Multimodal Medical Image Fusion using NSCT and DWT Fusion Frame Work

K. KoteswaraRao, K. Veera Swamy

Abstract: Image fusion is the process, which gathers significant details from two or more images. Implementation of fusion of images is carried out either in spatial or in transforms domains. In this work, fusion is done in both domains to get better performance. Energy of decomposed bands of NSCT is used to select important bands in NSCT based image fusion. Energy of decomposed bands of DWT is used to select important bands in DWT based image fusion. Fused images of NSCT and DWT are further fused by using spatial domain technique. In spatial fusion ESOP values are taken into consideration to perform fusion. Experiments are done on several medical images. Results show that the proposed method is giving perceptually meaningful fused images. Image metrics like entropy, edge based similarity measure and quality of mutual information have been used for the assessment of performance of the work. In this research work, two medical images (CT, MRI), after pre-processing, will be merged according to the wavelet and NSCT transformations using energy fusion techniques to generate two independent fusion images that will be merged again using spatial domain to get the desired output. In this way the large amount of comprehensive information can be presented in the merged image, all the comprehensive information obtained from the two medical images appears in the final output. The experimental outcomes on different CT and MRI images are analyzed qualitatively and quantitatively. Image fusion has been implemented in the various applications like remote sensing, space research, defence, medical imaging etc. The performance parameters show remarkable improvements.

Keywords: Medical image fusion, DWT, NSCT, Energy and Edge strength orientation preservation.

I. INTRODUCTION

Now a day, screening programmers focus on digital data and screening techniques are designed for detecting early symptoms of diseases and remedies for treatment. In medical imaging, there are different modalities with different capabilities to get useful information of human body. Even though, there may be many sources, a single source is not able to provide more valuable information in discriminating diseases. The problem with single source is costly, meticulous, causing error, time consuming and it requires more experience. These factors of single image motivated the researchers to get appropriate information. Furthermore, the latest image modalities are more costly, which are the additional burden for the individuals. So, it is necessary to combine individual images into a single image, which is more suitable for efficient diagnostic assessment.

Many researchers [1], [3] have developed different fusion algorithms Algorithms on image fusion are broadly categorized into two, one is the spatial domain and another one is the transform domain. Spatial methods deal directly with the pixel. Desired result is achieved by manipulating the pixel values. This method fuses source images by using spatial local features. The algorithms based on spatial methods are bravery method, HIS, PCA, averaging method, minimum absolute method [5], [6], averaging method and weighted averaging method, which are focused to reduce unwanted edge information. These methods are simple compared to transform methods. Spatial domain fusion rules like mean, minimum and maximum methods failed to get salient features of images. But, the edge strength and orientation preservation fusion rule gives more comprehensive information of fused image. The selection of block and its size decides the quality of the merged image.

Some authors approached transform domain techniques to increase the performance of fusion. In transform domain, images are transferred into frequency domain. In this domain, source images are projected into local bases and these are designed to convey sharpness and edges. Salient features are detected by transformed coefficients. These methods provide good quality spectral content. Image fusion based on the wavelets [7] was proven to be efficient in capturing one-dimensional singularity. DWT is good at isolated discontinuity. It is ideal fusion scheme. DWT captures point wise information at only few directions. DWT is shift variant and it requires down sampling. The drawback with wavelet fusion is limited directionality. Wavelet fusion does not give more information about edges [8]. To avoid the problems of wavelet fusion, the RT [9] was introduced to get edge information, but failed in capturing details of curve edges. Wavelets [7], contourlets[13],[14] curvelets [10],[11] and NSCT[16],[19] come under this category. Donoho introduced curvelets [10], which are capable of capturing 2D singularities of an arbitrary waveform. Srivasthava et al [12] used localized energy fusion rule using curvelets and it was proved as an efficient method than any other fusion of single pixel. After that, other transformation methods such as contourlet transform has been introduced [13],[14]. In this, shift variance and less directionality were observed. To avoid these problems, the NSCT has been presented and is broadly used in the image fusion. Cunha [16] proposed a non sub sampled contourlet transform. Yang [17] introduced a method, which uses wavelet-based NSCT image fusion approach. Ganasala [19] implemented image fusion by taking CT and MRI images in NSCT domain. Padma et al. introduced a fusion approach which is also NSCT based and proved better performance measures [18].

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In NSCT shift is not varied, image is viewed at different resolutions, scale is multiple and high directionality is achieved. It avoids the usage of up-sampling and down sampling. It gives more information about edges. Murphy, Azam and Sun revised the shearlet transform as non subsampled scheme named as non sub sampled shearlet transform. It avoids the usage of samplings in decomposition and inversion by keeping high directionality [28]. In [29], Guoronga revealed the superiority of NSST compared to NSCT and other wavelet fusion techniques. Recently, different fusion techniques with merits and demerits were stated [30]. By considering the outcomes of various methods, it is understood that still there are some parameters, which are to be improved so that the loss of meaningful information is reduced. These problems are addressed in the proposed method.

In this work, dual level fusion is framed by taking the concepts of NSCT [16] and DWT [7] at the first level and the concepts of spatial domain [6] in the second level. Energy fusion rule is taken for all the frequency coefficients of both NSCT and DWT at first level. Edge strength and orientation preservation fusion rule is applied to sub blocks of spatial domain. CT and MRI images are the inputs to both NSCT and DWT, and these are fused in NSCT domain and DWT domain independently. The outputs of both NSCT and DWT are again fused using spatial domain principles. The dual level fusion framework preserves relevant information and enhances visual quality of output image. The performance is analyzed subjectively and objectively. For fusing all frequency coefficients of both NSCT and DWT at the first stage, energy fusion rule is used and in the consequent stage ESOP fusion rule is used

Existing methods on spatial domain like mean, minimum, maximum were failed to give comprehensive information and to design good fusion algorithm but edge strength and orientation preservation fusion rule gives more meaningful information in the final fused output.

This paper is organized by presenting DWT, NSCT details in second section, proposed fusion frame work in third section, discussion of results in fourth section and finally Conclusions are in the fifth section.

II. METHODOLOGY

This part brings the depiction of concepts based on which the recommended framework is formed.

A. Non-Subsampled Contour Let Transform

NSCT is one type of multiscale, multidirectional and multiresolution framework for the computation of discrete images [16]. It comprises two stages which are, pyramid without subsampling (NSP) and bank of directional filters without subsampling (NSDFB). The first stage provides a multi-scale property using a non subsampled two-channel filter bank. Every NSP decomposition stage produces one LF and one HF components. The consequent stage NSP decomposes the low frequency components in the iterative manner to bring uniqueness. With this outcome, NSP produces N+1 sub images, with N high frequency images and single low-frequency and N represents number of levels of decomposition. After decomposition the sizes of source and sub images must be same. NSP decomposition with N = 3 levels is shown in Fig.1. The combination of fan filter banks produce NSDFB (Non sub sampled directional filter bank), which is a two-channel filter, that accepts directionality decomposition. For M levels, 2^M directional sub images are produced by NSP at every scale. As a consequence, the NSDFB provides NSCT a multidirectional ability that gives extra decisive information about the directionality. These details are illustrated in Fig.2.

Fig.1. Three Stage NSP decomposition

Fig.2. Four Channel NSDFB

Mathematically Energy of each sub band is calculated using the formula

\[ E_1(j,k) = \sum_{i=1}^{j+1} \sum_{k-1}^{i+1} A(j,k) \]  

\[ E_2(j,k) = \sum_{i=1}^{j+1} \sum_{k-1}^{i+1} B(j,k) \]  

Where A and B are two source images.

B. Discrete Wavelet transform

The theory and concept of wavelets have come from Mallat. Wavelet transform quantifies the matching of the signal with the wavelets. If the shape of the signal matches with wavelet, then higher value of transform is obtained. If the signal is not correlated well with wavelet, low transform value is obtained. The Transform is computed at various scales and locations. The wavelet transform is useful as a tool which detects regional characteristics in the processing of images. This transform gives time-frequency representation of an image. This transform conquers the defects of STFT, and it analyses non stationary signals also.
In this, signal is viewed at different resolutions. This transform is treated as mathematical microscope. The DWT decomposes the input sequence as low and high pass sub-bands. Each sub band consists of half samples of the original input. In DWT the input is analyzed with analysis filter bank succeeded by the operation called decimation. A 2D transform is obtained by using two one dimensional transforms. Firstly the input image is filtered along rows and decimated by two. Then it is followed by filtering sub image along column. This process separates the input into sub bands those are shown in the Fig.3.

Fig.3. DWT Decomposition

The two dimensional DWT is expressed

\[
\psi_{i,j}(x,y) = \frac{1}{\sqrt{N}} \sum_{u=-N/2}^{N/2-1} \sum_{v=-N/2}^{N/2-1} f(x,y) \psi_{i,j}(u,v) \phi_{i,j}(x-u,y-v)
\]

where \( \phi_{i,j}(x,y) = 2^{i/2} \phi(2^j x - u, 2^j y - v) \) is the scaling function and \( \psi_{i,j}(x,y) = 2^{i/2} \psi(2^j x - u, 2^j y - v) \) is the translated function. \( N \times N \) is the size of the image.

C. Spatial domain

Spatial domain directly manipulates the pixels. This domain is easier to understand, it is cheaper and it takes less time. The edge based similarity measure provides the analogy among the edges carried out. The edge based similarity measure provides the localization of this framework. This measure is described in the Eq(5).

\[
Q_{AB/F} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} |Q_{AB}^{ij} w_{ij} + Q_{BF}^{ij} w_{ij}|}{\sum_{i=1}^{M} \sum_{j=1}^{N} |w_{ij}|}
\]

where \( A, B, F \) are the inputs and output images respectively. The individual parameters are same and these are given as

\[
Q_{AB}^{ij} = Q_{BF}^{ij} = Q_{AF}^{ij}
\]

III. PROPOSED FUSION FRAMEWORK

This part shows the discussion of some of motivational factors in designing our idea for fusing medical images. The suggested work is taken into account, which requires two different images of the same source to get the compound image. The essential requirement of this framework is the source images must be registered for the alignment of pixels.

Proposed dual fusion methodology steps

To test the suggested fusion method, the image data typical of CT and MRI are taken and these are named A and B. The following steps are followed in our proposed algorithm.

Step 1: Take the images that will be merged from the database and the pre-processing treatment is done. As a general rule, images of 256 x 256 sizes are selected for evaluation.

Step 2: First level merge: Apply NSCT on the input images, it results one LF and set of HF coefficients in every level and orientation. In this decomposition, number of levels(n) taken are \([2, 2, 4]\). With these levels no. of sub bands formed are 4,4,16. For the pyramidal filter and directional filters, maxflat filter and dmaxflat7 filters have been used respectively.

Step 3: Energy of each co-efficient is calculated using the formula

\[
E_1(j,k) = \sum_{l=1}^{L} \sum_{k=1}^{K} A(j,k)
\]

\[
E_2(j,k) = \sum_{l=1}^{L} \sum_{k=1}^{K} B(j,k)
\]

Step 4: Low frequency fusion: The approximation of source images is represented by sub images of low frequency. Simple average methods are used for merging. However, because of low contrast, a high quality merged image cannot be obtained. So we use an Energy fusion rule

\[
F_1(j,k) = \begin{cases} F_1(j,k), & \text{if } E_1(j,k) > E_2(j,k) \\ F_2(j,k), & \text{if } E_2(j,k) < E_1(j,k) \\ \frac{E_1(j,k) + E_2(j,k)}{2}, & \text{else} \end{cases}
\]

Step 5: High-frequency fusion: The detailed components of source images correspond to sub images of high frequency. Energy of each sub band is calculated as

\[
F(j,k) = \begin{cases} F_1(j,k), & \text{if } E_1(j,k) \geq E_2(j,k) \\ F_2(j,k), & \text{if } E_2(j,k) < E_1(j,k) \end{cases}
\]

Step 6: Inverse operation of NSCT is done on all frequency sub bands to achieve the first level fused image F.
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Fig. 5. DWT fusion
The energy of all sub bands is calculated using (1). Compare energy of each sub band of both source images using the following relation

\[ C^l_f(j,k) = \begin{cases} C^l_A(j,k), & \text{if} \ E^l_A(j,k) > E^l_B(j,k) \\ \frac{1}{2} \sum_{\theta} C^l_{\theta}(j,k), & \text{if} \ E^l_A(j,k) = E^l_B(j,k) \\ C^l_B(j,k), & \text{if} \ E^l_A(j,k) < E^l_B(j,k) \end{cases} \] (12)

Fusion of High-frequency Sub-images: The HF sub-images correspond to detail components of the input images. Energy of each sub band is calculated as

\[ C^f_h(j,k) = \begin{cases} C^f_A(j,k), & \text{if} \ E^f_A(j,k) \geq E^f_B(j,k) \\ C^f_B(j,k), & \text{if} \ E^f_A(j,k) < E^f_B(j,k) \end{cases} \] (13)

The general principle is to keep the essential characteristics of new images, such as regions and contours. The largest energy transformation values in these sub bands correspond to sharper intensity variations.

Step 8: The two merged images which are F and C are again fused to get another fused image. This is the second level fusion. Spatial method is used to perform second level fusion. Both images F and C of sizes 256x256 are divided into 32 non overlapped 8x8 blocks.

Step 9: For every block apply edge strength and orientation preservation ESOP using (3)

Step 10: Select corresponding block from every source image according highest ESOP

\[ D_F(j,k) = \begin{cases} D_1(j,k) \text{ ESOP}_1(j,k) \geq \text{ ESOP}_2(j,k) \\ D_2(j,k) \text{ ESOP}_1(j,k) \leq \text{ ESOP}_2(j,k) \end{cases} \] (14)

Where \( \text{ESOP}_1(j,k) \) and \( \text{ESOP}_2(j,k) \) are respective blocks with highest ESOP (j, k). \( D_F(j,k) \) is the selected block. Fuse the corresponding block into the empty block.

Step 11: The entropy, edge based similarity measure and quality of mutual information values of the final merged images were recorded and presented in the table.

Fig. 6. Suggested System Block Diagram

IV. EXPERIMENTAL RESULTS AND PERFORMANCE MEASURES

This part shows the performance of the suggested fusion method. Fusion algorithm needs some requirements 1. It must extract comprehensive features from both input images. 2. Inconsistencies or artefacts should not be appeared. 3. It must be reliable. In general these are evaluated subjectively as well as objectively. Result analysis reveals remarkable improvements in the proposed method at the second level. In all the sets of images, all performance indices which are Entropy, Edge based similarity measure and Quality of mutual information using dual level fusion have been improved. Among all performance indices Entropy plays an important role and it is good for all sets of images in the second level fusion. Edge based similarity measure has been improved in all cases in the second level fusion. Quality of mutual information also has been improved at the second level fusion compared to DWT and NSCT.

Fig. 7. The multimodal medical image fusion results
V. CONCLUSIONS

Fusion of medical images from various modalities is examined as a topic of study for researchers due to its importance and usefulness for the health sector and a better diagnosis with merged images of quality information. Ideally, merged images should contain more comprehensive information than any input image, even if the redundant information is present. Typical images of MRI and CT and two transforms are made, namely a DWT and NSCT with different fusion rules at the first level, spatial domain method at the second level and their performance measures were studied. In this study, the authors tested a double fusion scheme by fusing the two merged images generated independently with DWT and NSCT. Performance indices, which are Entropy(E), Edge based similarity measure($Q_{AB/F}$) and Quality of mutual information ($Q_{MI}$) for DWT, NSCT and proposed method have been compared. By comparison, it has been observed that, the suggested algorithm which is dual level fusion given good results.

REFERENCES

1. A Garzelli, “Possibilities and limitations of the use of wavelets in image fusion” In IEEE Geoscience and Remote Sensing Symposium, Vol.1, pp. 66-68, 2002.
2. Jing, Z et al. “Evaluation of focus measures in multi-focus image fusion”, Pattern recognition. Lett. 28, (4), pp. 493-500. 2007
3. Dattatraya, Deepali, “Wavelet based Image Fusion using Pixel based maximum selection rule” International Journal of Engineering Science and Technology (IJEST), vol. 3, no. 7, pp.5572-5577, 2011.
4. Davy Sannen, Hendrik Brussel, “A multilevel Information Fusion Approach for visual quality inspection,” Information Fusion, Vol. 13, no.1, pp. 48-59, 2012.
5. Wan, T.,Zhu, C., Qin.Z. “Multifocus image fusion based on robust principal component analysis” Pattern Recognition, Lett. 34, (9), pp. 1001-1008, 2013.
6. Toet, A.“Image fusion by a ratio of low pass pyramid”, pattern recognition let.,9,(4), pp.245-253,1989.
7. Li, H., Manjunath, B.S., Mitra, S.K. “Multi sensor image fusion using wavelet transform” Graph. Modal Image processing. 57,(3), pp.235-245,1995.
8. Pajares, G., Manuel de la Cruz, J. “A wavelet-based fusion of multi-focus images” pattern recognition let.,37,(9), pp.1855-1872,2004.
9. Do, M.N, Vetterli, M “The finite ridgelet transform for image representation” IEEE Trans Image Process,12,(1),pp, 1855-1872,2003.
10. Starc J.L., Candes, E.J., Donoho, D.L.“The curvelet transform for image denoising” IEEE Trans Image Process,11,(6),pp, 670-684,2002.
11. Li, S.,Yang,B.: “Multifocus image fusion by combining curvelet and wavelet transform” pattern recognition let.,29,(9), pp.1295-1301,2008.
12. R. Srivastava, O. Prakash, and A. Khare, “Local energy based multi modal medical image fusion in curvelet domain” IET Comput. Vis., vol. 10, no. 6, pp. 513-527, Sep. 2016
13. S. Yang, M. Wang, L. Jiao, R. Wu, and Z. Wang, “Image fusion based on a new contourlet packet” Inf. Fusion, vol. 11, no. 2, pp. 78–84, 2010.
14. Bhatjia, H. Patel, A. Krishn, A. Sahu and A. Lay-Ekuakille “Multimodal medical image sensor fusion framework using cascade of wavelet and contourlet transform domains” IEEE Sensors J., vol. 15, no. 12, pp. 6783-6790, Dec. 2015
15. Kong, W., Lei, Y “Technique for image fusion between gray-scale visual light and infrared images based on NSST and improved RF”, Optik, 124, (23), pp. 6423-6431, 2013.
16. Da Cunha A L, Zhou J P, Do M N. “The nonsampled contourlet transform: theory design, and applications”. IEEE Transactions on Image Processing., 15(10):3089–3101, 2006
17. Yotam Ben-Shoshan, Yitzhak, “Improvements of Image Fusion methods” J. Electron Imaging, Vol. 23, no. 2, pp.1-12, 2014.

Table I: Performance indices of various algorithms

| Set No. | Parameter | DWT | NSCT | PROPOSED METHOD |
|---------|-----------|------|------|-----------------|
| SET-1   | Entropy   | 1.95504 | 2.452802 | 2.373966 |
|         | ESSIM     | 0.995825 | 0.997448 | 0.999999 |
|         | QMI       | 0.813499 | 0.688269 | 1.342255 |
| SET-2   | Entropy   | 1.001128 | 2.745131 | 4.991662 |
|         | ESSIM     | 0.994149 | 0.990964 | 0.99987 |
|         | QMI       | 0.7349 | 0.631618 | 1.318422 |
| SET-3   | Entropy   | 1.002352 | 2.755405 | 5.013958 |
|         | ESSIM     | 0.993504 | 0.996032 | 0.999809 |
|         | QMI       | 0.711381 | 0.554177 | 1.305525 |
| SET-4   | Entropy   | 1.051600 | 2.308314 | 5.098267 |
|         | ESSIM     | 0.994832 | 0.999891 | 0.999919 |
|         | QMI       | 0.756539 | 0.544444 | 1.297531 |
| SET-5   | Entropy   | 0.794191 | 1.251708 | 7.125139 |
|         | ESSIM     | 0.994797 | 0.998579 | 0.999884 |
|         | QMI       | 0.749336 | 0.619237 | 1.268498 |
| SET-6   | Entropy   | 0.584880 | 0.539592 | 2.782470 |
|         | ESSIM     | 0.940880 | 0.995850 | 0.999919 |
|         | QMI       | 0.644372 | 0.538880 | 1.257462 |

Fig. 8. Chart for the table - I
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18. Das, S., kundu M. “NSCT-based multimodal medical image fusion using pulse coupled neural network and modified spatial frequency” Med. Biol. Eng. Comput., 50,(10), pp.2596-2608, 2009

19. Ganasa, P., Kumar, V. “CT and MR image fusion scheme in non subsampled contour transform domain” J. Digit Imaging ,27, pp. 1-2, 2014

20. Wang, N., Ma, Y., Wang, W. “DWT-based multisource image fusion using spatial frequency and simplified pulse coupled neural network” J. Multimedia, 9,(1), pp. 159-165, 2014

21. Xu, X., Wang, Y., Chen, S. “Medical image fusion using discrete fractional wavelet transform” Biomed signal process. control 27, pp.103-111, 2016

22. Huimin Lu, Lifeng Zhang, Seichi Serkawa, “Maximum local energy: An effective approach for multi sensory image fusion in beyond Wavelet Transform Domain” Computers and Mathematics with Applications. Vol. 64, pp. 996-1003, 2012.

23. Yi, H. Li, Zhang, “Multi focus Image Fusion based on features contrast of multi scale products in Non Sub Sampled Contoulet Transform Domain” Optik, vol.123, no. 7, pp. 569-581, 2012

24. Chavan, S.S., Mahajan, A., Talbar, S.N., et al. “Nonsubsampled rotated complex wavelet transform (nsrcxwt) for medical image fusion related to clinical aspects in neurocysticercosis” Comput. Biol. Med., 81, pp.64-78, 2017.

25. Bhat, M., Karki, M.V. “Feature selection based on PCA and PSO for multimodal medical image fusion using DTCWT” arXiv preprint arXiv:1701.08918, 2017

26. Xu, J., Yang, L., Wu, D. “Ripplet a new transform for image processing” J. Vis. Commun. Image Rep., 21, (7), pp.627-639, 2010

27. Ghaahremani, M., Ghassemian, J. “Remote sensing image fusion using ripplet transform and compressed sensing” IEEE Geosci. Remote Sens., Lett., 12,(3), pp.502-506, 2014.

28. Kong, W., Liu, J. “Technique for image fusion based on NSST domain improved fast non classical RF”, INF. Phys. Technol.,61,(0), pp.27-36, 2013.

29. Guorong, G., Leping, X., Dongzhu, F. “Multi-focus image fusion based on non–subsampled shearlet transform” IET Image Process., 7,(6), pp.633-639, 2013.

30. Kavitha, C., Chellamuthu, C., Rajesh, R. “Medical image fusion using combined discrete wavelet and ripplet transforms”, Procedia Eng., 38, pp.813-820, 2012.

31. Deeppika, M.M., Varithyanathan, V. “An efficient method to improve the spatial property of medical medical images” J Theor. Appl. Inf. Technol., 35,(2), pp.141-148, 2012.

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