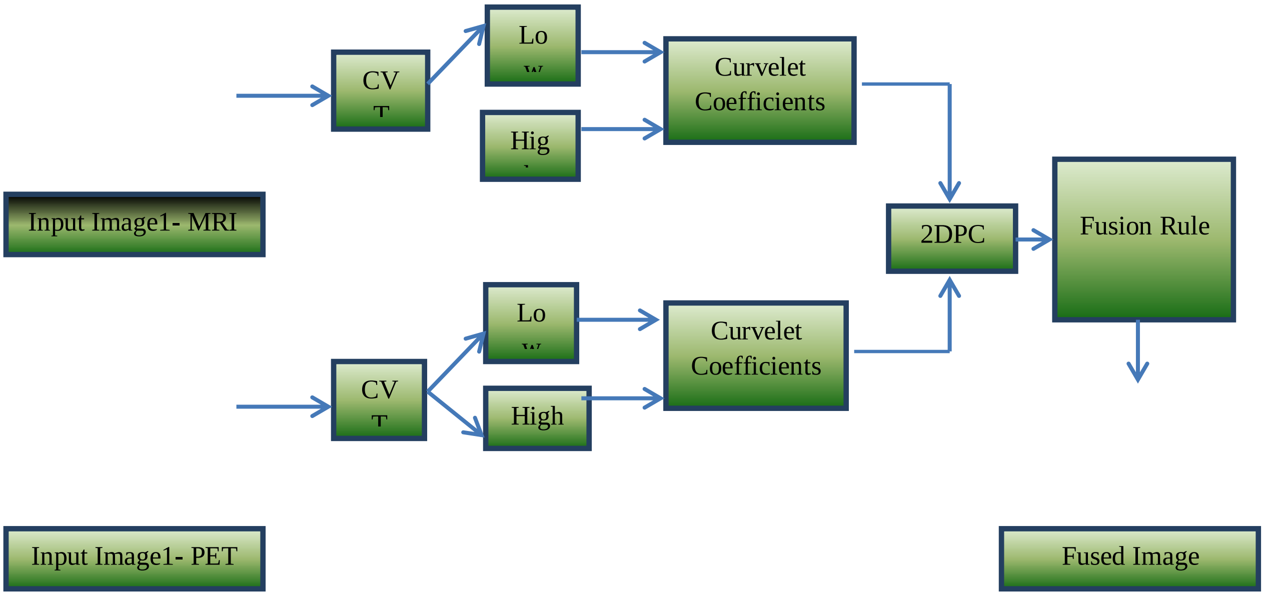

Figure 1 The Structure of the Proposed Hybrid Model

The procedure for the Hybrid Model is as follows,

- The registered images of multi-modality are used to generate curvelet coefficients.
- The fusion rules like Maximum and Minimum Selection and Simple-Average are processed.
- Reconstruction is performed both on the feature layers and bottom layers of the given input images.
- Inverse-Curvelet Transform (ICVT) is used to restructure the multimodal images.
- Now apply the 2DPCA for obtaining the quality fused image and hence it is displayed.

IV. EXPERIMENTAL SETUP& RESULTS

To analyze the performance of the proposed hybrid fusion algorithm, two input images of MRI and PET are taken into consideration each of having 256 pixels of width and height. The results are compared with the existing techniques like PCA, DWT. The experimental setup includes MATLAB R2013b using Windows 7 Operating Systems. The performance evaluation metrics Average Gradient (AG)[18], Standard Deviation (STD), Structural Similarity Index Metric (SSIM)[3], Feature-Similarity Index Metric and Mutual Information (MI) are used to evaluate the results of proposed method against the existing techniques.

Performance Metrics

a. Average Gradient (AG) gives the quantity of texture deviations from the image. The calculation of AG is given as,

$$g = \frac{1}{(R-1)(S-1)} \sum_{i=1}^{(R-1)(S-1)} \frac{\sqrt{(\frac{\partial f}{\partial x})^2+(\frac{\partial f}{\partial x})^2}}{2} \quad (1)$$

b. Standard Deviation (STD) finds the difference of data from the average or mean value. If STD value is larger the input image is meant to be clear. It is given in the equation (2),

$$STD = \frac{\sqrt{\sum_{i=1}^{R}\sum_{j=1}^{S}|f(i,j)-\mu|^2}}{RS} \quad (2)$$

c. SSIM (Structural Similarity Index Metric) shows the resemblance between two cordinates$w_x$and w_y of two images x and y.

$$SSIM = \frac{(2\bar{w}_x\bar{w}_y+C_1)(2\sigma w_x w_y+c_2)}{\bar{w}_x^2+\bar{w}_y^2+c1)(\sigma^2 w_x+\sigma^2 w_y+c2)} \quad (3)$$

where c1 and c2 are small constants. $\bar{w}_x$and$\bar{w}_y$are mean values, $\sigma^2 w_x$ and $\sigma^2 w_y$ are variance and $\sigma w_x w_y$ are co-variance of w_x and w_y respectively.

d. MI (Mutual Information) is a key used for calculating amount of dependency among two images say R and S respectively. The value of MI is calculated as follows in equation (4)

$$MI(r,s,f) = \frac{I(r,s)+I(r,f)}{H(r)+H(s)} \quad (4)$$

where H(r) and H(s) are entropies of images r and s.

e. Feature Similarity Index Metric (FSIM) represents the edge resemblance among input and fused images. The calculation of FSIM is given in equation (5)

$$FSIM = \frac{\sum_{x\in\Omega} S_L(x)PC_m(x)}{\sum_{x\in\Omega} PC_m(x)} \quad (5)$$

where Ω is the spatial domain of the image, $S_L(x)$ is the resemblance among the given images and $PC_m(x)$ is the segment congruency value.

The fusion results of the input images are shown in Figure 2a to 2e, their experimental results and performance analysis in the form of graph are shown in Table 1 and Figure 3 respectively.

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a. MRI **b. PET** **c. 2DPCA** **d. CVT** **e.Proposed Method**

Figure 2 Results of Image Fusion

Table 1. Performance Metrics for image fusion algorithms

Methods	Performance Metrics				
	AG	STD	SSIM	MI	FSIM
2DPCA	0.059	0.687	0.798	0.826	0.945
CVT	0.074	0.728	0.781	0.861	0.943
Proposed Method	0.092	0.868	0.789	0.871	0.978

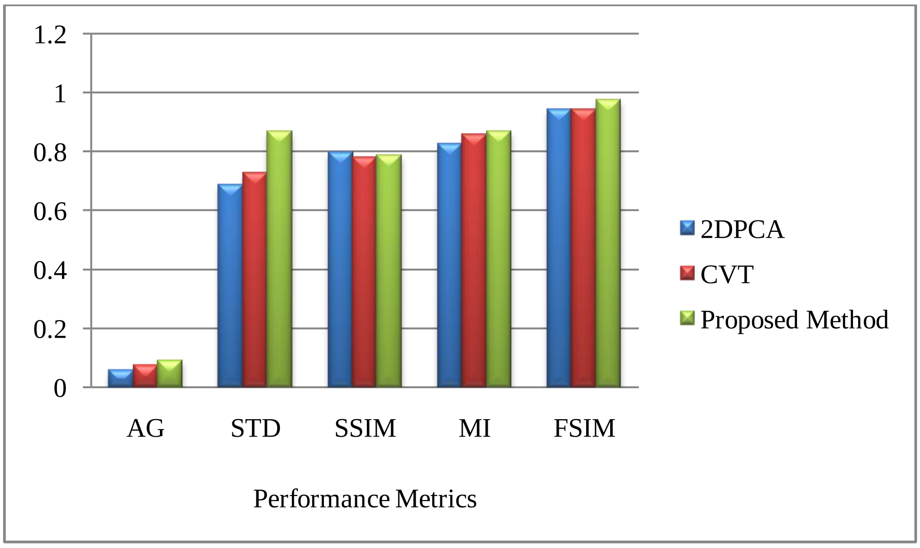

Figure 3 Performance Analysis for the input images

V. DISCUSSION

In the proposed system, the input images MRI and PET images of 512 x 512 size is considered. The Table 1 describes the performance metrics of the proposed system against the existing fusion techniques. For the purpose of evaluation of the proposed hybrid fusion model MRI and Pet images are taken into account as the multimodal medical images. The performance metrics of the proposed hybrid fusion model integrating Curvelet Transform and 2DPCA is compared against the 2DPCA and DWT. The performance metrics shown in Table 1 and Figure 3 depicts that the hybrid fusion model preserves edge information from the input images also it provides high details of spatial information which is greatly helpful in the medical diagnosis and treatment.

VI. CONCLUSION

The proposed work investigate the performance of hybrid fusion of multimodal medical images against the traditional techniques. It is shown that the proposed hybrid model employing Curvelet Transform and 2DPCA yields better fusion results by providing high image quality, short processing time, more precise image details and etc., By using the Curvelet Transform the curve edges of the images are obtained more precisely which is furthermore improved by the fusion rule 2DPCA thus reducing the processing time of the image by directly working on 2D images. The fusion of multimodal medical images shall be made more accurate by deploying hybrid fusion model as a good choice in the field of medical diagnosis and treatment.

REFERENCES

1. S. Chavan, A. Pawar and S. Talbar, "Multimodality Medical Image Fusion using Rotated Wavelet Transform", ICCASP/ICMMID-2016, Advances in Intelligent Systems Research, vol. 137, pp. 627-635.
2. Heba M. El-Hoseny, El-Sayed M. El. Rabaie, WaelAbdElrahman and Fathi E AbdElSamie, " Medical Image Fusion Techniques based on Combined Discrete Transform Domain", 34th National Radio Science Conference-NSRC 2017, IEEE 978-1-5090-4609-6/17-2017.

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3. A. Hore and D. Ziou, "Image Quality Metrics:PSNRvs SSIM", 20th International Conference on Pattern Recognition, pp. 2366-2369, 2010.
4. Jing-Jing Zonga and Tian-ShuangQuia, "Medical Image Fusion based on Sparse Representation of Classified Image Patches", Elsevier, Biomedical Signal Processing and Control, vol. 34, pp. 195-205, 2017.
5. JyotiAgarwal and Sarabjeet Singh Bedi, "Implementation of Hybrid Fusion Technique for Feature Enhancement in Medical Diagnosis", Human-centric Computing and Information Sciences, pp- 1-17, 2015.
6. C. Karthikeyan and B. Ramadoss, "Comparative Analysis of Similarity Measure Performance for Multimodality Image Fusion using DTCWT and SOFM with various Medical Image Fusion Techniques", Indian Journal of Science and technology, vol. 9(22), 2016.
7. Mamatha M.V, Chandrakala, "Image Fusion based on Joint Sparse Method with DWT for Medical Applications", International Journal on Advanced Electrical and Computer Engineering-IJAECE, vol. 2, issue. 2, pp.7-10, 2015.
8. P. Mathiyalagan, "Multi-modal Medical Image Fusion using Curvelet Algorithm", International Conference on Advances in Computing Communications and Informatics-ICACCI, pp. 2453-2458, 2018.
9. Mohamed Basil Abdulkareem, "Design and Development of Multimodal Medical Image Fusion using Discrete Wavelet Transform", Proceedings of 2nd International Conference on Inventive Communication and Computational technologies-ICICCT, pp. 1629-1633, 2018.
10. PeriyavattamShanmugamGomathi, BhuvaneshKalavathi, "Multimodal Medical Image Fusion in Non-Subsampled Contourlet Transform Domain", Scientific research Publishing Circuits and Systems, vol. 7, pp. 1598-1610, 2016.
11. Qamar Nawaz, Xiao Bin, Li Weisheng, Isma Hamid, "Multi-modal Medical Image Fusion using 2DPCA", 2nd International Conference on Image Vision and Computing, pp. 645-649, 2017.
12. Qiang Cao, Baosheng Li, Liyuan Fan, "Medical Image Fusion based on GPU Accelerated Non-Subsampled Shearlet Transform and 2D Principal Component Analysis", IEEE 2nd International Conference on Signal and Image Processing, pp. 203-207, 2017.
13. B. Rajalingam, Dr. R. Priya, "A Novel Approach for Multimodal Medical Image Fusion using Hybrid Fusion Algorithms for Disease Analysis", International Journal of Pure and Applied Mathematics, vol. 117, no. 15, 2017.
14. B. Rajalingam, Dr. R. Priya, "Hybrid Multimodality Medical Image Fusion Technique for Feature Enhancement in Medical Diagnosis", International Journal of Engineering Science Invention-IJESI, pp. 52-60, 2018.
15. RajashreeNambiar P, Usha Desai, Vibha B. Shetty, "Medical Image Fusion Analysis using Curvelet Transform", International Conference on Adv. in Comp., Comm., and Inf. Sci. pp. 1-12, 2014.
16. RichaGautam and ShilpaDatar, "Application of Image Fusion Techniques on Medical Images", International Journal of Current Engineering and Technology, 2017.
17. UdhayaSuriya TS, Rangarajan P, "Brain Tumour Detection using Discrete Wavelet Transform based Medical Image Fusion", Biomedical Research, 2017.
18. S. Zebhi, "Image Fusion using PCA in CS Domain", Signal Image Process. Int. Journal, vol. 3, no. 4, pp. 153-161, 2012.