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Research Article

Fuse the Multimodality Medical Images using Transforms with Neuro Fuzzy based Hybrid Fusion Techniques

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Abstract

A great challenge in medical image processing is combining the complement pathological features into a single image. Various issues are faced by the images that undergo fusion. Some examples are the way the fusion artifacts, appear, edge strength, contrast of input medical image finally the cost of computation. Here the input image is decomposed by applying Non-Subsampled Contourlet Transform (NSCT) The averaging fusion rule with type two fuzzy logic is employed in components of lower frequency. The maximum fusion rule with PCNN is applied in components of high frequencies. The inverse transforms and coefficients of frequency bands are used to derive fused image. The best diagnosis of the health issues from the given sources' are obtained from the fused image.

Keywords:

Multimodal Medical Image Fusion, CT, MRI, PET, SPECT, Neurocysticercosis, Neoplastic, Astrocytoma, Anaplastic Astrocytoma.

1. Introduction

This paper focuses on the NSST as a decomposition tool. In this algorithm, the flexible multiresolution, shift-invariant and lossless feature of the NSST are related to the two features of PCCN i.e., global coupling and pulse synchronization. The PCNN is similar to the visual neural system of man. The PCNN produces a binary pulse image sequences when stimulated with a grayscale or color image. PCNN is different from ANN in the sense that it does not train like ANN. The additive nature of the neighboring neurons helps in activation with no input in ANN. On the contrary in PCCN, the neuron doesn't get activated by the coupling input. This serves to be a vital and beneficial part in the image processing. The PCNN is used as a nonlinear filter to select the coefficients in the NSST decomposed images. The combining method is applied separately for the

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regions of less frequency and the regions of higher frequency and finally the inverse NSST is utilized to obtain images that are fused.[19],[20] Here a new PCNN dependent hybrid image fusion method is introduced and discussed. Section 1 describes the introduction of MMIF. Section 2 describes the presented hybrid fusion algorithm. Section 3 compares the capability of the existing and proposed fusion technique. Section 4 concludes the manuscript.

2. Literature Review

The author and his colleagues [1] demonstrated a new fusion framework for the multimodal medical images by the NSCT. The final answers and the comparison trial proved that the demonstrated fusion framework gives a potential method to give more accurate analysis of multimodality images. On another paper [2] proposed a 2-stage framework for multimodal fusion with the help of cascaded combination of stationary wavelet transform and Non-Subsampled Contourlet Transform domains for pictures obtained from 2 different sensor modality clinical imaging (MRI and CT-Scan). A new framework for spatially registered MMIF has been demonstrated by the author [3], which is primarily dependent on the NSCT. Periyavattam Shanmugam Gomathi, *et al.* [4] proposed NSCT dependent image fusion techniques for the MMIF. Performance parameters comparison has been done for the results of 6 pairs of clinical images. The author [5] proposed multimodal fusion in contourlet domain by weighted PCA approach. Xiao-Qing Luo, *et al.* [6] used the circumstance-based information to propose a new multi-modal medical image fusion technique. When compared with other fusion techniques, the study results of this shows a better quality because of the effective suppression of the distorted colors. Nancy Mehta, *et al.* [7] proposed a modified fusion method. Here, wavelet coefficients got from wavelet decomposition is decomposed with NSCT decomposition. Kun Wang [8] proposed a fusion method for retaining the particulars and intensity information of rock particle image based on sparse representation and NSCT. The author and his colleagues [9] proposed a new MMIF method that accepts a multiscale geometric analysis of the Non-Subsampled Contourlet Transform that has type-2 fuzzy logic method. Meenu Manchanda, *et al.* [10] proposed a new technique of MMIF with fuzzy-transform.

Study reports and analyzing by comparison shows the method as effective and gives improved results in the demonstrated algorithm. Niladri Shekhar Mishra, and colleagues. [11] proposed a new MMIF method with a neuro-fuzzy technique in the transformation of NSST domain for spatially registered, multi-modal medical images. The author [12] presented an improved scheme for data fusion in diagnosing brain tumor with both MRSI and Magnetic resonance imaging related information to enhance MRSI's accuracy for differentiating tumors. Jing-jing Zong, *et al.* [13] presents a novel scheme for fusion of medical images by sparse presentation of patches of classified images. Yong Yang, and colleagues [14] presented a new MMIF technique by a structural patch decomposition and fuzzy logic technology. Study results demonstrates an obviously improved performance compared to the state-of-the-art method with respect to subjective visual and quantitative evaluations. Huafeng Li, *et al.* [15] proposed a new technique for fusion of medical images, denoising and enhancement by a low-rank sparse component decomposition and dictionary learning. Meenu Manchanda, and colleagues[16] proposed an improved MMIF algorithm using fuzzy transform. Xiaonan Liu, *et al.* [17] focused to look at the results of the studies conducted in the past 10 years which analyzes quantitatively the multi-modality of data of images for diagnosing and understanding the prognostic values of AD at the MCI or preclinical stages with statistical machine learning/artificial intelligence techniques. T. Tirupal, *et al.* [18] proposed a method for effective MMIF. Here, first of all the images are changed to intuitionistic fuzzy images.

3. Proposed Hybrid Fusion Algorithm (NSCT-Neuro Fuzzy)

In this methodology, NSCT and Neuro fuzzy methods are used to both input multimodal medical images. Figure 1 shows the overall block diagram of hybrid algorithm (NSCT-Neuro Fuzzy).

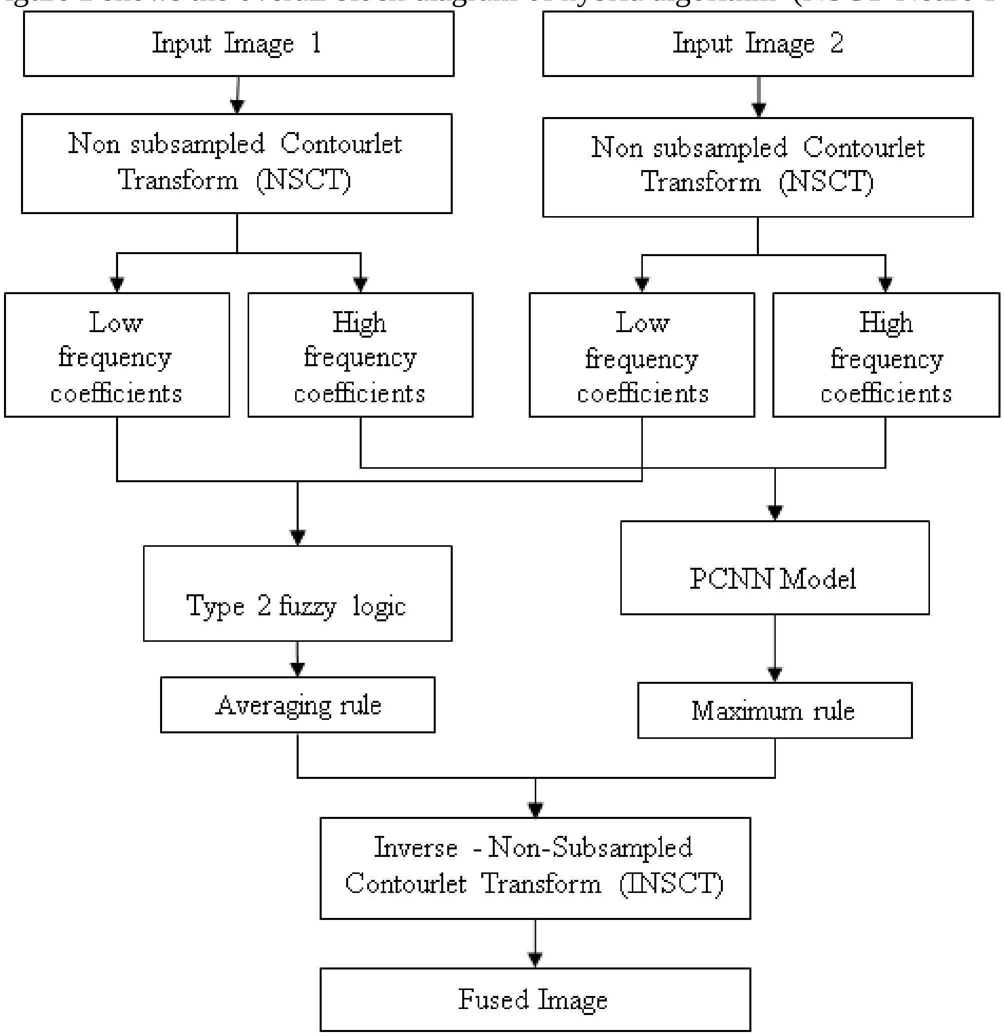

Fig. 1 Block diagram for proposed hybrid algorithm (NSCT-Neuro Fuzzy)

Procedure for hybrid fusion algorithm (NSCT-Neuro Fuzzy)

Step 1: Perfectly registered Computed Tomography and Magnetic Resonance Imaging, Positron Emission Tomography & MRI and SPECT & MRI Images are given as input.
Step 2: The source images are decomposed using the NSCT.

Step 3: Apply the PCNN-Type 2 Fuzzy logic fusion rule to the NSCT coefficients to get the fused coefficients.
Step 4: Fused image is got by transforming it inverse.
Step 5: Analyses the fused images both subjectively and objectively.

Type-2 Fuzzy Logic System
The fuzzy set concept created by Zadeh effectively solves the fuzziness problem which is difficult to handle by using classic mathematics. Type-1 fuzzy is not flexible, so it is difficult to minimize uncertainty effects by using any kind of membership function algorithm. To address this problem, type-2 fuzzy concept is proposed. [22]

Non-Subsampled Contourlet Transform (NSCT)
NSCT is from the contourlet transformation theory that attains enhances outputs in image processing in geometric transformations. It is a shift variant as it has both up-samplers as well as down-samplers in LP and DFB. Non-Subsampled Contourlet Transform is a shift invariant, multiscale and multi-directional transform that has a highly valuable application. It is derived by applying the NSPFB and the NSDFB.[21]

4. Experimental Results

The demonstrated HMMIF method is studied on pilot study sets combination of CT/MRI, MRI/PET and MRI/SPECT of brain of the patients who have neurocysticercosis infection, degenerative or neoplastic diseases. The combination of input images all pairs of both Computed Tomography and Magnetic Resonance Image slices, MRI and PET slices and MRI and SPECT slices of the same patient are chosen by anatomical and functional similarities.[23] The fusion results of the presented hybrid image fusion technique and other existing techniques are shown in figures 2, 3, 4, 5, 6 and 7. Six different sets of Computed Tomography /Magnetic resonance Imaging, Magnetic Resonance Imaging/Positron Emission Tomography as well as MRI/SPECT images are taken for the image fusion. The first set of input images represents the neurocysticercosis disease affected images taken from CT and MRI scanners respectively**.** Second set of input images represents the metastatic bronchogenic carcinoma disease affected brain images in the combination of MRI/SPECT. Input images collected from online databases Harvard medical school [24] and radiopaedia [25].

Third and fourth sets of input images represent the astrocytoma and anaplastic astrocytoma disease affected brain images in the combination of MRI/SPECT respectively. Fifth and sixth sets of input images represent the alzhimer's and mild alzhimer's disease affected brain images in the combination of MRI/SPECT and MRI/PET respectively. The table shows the fusion results of the same input images are using PCA, DWT, PCNN, NSCT, NSST and the proposed hybrid technique using the combination of NSCT – Neuro fuzzy. Out of all the traditional fusion techniques, the simulation result of the proposed hybrid technique provides better performances both qualitatively and quantitatively. Quantitative analysis is required for analyzing the image after fusion. The effectiveness of the fused image is proved by evaluating the values of the performance metrics results as shown in Tables 1 and 2. One complete dataset of CT and MRI, MRI and PET and MRI and SPECT are fused. From the tabulated values, it is understood that the proposed NSCT-Neuro

Fuzzy method has better values for Fusion factor, IQI, EQM, mSSIM, STD, MI and PSNR than the existing conventional methods.

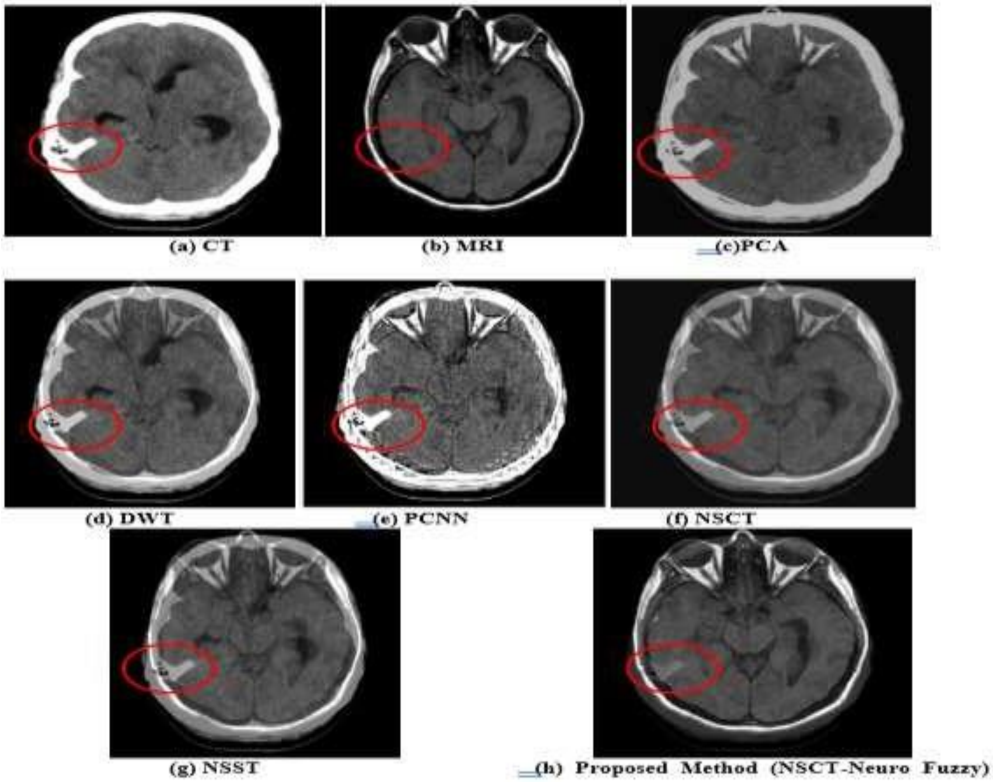

Fig. 2 Experimental results for neurocysticercosis disease affected images (Set 1)

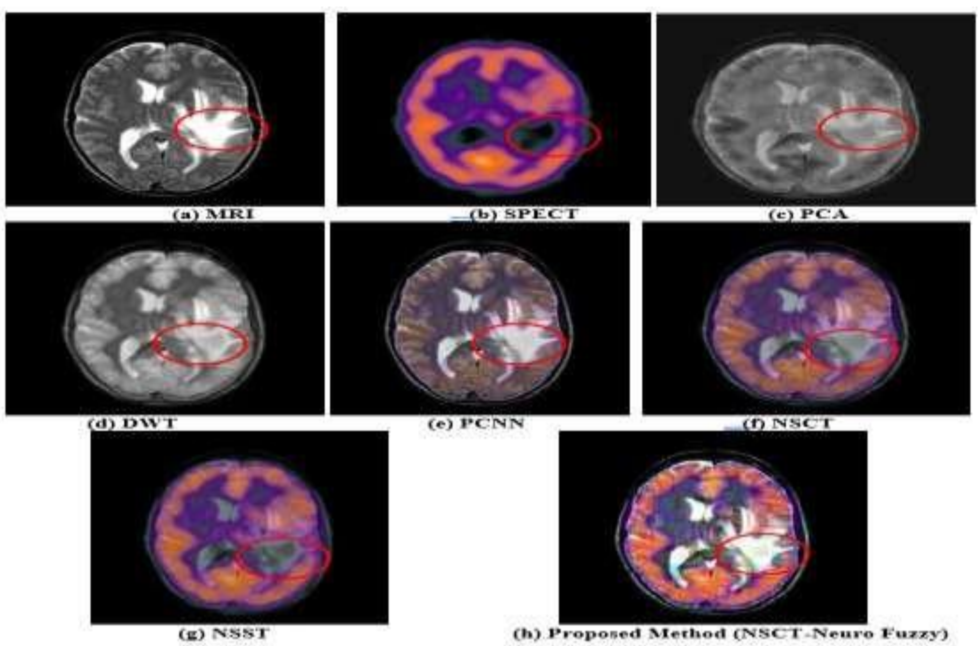

Fig. 3 Experimental results for metastatic bronchogenic carcinoma affected images (Set 2)

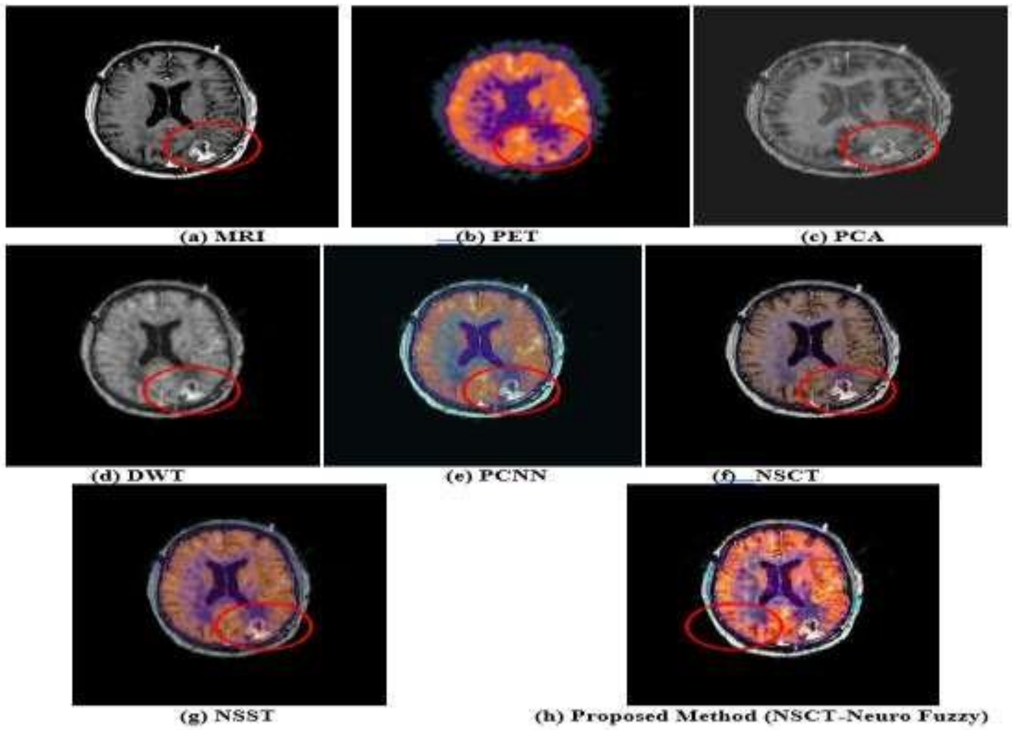

Fig. 4 Experimental results for astrocytoma disease affected images (Set 3)

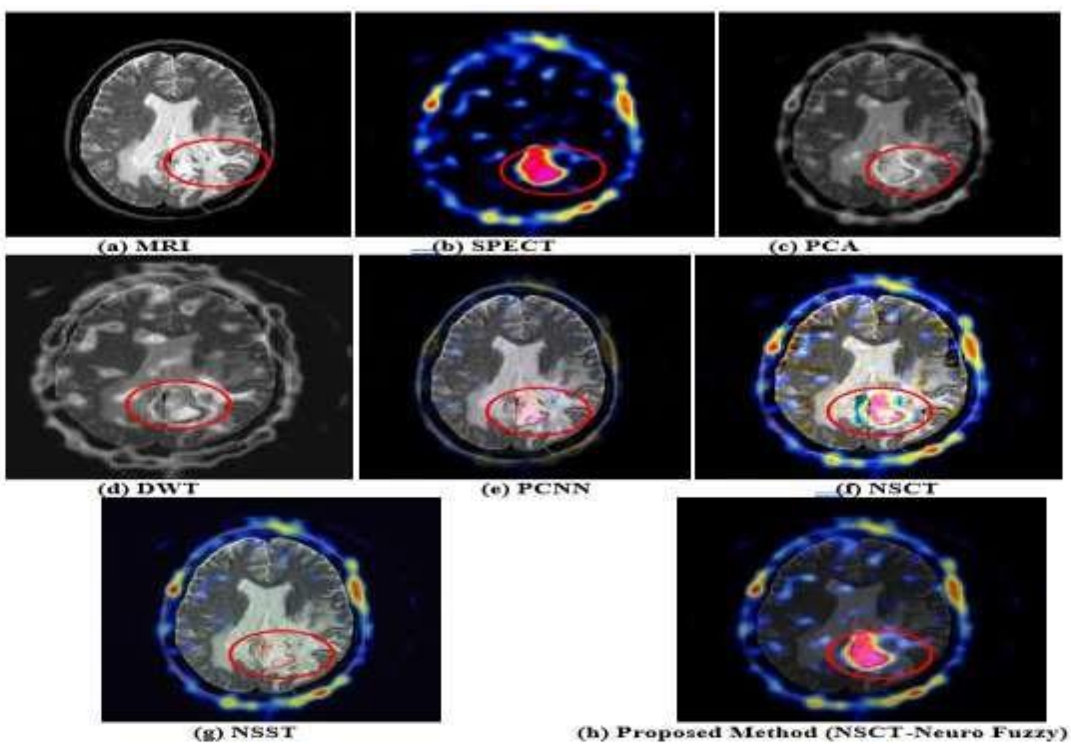

Fig. 5 Experimental results for anaplastic astrocytoma affected images (Set 4)

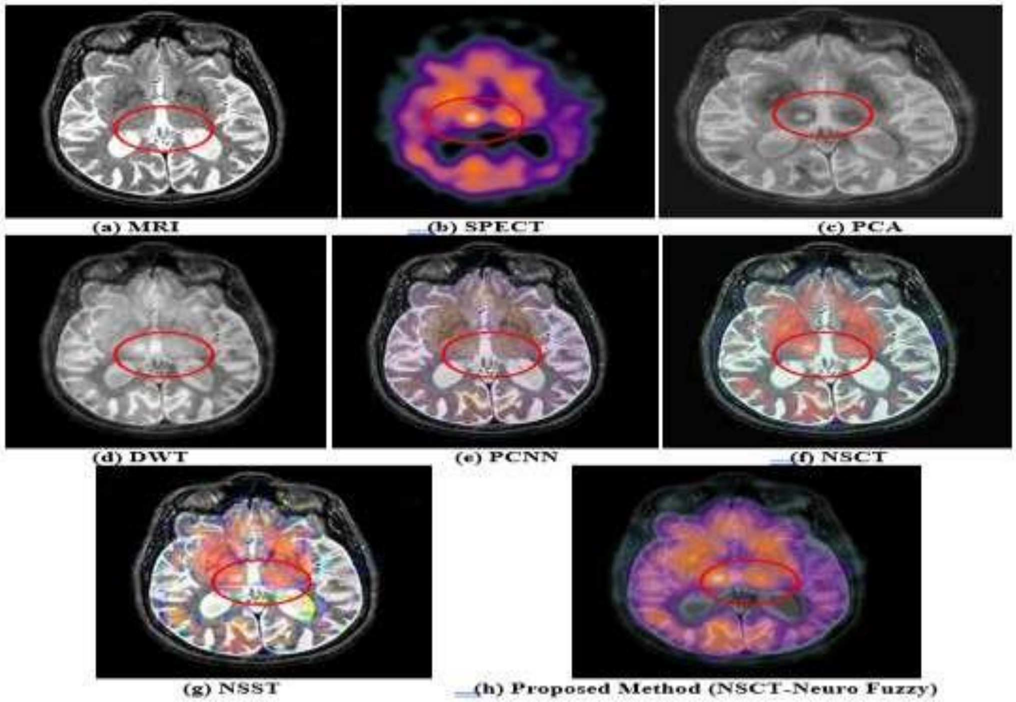

Fig. 6 Experimental results for alzimer's disease affected images (Set 5)

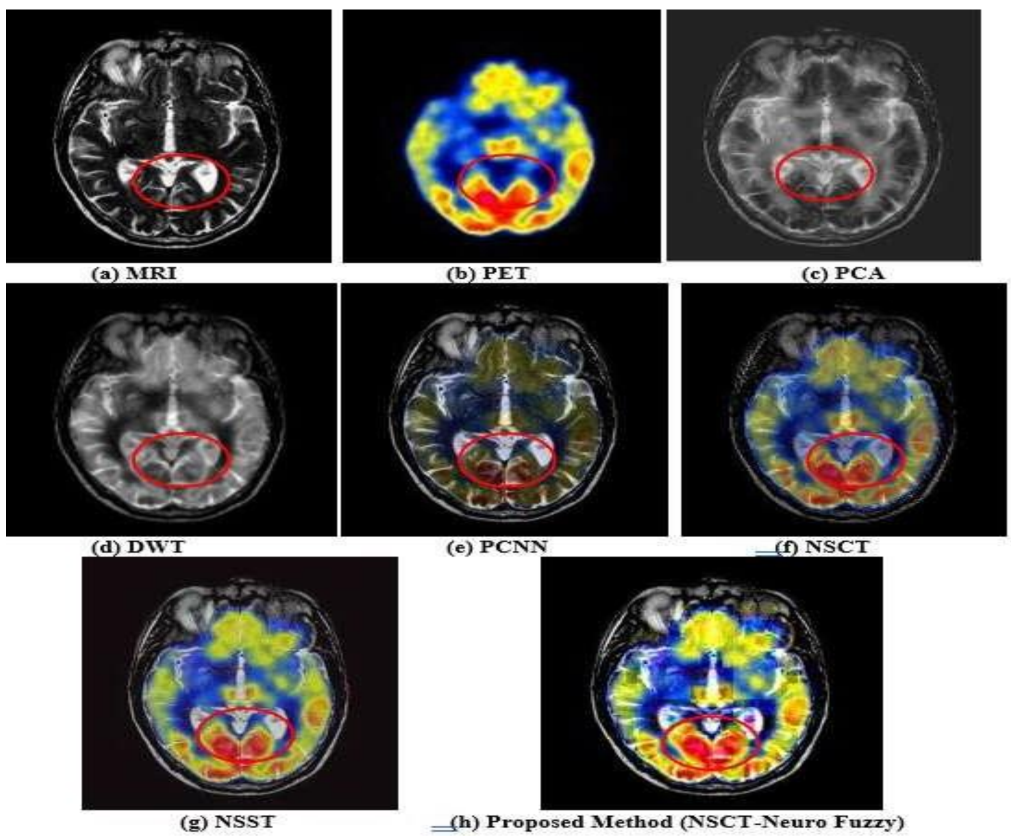

Fig. 7 Experimental results for mild alzheimer's disease affected images (Set 6)

A method of image fusion can be called effective when the limit of the values of performance metric is high, the IQI, mSSIM, EQM and cross entropy should get the highest value. It should be almost '1' is accepted that the fused output image is of enhanced quality. The demonstrated hybrid fusion algorithm is differentiated with various traditional fusion algorithms namely PCA, DWT, NSCT, NSST and PCNN.

Table 1 Performance Metrics Comparative analysis for different fusion methods (Set 1, Set 2 and Set 3)

Study Set	Metrics / Algorithm	FusFac	IQI	mSSIM	CE_n	EQM	MI	PSNR	STD
Set 1	PCA	2.187	0.401	0.472	2.261	0.471	2.903	29.60	15.30
	DWT	2.265	0.522	0.499	2.174	0.522	2.998	32.43	17.20
	PCNN	2.471	0.581	0.516	2.017	0.571	2.801	32.53	16.40
	NSCT	2.693	0.605	0.542	1.997	0.605	2.703	33.70	23.54
	NSST	2.880	0.698	0.681	1.378	0.638	3.205	37.70	25.78
	Proposed (NSCT-Neuro fuzzy)	4.950	0.93	0.904	0.756	0.937	3.730	50.43	31.20
Set 2	PCA	1.316	0.498	0.452	1.272	0.719	2.403	30.12	17.39
	DWT	2.362	0.511	0.502	1.182	0.728	2.684	33.50	18.30
	PCNN	2.712	0.532	0.629	1.198	0.767	2.530	32.65	19.50
	NSCT	2.862	0.582	0.635	1.207	0.801	2.839	34.67	25.67
	NSST	3.298	0.682	0.699	1.101	0.837	2.973	39.43	28.67
	Proposed (NSCT-Neuro fuzzy)	4.804	0.985	0.923	0.900	0.421	3.602	47.50	33.65
Set 3	PCA	2.571	0.514	0.523	1.452	0.517	2.402	28.60	18.30
	DWT	2.671	0.538	0.443	1.298	0.529	2.503	29.60	19.30
	PCNN	2.712	0.554	0.585	1.389	0.534	2.603	29.65	23.54
	NSCT	2.811	0.597	0.594	1.078	0.597	2.703	32.60	25.40
	NSST	3.181	0.662	0.702	0.993	0.698	3.012	39.80	26.40
	Proposed (NSCT-Neuro fuzzy)	4.830	0.905	0.904	0.740	0.980	3.830	50.56	32.30

Table 2 Performance Metrics Comparative Analysis for different fusion methods (Set 4, Set 5 and Set 6)

Study Set	Metrics / Algorithm	FusFac	IQI	mSSIM	CE_n	EQM	MI	PSNR	STD
Set 4	PCA	2.351	0.498	0.4016	2.012	0.681	2.503	28.67	24.30
	DWT	2.412	0.521	0.528	1.992	0.712	2.865	29.60	25.76
	PCNN	2.561	0.559	0.561	1.862	0.751	2.903	30.45	27.40
	NSCT	2.718	0.571	0.581	1.251	0.781	2.863	32.50	28.64
	NSST	3.181	0.621	0.691	1.162	0.801	3.196	34.60	29.54
	Proposed (NSCT-Neuro fuzzy)	5.019	0.940	0.920	0.950	0.930	3.506	46.60	36.67
Set 5	PCA	2.151	0.498	0.517	1.312	0.519	2.730	28.60	21.54
	DWT	3.322	0.501	0.521	1.251	0.527	2.832	29.50	23.60
	PCNN	3.376	0.529	0.556	1.102	0.551	2.750	31.50	24.64
	NSCT	3.214	0.543	0.581	0.998	0.571	2.849	34.59	26.07
	NSST	3.428	0.681	0.609	0.981	0.651	3.064	36.50	27.60
	Proposed (NSCT-Neuro fuzzy)	4.501	0.920	0.930	0.712	0.950	3.732	45.34	32.36
Set 6	PCA	2.312	0.567	0.534	1.162	0.634	2.201	28.50	20.10
	DWT	2.471	0.618	0.525	1.052	0.625	2.578	29.54	24.03
	PCNN	2.528	0.630	0.542	1.592	0.632	2.720	31.45	23.30
	NSCT	2.692	0.655	0.575	1.224	0.655	2.842	34.65	26.32
	NSST	2.982	0.725	0.698	1.092	0.708	3.206	35.49	28.32
	Proposed (NSCT-Neuro fuzzy)	4.018	0.893	0.920	0.703	0.960	3.692	47.50	32.43

These methods are applied with fusion rules as averaging for approximate subband coefficients and maximum value selection for high-pass subband coefficients. Qualitative and quantitative parameter analysis is used to evaluate the algorithm. Qualitative analysis is done by visual assessment by experienced radiologists; quantitative evaluation is done by estimation of the fusion parameters. It is obvious that the presented NSCT – Neuro Fuzzy method has enhanced capability compared to the conventional methods.

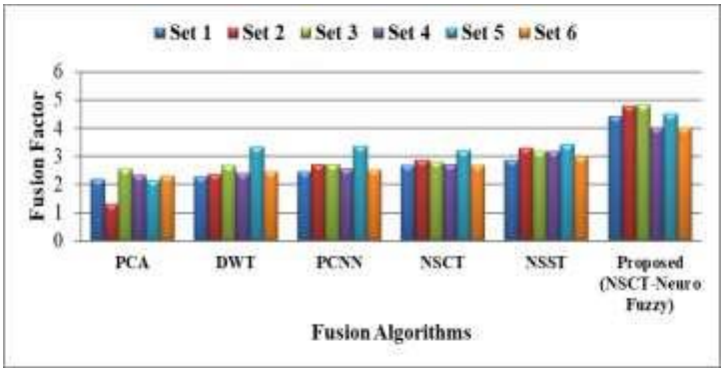

Fig. 8 Comparative Analysis for Fusion Factor

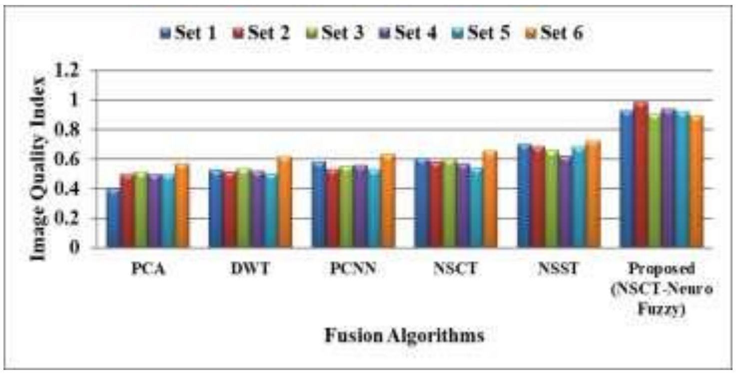

Fig. 9 Comparative Analysis for Image Quality Index

Figures 8 and 9 show the fusion factor and IQI for the six set of images CT-MRI, MRI-SPECT as well as MRI-PET. The results of studies are differentiated with PCA, DWT, PCNN, NSCT and NSST methods. The proposed NSCT-Neuro fuzzy has higher fusion factor and IQI value in comparison with the conventional methods already existing.

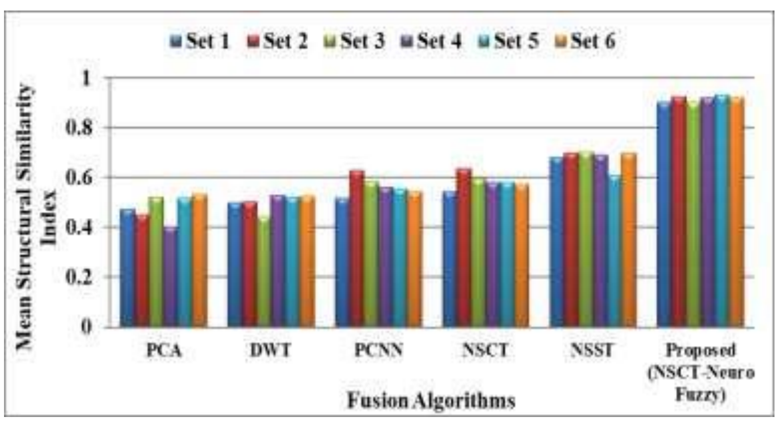

Fig. 10 Comparative Analysis for mean Structural Similarity Index

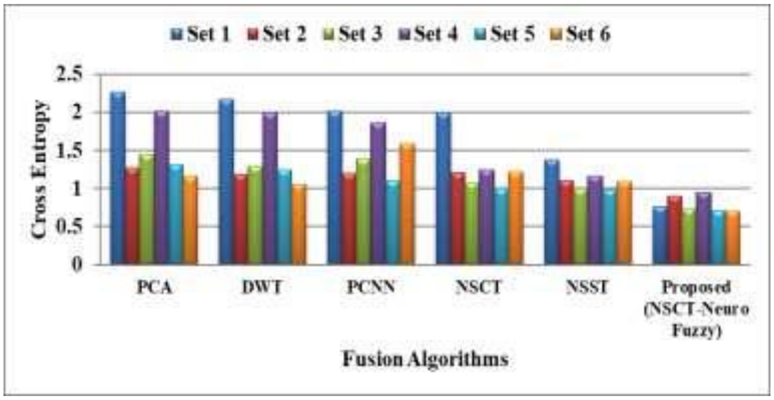

Fig. 11 Comparative Analysis for Cross Entropy

Figures 10 and 11 show the comparative analysis for the mSSIM and cross entropy for the six sets of image CT-MRI, MRI-SPECT, MRI-PET. The results of studies are differentiated with PCA, DWT, PCNN, NSCT and NSST methods. The demonstrated NSCT-Neuro fuzzy has higher value for mSSIM and get lesser value for cross entropy comparison with the conventional methods already existing.

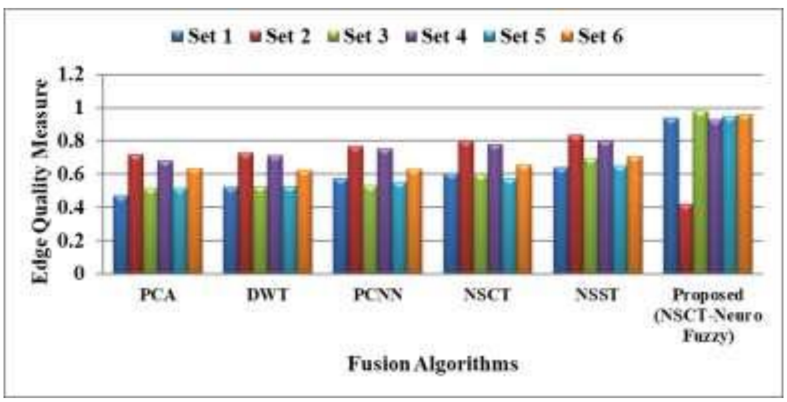

Fig. 12 Comparative Analysis for Edge Quality Measure

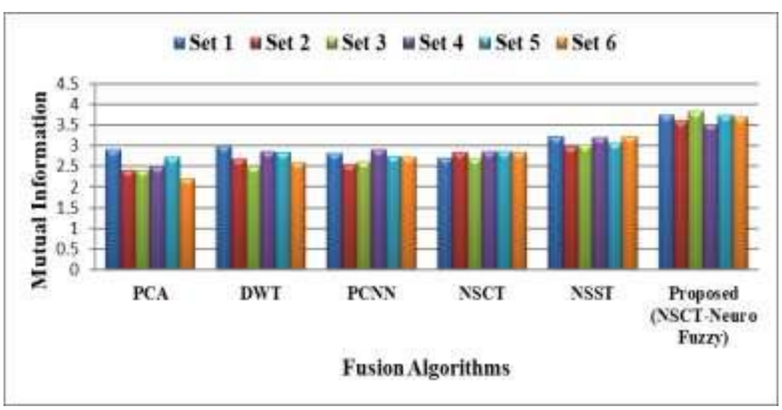

Fig. 13 Comparative Analysis for Mutual Information

Figures 12 and 13 show the comparative analysis for the EQM and MI for the six sets of image CT-MRI, MRI-SPECT and MRI-PET. The results of studies are differentiated with PCA, DWT, PCNN, NSCT and NSST methods. The NSCT-Neuro fuzzy has higher value for EQM as well as MI in comparison with the conventional methods already existing.

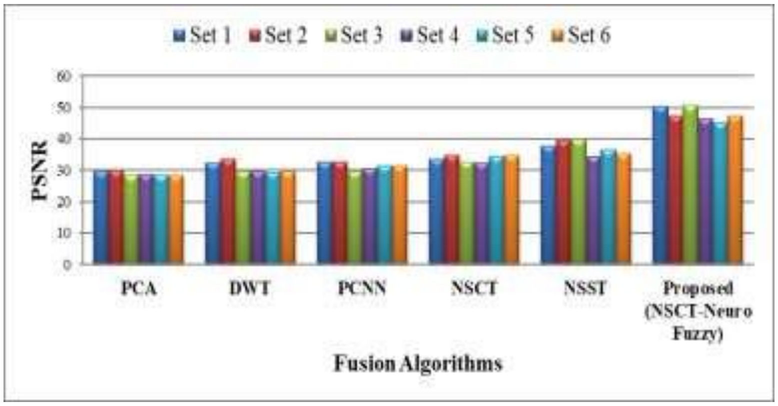

Fig. 14 Comparative Analysis for PSNR

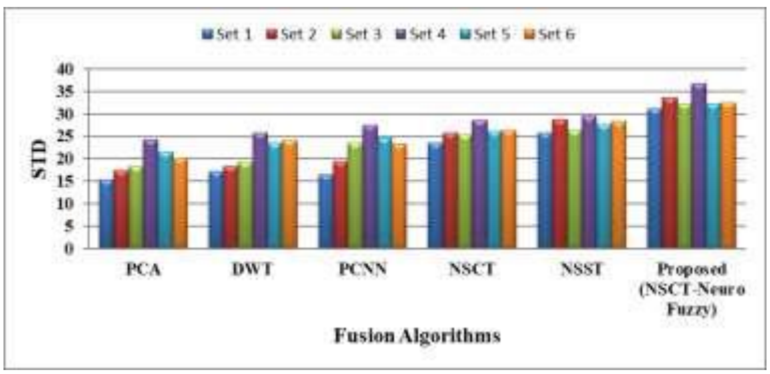

Fig. 15 Comparative Analysis for standard deviation

Figures 14 and 15 show the comparative analysis for the PSNR and standard deviation for six sets of images CT-MRI, MRI-SPECT and MRI-PET. The results of study are differentiated with PCA, DWT, PCNN, NSCT and NSST techniques. The demonstrated NSCT-Neuro fuzzy has higher value for PSNR and standard deviation in comparison with the conventional methods already existing.

5. Conclusion

In this chapter, multimodal medical image fusion has been performed using NSCT with Neuro Fuzzy hybrid algorithm. Pixel based activity measurement was used. The PCNN uses the modulatory coupling. The average fusion rule is applied for fusing the low frequency region, and the maximum coefficient rule is used for fusing the high frequency region. The results are compared with the conventional PCA, DWT, PCNN, NSCT and NSST method. Objective and subjection evaluation of the fused images was carried out. The performance evaluation shows that the proposed methods outperform the other methods already present with respect to information content, the data spread and the volume of data transferred from the source images to the fused image. The results are also compared with the recent research work, going on in the field of image fusion. The performance metrics used for the comparisons are fusion factor, IQI, EQM and mSSIM, cross entropy, MI, standard deviation and PSNR. Compared to the existing works, the NSCT – Neuro fuzzy based hybrid method gives good characteristics for the fused image.

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