Texture analysis and Characterization of Fused Medical Images using NLAF-PCA and SVM

Suneetha Rikhari, Sandeep Jaiswal

Abstract*: Texture is one of the important characteristic of an image. Texture analysis provides the details about the arrangement of pixel intensity values in the spatial domain. The input image is a fused image obtained from Non-Linear Anisotropic filtering in PCA domain (NLAF-PCA) method. Fusion process gives highly informative image as it combines the information from two or more images into a single image. Effective fusion algorithms are required to obtain accuracy of successful diagnosis of diseases. Magnetic resonance (MR) and computed tomography (CT) images are most widely utilized images for analyzing the human body. Any fusion technique is said to be efficient if it is able transfer maximum information from the input image into the fused image without information loss. The features from the fused image are extracted using Discrete Wavelet Transform (DWT). The features Homogeneity, Correlation, Entropy, variance etc. are calculated which describe the texture analysis. The extracted features are segmented using Support Vector Machine (SVM) classifier. The combination of NLAF-PCA and SVM produces robust results compared to traditional SVM classifier.

***Index Terms*: MR and CT images, image fusion, non-linear anisotropic filtering, principal component analysis and SVM.**

I. INTRODUCTION

Texture is a visual pattern of repeated elements that have some amount of variability in element appearance and relative positions. Different methods are available for performing the textural analysis. These are classified as structural, statistical, model based and transform based. In structural approach the texture is represented by primitives who are well defined and depends upon the hierarchy of the defined primitives. The advantage of this method is it gives a good symbolic representation of an image. Statistical approaches depend directly upon the relationship between the pixels, rather than depending upon the hierarchical arrangement of the texture. In statistical method the second order statistical characteristics of the image are considered. The mostly used technique is the feature extraction using co-occurrence matrix [10]. Model based method uses stochastic model to interpret the characteristics of the image texture. Transform based methods uses Fourier transform [15], Gabor [11] and wavelet transforms [12][13][14]. Fourier based methods are not accurate because of poor spatial localization. Gabor filter method eliminates the localization problem but fails to produce efficient results. Wavelet methods are efficient compared to Fourier based and Gabor filter methods.

In this work we have proposed a texture analysis method for the input image obtained from the output of a Fusion algorithm. The Nonlinear Anisotropic Filtering in PCA domain [16] (NLAF-PCA) fusion algorithm is discussed briefly. Image fusion treats the diverse mixes of images detected from various sensors which incorporate multi-angle viewing and multi-spectrum, high-spectrum and multi-resolutions. This upgrades the extension for achieving the quality of images. Multi-sensor images are utilized in a few fields, for example, machine vision, remote sensing and medical imaging.

Medical image fusion methods give better biomedical data to clinical assessment. In medical diagnosis multimodal intertwined images has more critical job than individual images. The multi model medicinal image combination is the way toward consolidating compliment fusion techniques for clinical investigation.

To help more precise clinical data for doctors to manage medical diagnosis and evaluation, multimodality medicinal images are required, for example, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), or Positron Emission Tomography (PET) etc. For instance, the CT picture can give thick structures like bones and embeds with less distortion yet can't recognize physiological changes. In any case, the MRI can give data of normal and pathological soft tissues and it can't support the bone data. In this situation, a single image can't be suitable to convey ideal clinical prerequisites for the doctors. Henceforth the fusion of the multimodal medical images is fundamental, and it has turned into a promising and exceptionally difficult research territory as of late [3].

A Novel utilization of non-linear anisotropic filtering in PCA domain is used for extracting the features from the input MR and CT images for fusion. According to the literature survey, stationary wavelet transform (SWT) [9], discrete wavelet transform (DWT) [5], principal component analysis (PCA) [6], DWT+PCA, SWT+PCA and fast discrete curvelet transform (FDCT) aimed at enhancement in the performance of fusion process only. These methodologies haven't concentrated on the visual texture of fused medical images.

Rest of the paper structure is as follows: Section II describes the NLAF briefly. Section III presents the DWT and SVM. Section IV presents the results and discussion. Section V includes the conclusions and future enhancements.

Revised Manuscript Received on December 22, 2018.

Suneetha rikhari, ECE Deptt., SET, MUST, Lakshmangarh, Sikar India.

Sandeep Jaiswal, BME Deptt., SET, MUST, Lakshmangarh, Sikar India.

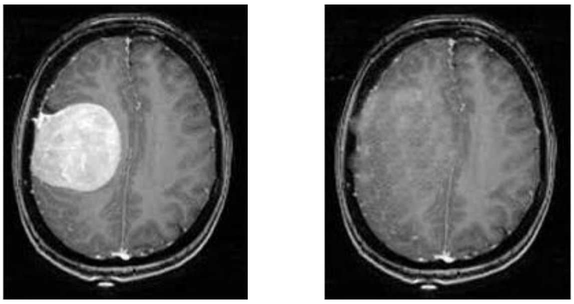


Figure 1.1 MR images input dataset 1 (a) Tumour Image (b) Non Tumour Image

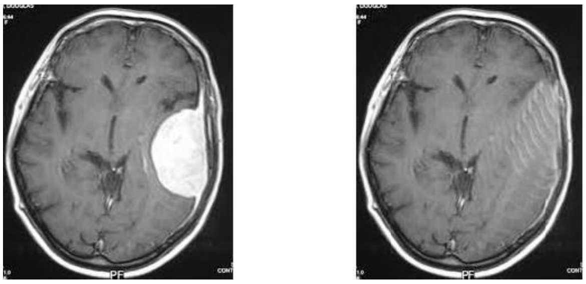


Figure 1.2 MR images input dataset 2 (a) Tumour Image (b) Non Tumour Image

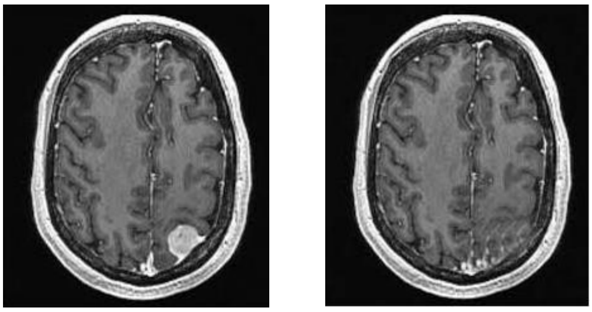


Figure 1.3 MR images input dataset 3 (a) Tumour Image (b) Non Tumor Image

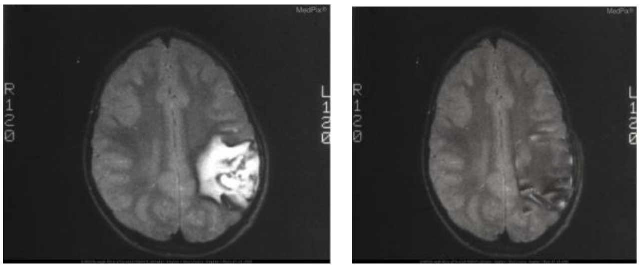


Figure 1.4 MR images input dataset 4 (a) Tumor Image (b) Non Tumor Image

II. NON-LINEAR ANISOTROPIC FILTERING

The NLAF process uses partial differential equations (PDE) to smooth the given input image by. The smoothing is done while preserving the nonhomogeneous regions i.e. edges. Non-linear isotropic filtering uses inter-region smoothing and hence edge information is lost, whereas NLAF uses intraregional smoothing to generate coarser resolution images. Hence, NLAF eliminates the drawbacks of non-linear isotropic filtering. At each coarser resolution edges are sharp and meaningful.

The NLAF equation uses flux function to control the diffusion of an image I as,

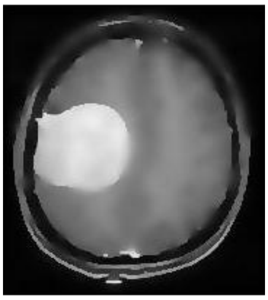
$$I_t = \mathbb{F}(x, y, t)\Delta I + \nabla\mathbb{F} \cdot \nabla I \qquad (1)$$

Where $\mathbb{F}(x, y, t)$is flux function, Δ is a Laplacian operator, $\nabla$is a gradient operator and $t$is time or scaling constant.

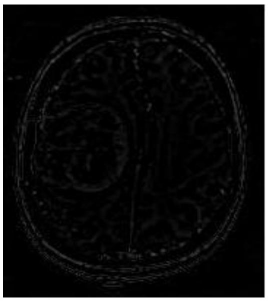
We can also term (1) as heat equation. Forward-time-central space (FTCS) scheme is used to solve this equation. The solution for this PDE is

$$I_{i,j}^{t+1} = I_{i,j}^{t} + \beta\left[\mathbb{F}_N \cdot \overline{\nabla}_N I_{i,j}^{t} + \mathbb{F}_S \cdot \overline{\nabla}_S I_{i,j}^{t} + \mathbb{F}_E \cdot \overline{\nabla}_E I_{i,j}^{t} + \mathbb{F}_W \cdot \overline{\nabla}_W I_{i,j}^{t}\right] \qquad (2)$$

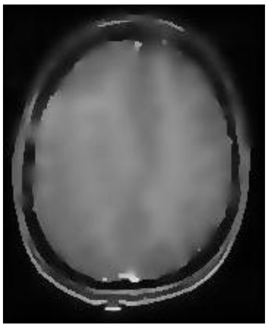
In above eq., $I_{i,j}^{t+1}$is the coarser resolution image at $t+1$ scale which depends on the previous coarser scale image $I_{i,j}^{t}$. β is a stability constant satisfying $0 \le \beta \le 1/4$.



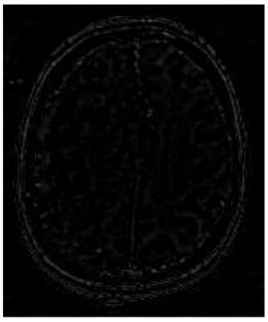
Approximate layer of Fig. 1.1(a)



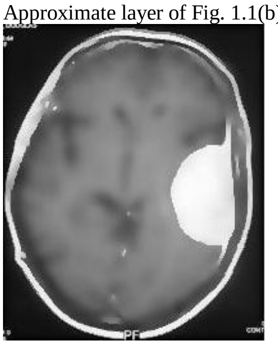
Detail layer of Fig. 1.1(a)



Approximate layer of Fig. 1.1(b)



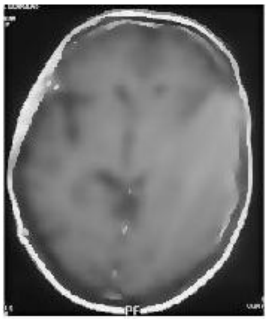
Detail layer of Fig. 1.1(b)



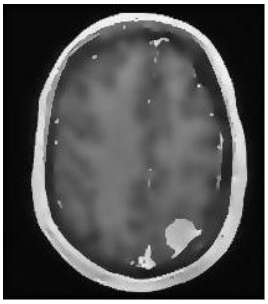
Approximate layer of Fig. 1.2(a)

Detail layer of Fig. 1.2(a)

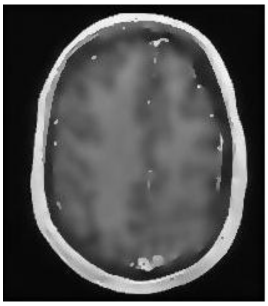
Published By:
Blue Eyes Intelligence Engineerin
& Sciences Publication


Approximate layer of Fig. 1.2(b)

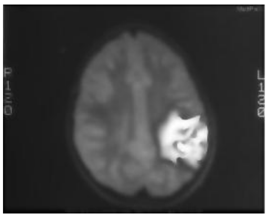

Detail layer of Fig. 1.2(a)


Approximate layer of Fig. 1.3(a)

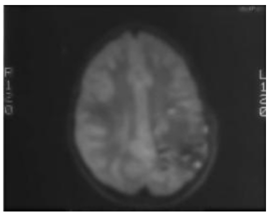

Detail layer of Fig. 1.3(a)


Approximate layer of Fig. 1.3(b)


Detail layer of Fig. 1.3(b)


Approximate layer of Fig. 1.4(a)


Detail layer of Fig. 1.4(a)


Approximate layer of Fig. 1.4(a)


Detail layer of Fig. 1.4(a)

III. PROPOSED FRAME WORK

This section explains the proposed method for the texture analysis and characterization of the medical image data sets considered. The process flow of the proposed technique is shown in fig.2

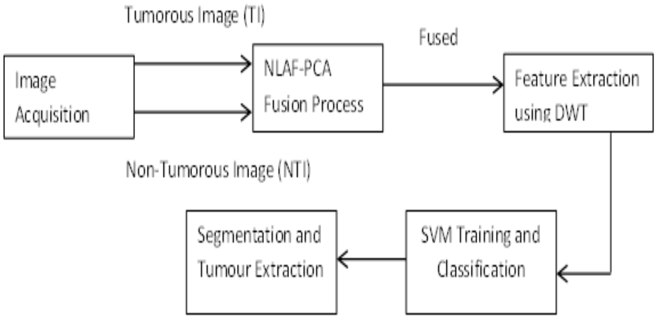


Figure 2. Process Flow of the proposed technique

A. NLAF-PCA Fusion

a. Extraction of approximate and detail layers

Let the source MR and CT images are denoted as $I_n(x,y)$, $J_n(x,y)$ respectively with a size of $p \times q$ and these two images are co-registered images. As shown in figure 2, these two source images are passed through the NLAF block to obtain the approximate layers.

$$A_{In}(x,y) = nlaf\left(I_n(x,y)\right) \tag{3}$$

$$A_{Jn}(x,y) = nlaf\left(J_n(x,y)\right) \tag{4}$$

Where $A_{In}(x,y)$ and $A_{Jn}(x,y)$ are n^{th} approximate layers and $nlaf$ is a sub function that process the source image (refer section II for more information). Now, the detail layers are obtained by subtracting the output of NLAF by utilizing eq. (3) and (4).

$$D_{In}(x,y) = I_n(x,y) - A_{In}(x,y) \tag{5}$$

$$D_{Jn}(x,y) = J_n(x,y) - A_{Jn}(x,y) \tag{6}$$

Fig 3 depicts the approximate and detail layers derived using NLAF procedure.

b. Principal Component Analysis

One of the troubles innate in multivariate insights is the issue of envisioning data sets with multiple variables. The data sets with multiple variables or group of variables often change together. This may be because the multiple variables govern the system behavior with the same driving principle. Considering the redundancy of system variables one can replace multiple variables with a new single variable. Principal component analysis is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. It is a powerful tool for analyzing the data.

The main advantage of PCA is that, once the patterns are found in the data, the data can be compressed by reducing the number of dimensions, without much loss of information.

c. Fusion Rule

After obtaining the approximate and detail layers from the source MR and CT images PCA is applied to find out principal components (as described in section b) for getting better analysis over conventional fusion algorithms presented in the literature. Now, to get a fused output image a rule must be utilized to obtain optimum output from the proposed NLAF-PCA fusion process. We first combine the approximate layers of MR and CT images using equations (3) and (4). Then sum the detail layers obtained from (5) and (6) by multiplying with the principal components denoted as p obtained by PCA algorithm. Finally, integrate these two process outputs to obtain fused image.

$$\mathcal{F}(x,y) = A(x,y) + D(x,y) \quad (7)$$

Where (8)

$$A(x,y) = A_{In}(x,y) + A_{Jn}(x,y)$$

$$D(x,y) = p(1) * D_{In}(x,y) + p(2) * D_{Jn}(x,y) \quad (9)$$

Algorithm: NLAF-PCA Algorithm

Step 1: *Select and read MR and CT source images from the MATLAB current directory*
(input dataset shown in figure 1).
Step 2: *in case of RGB images convert the source images into gray scale.*
Step 3: *Obtain approximate layers of MR and CT images by applying NLAF process as described in section II.*
Step 4: *Obtain the detailed layers by subtracting the source images from the approximate layers calculated in step 2.*
Step 5: *From the detailed layers obtained in step 4 , compute the covariance*
Step 6: *Calculate the Eigen vectors for step 5 output.*
Step 7: *Now, apply PCA fusion rule to obtain final fused output of MR and CT images.*

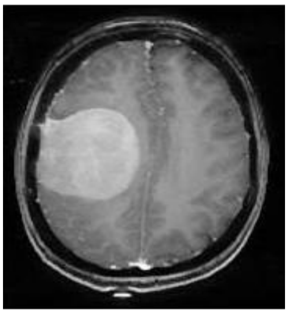


Fig 4 (a). Fused image of input data set in fig 1.1 (a) & (b)

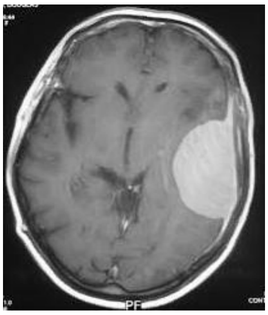


Fig 4 (b). Fused image of input data set in fig 1.2 (a) & (b)

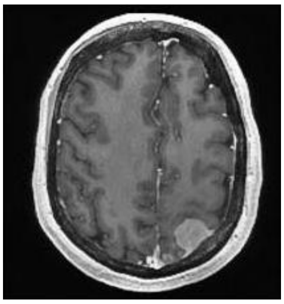


Fig 4 (c). Fused image of input data set in fig 1.3 (a) & (b)

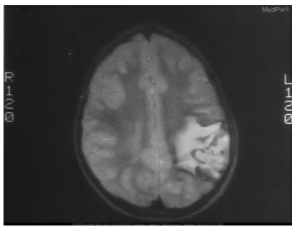


Fig 4 (c). Fused image of input data set in fig 1.4 (a) & (b)

A.DWT AND SVM

a. DWT

Discrete Wavelet Transform (DWT) is an efficient tool for extracting features from an image. The continuous wavelet transform of a square integrable function x(t)with respect to a given wavelet ψ(t) is

$$W_\psi(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \quad (10)$$

where,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right) \quad (11)$$

$\psi_{a,b}(t)$ is the translated and dilated version of the mother wavelet $\psi(t)$, a is the dilation parameter, b is the translation parameter. Equation (10) can be discretized to form DWT upon considering $a = 2^b \, and \; a > 0$ as in equation (12).

$$a_{j,k}[n] = \downarrow\left[\sum_n x[n] l_j^*[n-2^j k]\right]$$

$$d_{j,k}[n] = \downarrow\left[\sum_n x[n] h_j^*[n-2^j k]\right] \quad (12)$$

$a_{j,k}$ coefficient of approximate component of $x[n]$, $d_{j,k}$ the coefficients of detail component of $x[n]$, $l[n]$ and $h[n]$ are the low pass filter and high pass filter respectively.↓ is the down sampling operator.

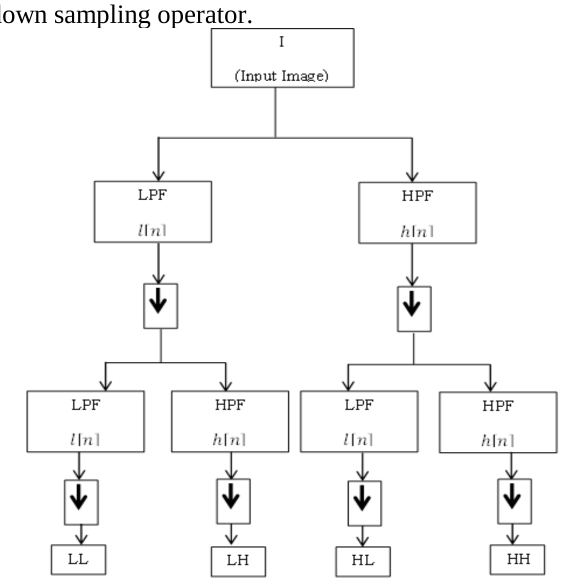


Fig 5. Sub bands of 2D DWT

Equation (12) explains the decomposition of $x[n]$ into approximation and detail components in the first level of decomposition. Similarly, any signal can be decomposed iteratively into $a_{j,k}$ and $d_{j,k}$ at each level of decomposition.

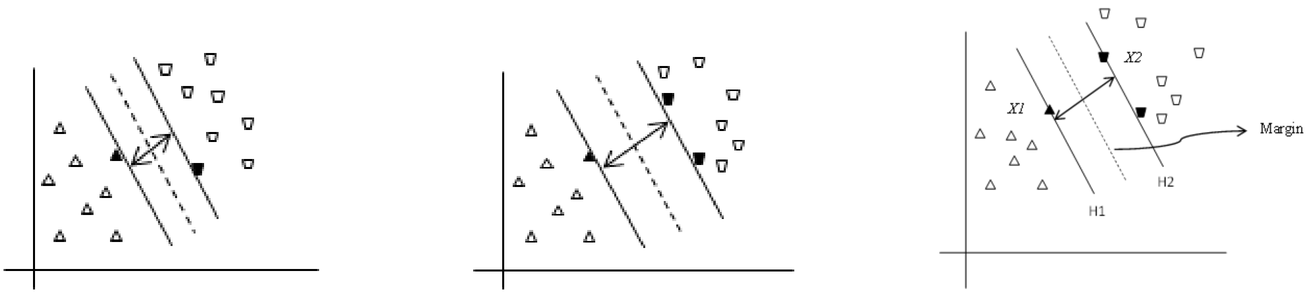


Fig.6.(a) Hyper plane with small margin Fig.6.(b) Hyper plane with larger margin Fig.6.(c) Optimal Hyper plane

Fig.6. Representation of different Hyper Planes

For two dimensional case (2D), the wavelet transform is applied separately for each dimension as shown in fig 5. At each scale there are 4 sub bands LL, LH, HL and HH respectively. LL sub band is the approximate component and the remaining three bands LH, HL and HH are the detailed components of the input image I. These decompositions provide a hierarchical way of image interpretation. The boundaries are taken care of by symmetric padding.

b. Support Vector Machine (SVM)

SVM classifier is based on the theory of statistical learning. It is a supervised learning algorithm. Considering a training data set, S={|p,q|} where p represents a data sample and q represents a class label.

The classifier generates a mapping such that f(p)=q upon considering all the samples of the input data set. In SVM the classification is done by feed forward network defined by

$$S(I) = sign\left(\sum_{n=1}^{N} \alpha_n q_n k(i, S_n) + b\right) \qquad (13)$$

where, α_n is the alpha coefficients, q_n are the class labels, S_n are the support vectors, I is the input vector, $k(i, S_n)$is the kernel function chosen, b is bias. The basic idea of SVM is to maximize the distances between the classes with a hyper plane.

The hyper plane can be obtained by estimating a function f using the training data. A trained data is usually a set of labeled classes. The nature of the training data decides the application of the SVM algorithm. In general, the data may be of two types: linearly separable and non- linearly separable.

In linearly separable data type, the similar class of information could be separated by a straight line, where as in non- linearly separable data type, the similar class of information cannot be separated by a straight line. For linearly separable case, the hyper plane equation is defined by

$$wx_i + b = 0 \qquad (14)$$

where, w is the weight vector normal to the hyper plane, b is the bias vector, x_i is the data point at i. The aim of the SVM is to find the optimal hyper plane that separates the classes and maximizes the margin. The margin is defined as the minimal distance of an object to the decision surface i.e. the hyper plane. In other words, the optimal separating hyper plane separates the classes and maximizes the distance between the closest points from each class.

The data points lying on these hyper planes are expressed as

$$wx_i + b = +1 \qquad (15)$$

$$\text{and} \quad wx_i + b = -1 \qquad (16)$$

$$\text{In general,} \quad wx_i + b = y_i \qquad (17)$$

y_i differs from one hyper plane to another hyper plane. The following two cases can be considered: Optimal hyper plane $\rightarrow y_i$ will be 0 and Boundary hyper plane $\rightarrow y_i$ will be +1 or -1. In other words,

$$wx_i + b \geq 1 \forall x_i \epsilon\, class + 1 \qquad (18)$$

$$wx_i + b \leq 1 \forall x_i \epsilon\, class - 1 \qquad (19)$$

Assume two points x_1 and x_2 from two different classes as shown in fig 6.1(c), so that $|wx_1 + b| = 1$ and $|wx_2 + b| = 1$. These two points are differed by a distance $\frac{2}{\|\vec{w}\|}$ [18] which is defined as the margin. The optimal margin can be obtained by solving the convex optimization problem

$$min\, \frac{2}{\|\vec{w}\|^2} \qquad (20)$$

Lagragian method can be employed to solve equation (20) by introducing Lagragian multiplier α_i. Hence, the optimization problem can be expressed as

$$L_s = \frac{2}{\|\vec{w}\|^2} - \sum_{i=1}^{n} \alpha_i [y_i (wx_i + b) - 1] \qquad (21)$$

L_s can be minimized w.r.t $'w'$ and $'b'$ by differentiating equation (21) w.r.t. $'w'$ and $'b'$ as given below:

$$\frac{\partial L_s}{\partial w} = 0\ i.e. \qquad (22)$$

$$\frac{\partial L_s}{\partial w} = w - \sum_{i=1}^{n} \alpha_i y_i x_i = 0$$

$$\Rightarrow w = \sum_{i=1}^{n} \alpha_i y_i x_i$$

Similarly, (23)

$$\frac{\partial L_s}{\partial b} = 0\ i.e.$$

$$\frac{\partial L_s}{\partial b} = -\sum_{i=1}^{n} \alpha_i y_i = 0 \Rightarrow \sum_{i=1}^{n} \alpha_i y_i = 0$$

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

If $\alpha_i > 0, x_i$ is said to be on the hyper plane. If $\alpha_i = 0, x_i$ is said to be on the boundary. By training a data set which consists of the support vectors, the optimal hyper plane can be obtained.

TABLE I. STATISTICAL PARAMETERS OF THE SEGMENTED TUMOUR USING TRADITIONAL SVM AND PROPOSED METHOD

Statistical Parameter	Input data set1		Input data set 2		Input data set 3		Input data set 4	
	SVM	Proposed	SVM	Proposed	SVM	Proposed	SVM	Proposed
Contrast	0.2088	0.3067	0.3459	0.3437	0.215	0.307	0.255	0.3151
Correlation	0.1990	0.1787	0.0994	0.0730	0.095	0.094	0.089	0.0709
Energy	0.7621	0.8180	0.8334	0.8037	0.737	0.775	0.755	0.7901
Homogeneity	0.9352	0.9468	0.9514	0.9422	0.927	0.936	0.931	0.9376
Mean	0.0031	0.0017	0.0030	0.0046	0.002	0.003	0.002	0.0023
Standard Deviation	0.0898	0.0898	0.0898	0.0897	0.089	0.089	0.089	0.0898
Entropy	3.1735	2.0736	2.8061	2.6582	3.628	2.349	3.075	2.2186
RMS	0.0898	0.0898	0.0898	0.0898	0.089	0.089	0.089	0.0898
Variance	0.0080	0.0080	0.0081	0.0080	0.008	0.008	0.008	0.008
Kurtosis	7.3282	19.4690	19.301	17.3878	5.323	16.059	7.797	16.611

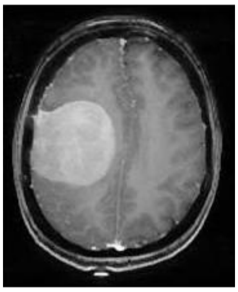


Fig 7 (a). Fused image obtained from input data set in fig 1.1 (a) & (b)

Fig 7 (b). Segmented Tumor from fig 7 (a)

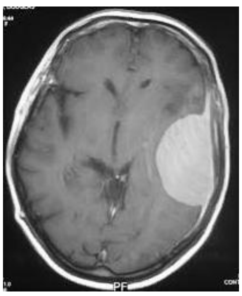


Fig 7 (c). Fused image obtained from input data set in fig 1.2 (a) & (b)

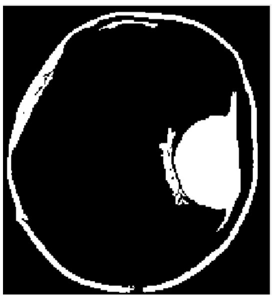


Fig 7 (d). Segmented Tumor from fig 7 (c)

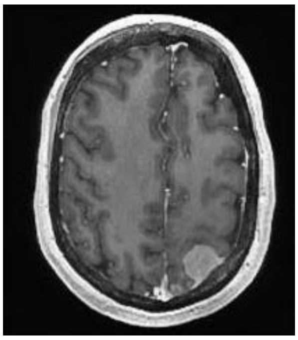


Fig 7 (e). Fused image obtained from input data set in fig 1.3 (a) & (b)

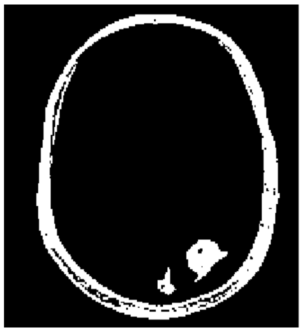


Fig 7 (f). Segmented Tumor from fig 7 (e)

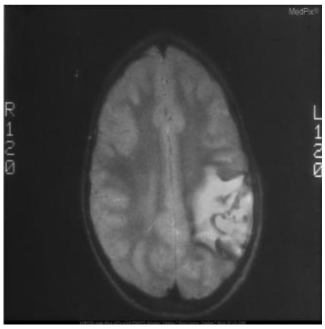


Fig 7 (g). Fused image obtained from input data set in fig 1.4 (a) & (b)

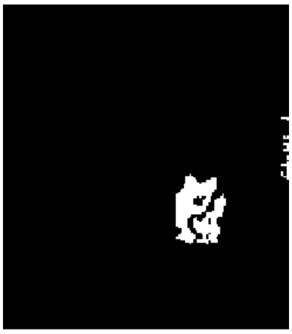


Fig 7(h). Segmented Tumor from fig 7 (g)

IV. RESULT AND DISCUSSION

All the images used in this work were obtained from publically available source . The experiments were performed at Biomedical Signal and Image Processing Lab, SET, Mody University of Science and Technology using MATLAB. Figure 1 represents the input data sets 1.1, 1.2, 1.3 and 1.4 respectively. These images were fused using our previously developed NLAF-PCA [16] algorithm. After fusion, the output images of the NLAF-PCA block are fed to feature extraction block and the features like contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, RMS, variance and kurtosis are calculated for SVM and proposed method. The 2D DWT decomposition is used to reduce the size of the extracted features to a great extent. The fused images obtained from NLAF-PCA algorithm is used for efficient characterization of the medical images instead of using the original images. The extracted statistical features presented in Table I were extracted for tumorous and fused tumorous images.

All these statistical parameters were compared using and analyzed for the Tumorous and Fused Tumorous images. Contrast is the element wise difference between the second order moments. When the higher values of the co-occurrence matrix are near the main diagonal, contrast will have a low value. After analysis, contrast was increased for data set 1.1, 1.3 and 1.4. Correlation checks the dissimilarity of the images. Lower the value of correlation, higher are the chances of dissimilarity. If the two images are entirely different, their correlation will be near to zero.

Analyzing the correlation values, the dissimilarity is increased for the proposed method for the data set 1.1, 1.2 and 1.4. Energy of an image will be high when the values of the Co-occurrence matrix are equal to 1. Homogeneity deals with the closeness of the distribution of elements in Co-occurrence Matrix (CM). Mean gives the average of all the gray level values in the CM. It explains the measure of dissimilarity. Kurtosis is a measure of the concentration of the gray level values around the mean.

No noticeable changes were found for RMS, Variance and Standard Deviation. Better results are obtained for contrast, correlation and kurtosis using the proposed method. The proposed algorithm shows improved results in comparison to SVM algorithm and the extracted tumour images are presented in fig.7.

V.CONCLUSIONS

The NLAF-PCA algorithm effectively fuses the MR images by utilizing the extracted approximate and detail layers. During fusion process it also preserves the texture of MR medical images. The tumor image obtained from this algorithm provides more detailed visual information for diagnosis of the disease and characterization of the tumor. The classification is done using SVM by training the medical image data set. The trained data set effectively does the classification and segments the tumor from the MR image. It helps the surgeon to estimate the nature and volume of the tumor for the surgery. Because the texture information is highly preserved by the NLAF-PCA algorithm the proposed NLAF-SVM method yields better results in terms of the visual assessment and similarity metrics calculated.

REFERENCES

1. Peter J. Burt, Edward H. Adelson, “The Laplacian Pyramid as a Compact Image Code”, IEEE Transactions on Signal Processing, vol. 31, no. 4, pp. 532-540, April 1983.
2. K Sharmila, S Rajkumar, V Vijayarajan, “Hybrid method for Multimodality Medical image fusion using Discrete Wavelet Transform and Entropy concepts with Quantitative Analysis”, Proceedings of IEEE International conference on Communication and Signal Processing, April 2013.
3. Jorge Nunez, Xavier Otazu, Octavi Fors et al., “Multiresolution Based Image Fusion with Additive Wavelet Decomposition”, IEEE Transactions on Geoscience and Remote Sensing, vol. 37, no. 3, pp.4-11, May 1999.
4. Prakash O., Khare A., “CT and MR Images Fusion Based on Stationary Wavelet Transform by Modulus Maxima”, Computational Vision and Robotics, Advances in Intelligent Systems and Computing, vol. 332, pp. 199-204, Springer, New Delhi, 2015.
5. Bhavana V and Krishnappa H K., “Multi-modality Medical Image Fusion Using Discrete Wavelet Transform”, 4th International Conference on Eco-friendly Computing and Communication Systems (ICECCS), vol. 70, pp. 625-631, 2015.
6. Meisen Pan, Jianjun Jiang, Fen Zhang and Qiusheng Rong, “Medical Image Registration and Fusion Using Principal Component Analysis”, The International Arab Journal of Information Technology, vol. 14, No. 4, pp. 512-520, 2017.
7. B Sudharani, A V Kiranmai and N Suguna, “Image Fusion Using Fast Discrete Curvelet Transform”, International Journal of Computer Science, Mathematics and Engineering, vol. 3, No. 12, pp. 7-9, 2016.
8. Guru Prasad S, M Z Kurian and H N Suma, “Fusion of CT and PET Medical Images using Hybrid Algorithm DWT-DCT-PCA”, 2nd International Conference on Information Science and Security, Seoul, South Korea, 2015.
9. Samet Aymaz and Cemal Kose, “Multi-Focus Image Fusion Using Stationary Wavelet Transform (SWT) and Principal Component Analysis (PCA)”, 10th International Conference on Electrical and Electronics Engineering, pp. 1176-1180, Bursa, Turkey, 2018.
10. Haralick, Robert & Shanmugam, K & Dinstein, Ih, “Textural Features for Image Classification”, IEEE Trans Syst Man Cybern. SMC-3. 610-621, 1973.
11. Daugman, John G, "Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters." JOSA A 2.7 1160-1169, 1985
12. Mallat SG, “A theory for multiresolution signal decomposition: the wavelet representation” IEEE transactions on pattern analysis and machine intelligence. vol.11 (7), pp. 674-93, Jul. 1989.
13. Laine A, Fan J, “Texture classification by wavelet packet signatures” IEEE Transactions on pattern analysis and machine intelligence, vol.15(11), pp.1186-91, Nov.1993.
14. Lu CS, Chung PC, Chen CF, “Unsupervised texture segmentation via wavelet transform” Pattern Recognition, vol.30(5), pp.729-42, May 1997.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

15. Rosenfeld A, Weszka JS, "Picture recognition. In Digital pattern recognition" Springer, Berlin, Heidelberg, pp. 135-166, 1980.
16. Suneetha Rikhari, Sandeep Jaiswal, "MR and CT Image Fusion using Nonlinear Anisotropic Filtering in PCA domain", Jour of Adv Research in Dynamical & Control Systems, vol. 10, 03-Special Issue, 2018.