Medical Image Fusion based on Hybrid Algorithms for Neurocysticercosis and Neoplastic Disease Analysis

B. Rajalingam¹, R. Priya², R. Bhavani³

¹Research Scholar, ²³Professor
Department of Computer Science and Engineering, Annamalai University, Annamalainagar, Tamilnadu, India
rajalingam35@gmail.com¹, prvknmd@yahoo.com², bhavaniaucse@gmail.com³

Corresponding Author: B. Rajalingam

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Abstract

A Neurocysticercosis is an avoidable parasitic infection caused by larval cysts of the pork tapeworm. The larval cysts can affect different parts of the human organs causing a condition known as cysticercosis which can direct to seizures it is called neurocysticercosis. A neoplasm is an abnormal growth of cells in the brain, also known as a tumor which causes growth of tumor triggered by DNA mutations within your cells. The neoplastic disease causes two types of tumor growth. The benign tumors usually grow which grow slowly and cannot spread to other tissues are called as noncancerous growth. The Malignant brain tumors grow quickly and spread to multiple tissues, organs are known as cancerous growth. In spite of huge progresses, still there is no single modality which can represent all aspects of the human body. In this paper a novel method has been proposed for Dual tree complex wavelet Transform (DTCWT) with Non-subsampled shearlet transform (NSST) hybrid fusion algorithm. The developed fusion algorithm is experienced on the pilot study datasets of patients affected with Neurocysticercosis and neoplastic diseases. The fused image conveys the superior description of the information than the source images. Experimental results are evaluated by the number of well-known performance evaluation metrics.

Keywords: Multimodality medical image, Neoplastic, Neurocysticercosis, CT, MRI, SPECT, DTCWT and NSST

I. Introduction

Medical imaging has been the most critical and vital part of the modern health care practices. Medical image processing plays a significant role in the patient management system starting from diagnosis to post treatment analysis. To diagnosis of the disease involves non – invasive acquisition of information about the human body organs through imaging. There are several modalities (CT, MRI, PET and SPECT) available for capturing the data from affected part of the body. CT provides the information related to calcifications, bone structures, tumour outline prominently
but it has poor contrast for soft tissues. MRI is the best modality for soft tissue anatomy and displays the lesions distinctly but it cannot detect calcifications. PET and SPECT images give abnormal metabolism at cancer infected tissues. PET and SPECT have very poor spatial and structural discrimination. Every modality may not exhibit all the necessary information related to a particular disease. Physicians always recommend various modalities imaging before making final diagnosis. [IX], [X], [XI] Acquisition of combined details regarding deferent modalities with a single machine is unavailable in all the health centers. No hospital in India has such hybrid modality imaging because high cost of the device. There is social and urgent need to a software solution which will provide combined information from different imaging modalities in a single frame with the minimum cost. It is called multimodal medical image fusion (MMIF).

(i) **Neurocysticercosis**

It is a disease that affects the brain and is considered a neglected parasitic infection that can cause seizures and sometimes death. The Neurocysticercosis disease affected person will get swallowing microscopic eggs passed in the feces of a person who has an intestinal pork tapeworm. [XI]

(ii) **Neoplastic Disease**

The neoplastic disease is a disease wherein cells divide rapidly, causing them to form abnormal tissues called neoplasm. These abnormal growths, also known as tumors, can form in any part of the body. The neoplastic disease causes two types of tumor growth. The benign tumors usually grow slowly and cannot spread to other tissues are called as noncancerous growths. The Malignant tumors are growing quickly and spread to multiple tissues, organs are known as cancerous growth. Symptoms of neoplastic disease greatly depend on where the neoplasm is located. The following risk factors that may lead to the development of malignant neoplastic disease are Excessive alcohol consumption, Obesity or being overweight, Smoking, Genetics, Disorders of the immune system, Chemical toxins, Excessive exposure to radiation. Chemotherapy, Surgery and Radiation therapy are the types of treatment available in the medical field. [XVII]

This paper is follows: Section II explains the survey of literature on multimodal medical image fusion. Section III tells the traditional and hybrid methods. Section IV explains the performance evaluation metrics for this experimental work. Section V discusses the implementation results and evaluation analysis. Section VI gives the conclusion.

**II. Related Works**

Deep Gupta [I] proposed the medical image fusion in NSST domain using the adaptive spiking neural model. Ebenezer Daniel [II] proposed an image fusion system based on hybrid genetic grey wolf optimization. Hamid Reza Shahdoosti, et al [III] proposed the tetrolet transform for multimodality image fusion. Heba M., et al [IV] examines some of the algorithms to develop the hybrid algorithm for enhancing the quality of fused image. Jingming Xi, et al [V] developed the fusion algorithm combined sparse representation with PCNN for clinical treatment analysis. S.
Chavan, et al [VI] developed the NSxRW transform based image fusion method used for the analysis the neurocysticercosis. Sharma, et al [VII] proposed fusion algorithm for based on NSST with simplified model of PCNN. Sreeja, et al [VIII] proposed fusion algorithm to enhance the quality of the image. Xiaojun Xua [IX] proposed the DFRWT method for medical image fusion. X Liu, et al [X] developed the structure tensor, NSST and applies the unified optimization model to perform the image fusion. Xingbin Liu, et al [XI] proposed NSST based fusion algorithm exploiting moving frame based decomposition.

III. Proposed Work

(A) Conventional Fusion Algorithms

This research paper experiment the some of the conventional and hybrid methods for different types of source images.

(i) Dual Tree Complex Wavelet Transform (DTCWT)[IX]

It is uses two real DWT in parallel. One DWT generates real part and the other generates imaginary part of DTCWT. Dual tree complex wavelet transforms having following important properties: High Directionality, Shift Invariance, Perfect Reconstruction and Computational Efficiency. The analysis and synthesis filter banks of DTCWT are described in Fig. 1 and Fig. 2.

![Fig. 1 Synthesis Filter bank for DTCWT](image_url)

DTCWT perform medical image fusion based on the following procedure. First, the disease affected input multimodal medical images are decomposed by DTCWT into coefficient sets; fuse the transformed coefficients using an appropriate rule. A new threshold based fusion rule has been applied. The overall structure of the DTCWT based fusion method is shown in Fig. 3.
The Threshold and Fusion Rule

The threshold value depends on the statistical properties and decomposition levels of the wavelet coefficients. Generally, threshold is used for denoising but, in this DTCWT method is use the image fusion. In wavelet based thresholding, the coefficients having absolute values lower than the threshold are discarded, because the noise affects the small value wavelet coefficients substantially more than the high valued wavelet coefficients. In multimodal medical image fusion also, the wavelet coefficients having high absolute values are selected. Therefore, the wavelet coefficients whose absolute difference from the threshold is higher are selected. The threshold is defined in equation as,

$$\lambda = \frac{1}{2^{(l-1)}} \frac{\sigma}{\mu} M$$

(1)

Where, $\sigma$ – standard deviation of wavelet coefficients, $\mu$ – mean, $M$ is median of absolute DTCWT coefficients and $l$ is the level of decomposition. These statistical parameters jointly represent the variation in the intensity of wavelet coefficients which is used in the fusion algorithm to select the better coefficients.

DTCWT Algorithm steps for image fusion

- Let Image$_1$, and Image$_2$ be two input multimodal medical images. Medical Images are decomposed by dual tree complex wavelet transform into complex coefficient sets $Cof_1$ and $Cof_2$.

\[
\text{Image 1} \xrightarrow{DTCWT} \text{cof}_1 \\
\text{Image 2} \xrightarrow{DTCWT} \text{cof}_2
\]

- For both the coefficient sets, thresholds are calculated for each decomposition level by using equation (1)
Absolute difference of all wavelet coefficients from their corresponding threshold are calculated, as below-

\[ D_1 = |Cof_1| - |\lambda_1| \]  \hspace{1cm} (2)

\[ D_2 = |Cof_2| - |\lambda_2| \]  \hspace{1cm} (3)

Absolute differences of corresponding coefficients of source images are compared; the coefficient having larger value of absolute difference from the threshold is selected, to form coefficient set of the fused multimodal medical image.

\[ Cof(i,j) = \begin{cases} Cof_1 & \text{if } |D_1| \geq |D_2| \\ Cof_2 & \text{if } |D_1| < |D_2| \end{cases} \]  \hspace{1cm} (4)

Finally, inverse DTCWT is applied on the fused coefficient set to obtain the output.
(ii) Non-subsampled Shearlet Transform [19], [21]

Fig. 4 Overall structure for NSST for fusion

NSST algorithm steps for image fusion

- Obtain the images.
- Resizing the input images
- Decompose the source images based on transform technique
- Calculate the sub-band coefficients of the NSST method
- Fuse the transforms coefficients of the selected fusion rule
- Apply the INSST to get the fused image.

(B) Hybrid fusion Algorithm

Existing methods require the potential to get superior quality images. To enhance the visual quality of the output the proposed algorithm is used to combine the NSST with DTCWT. Before fusion process the two level conversions on source images are applied. These outcomes give best quality, superior handling of curved shapes and improved characterization of input images.

(i) Hybrid Algorithm (NSST – DTCWT)

- Get the images.
- Resize the source images.
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- Source images are decomposed by DTCWT into complex coefficient sets. For both the coefficient sets, thresholds are calculated for each decomposition level.
- Absolute difference of all wavelet coefficients from their corresponding threshold are calculated.
- Decompose the input images using selected transform technique.
- Calculate the low bass and high bass sub-band coefficients of the NSST method
- Absolute differences of corresponding coefficients the source images are compared; the coefficient having larger value of absolute difference from the threshold is selected, to form coefficient set of the fused image.
- Finally, inverse DTCWT and inverse NSST is applied on the fused coefficient set to obtain the final fused image.

Fig. 5 proposed diagram of the hybrid algorithm (NSST-DTCWT)

IV. Results and Discussions

The traditional and hybrid techniques are applied into to input images and get the fused image. [X] Input data are gathered from the Radiopedia [V], Whole brain atlas [VI]. The experimental performance evaluation metrics results of the conventional and hybrid fusion techniques are shown in Table 1 and 2. For the experimental work eight set of Neurocysticercosis, Neoplastic affected multimodal medical images are taken. Figures 7, 8, 9, 10, 11, 12, 13, 14 shows the experimental results of eight pairs: a, b are the source images c, d, e, f, g are the fused images.

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Figures 14 (A-H) shows the performance comparative analysis for eight pairs of the input images.

(A) Performance Evaluation Metrics

The performance metrics are evaluated on proposed hybrid algorithms. The similarities and dissimilarities, the output images are compare to source images. Some of the performance evaluation metrics are fusion factor, Fusion Symmetry, image quality index, edge quality measure and correlation coefficient. [XIII], [XIV], [XV]
### Table 1: Performance metrics values obtained from different fusion algorithms

| Study set | Algorithm | Fus Fact | Fus Synt | IQI | EQM | MSSIM | CE | CCR |
|-----------|-----------|----------|----------|-----|-----|-------|----|-----|
| SET 1     | DWT       | 3.1513   | 0.4052   | 0.6981 | 0.8192 | 0.7172 | 1.3127 | 0.7512 |
|           | CVT       | 3.3223   | 0.3815   | 0.7012 | 0.8273 | 0.7516 | 1.2511 | 0.7719 |
|           | DFRWT     | 3.4762   | 0.3682   | 0.7291 | 0.8517 | 0.7768 | 1.1023 | 0.8012 |
|           | NSST      | 3.7141   | 0.3216   | 0.7431 | 0.8712 | 0.7912 | 0.9981 | 0.8271 |
|           | DTCWT     | 3.8282   | 0.2821   | 0.7812 | 0.8814 | 0.7991 | 0.9812 | 0.8318 |
|           | Proposed  | 4.0191   | 0.1542   | 0.9012 | 0.9312 | 0.8512 | 0.6981 | 0.8912 |
| SET 2     | DWT       | 2.2861   | 0.0981   | 0.7891 | 0.7012 | 0.7141 | 1.3451 | 0.6312 |
|           | CVT       | 2.4181   | 0.0871   | 0.8012 | 0.7231 | 0.7361 | 1.2711 | 0.6952 |
|           | DFRWT     | 2.6585   | 0.0776   | 0.8281 | 0.7412 | 0.7487 | 1.0251 | 0.7218 |
|           | NSST      | 2.7890   | 0.0691   | 0.8417 | 0.7891 | 0.7687 | 0.9987 | 0.7571 |
|           | DTCWT     | 2.8332   | 0.0591   | 0.8812 | 0.8412 | 0.7618 | 0.8012 | 0.7819 |
|           | Proposed  | 2.9891   | 0.0401   | 0.9316 | 0.9012 | 0.8012 | 0.6021 | 0.8517 |
| SET 3     | DWT       | 4.3511   | 0.3371   | 0.5981 | 0.6812 | 0.7016 | 2.012 | 0.7812 |
|           | CVT       | 4.4125   | 0.3298   | 0.6718 | 0.7128 | 0.7289 | 1.9920 | 0.8012 |
|           | DFRWT     | 4.5612   | 0.3623   | 0.7192 | 0.7518 | 0.7618 | 1.8623 | 0.8321 |
|           | NSST      | 4.7189   | 0.3317   | 0.7317 | 0.7819 | 0.7812 | 1.2517 | 0.8412 |
|           | DTCWT     | 4.8812   | 0.3281   | 0.7518 | 0.8012 | 0.8012 | 1.1620 | 0.8912 |
|           | Proposed  | 5.1782   | 0.2317   | 0.8418 | 0.9157 | 0.9062 | 0.9743 | 0.9954 |
| SET 4     | DWT       | 2.3128   | 0.0872   | 0.8672 | 0.6341 | 0.6651 | 1.1620 | 0.7891 |
|           | CVT       | 2.4712   | 0.0782   | 0.8787 | 0.7052 | 0.6982 | 1.0521 | 0.8023 |
|           | DFRWT     | 2.6281   | 0.0698   | 0.8898 | 0.7128 | 0.7021 | 0.9621 | 0.8326 |
|           | NSST      | 2.7921   | 0.0562   | 0.9053 | 0.8051 | 0.7528 | 0.9467 | 0.8723 |
|           | DTCWT     | 2.8882   | 0.0459   | 0.9256 | 0.8281 | 0.7628 | 0.9217 | 0.8992 |
|           | Proposed  | 3.0213   | 0.0321   | 1.4211 | 0.9011 | 0.8172 | 0.8621 | 0.9562 |
Table 2: Performance metrics values obtained from different fusion algorithms

| Study set | Algorithm | Fus Fact | Fus Symt | IQI   | EQM   | MSSIM | CE    | CCR  |
|-----------|-----------|----------|----------|-------|-------|-------|-------|------|
| SET 5     | DWT       | 4.5712   | 0.1978   | 0.6543 | 0.8176 | 0.6231 | 1.1520 | 0.6782|
|           | CVT       | 4.6712   | 0.1891   | 0.6681 | 0.8298 | 0.6432 | 1.0981 | 0.6892|
|           | DFRWT     | 4.7123   | 0.1793   | 0.6742 | 0.8342 | 0.7052 | 1.0892 | 0.8021|
|           | NSST      | 4.8112   | 0.1654   | 0.6876 | 0.8476 | 0.7341 | 0.9782 | 0.8251|
|           | DTCWT     | 4.8812   | 0.1583   | 0.6923 | 0.8587 | 0.7521 | 0.9234 | 0.8527|
|           | Proposed  | 5.0123   | 0.1109   | 0.7276 | 0.9012 | 0.8012 | 0.7451 | 0.9123|
| SET 6     | DWT       | 1.2562   | 0.0783   | 0.7832 | 0.6921 | 0.6782 | 1.9827 | 0.6782|
|           | CVT       | 1.3612   | 0.0686   | 0.8342 | 0.7093 | 0.6982 | 1.8721 | 0.7162|
|           | DFRWT     | 1.5771   | 0.0623   | 0.8472 | 0.7324 | 0.7052 | 0.9982 | 0.7821|
|           | NSST      | 1.7892   | 0.0598   | 0.8764 | 0.7542 | 0.7261 | 0.8972 | 0.7998|
|           | DTCWT     | 1.8018   | 0.0509   | 0.8989 | 0.7892 | 0.7452 | 0.8231 | 0.8016|
|           | Proposed  | 2.0521   | 0.0302   | 1.6521 | 0.9172 | 0.9882 | 0.4982 | 0.9873|
| SET 7     | DWT       | 4.1879   | 0.5680   | 0.6016 | 0.7392 | 0.6721 | 1.2610 | 0.8221|
|           | CVT       | 4.2652   | 0.5012   | 0.6426 | 0.7571 | 0.6998 | 1.1744 | 0.8521|
|           | DFRWT     | 4.4711   | 0.4989   | 0.6816 | 0.7982 | 0.7162 | 1.0179 | 0.8729|
|           | NSST      | 4.6932   | 0.4326   | 0.7251 | 0.8043 | 0.7426 | 0.9971 | 0.8888|
|           | DTCWT     | 4.8804   | 0.4123   | 0.7788 | 0.8373 | 0.7812 | 0.9782 | 0.8921|
|           | Proposed  | 5.0123   | 0.3023   | 0.9251 | 0.9123 | 0.8218 | 0.7821 | 0.9922|
| SET 8     | DWT       | 2.3162   | 0.0787   | 0.6981 | 0.7191 | 0.6327 | 1.2720 | 0.7821|
|           | CVT       | 2.5621   | 0.0699   | 0.7012 | 0.7287 | 0.6821 | 1.0280 | 0.8012|
|           | DFRWT     | 2.7120   | 0.0622   | 0.7527 | 0.7678 | 0.7092 | 0.9982 | 0.8218|
|           | NSCT      | 2.8621   | 0.0598   | 0.8123 | 0.8012 | 0.7354 | 0.9475 | 0.8412|
|           | DTCWT     | 2.9982   | 0.0512   | 0.8327 | 0.8372 | 0.7892 | 0.9212 | 0.9014|
|           | Proposed  | 3.2011   | 0.0410   | 1.0912 | 0.9428 | 0.9321 | 0.8872 | 1.2010|

Figu.12: Experimental results pair 6
Fig. 13 Experimental results pair 8

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Fig. 14 (A-H) Performance Comparative analysis for 8 set of input images
V. Conclusion

Multimodal medical image fusion has played a vital role to diagnose the disease for clinical treatment analysis and improving the performance and precision of the computer assisted system. The image fusion is an efficient procedure functional in diagnosis, medical analysis of severity of disease and clinical review in Neurocysticercosis and neoplastic diseases. The proposed method is better for visualization, accurate interpretation and precise localization of the tumor and lesions formed in the brain. Proposed a hybrid algorithm is developed for multimodality images to analyze and review the Neurocysticercosis and neoplastic diseases. The proposed hybrid fusion algorithm was verified through a simulation experiment on multimodality images. The proposed algorithm gives better results.

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