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Image Fusion using Waveatom Transform for Medical Applications

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Abstract: *Image fusion is the process of gathering all the important information of multiple images into a single fused image. It is used in many fields like medical, military, remote sensing etc... Image fusion in a medical field is extensively used by physicians for analysis and treatment, as the fused image contains complementary features present in different medical images obtained from imaging devices. The wave atom transform based medical image fusion is proposed as the potential capabilities of wave atoms have been exploded in many applications like image denoising, fingerprint identification, compression etc. Medical image techniques became important tool for medical diagnosis and treatment. Medical images of different modalities such as MRI, CT, PET, SPECT provide information in a limited domain. In medical resources, MRI and CT images contain structural information whereas PET and SPECT images contain functional Information. Thus, single modality does not provide complete and accurate information, both structural as well as functional information is required. So far, many medical image fusion methods have been developed. The easiest way to perform image fusion is to perform weighted average of input images pixel by pixel. But this method produces side effects such as artifacts & contrast reduction. The proposed method is experimented on various medical images and compared with recent state of fusion methods. Results prove that images obtained from proposed method have better clarity and enhanced information and are practically more helpful for better treatment and quick analysis.*

Keywords: MRI, CT,PET, SPECT, Image Fusion, Contrast Reduction

I. INTRODUCTION

The image Fusion method is used to combine a high-resolution panchromatic image with a low-resolution multi-spectral image. It is used for the development of a high-resolution multi-spectral image that both contain high resolution panchromatic spatial information and multi-spectral image color information. Multi-modal medical images such as x-rays, Computed Tomography (CT), Magnetic Resonance Angiography (MRA), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET) is needed to support medical diagnosis and evaluation. Such multi-modal medical images often include knowledge that is complementary and sometimes conflicting. For dense structures such as bones, implants, and physiological changes, such as the CT image can cause less distortion. The MR image can still provide abnormal and information about soft tissues, but it cannot help bone information. In this situation, only a single image type may not be enough to give doctors specific clinical requirements. The integration of multi-modal medical images is, therefore, significant and became an up-and-coming and challenging field of research in recent years. Medical image fusion is the method that, according to specific rules, could combine two mutual images into one for an apparent visual effect. The doctor could easily confirm the location of the disease by looking at a medical fusion image. The medical image offers a range of clinical diagnostic information, like CT, DSA, X-ray, PET, SPECT, MRI etc.

Every medical image has various features, which may provide different organs with essential information; for example, high spatial resolution CT and MRI can provide anatomical organ structure information. PET and SPECT, however, provide information on organ metabolism. Increasing modality offers a different representation of the anomalies, as

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shown in Figure 1(a-h). CT provides information about calcifications, bone structures, and tumor contours prominently. MRI for soft tissue anatomy is the best modality.

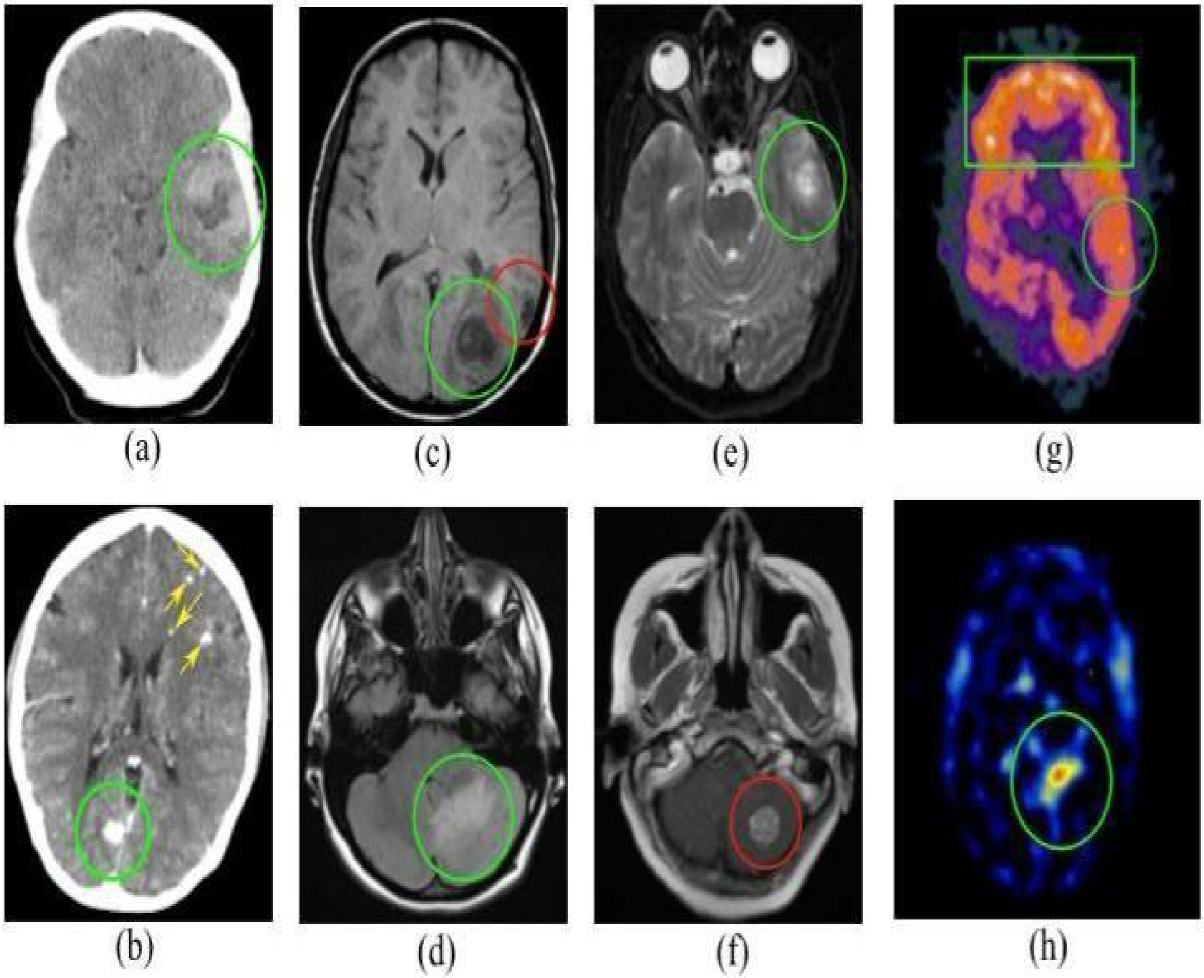

Figure 1: Medical image modalities and their ability to represent abnormalities in brain
(a) lesion with necrosis and edemain CT, (b) Calcifications in CT, (c) lesions with necrosis and edema in T1 weighted MRI, (d) edema in MRI FLAIR, (e) lesion with edemain T2 weighted MRI, (f) distinct mass in T1 weighted MRI with contrast, (g) Abnormal metabolic representation in PET, (h)central functional activity map in SPECT

II. LITERATURE SURVEY

According to **Alfano*etal.*,(2019),** image synthesis techniques are mostly founded on an MRA that can decompose imageries into various sections at various measures [1] & [6]. The author presented a wavelet-based fusion method that merged medical images to Variance and MRA standards module highest as dual essential mechanisms. Their findings were generally positive and resulted in quantitatively and quantitatively enhanced image fusion results.

Bhanusree CH *et al.*, (2018)[2] Research the transformation of the wavelet of second-generation image fusion and review apps coefficients of the multiple realms of frequencies. Typically low-frequency coefficients are used. The image regional pixel characteristics are observed to determine the local area measurement parameters, while high-frequency coefficients for window properties are used.

Chauhan *et al.*, (2017)[4], the main inspiration for transforming the invariance of transition was the Dual-Tree Complex Wavelet Transform (DTCWT). In typical wavelet worsening, little change in the data sign may affect the yield subgroups' energy. In variance of movement is also accomplished by multiplying the DWT inspection rate. In the DTCWT, the down check is removed by two afterward, the first wave. Two destroyed trees are then formed by inspection, which is initially pretentious by attractive even and later strange samples after the primary channel grade. The resulting channels require a large proportion of a different example delay in a single tree to achieve between the two measurements of trees, standardized interims.

In **Cui, Z. *et al.*, (2019)**[5], multimodal medical image fusion was addressed using RDWT. Here, an imaging fusion algorithm incorporates multi-spectral MRI pair's proton density, for example,T1 and T2 weighted representations of the brain. Its algorithm uses different non-linear features, shared knowledge Registration, knowledge on entropy, and RDWT to improve results.

Darwish, (2018)[7], presenting the fusion of Multimodal photos is one of the most common and effective medical imaging diagnostic methods. This work proposes a Contourlet Transform(CNT)-based and multilevel, fuzzy justification method for fusion images from medical engineering. The useful data from two medical images captured in space are merged in a new image to improve clinical and recovery diagnosis.

Demirel and Anbar Jafari(2020)[8], proposed Complex Wavelet Transformation (CWT) theory and applications of image processing. Complex Wavelet Transform is a group of low-frequency and high-frequency images used by the fusion of various sub-band frequencies of source images to collect the original images. The two frequency bands are used primarily obtain the real and imaginary components of complex images.

Deng *et al.*, (2019)[9], Describes the canny operator edge detection technique and the new transform algorithm based on a wavelet to fuse the input images. To obtain border information, identify the low-level frequency and high-level frequency components with the new vertical and diagonal rim. Several methods have been used in the composition of multi-scale images using a DWT to compare the energy per pixel and decide on edge point stability. This work uses three independent variables, combined factors, and specific evaluation parameters. This approach is worth maintaining the details on edge and enhancing visual effect.

Desale*et al.*, (2018) [10], Illumined that the combine's fusion of the image process different images based on the critical data in a fused image, where the outcome image is more informative and straightforward than any one of the source data images. Also, the findings are detailed in the tables and statistics for a detailed machine analysis mentioned. Here addresses the principles, plans for procedural implementation, and estimates of image fusion routines based on DCT, PCA, and DWT. DCT and PCA, however, are standard fusion frames with many defects. Also, DWT-based strategies are very reliable because they produce good image synthesis results.

Jaywantrao and Hasan(2020)[11], proposed DTCWT approach that distinguishes directionally between the fusion of the image. That is the constant change to deals with the discrete time-invariant corresponding. Medical imagery, industrial use, remote sensing, video monitoring, and defense valued the successful fusion technique with several modes or instruments. The fusion of 2D and 3D images is extensively utilized to transmit the arrangement, such as SAR. The approach for 2Dand 3D models is therefore necessary. The critical feature for 2D and 3D images used the real-time fusion systems implemented for experiments with multi-point images. The current research is to create a method, which uses the time function to generate the different results from which previously perform.

Krishna, A. *et al.*, (2016)[13] Medical image synthesis was performed with the WT and PCA technique's support to merge the complementary diagnostic content. To save space with spectral information, scientists have disintegrated the sub-band with2D-DWT. They used the PCA to improve spatial resolution using broken coefficients. They also have an optimal version picked a member of the wavelets to obtain the fusion's improvised results. For scientific aspects, however, medicinal images have unusual attributes that differ from picture to picture.

Kusuma and Murthy(2017)[14] the author combined various data sources, including multimodal medical imagery, image combination increases the accuracy and reliability of information steadily. The fused multimodal image should be virtually free of objects. Therefore, no relevant information must be omitted from the original info-the original data. ST is a new technique designed to enhance image detail quality by using the SVD. The image and strive for data fusions to provide medical info. Thus, the fusion of the image increases the image information's accuracy and reduces the randomness and redundancy used in medical applications A PSNR is characterized as a proportion of the differences between flag exchange and reproduction. The accompanying articulations provide suggested honest mistakes, the high signal for the Noise Ratio (Eqn. 2.1), and Compression ratios(Eqn.2.2).

PSNR = 10 log($\frac{p_o}{p_i}$) ----------- (2.1)

Compression Ratio = $\frac{Original\ Image\ Size}{Compressed\ Image\ Size}$ -----------(2.2)

Any weight is encoded using one of the coding techniques facts. The coding motion is of great importance for the efficiency of the load gadget. It consists ofdepictingtheeffectsinaformthatispracticalforrestrictingandtransmitting.The time required to perform this function is referred to as the time of encoding. The turnaround method for encoding is detaching, and the time needed by unwind encoded statistics is time for interpretation. While all is indicated in the results,the statistics to be compacted may be considered in time or space. To a percentage of the documents, it was observed that it is worthwhile to deal with repetitive results. The data should, therefore, be updated into the repeat region in time- space. The Haar Wavelet(HW) is defined in(Eqn.2.3) in table 2.1

$\psi(x) = f(x) = \{1, x \in (1,0)\}$ --------(2.3)

Image	Parameter	Haar	Daubechies	Biorthogonal	Demeyer	Coiflet	Symlet
CT	CR (bpp)	3.4	1.77	3.05	1.9	2.89	1.88
	PSNR(dB)	24.7	24.3	26.7	24.6	45.5	24.6
MRI 1	CR (bpp)	3	2.6	2.7	1.62	2.4	2.7
	PSNR(dB)	24.8	30.9	32.18	30.8	49.8	30.9
MRI 2	CR (bpp)	2.9	2.6	2.7	1.61	2.4	2.7
	PSNR(dB)	25.2	31	32.8	31.3	50	31.5
MRI 3	CR (bpp)	3.62	3.478	3.53	2.12	3.2	3.57
	PSNR(dB)	23.1	23.74	24.07	3.77	40.0	23.7
MRI 4	CR (bpp)	3.03	2.6	2.73	1.63	2.4	2.72
	PSNR(dB)	24.2	30.54	31.39	30.4	49.2	30.4
MRI 5	CR (bpp)	3.05	2.6	2.7	1.63	2.n56 n	2.73
	PSNR(dB)	23.9	30.1	31	30.5	48.8	30.42
MRI 6	CR (bpp)	3.05	2.69	2.75	1.64	2.27	2.75
	PSNR(dB)	24.7	30.87	32.44	30.62	50.1	30.91

Table 2.1: Comparison of Pyramid based Image Fusion

III. EXISTING METHOD

In this research, an optimized image coalition algorithm is developed to combine visible and thermal images using curvelet transform and PSO. The curvelet transform is designed to represent edges much more efficiently than traditional transforms. The motto is to achieve better situational evaluation rather than using any of the source images

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individually. The removal of redundant information improves accuracy and reliability of the resultant image. Another positive aspect is the possibility to integrate complementary information which in turn improves the interpretability of the image.

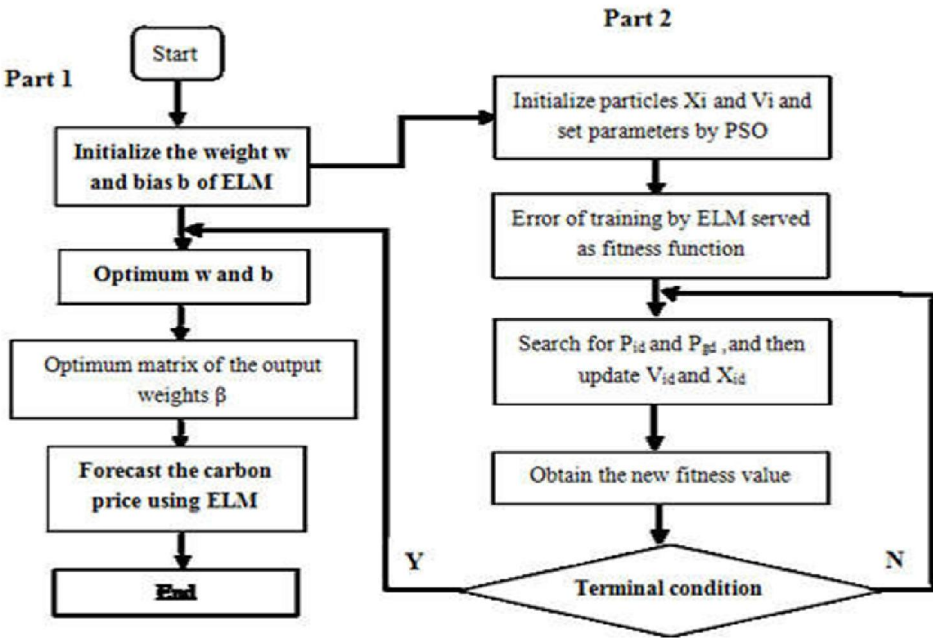

Figure 3.1: PSO Flowchart

Figure 3.1 shows the system architecture where a thermal image and a visible image captured with two cameras are taken. The thermal image needs to be resized and the resized thermal image needs to be registered to bring the thermal im-age to the same size of the captured visible image. Both these images are then decomposed to obtain different frequency sub bands. The fusion process is carried out by combining the low and high frequency sub bands of thermal image with that of the visible image respectively. Inverse curvelet transform is applied to obtain the fused image which is richer in content and more informative.

3.1 Image Resizing

The thermal image (target image) needs to be brought to the same size of that of the visible image (reference image). It returns an image that is scale times the size of reference image. Image is resized using bicubic interpolation. Bicubic interpolation is the process of taking the weighted average of the pixels that belong to the nearest 4 by 4 neighborhood. This technique is most used for video and image scaling for display. The image is slightly sharper than that produced by other interpolation techniques and it does not have disjointed appearance. It is mainly used in image magnification, image resizing, image registration and to correct spatial distortions and image decompression [14].

3.2 Image Registration

This is a very important step when different sets of data is to be transformed in a common coordinate system. Data may be obtained from multiple devices, sensors and depths. Registration makes it easier to be able to compare or integrate the data obtained at different angles and from various measurements. Affine transform is a mapping technique which helps in preserving the most corner and interesting points, straight lines and planes. It is also used to correct geometric distortions that occur due to non-ideal camera orientations.

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3.3 Image Decomposition using Curvelet Transform

Curvelet transform is a directional transform that allows optimal edge representation of objects in the scene. Mostly, natural images contain edges that look like lines, curves which may contain discontinuities. Wavelets do not solve the issues like curve singularities due to which many geometric properties of structures are affected and they do not exhibit edge regularity for which curvelet based decomposition approach is used that represent edges with better accuracy.

3.4 Determination of Optimized Weights using PSO

PSO is an iterative based computational approach that provides optimal solution by iteratively improving a candidate solution. It solves a problem by taking a population of solutions or particles and obtaining the solution by moving the particles in the search space. This is done using a mathematical equation over the particles by changing the position and velocity to find the interesting regions in an image shown in figure 3.2.

(a) Visible Image. (b) Thermal Image.

Figure 3.2: Input Images

3.5 Image Fusion

Image is fused by computing the inverse curvelet trans-form. In inverse curvelet transform procedures like ridge let synthesis, renormalization, smooth integration and sub band re-composition is performed. The fused image contains the most pertinent features like corners, edges, points and curves and it increases edge content and reduce information

IV. PROPOSED METHOD

Medical image fusion is extensively used by the physicians for better clinical investigation and disease diagnosis. Further, complex wave atom, a variant of wave atom transform, possesses important property (explanation given in Sect. 3.1) that influences the performance of image fusion methods and therefore, wave atom transform-based medical image fusion is proposed.

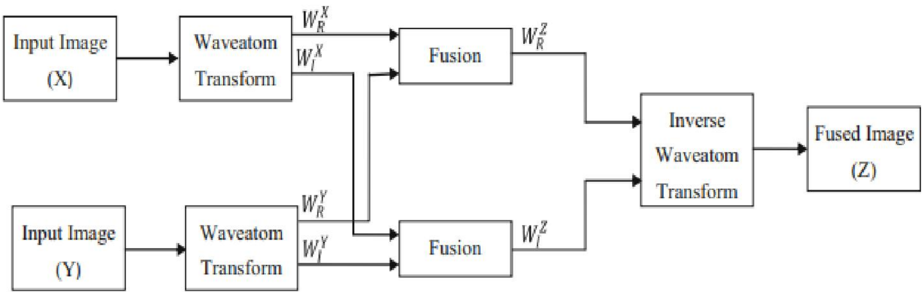

Figure 4.1: Image fusion method

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The block diagram of the proposed method is shown in Fig.4.1 and is explained as follows:

1. Input multimodal medical images are first decomposed into 'α' levels using wave atom transform.
2. Since maximum coefficient corresponds to sharper intensity, the complex wave atom coefficients with maximum values are selected as wave atom coefficients of fused image. Mathematically

$$W_{z}{}_{I}^{R} = \begin{cases} W_{x}{}_{I}^{R}, & if\ W_{x}{}_{I}^{R} > W_{y}{}_{I}^{R} \\ W_{y}{}_{I}^{R}\ , & if\ W_{x}{}_{I}^{R} < W_{y}{}_{I}^{R} \\ 0.5\left(W_{x}{}_{I}^{R} + W_{y}{}_{I}^{R}\right), & if\ W_{x}{}_{I}^{R} = W_{y}{}_{I}^{R} \end{cases} \quad \text{-----------(4.1)}$$

here $W_X^{R/I}$, $W_Y^{R/I}$ and $W_Z^{R/I}$ represent the real (R)/imaginary (I) wave atom coefficients of input images X, Y and the fused image Z respectively.

4.2 Wave Atoms

In this section we show how to implement wave atoms as a fast digital transform. The requirements we put on a family of basis function to be called "wave atoms" . They have to do with uniform space frequency localization, and put the general architecture.

We write wave atoms as ϕμ(x), with subscript μ = (j, m, n) = (j, m1, m2, n1, n2). All five quantities j, m1, m2, n1, n2 are integer-valued and index a point (xμ, ξμ) in phase-space, as

x_μ=2^(-j) n, ξ_μ=π2^j m, C_1 2^j≤max┬(i=1,2) |mi |≤C_2 2^j -----------(4.2)

where C1, C2 are two positive constants left unspecified for convenience, but whose values will be implied by the specifics of the implementation.

According to the assumption of waveatom, Let xμ and ξμ be as in equations for some C1, C2. The elements of a frame of wave packets {ϕμ} are called wave atoms when

|φ^_μ (ξ)|≤C_M.2^(-j) (1+2^(-j) |ξ-ξ_μ |)^(-M)+C_M.2^(-j) (1+2^(-j) |ξ+ξ_μ |)^(-M), for all M>0,

and

|φ_μ (x)|≤C_M.2^j (1+2^j |x-x_μ |)^(-M), for all M>0. --------(4.3)

Mean Square Error (MSE) provides the square of the mean error between an original and fusedimage. MSE can be defined as

$$\varphi_{\mu}^{+}(x_1, x_2) = \psi_{m1}^{j}\left(x_1 - 2^{-j}n_1\right)\psi_{m2}^{j}\left(x_2 - 2^{-j}n_2\right), \quad \text{------------(4.4)}$$

where S and F are a source and fused image respectively. The value of MSE should be between 0 and 1, when it gives an insight in terms of the energy contents of the images. As before, M × N is the size of the images in pixels.

Root Mean Square Error (RMSE) can be represented as :

$$RMSE = \frac{1}{c}\sum_{k}\sqrt{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}\left((x,y) - F_k(x,y)\right)^2}{M \times N}} \quad \text{--------------------(4.5)}$$

where for a color image c = 3 and k= R, G, B and c = 1 for a gray-scale image. Obviously a smaller value of RMSE means a better performance for the fusion algorithm.

Peak Signal-to-Noise Ratio (PSNR) is a metric that defines the ratio between the maximum possible signal power and the power of a noisy image, which affects the fidelity of the representation. It can be defined mathematically as:

$$A = \pi r^2 \frac{10\log_{10} L^2}{MSE} \quad \text{-----------------(4.6)}$$

Normalized Cross Correlation (NCC) describes the similarity between small structures in an original and fused image. If the value of cross correlation is high then more information has been retained. It can be expressed mathematically

$$NCC(f,d) = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(F(i,j) - {}^{-}F)(d(i,j) - {}^{-}d)}{\sqrt{\sum_{i=0}^{M}\sum_{j=0}^{N}\left((i,) - {}^{-}F\right)^2 \sum_{i=0}^{M}\sum_{j=0}^{N}\left((i,) - {}^{-}d\right)^2}} \quad \text{---------------(4.7)}$$

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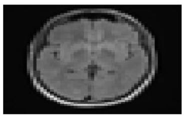
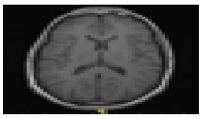
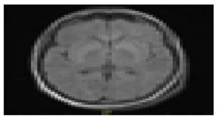
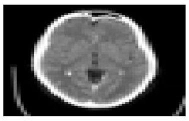
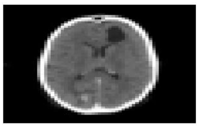
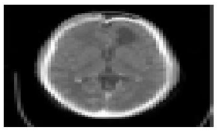
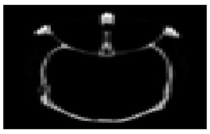
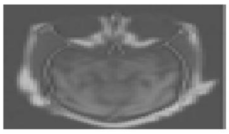
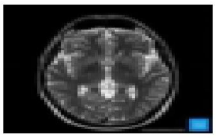
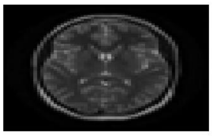
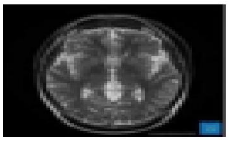
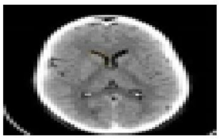
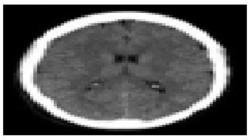
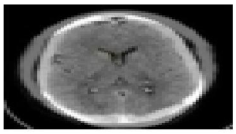
V. RESULTS AND DISCUSSIONS

In every case we can get more detailed and informative image from the source images of multi-modal, and are less informative when compared with the fused image. We used all images medical as well as the general images and compared the quality of the fused image with the input images as shown below in table 5.1:

S.No.	Input Image1	Input Image2	Fused Image
1			
2			
3			
4			
5			

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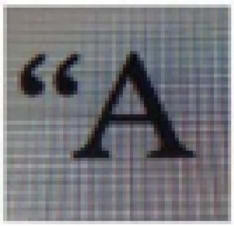
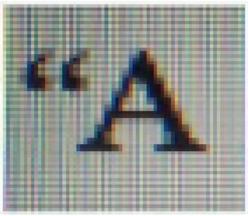
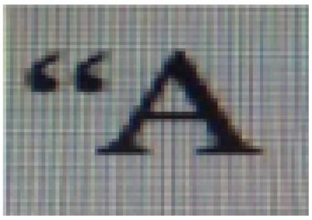
7			
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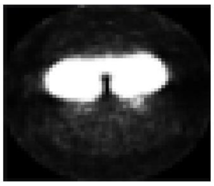
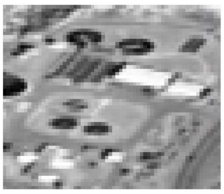
9			
10			
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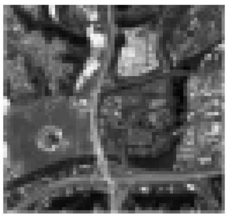
12			
13			
14			
15			

Table 5.1: Input images and image fusion

Parametric analysis of the fused image along with two source images is done by using MATLAB, we analyzed the different performance metrics for all fused images and the source images and we calculated the parameters they are average information(Entropy), peak signal to noise ratio (PSNR), standard deviation (SD) for the medical images like MRI, CT, Stereo images and satellite imaging (remote sensing) in table 5.2.

This is the basic information we have to keep in mind while writing the code for the SWT and PCA image fusion techniques for multi-modal imagery, and the following table represents the two input images which are multi-modal in nature and their corresponding fused image

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S. No.	Image 1	Image 2	Fused image Entropy	PSNR1	PSNR2	SD
1	C01_1	C01_2	5.943781	31.474271	37.599999	0.124919
2	C01_1	S09_MRI	4.535441	31.475756	36.649821	0.098710
3	C01_1	S09_SPECT	3.007386	31.468905	22.942826	0.101282
4	C01_1	S29_MRI	4.443079	31.477828	35.271238	0.107330
5	C01_1	S29_PET	4.464329	31.477230	37.945363	0.128071
6	C01_2	S09_MRI	6.389457	37.592853	36.641183	0.141323
7	C01_2	S09_SPECT	6.003132	37.594071	22.931912	0.143922
8	C01_2	S29_MRI	6.392631	37.594797	35.262587	0.152905
9	C01_2	S29_PET	6.403166	37.592167	37.939328	0.167465
10	S09_MRI	S09_SPECT	4.294690	36.645168	22.921462	0.099672
11	S09_MRI	S29_MRI	4.441894	36.643783	35.261938	0.115699
12	S09_MRI	S29_PET	4.490331	36.636803	37.936929	0.140924
13	S09_SPECT	S29_MRI	4.004484	22.943040	35.272406	0.084661
14	S09_SPECT	S29_PET	4.263748	22.924978	37.937675	0.144562
15	S29_MRI	S29_PET	4.266787	35.258260	37.940127	0.142088

Table 5.2: Parametric Analysis

VI. CONCLUSION

Image fusion include image sharpening, feature enhancement, improved classification, and creation of stereo data sets. It extracts the information from several images of a given scene to obtain a final image which has more information for human visual perception and become more useful for additional vision processing. Final outcome is to obtain better clarity and enhanced information. The image obtained from proposed method will be more informative and plays important role in better treatment and quick diagnosis. Medical image fusion is a process of fusing complementary information contained in multiple medical images into a single image that is more informative and plays an important role in quick diagnosis and better treatment. This paper pro- poses wave atom transform-based multimodal medical image fusion. Experiments are conducted on different pairs of medical images. The proposed method is also compared with recent state of the art medical image fusion methods. Experimental results and comparisons prove that the fused images obtained from the proposed method have better clarity and enhanced information and are therefore practically more helpful for medical applications and it can also be used in many applications of image processing domain.

VII. FUTURE SCOPE

The future of image processing will be to develop such techniques that automatically combined images of a screen captured under different illumination. Beyond providing digital tools for artists for creating surrealist images and videos, the methods can also be used for practical applications. For example, the non-realistic appearance can be used to enhance the context of night time traffic videos so that they are easier to understand. The context is automatically captured from a fixed cameras and inserted from a day time image. The use of scanning techniques and statistical analyses for image analysis are needed to extract valid image values. Our approach is based on wave atom transform which fuses the input images and gives an effective information which is more informative.

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