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Impact Of Average, Maximum And Energy Fusion Rules On The Performance Of DWT, SWT and NSCT Based Fusion On Bio-Medical Images.

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ABSTRACT

Medical image fusion is the technique for consolidating and merging correlative data from two or more input pictures into a composite image to improve the diagnostic ability. In this work, Non Subsampled Contourlet Transform (NSCT), Stationary Wavelet Transform (SWT) and Discrete Wavelet Transform (DWT) based image fusion techniques utilizing distinctive fusion rules are performed on real time PET and CT images. For fusing low frequency coefficients, average and choose maximum fusion rules are utilized. For the fusion of high frequency coefficients energy fusion rule has been utilized on pixel level. The proposed methodology is performed utilizing eight sets of Positron Emission Tomography and Computed Tomography medical images. The performance evaluation of DWT, SWT and NSCT are analysed using four different quality metrics. From experimental analysis it is clear that Non-Subsampled Contourlet Transform (NSCT) performs superior than Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) from both subjective and objective estimation.

Keywords: Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Non Subsampled Contourlet Transform (NSCT), Average, Choose maximum, Energy fusion rules.

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INTRODUCTION

Image fusion can be characterized as the synergistic utilization of knowledge from distinctive sources to assist in overall apprehension of an event. Image fusion alludes to the procedure of joining two or more images into 1 composite image, which coordinates the data contained within the individual images. The outcome is an image that has a higher data content compared to each of the individual

images.[1]Different types of imaging procedures such as X-ray, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single Positron Emission Tomography (SPECT) provides information in a limited province. For example, X-ray and Computed Tomography reveals information about bones while information regarding soft tissues are revealed by Magnetic Resonance Imaging whereas Positron Emission Tomography reveals information regarding functional activity of the body.[2] Hence it is necessary to combine both the anatomical and functional information for a compact view. Image fusion can be accomplished at three levels-Pixel level, feature level and decision level . In this paper, image fusion is performed on pixel level. The main advantage of pixel level fusion is that the fusion will be performed at pixel level. Further, pixel level algorithms are computationally efficient and easy to implement.

In this paper two different fusion rules are used for Stationary Wavelet Transform (SWT) and Non Subsampled Contourlet Transform (NSCT) and Discrete Wavelet Transform (DWT). Choose max, average fusion rules are applied for low frequency coefficients and for high frequency coefficients energy fusion rule has been employed and the performance of these fusion rules has been analyzed qualitatively and quantitatively by using eight sets of Positron Emission Tomography(PET) and Computed Tomography(CT). Section 2 briefly explains about the related work done so far, proposed methodology is given in section 3, fusion results are given in section 4,quantitative analysis of different fusion rules is given in section 5, global comparison between different fusion rules is given in section 6 and Conclusion is provided in section 7.

Related work

Gaurav Bhatnagar et al has proposed a new fusion methodology using Non-Sub inspected Contourlet Transform (NSCT).[3] Pixel level fusion has been utilized to disintegrate high frequency and low frequency coefficients. Initially the images are deteriorated employing NSCT method. After disintegration the high frequency coefficients are fused manipulating directive contrast technique whereas low frequency coefficients are fused by employing congruency technique . Experimental analysis has demonstrated that the proposed methodology is more proficient than existing multi-scale techniques.

Sneha Singh et al has proposed a new fusion methodology that utilizes the features of both non subsampled shearlet transform (NSST) and spiking neural network. [4] Initially, the source CT and MRI images are disintegrated by the NSST technique into several sub images. Regional energy technique is used to fuse the low frequency coefficients while pulse coupled neural network model has been utilized to fuse high frequency coefficients. Finally, inverse NSST is employed to obtain the fused image. Performance analysis of the proposed fusion algorithm is evaluated by conducting several experiments on the CT and MRI medical images. Experimental results proves that the proposed algorithm provides better quantitative results than existing algorithms.

Yudong Zhang et al has proposed another strategy called as Stationary Wavelet Transform (SWT) for extracting features from brain images. [5]Traditional Discrete Wavelet Transform (DWT) experiences translation variation property. Thus the yield produced will have slight movement when compared with the input images. To solve the above downside, Stationary Wavelet Transform (SWT) has been proposed. Haar wavelet transform has been utilized and the decomposition level is set as 3. Experimental analysis demonstrates that Stationary Wavelet Transform (SWT) is better than Discrete Wavelet Transform (DWT) in concerning the shift invariance property.

PROPOSED METHODOLOGY

The block diagram representation of proposed methodology is shown in the figure below. Initially CT and PET images are acquired followed by suitable processing steps such as image resizing, RGB to gray scale conversion etc. After preprocessing, the input images are decomposed into low and high frequency coefficients by employing DWT, SWT and NSCT methodologies. After decomposition average and choose maximum fusion has been employed for fusing low frequency coefficients while energy fusion rule has been employed for fusing high frequency coefficients. Reconstruction of the image is performed by utilizing suitable inverse transform.

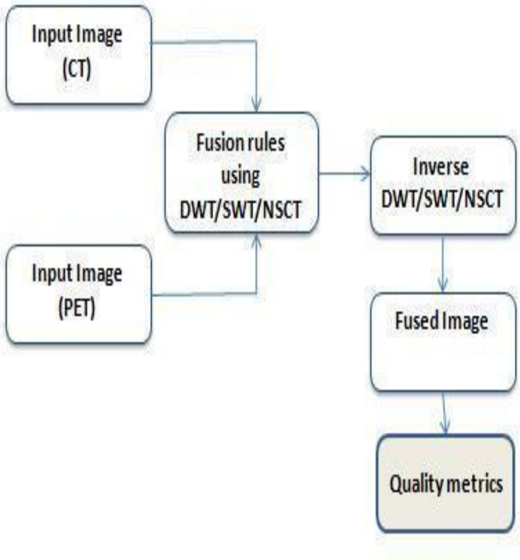


Figure 1: Block diagram of proposed methodology

Discrete Wavelet Transform

A signal analysis technique similar to image pyramids is the wavelet transform. The fundamental difference is that image pyramids will lead to a complete set of transform coefficient while the wavelet transform terminates in a non-redundant image depiction. The discrete 2-D wavelet transform is computed by the recursive utilization of low pass and high pass filters in each direction of the input image (i.e. rows and columns) followed by sub sampling. In numerical and functional inspection, a Discrete Wavelet Transform (DWT) is a methodology in which the wavelets are discretely sampled. The major advantage of Discrete Wavelet Transform is that it can acquire both functional and locale information. [8]Although Discrete Wavelet Transform apprehends spectral as well as directional information it suffers from various impediments such as shift-variance ,loss of edge information blurring effect etc. To overcome these disadvantages, Stationary Wavelet Transform (SWT) technique has been proposed.

Stationary wavelet Transform

The stationary wavelet transform is an expansion of the standard discrete wavelet transform. Stationary wavelet transform utilizes high and low pass filters. SWT applies high and low pass filters to the data at each level and during the next stage it will produce two sequences. The two sequences produced will have the same length as that of the original sequence. In SWT, the filters at each level are padded with zeroes instead of applying decimation at each level. [9] Though Stationary wavelet transform is efficient than Discrete Wavelet Transform, it is computationally more complex.

Non Subsampled Contourlet Transform

NSCT is a multi scale geometric analysis which utilizes the geometric regularity in the image and provides asymptotic ideal representation in terms of better localization, multi direction and shift invariance. Though wavelet transforms performs well at isolated discontinuities they are not good along edges and textured locale. Additionally, they capture limited directional information along three spatial directions. Subsequently, NSCT methodology captures 2D geometrical structures in a more effective manner than existing multi scale transforms. To retain the directional properties of the transform, laplacian pyramid has been replaced by a non sub sampled pyramid structure. Down sampling has been eliminated in the forward direction while up sampling has been removed in the reverse direction. Processing the coarser levels of the pyramid will lead to loss in resolution of an image which has been avoided in NSCT by up sampling the Directional Filter Bank(DFB).

Fusion rules

Fusion rule plays a vital role in image fusion algorithms. Fusion rule is an essential processing step that determines the formation of fused multi scale representation from multi scale representation of source images. [10] Most of the data content will be available in low frequency coefficients hence average and choose maximum fusion rule has been employed for low frequency coefficients while high frequency coefficients contains information about edges hence energy fusion rule has been used to fuse high frequency coefficients.

Average fusion rule

The resultant pixel in the fused image is obtained calculating the average of corresponding pixels in the input source images.

f1(i,j) = (LL1(i,j) + LL3(i,j))./2;

Where f1(i,j)-Pixel intensity of resultant fused image LL1(i,j)-Pixel intensity of input CT image LL3(i,j)-Pixel intensity of input PET image

Choose Maximum rule

The resultant pixel in the fused image is determined by comparing the pixel intensity of the input images and chosing the maximum pixel intensity among them as the output.

W(i,j)={W1(i, j)if W1(i, j) > 2(i, j)} W(i,j)={W2(i, j)if W2(i, j) > 1(i, j)}

Where W(i,j)-Pixel intensity of the fused image W1(i,j)- Pixel intensity of the CT image W2(i,j)-Pixel intensity of the PET image.

Energy rule

Energy is a measure of homogeneousness of the image and calculated from the high frequency bands that contains detailed coefficients .

E = sum(sum(Dij^2))/ N Dij – Coefficient at ij coordinates and

N – Number of coefficients at each window(3*3). [11] The energy will be measured for each coefficients with their neighbourhood coefficients and fusion of high frequency coefficients will be performed through high energy valued coefficient selection.

RESULTS AND DISCUSSION

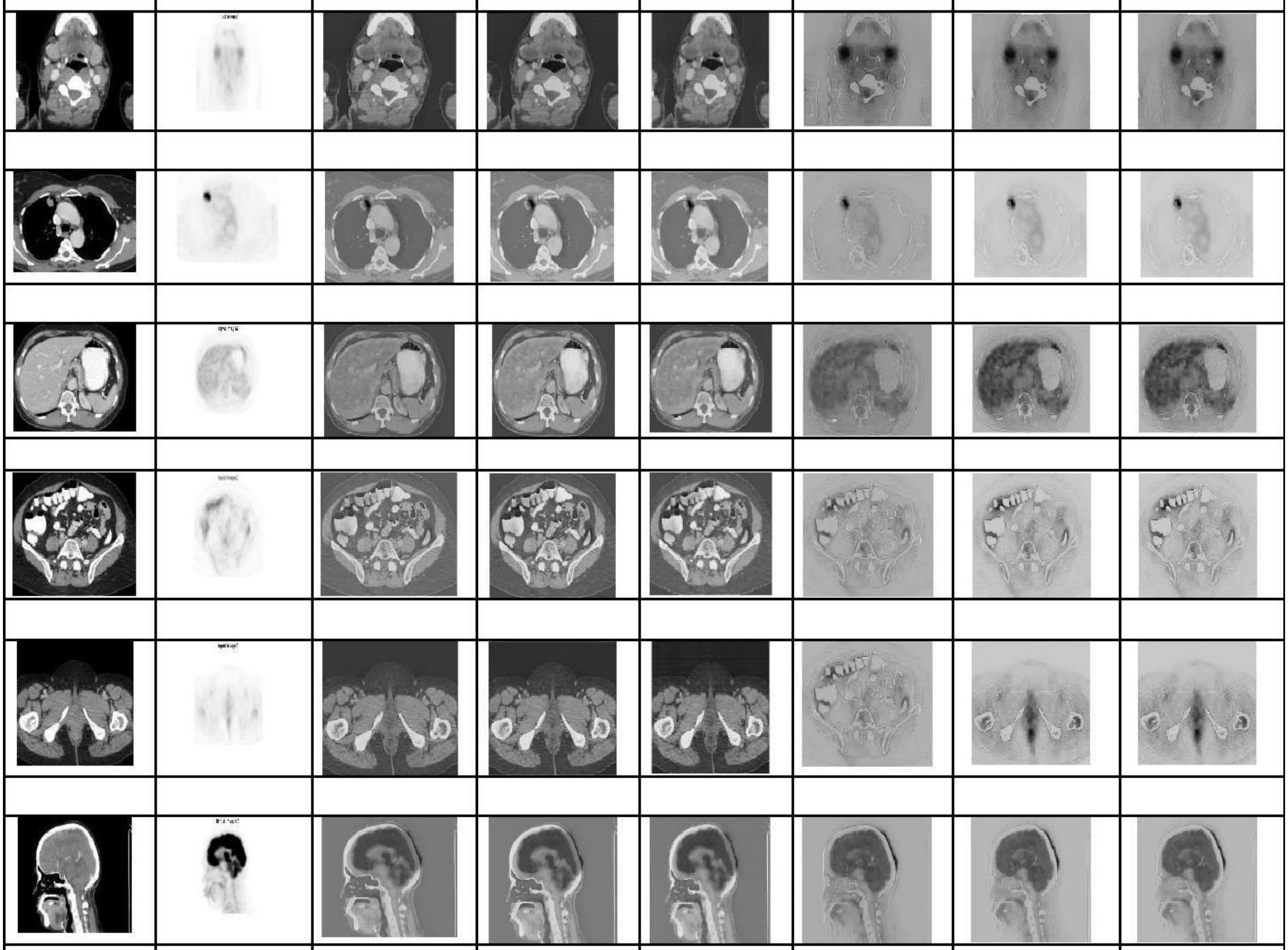
The performance of the proposed technique is analysed using eight sets of real time medical images obtained from Bharat Scans. For the fusion of low frequency coefficients choose max and average fusion rules are applied whereas energy fusion rule has been used for high frequency coefficients. Qualitative measurements of the proposed technique is given in table 4. In table 4, column A1 represents Computed Tomography (CT) and A2 represents Positron Emission Tomography (PET) images. The results of the corresponding outputs of CT ,PET

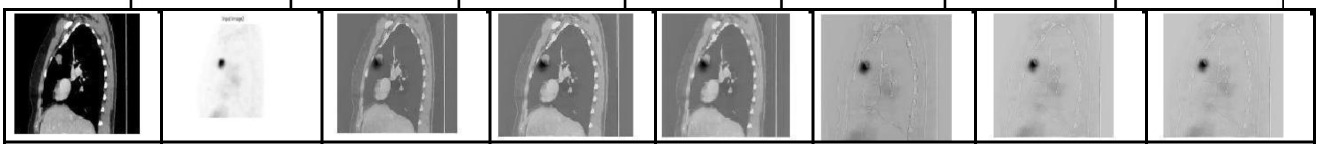
H3-H6.

images are given as output images from A3-A6------

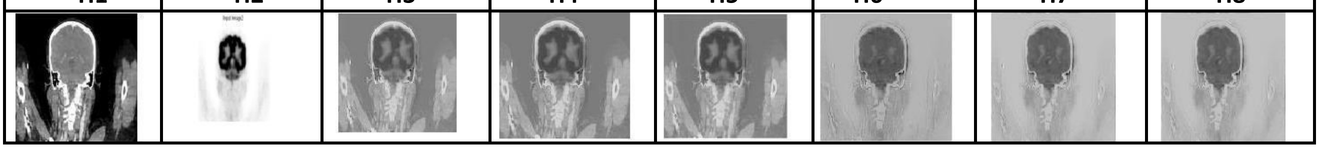
4. FUSION RESULTS OF CT AND PETIMAGES

CT	PET	DWT	SWT	NSCT	DWT	SWT	NSCT
		Avg, Energy	Avg, Energy	Avg, Energy	Max, Energy	Max, Energy	Max, Energy
A1	A2	A3	A4	A5	A6	A7	A8





H1	H2	H3	H4	H5	H6	H7	H8



Quantitative analysis Standard Deviation (SD)

Data Set	DWT (Avg, Energy)	SWT (Avg, Energy)	NSCT (Avg, Energy)	DWT (Max, Energy)	SWT (Max, Energy)	NSCT (Max,Energy)
1	10.7274	10.8134	**10.4506**	7.4197	7.44030	**6.6693**
2	6.9852	6.8864	**6.6483**	9.9203	10.1032	**9.8852**
3	10.7415	10.6680	**10.2201**	7.4177	7.46110	**6.7077**
4	9.0635	8.9489	**8.6285**	6.9127	6.54220	**6.1244**
5	6.5165	6.4617	**6.4616**	3.7990	4.06370	4.0395
6	24.5740	24.4870	**23.2612**	22.6949	22.4823	**20.8328**
7	16.8912	16.8702	**15.8572**	10.8291	10.3905	**9.5425**
8	16.1048	16.0653	**15.8008**	19.8990	20.0529	**19.5415**

Mutual Information(MI)

Data Set	DWT (Avg, Energy)	SWT (Avg, Energy)	NSCT (Avg, Energy)	DWT (Max, Energy)	SWT (Max, Energy)	NSCT (Max, Energy)
1	5.2426	5.4507	**6.6071**	2.2360	2.2255	**2.9024**
2	7.6155	7.9281	**7.9815**	2.6559	2.3534	1.5622
3	6.2641	5.9387	**6.9499**	3.1934	3.3040	**4.0408**
4	5.8126	6.0269	**6.6099**	2.2689	2.1337	2.2569
5	6.6565	6.8033	**8.3990**	2.8176	2.8324	**3.2557**
6	5.2178	5.2693	**5.5221**	4.2752	4.3150	**4.8586**
7	5.6162	5.8477	5.2159	1.5255	1.3288	1.1760
8	6.2235	6.3780	5.6544	3.7748	3.7775	**3.8186**

Entropy

Dataset	DWT (Avg, Energy)	SWT (Avg, Energy)	NSCT (Avg, Energy)	DWT (Max, Energy)	SWT (Max,Energy)	NSCT (Max, Energy)
1	2.7700	2.7781	**7.2960**	2.4324	2.4406	**7.2960**
2	3.0121	3.0152	**7.2958**	2.4318	2.4099	**7.2960**
3	2.9004	2.9062	**7.2941**	2.5970	2.6223	**7.2936**
4	3.0289	3.0270	**7.2960**	2.4405	2.4482	**7.2959**
5	2.6825	2.6941	**7.2730**	2.1874	2.1852	**7.2730**
6	2.5677	2.5891	**7.2933**	2.2625	2.2803	**7.2807**
7	2.7290	2.7296	**7.2900**	2.3011	2.2872	**7.2900**
8	2.8738	2.8930	**7.2954**	2.4093	2.4280	**7.2943**

Structural Similarity(SSIM)

Dataset	DWT (Avg, Energy)	SWT (Avg, Energy)	NSCT (Avg, Energy)	DWT (Max, Energy)	SWT (Max, Energy)	NSCT (Max, Energy)
1	0.4402	0.4405	**5.0361**	0.1946	0.1946	**20.1912**
2	0.4124	0.4125	**4.1459**	0.1810	0.1807	**16.7969**
3	0.6384	0.6388	**5.7344**	0.3646	0.3641	**11.9362**
4	0.4977	0.4981	**5.1602**	0.2359	0.2356	**20.2074**
5	0.3856	0.3858	**4.9990**	0.1676	0.1676	**29.1662**
6	0.5562	0.5564	**4.1919**	0.2134	0.2129	**3.1171**
7	0.3169	0.3172	**4.0621**	0.1207	0.1203	**13.1837**
8	0.5271	0.5273	**3.6947**	0.2285	0.2283	**3.5219**

Global Comparison

Entropy: On comparing entropy values of DWT , SWT and NSCT for the above fusion rules, it is clear that the Average, Energy and Maximum, Energy fusion rule provides better results for all datasets.

Standard Deviation(SD): On comparing SD values of DWT, SWT and NSCT for the above fusion rules, it is distinct that average, energy fusion rule provides better results for all datasets while maximum, energy fusion rule provides better results for 1,2,3,4,6,7 and 8th dataset while DWT provides better results for 5th dataset.

Structural Similarity (SSIM): On comparing SSIM values of DWT, SWT and NSCT for the above fusion rules, it is apparent that the Average, Energy and Maximum, Energy fusion rule provides better results for all eight datasets.

Mutual Information(MI): On comparing SD values of DWT, SWT and NSCT for the above fusion rules, it is obvious that average, energy fusion rule provides better results for 1,2,3,4,5 and 6th dataset while SWT provides better response for 7th and 8th dataset. Maximum, energy fusion rule provides better results for 1,3,5,6and 8th dataset while DWT provides better results for 2,4 and 7th dataset.

CONCLUSION

A pixel based image fusion approach using two different fusion rules are proposed in this paper and the results are emphasized in section 4 for Discrete Wavelet Transform , Stationary Wavelet Transform and Non Subsampled Contourlet Transform. From the qualitative and quantitative analysis it is clear that Non Subsampled Contourlet Transform provides better results than Discrete Wavelet Transform and Stationary Wavelet Transform.

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