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BIOMEDICAL IMAGE FUSION FOR BRAIN CANCER DETECTION

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Abstract— Biomedical image processing includes biomedical data gathering, Image forming and processing for diagnosis of various diseases. Image Fusion can be an important tool for diagnosis of diseases from the data provided by medical imaging. The main objective of this analysis is to identify human brain cancer through fusion of different multi modal images. It consist of application of Gaussian and Laplacian Pyramid Decomposition based multi modal medical image fusion, which improves visibility of image details which results in an easy detection of infected areas. In the proposed work image fusion based on Gaussian and Laplacian pyramid decomposition has been considered that present better result compared to DWT. For the Performance analysis few parameters like Mean square error(MSE), Peak signal to noise ratio(PSNR), Structural content(SC), Standard deviation(SD) and Entropy are used. The proposed method has worked successfully and shown better results without introducing any artifacts and illustrate the usefulness of image fusion for image enhancement applications.

Index Terms— Image fusion, Gaussian pyramid decomposition, Laplacian pyramid decomposition

I. INTRODUCTION

Cancer is not just a disease but a lot more. There are more than 100 different types of cancer. Most types of cancer are called where they start. For example, lung cancer begins with the lungs and brain tumors begin in the brain.

In the world today, the early detection of cancer is the first activity to reduce the risk of cancer. Neural images are the process of obtaining brain images through magnetic scanning (MRI) or CT (CT). While both approaches are very similar in their physical dynamics, they differ in many ways. Doctors may combine CT and MRI each year with patients with tumors diagnosed correctly, but it's awkward and frustrating to complete this job. Therefore, improving the correlation of diagnosis, it is essential to develop effective synthetic techniques that reduce the workload of physicians.

The first evolution of image research is the combination of simple images that process basic pixel through pixel-related operations, such as adding subtraction, subtraction, and division. Simple synthetic techniques that rely on simple pixel operations on image input values. The second evolution of image studies is a pyramid synthesis based on interpretation. The first synthesis scheme has the right to include source images that often have a serious effect, such as reducing color contrast. With the introduction of pyramid shifting in the mid-1980s, some complicated methods appeared. People have found that it is better to apply the merger in the field of change. Recently, by creating a human-wave theory, people began to analyze the wavelengths to occupy the position of the pyramid to break the image. In fact, wavelength transformation can be considered a special type of pyramid decomposition. [1]

Generally synthetic techniques can be classified according to different levels. These are signal level, pixel level/data level, feature level and decision levels.

Signal level fusion In signal based fusion, signals from different sensors are combined to create a new signal with a better signal to noise ratio than the originals signals.

Pixel/ Data level fusion is the combination of raw data from multiple sources into single resolution data, which are expected to be more informative and synthetic than either of the input data or reveal the changes between data sets acquired at different times.

Feature level fusion extracts various features, e.g. edges, corners, lines, texture parameters etc., from different data sources and then combines them into one or more feature maps that may be used instead of the original data for further processing. It used as input to preprocessing for image segmentation or change detection.

Decision level fusion combines the result from multiple algorithms to yield a final fused decision. When the results from different algorithms are expressed as confidences rather than decisions, it is called soft fusion. Otherwise it is called hard fusion. Methods of decision fusion include voting methods, statistical methods and fuzzy logic based methods

The difference of these three levels is that they have different objects of study. Pixel-level fusion belongs to low-level fusion which is the foundation of the others. Pixel-level fusion directly computes the final value of every pixel from input images based on some rules. Until now the image fusion technique has been widely applied into many fields such as the defense industry, robot vision, digital camera application (e.g., multi-focus image fusion), medical imaging, and satellite image(e.g., remote sensing image). [2,3]

Image fusion aims to merge the significant aspects of two or more source images from these sensors to produce a singular output image, that contains all relevant image features. An important factor why fusion has been so successful is that engineers, developers and users are able to save costs by utilising signal processing techniques in lieu of designing an expensive system for image acquisition.

Over the past two decades, a number of synthetic techniques have been proposed. Most of these techniques are based on a compromise between the desired size gain and the spectral sequence. Among the hundreds of variations of the technique for the synthesis of the image that has been widely used method includes, but is not limited to the intensity-hue-saturation (IHS), filtration, principal component analysis (PCA), different arithmetic combination(e.g.Brovey transform), multi-resolution analysis-based methods (e.g.

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pyramid algorithm, wavelet transform), and Artificial Neural Networks (ANNs),etc. Decreasing the size of the data, while keeping the content of important information, thereby reducing storage costs.[4]

In medicine, image fusion and other technological advances are increasingly being relied upon for diagnostics and treatment of patients. An overview of medical image fusion was given by Pattichis. Fusion aids medical imaging by providing a complementary composite of various image formats stemming from multiple modalities, such as ultrasound, magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET), and single photon emission computed tomography (SPECT) which in turn helps to identify differences and target areas of interest such as tumors and blood vessels. In radiation oncology, a treatment plan for radiotherapy involves CT data primarily for patients' dose calculation, while the outlines of tumour are better represented in MRI. For medical diagnosis, CT best illustrates denser tissues with low distortion, while MRI offers more comprehensive information on soft tissues with higher distortion and PET provides better information on blood flow with a generally low spatial resolution. Using an image synthesis helps to divide the main anatomical sites of interest from both sources.[5]

Image fusion has been used in many application areas. In remote sensing and in astronomy, multisensor fusion is used to achieve high spatial and spectral resolutions by combining images from two sensors, one of which has high spatial resolution and the other one high spectral resolution. Numerous fusion applications have appeared in medical imaging like simultaneous evaluation of CT, MRI, and/or PET images. Plenty of applications which use multisensor fusion of visible and infrared images have appeared in military, security, and surveillance areas.

This paper introduces a new approach to computed tomography (CT) images and magnetic resonance images (MRI) fusion based on the decomposition of Gaussian and Laplacian pyramid. Then, different rules are made for the synthesis of the decomposed factors derived from the decomposition of Gaussian and Laplacian pyramids. Computer tomography (CT) and magnetic resonance imaging (MRI) images of the same people and same spatial parts have been used for the analysis.

II. IMAGE FUSION BASED ON PYRAMID

The advent of multisensory applications in the 1980's particularly in the field of remote sensing, coinciding with extensive research discoveries in pyramid-based transform methods, introduced image fusion as a research area for the acquisition of higher quality images for human visualization. A more tangible approach to image fusion is by pyramid decomposition. An image pyramid, an early form of multiresolution analysis (MRA), comprises a set of filtered and scaled representations of the image. Fusion is performed through selection of coefficients at every scale from the source image pyramids, followed by the inverse transform of the resulting pyramid. The pyramid method was first proposed by Burt (1984) , who introduced the low-pass Laplacian pyramid for binocular fusion. A Laplacian pyramid is the bandpass equivalent of the Gaussian pyramid, and is obtained by the subtraction between two successive lowpass Gaussian pyramid levels. In ratio of low-pass (RoLP) pyramid the level is scaled to a ratio of two from its preceding level, whilst contrast pyramids are similar to RoLP but measure the ratio of luminence of a certain region within an image to the local background luminence. Eventually a host of improved pyramid-based schemes, including filter-subtract-decimate (FSD), morphological and gradient pyramids have been proposed and used in fusion literature. 1988 saw the first application of fusion on visible, thermal and infrared images through works by Lillquist, Nandhakumar and Aggarwal and Rogers, whilst Ajjimarangsee and Huntsberger have suggested utilising neural networks for fusion of these modalities. A weakness of the neural network method is the large overhead entailed from processing whole images. MRA techniques overcome this by decomposing images into details and average channels, where fusion can be performed in the wavelet coefficient space.[5,6,7]

A. Gaussian pyramid decomposition

The Gaussian pyramid is a sequence of low-pass, down sampled images. Gaussian pyramids are efficient to compute coarse-scale images. Gaussian pyramid construction is equivalent to convolving the original image with a set of gaussian- like weighting functions. The generation of n-level gaussian pyramid is illustrated in figure 1.

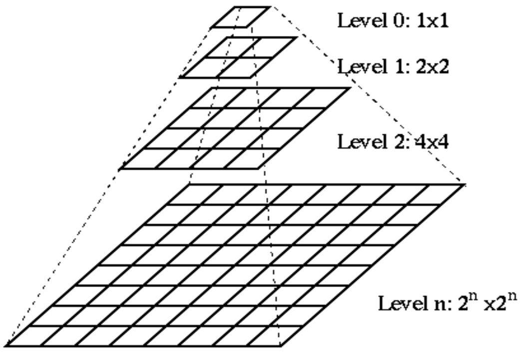

Fig. 1. Gaussian pyramid

In Gaussian pyramid decomposition the original image is repeatedly filtered and sub-sampled to generate the sequence of reduced resolution images. These consist of a set of low-pass filtered copies of the original image in which the bandwidth decreases in one octave steps. In Laplacian pyramid decomposition is computed as the difference between the original image and the low pass filtered image. This process is continued to obtain a set of band-pass filtered images (since each is the difference between two levels of the Gaussian pyramid). Thus the Laplacian pyramid is a set of band pass filters.

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Gaussian Pyramid is said to be a cross-section of the pyramid, because each level has all the frequencies of the image below some values. Gaussian pyramid is a hierarchy of the lower filtered version of the original image, so each subsequent level corresponds to the low frequency. Low pass filtering is done by unifying using the Gaussian filter kernel. Where the filter overhangs the image edges we reflect the image about its edge. Since the lowest frequencies have been removed, the full-size image contains redundant pixels. [8,9]

Properties of Gaussian pyramid:-

- used for multi-scale edge estimation,
- efficient to compute coarse scale images. Only5-tap 1D filter kernels are used.
- highly redundant, coarse scales provide much of the information in the finer scales.

B. Laplacian pyramid decomposition

The Laplacian pyramid is a decomposition of the original image into a hierarchy of images such that each level corresponds to a different band of image frequencies. A Laplacian pyramid can be described as a data structure composed of band-pass copies of an image. As a band-pass filter, pyramid construction tends to enhance image features such as edges, which are vital for image interpretation. Each band of the Laplacian pyramid is the difference between two adjacent low-pass images of the Gaussian pyramid. Figure 2 shows construction of Laplacian pyramid.[9,10]

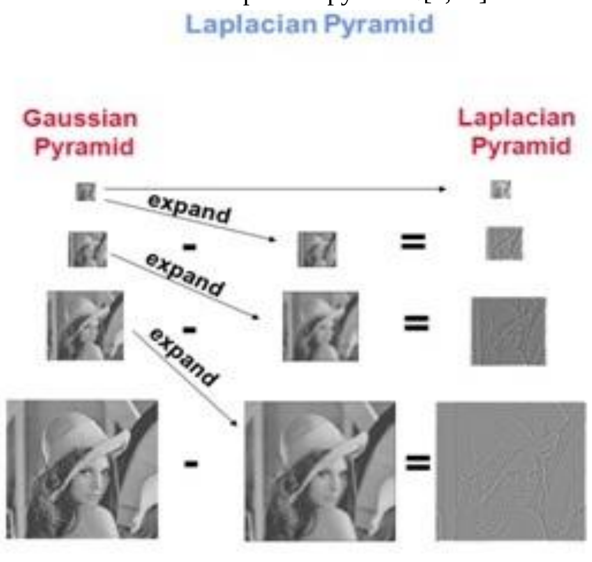

Fig. 2. Laplacian pyramid

Advantages of Laplacian pyramid:-

- Eliminates blocking artifacts of JPEG at low frequencies because of the overlapping basis functions.
- coding and image reconstruction are simple.
- allows for progressive transmission,since low-pass representations are reasonable approximations to the image.

Fig. 3. Gaussian and Laplacian images

C. Proposed Algorithm

The implementation of the fusion process of any image is done by first decomposing it using a Gaussian pyramid decomposition of the original image into a hierarchy of images such that each level corresponds to a different band of image frequencies. The next step is to compute the Laplacian pyramid of the same image by calculating difference between two adjacent low-pass images of the Gaussian pyramid. The decomposed Gaussian and Laplacian images are then Fused together to obtain an enhanced image. Therefore, the steps carried out in fusion process with respect to wavelet transform are stated below:-

Step 1: The multi-modality images which are undergo fusion process must be registered for the respective pixels alignment.

Step 2: The CT image is decomposed into Gaussian pyramid(G_{11}, G_{12} ,G_{13}, G_{14})and Laplacian pyramid(L_{11}, L_{12}, L_{13}).

Step 3: The decomposed images G_{11} and L_{11} are fused together to obtain an image $CT_{1.}$

Step 4: Again the same CT Image undergoes the same process as shown is step 2 and 3 to obtain an image $CT_{2.}$

Step 5: The image obtain from step 3 and 4 are fused to obtain an enhanced image(CT_E).

$$CT_E = CT_1 + CT_2;$$

Step 6: The MRI image then undergoes the same steps 3, 4 and 5, which produces an image $MRI_{E.}$

$$MRI_E = MRI_1 + MRI_2;$$

Step 7: At last the enhanced CT and MRI images are fused to get an improved image.

$$\text{Resultant Fused image} = CT_E + MRI_E;$$

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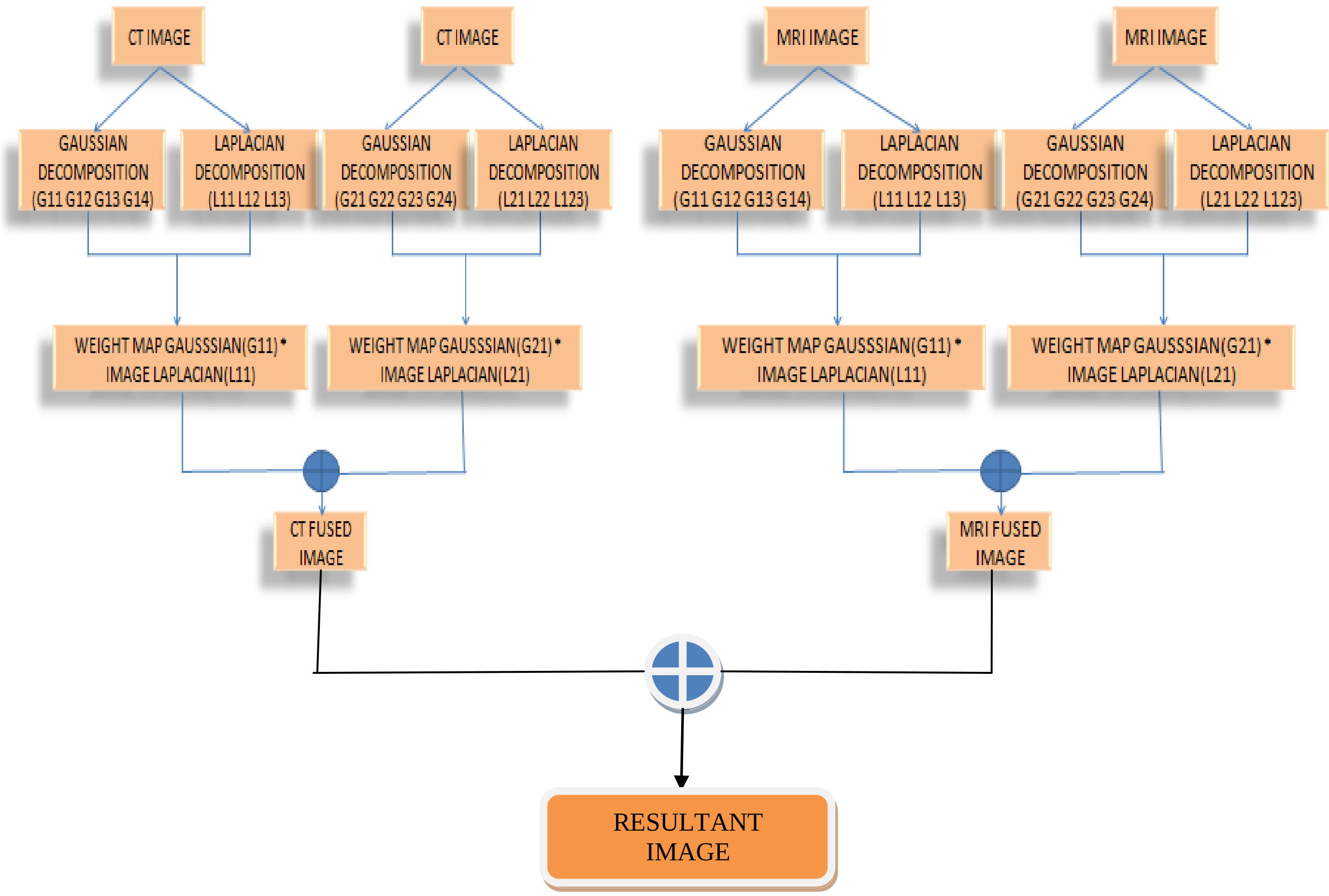
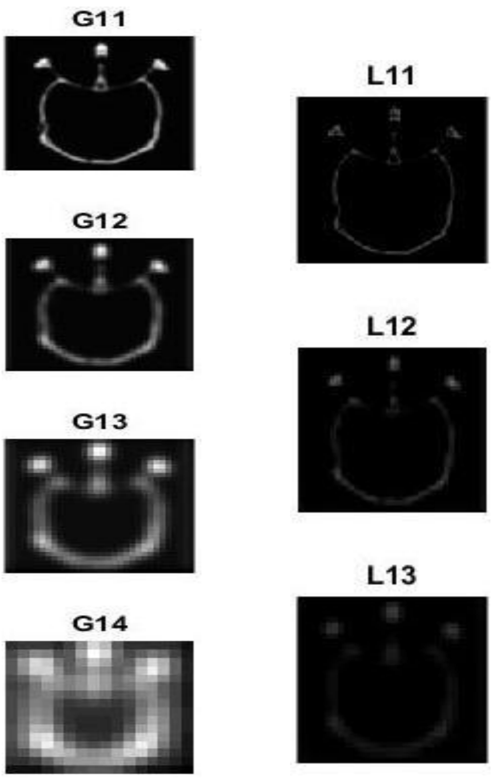


Fig. 4. Proposed Algorithm flowchart



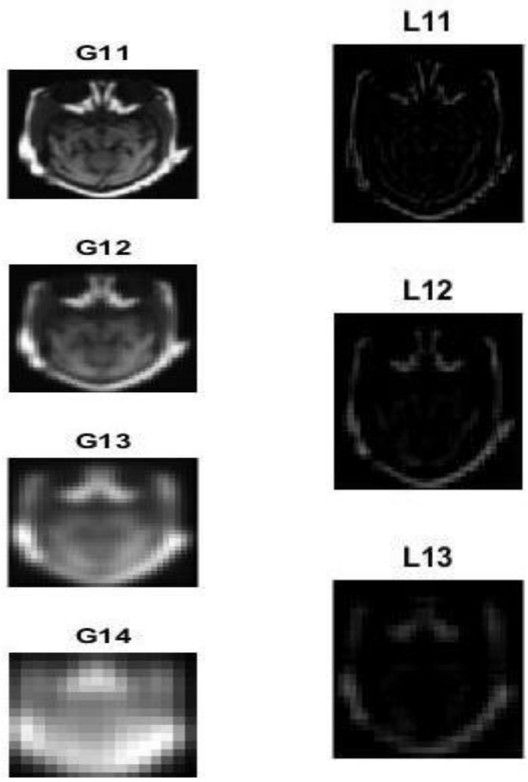


Fig. 5. a. Gaussian and Laplacian decomposition of CT image b. Gaussian and Laplacian decomposition of MRI image

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D. Quality Assessment Parameters

Parameters such as mean squarer error, peak signal to noise ratio, structural content, standard deviation and entropy are useful in increasing the classification and improving diagnostic procedures for doctors.

1. *Mean Square Error*

The MSE is the cumulative squared error between the reconstructed and the original image.

$$\frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2$$

where I(x,y) is the original image, I'(x,y) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error.

2. *Peak Signal to Noise Ratio*

Peak Signal to Noise Ratio is a measure of the peak error between the reconstructed and the original image.

PSNR = 20* log10 (256*256 / sqrt(MSE))

3. *Structural Content*

The difference between image information and image quality needs to be emphasized. Measures of quality compare images with identical contents for their appearance. Structural content evaluates the different amount of structural details present (edges, textures, shading) as well as their degradation due to any noise that may be present.

4. *Standard Deviation*

The standard deviation is similar to the average deviation, except for the average that is applied by the energy to the size. This is achieved by calculating each of the pre-median deviations. To finish, the square root is taken to compensate for the initial squaring. In equation form, the standard deviation is calculated:

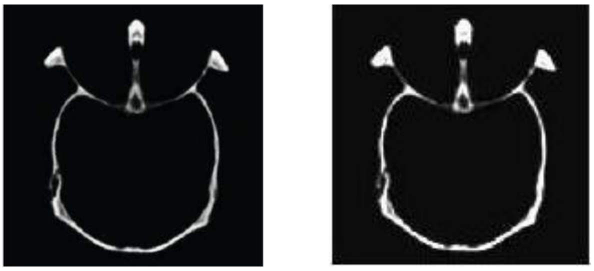
$$\sigma^2 = \frac{1}{N-1}\sum_{i=0}^{N-1}(x_i - \mu)^2$$

5. *Entropy*

Image entropy is a quantity which is used to describe the `business' of an image, i.e. the amount of information which must be coded for by a compression algorithm. Low entropy images, such as those containing a lot of black sky, have very little contrast and large runs of pixels. The flat image will have zero entropy. On the other hand, high-moving images, such as the image of the heavily-criticized zone of the moon, differ significantly from one pixel to another are low entropy images.[1]

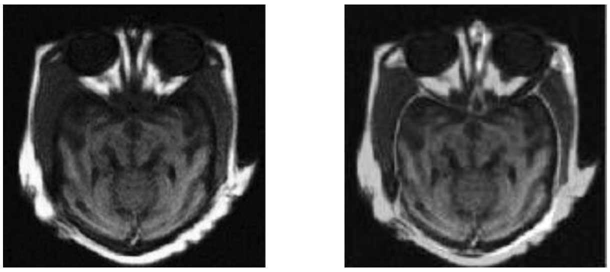
III. RESULTS AND DISCUSSION

In this example, we have taken a set of brain image where a data set contains one CT scanned image and one MR image. These two images are the separately decomposed using Gaussian and laplacian pyramids. Fig.5(a),shows the gaussian and laplacian decomposition of CT image. Fig.5(b),shows the gaussian the laplacian decomposition of MRI image. After decomposition the set of CT image and MR image are fused together. Fig.6(a) shows the original CT image and Fig.6(b) shows the Resultant CT image. Fig.7(a) shows the original MRI image and Fig.7(b) shows the Resultant MRI image. Finally the resultant CT image and the resultant MRI image are fused are fused together to produce the resultant fused image which is shown in Fig.8(b). The set of brain images used for fusion process is shown below,



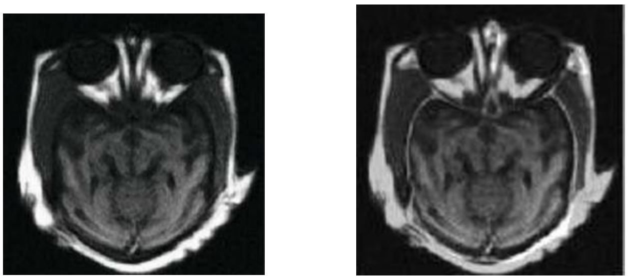
(a) (b)

Fig. 6.(a)Original CT image (b)Resultant CT image



(a) (b)

Fig. 7.(a) Original MRI image (b)Resultant MRI image



(a) (b)

Fig. 8.(a) Original Image to which results are compared (b) Resultant fused CT and MRI image

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PARAMETERS	CT IMAGE		MR IMAGE		FUSED IMAGE	
	DWT	PROPOSED METHOD	DWT	PROPOSED METHOD	DWT	PROPOSED METHOD
MSE	602.3	303.4575	845.38	600.0652	797.83	667.8350
PSNR	24.89	30.3027	24.77	26.4535	25.21	25.8493
STRUCTRAL CONTENT	0.96	0.5805	1.05	0.9067	1.15	0.9158
STANDARD DEVIATION	63.94	53.2769	61.72	55.1038	64.4	55.1038
ENTROPY	1.11	2.0255	1.11	6.7933	1.83	6.7933

Table 1. Shows the comparative performance of the proposed method in terms of MSE, PSNR, Structural content, Standard deviation and Entropy.[1]

In this paper we have five parameters to diagnose the disease. These parameters are shown below in table 1.

It has been observed that proposed method shows better results compared to DWT and significant improvement in MSE, PSNR, Structural content, Standard deviation and Entropy is achieved.

IV. CONCLUSION

In the proposed work we have fused CT and MRI images obtained from Gaussian and Laplacian decomposition. The results are compared with DWT by visual inspection and statistical analysis in terms of MSE, PSNR, Structural content, Standard deviation and Entropy. Compared with the DWT, the proposed method better fuse the detail information and decrease the distortion. The presented system may help to diagnose the brain cancer earlier and to provide appropriate treatments. It helps the radiologist and also the physician to identify the suspicious tumour of cancers, increasing the accuracy, sensitivity & efficiency of cancer diagnosis.

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