International Journal of Engineering & Technology, 7 (3.34) (2018) 752-757

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Fusion and Segmentation of Abdominal Cancerous Images

Nischitha#, Padmavathi K*

#PG Scholar, NMAM Institute of Technology, Karkala, India
**Associate Professor, NMAM Institute of Technology, Karkala, India*
**Corresponding author Email: p.nischitha94@gmail,com . padmavathik@nitte.edu.in*

Abstract

In the field of medicine, multimodal image analysis is attaining importance due to the fact that large number of images with clinical data has to be examined to analyze different types of results. Fusion of multimodal images merges required details from a single or multiple images into a solitary image. Fusion provides increased clinical applicability of medical images which aids in the diagnosis of diseases. Segmentation of fused images will help in identifying meaningful objects in an image based on the problem being solved. Multimodal image fusion is carried using curvelet transform and MSVD (Multi-resolution Singular Decomposition) method. The fused images are segmented using various segmentation techniques such as K means clustering, Mean shift segmentation and Normalized cut segmentation. The performance of various segmentation methods are analyzed using different metrics such as entropy, PSNR (Peak Signal to Noise Ratio) and RMSE (Root Mean Square Error).

Keywords: *Fusion, Curvelet transform, MSVD, Multimodal images, K means clustering, Mean shift segmentation, Normalized cut segmentation.*

1. Introduction

Image fusion has found its implementation in diverse image processing areas such as remote sensing, satellite imaging and medical imaging. The aim of medical imaging is to acquire a high resolution image for the purpose of diagnosis. Multimodal medical images such as CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography), SPECT (Single Positron Emission Computed Tomography) [7] etc. are fused which replicates different information of human organs and tissues. Image segmentation partitions the medical image into various no –overlapping regions which simplifies the representation of an image into segments which are meaningful and easier to analyse [1].
Gastric Adenocarcinoma is a type of abdomen cancer that develops from the lining of stomach. It can be benign or malignant. The symptoms of the disease are related to the organs affected and it includes abnormal bleeding and defecating. The treatment of the disease depends on the location of the tumor as well as the cancer type. The diagnosis requires endoscopy and biopsy of the affected tissue.
James et al. [1] has presented a review article that summarizes the broad scientific challenges faced in the field of image fusion. Various fusion methods are explained in detail along with its applications. Mehta et al. [4] introduced Curvelet Transform for image fusion. Bahri et al. [8] proposed the MSVD (Multi-resolution Singular Value Decomposition) methodology to improve the performance of the image fusion. Vij et al. [5] presented a quantitative evaluation measures for color image segmentation based on K means and watershed segmentation techniques.

2. Proposed Methodology

Fusion and segmentation methods play an important part in the context of medical image study. Hence, it is necessary to consider the techniques which are best suitable for the diagnosis purpose. The outline of the system is shown in Fig.1. It involves four steps namely, considering multimodal images, fusing the input descriptions using curvelet and MSVD fusion transforms to acquire fused image. After the finalization of the fused coefficients, inverse fusion transform is applied to obtain the image into spatial domain. Fused images are segmented using various segmentation techniques such as K means clustering, Mean shift segmentation and Normalized cut segmentation methods to obtain segmented image.

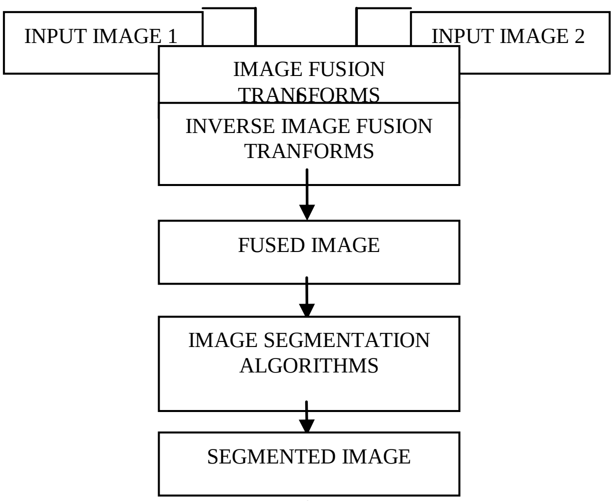


Fig1: Overview of the system

2.1 Curvelet Image Fusion Transform

Curvelet transform is employed to overcome the limitation of wavelet transform in fusing curved shapes with higher fusion efficiency. The higher directionality of the transform makes it possible to represent the edges of an image. In curvelet image fusion algorithm two input images are registered initially. Individual images are then analyzed to obtain the curvelet coefficients which generate the fused image. These coefficients are put through inverse curvelet transform to acquire the fused image in the spatial domain. Curvelet transform based image fusion is exposed in Fig. 2. Curvelet coefficients are obtained by decomposing the image into wavelet sub-bands and these wavelet sub-bands are converted into curvelet sub-bands by performing partial reconstruction [4].

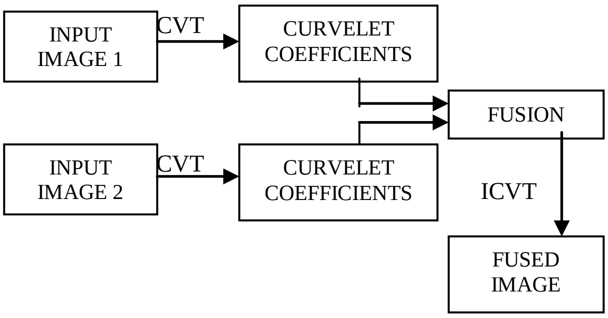


Fig. 2: Curvelet transform based Image Fusion

2.1.1. Multi-Resolution Singular Value Decomposition (MSVD)

In MSVD method, source image is filtered independently using low pass and high pass finite impulse response filters and the output obtained is downsampled by the factor of two to get the initial level of decomposed coefficients. The output obtained is further decomposed and decimated to obtain second level of decomposition. The above procedure is repeated till the desired number of decomposition levels is reached. The decomposed image consists of low-low, low-high, high-low and high-high regions. Low-low region represents down sampled image, low-high region depicts the horizontal characteristic of an image, high-low region represents the vertical characteristic of an image and high-high region represents the high frequency characteristic of an image [8].

2.2 Segmentation Using Mean Shift Method

It is an unsupervised algorithm which is usually used in segmentation, tracking and filtering problems. In Mean shift algorithm the feature points move towards significant modes and they cluster themselves automatically. This property makes it an ideal method for medical image segmentation [3].

For n data points x_i, $i = 1, \dots .n$ in the d-dimensional area R^d, feature points $\{x_i\}$ are clustered by placing a point y_o^i at each x_i ,

$$y_{j+1}^i = \frac{\sum_{K=1}^{M} x_k g \left\| \frac{x_i - x_k}{h} \right\|}{\sum_{K=1}^{M} g \left\| \frac{x_i - x_k}{h} \right\|} \quad j=1,2.... \tag{1}$$

where y_{j+1}^i represents the weighted mean at y_j^i and y_0^i represents the centre of the kernel *G* which has the profile g: $[0, \infty)$ that tends to *R*. Feature points which correspond to the same mode are grouped automatically. Mean shift segmentation method suffers from over-segmentation which is overcome using K mean clustering approach.

2.3 Segmentation Using K Means Clustering

In image segmentation, clustering is used to update the centroid value according to the distance between the objects in an image. The most commonly used clustering algorithm is K means clustering. In K means clustering method objects are clustered as belonging to one of K groups. Centroid of each group is found and the objects in an image are allotted to the group with the nearest centroid value. The clustering process is as follows. Initially K centroids are considered, where K is user selected which represents the required number of clusters. Each point of an image is then allotted to the closest centroid to form a group. The centroid in every group is then updated. This process is continued until none of the pixel values changes the clusters [5].

2.4 Segmentation Using Normalized Cut Method

It is an unsupervised segmentation technique. It solves segmentation problem using graph partitioning method. It is based on the criterion which increases the overall difference between the unusual groups and the likeness inside the groups. In this method, each voxel is represented as a node. The measure of variation between the nodes is represented based on the distance, color and brightness etc. which creates an edge. The edges are weighted with an exponential factor which is given by,

$$w_{ij} = e^{-\frac{d(i,j)}{\sigma_d}} \tag{2}$$

where $d(i, j)$ represents the contrast linking the nodes *i* and *j*, and σ_d pedals the scaling quantity.

In graph partitioning method, the image is transformed into an undirected weighted graph. Weight on an edge is assigned relying on the similarity between the pixels. Similarity between the pixels is defined based on the gray level, textures, color and distance. Unlike other edge cut algorithms Normalized cut method measures both the total similarity within the clusters and the total dissimilarity between various clusters [6].

3. Performance Metrics for Fusion and Segmentation

Performance evaluation is an important step in the development of image fusion methods. For the performance evaluation no reference parameters like entropy, Standard Deviation (SD) and reference parameters like PSNR, RMSE, Fusion Factor (FF), SSIM (Structural Similarity Index Measure) and Correlation measure (CR) are considered.

3.1 Entropy

Entropy measures the information content of a combined picture. The fused image is said to have high quality if the entropy is high [7]. Entropy is represented as,

$$He = \sum_{i=0}^{L} h_{I_f}(i) \log_2 h_{I_f}(i) \tag{3}$$

where h_{I_f} gives the histogram count of a fused image.

3.2standard Deviation

Standard deviation represents the disparity in a fused image [7]. High discrepancy image will have higher standard deviation which is given by,

$$\sigma = \sqrt{\sum_{i=0}^{L} \left(i - \bar{i}\right)^2 h_{I_f}(i)} \tag{4}$$

Where h_{I_f} is the histogram count and 'i' represents the summation index and '$\bar{i}$' gives the mean of histogram count.

3.3 Fusion Factor

Fusion factor represents the degree of dependence between the images which is given by,

$$FMI = I_{AF} + I_{BF} \tag{5}$$

where I_{AF} represents the mutual information amid the input image A and fused image and I_{BF} represents the mutual information amid input image B and fused image [7].

3.4 Structural Similarity Index

SSIM ranges between -1 to +1. If SSIM is equal to 1then the fused and the reference images are similar. SSIM is expressed by,

$$SSIM = \frac{(2\mu_{I_r}\mu_{I_f} + C_1)(2\sigma_{I_rI_f} + C_2)}{({\mu^2}_{I_r} + {\mu^2}_{I_f} + C_1)({\sigma^2}_{I_r} + {\sigma^2}_{I_f} + C_2)} \tag{6}$$

where μ_{I_r}, μ_{I_f}, σ_{I_r},σ_{I_f}, and $\sigma_{I_rI_f}$, represents the local means, standard deviations, and cross-covariance of images I_r, I_f, $C_1 = (0.01 * L).\hat{}2$, $C_2 = (0.03 * L).\hat{}2$ where L indicates specified dynamic range value of a pixel [7].

3.5 Correlation Measure

Correlation measure represents the fusing ability of a fusion algorithm [7]. The correlation measure between the two images $f(x,y)$ and $g(x,y)$ is expressed as,

$$CR(f,g) = \frac{\sum_{x,y}(f(x,y) - \overline{f})\ (g(x,y) - \overline{g})}{\sqrt{\sum_{x,y}(f(x,y) - \bar{f}\,)^2}\ \sqrt{\sum_{x,y}(g(x,y) - \bar{g}\,)^2}} \tag{7}$$

3.6 Peak Signal To Noise Ratio(PSNR)

PSNR value could be computed as the proportion of the number from claiming gray levels in an image to the corresponding pixels in the segmented and the fused image [7]. Higher PSNR value indicates superior fusion [7]. PSNR is expressed by,

$$PSNR = 20log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_r(i,j) - I_f(i,j))^2}\right) \tag{8}$$

Where $I_r(i,j)$ is $M \times N$ segmented image and $I_f(i,j)$ is $M \times N$ fused image, $'L'$ is pixel dimension of fused image.

3.7 Root Mean Square Error (Rmse)

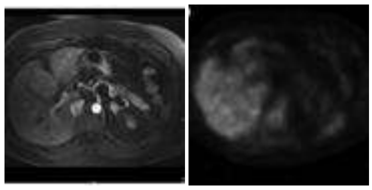
RMSE is ascertained as the root mean square error of the respective pixels in the fused and the segmented image. RMSE will be zero if the fused and the segmented images are similar. It is expressed as,

$$RMSE = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(I_r(x,y) - I_f(x,y))^2} \tag{9}$$

Where $I_r(x,y)$ is $M \times N$ reference image and $I_f(x,y)$ is $M \times N$ fused image.

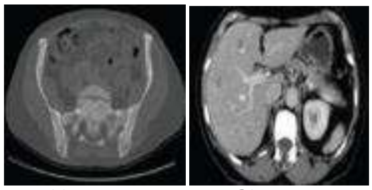
4. Results and Discussions

Experiments have been conducted for multimodal images of size 256x 256. The database of 25 images that represents Gastric Adenocarcinoma disease of persons belonging to the age group between 40 to 70 years are obtained from "The Cancer Imaging Archive" repository. Simulation is carried using MATLAB R2016a software.
The input image set 1 MRI and PET images of abdomen lesion are demonstrated in Fig.3(a) and 3(b). Another set of images used are CT and MRI of abdomen lesion shown in Fig.4(a) and 4(b).



(a) (b)

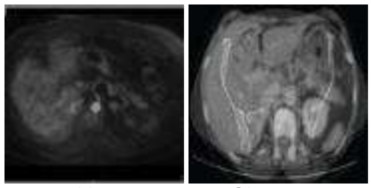
Fig.3: Input image set 1 (a) MRI of abdomen (b) PET of abdomen



(a) (b)

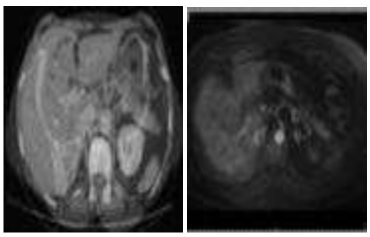
Fig. 4: Input image set 2 (a) CT of abdomen (b) MRI of abdomen

The Curvelet and MSVD fusion methods are applied to the input datasets and fused images are obtained as shown in Fig.5(a), 5(b), 6(a) and 6(b).



(a) (b)

Fig. 5: Output of Curvelet fusion method for (a) Image set1 (b) Image set 2



(a) (b)

Fig. 6: Output of MSVD fusion method for (a) Image set1 (b) Image set2

The performance of fusion is analysed using quality metrics like entropy, SD, fusion factor, SSIM and correlation measure. Table I demonstrates the feature values for the input images without fusion. Table II represents the feature values for the fused images.

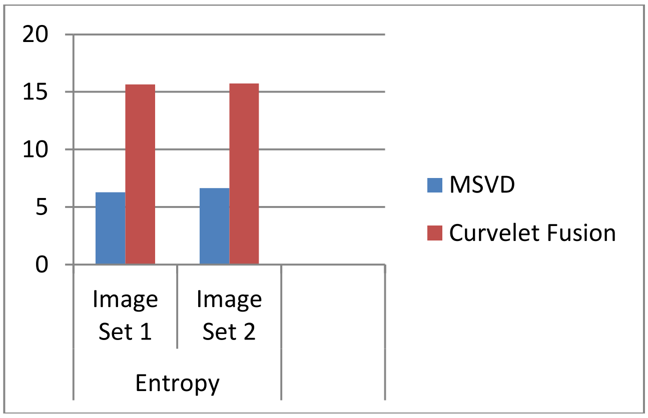
Table I: Statistical Analysis Of Features For Input Images Without Fusion

Metric	MRI Image (Image set 1)	PET Image (Image set 1)	CT Image (Image set 2)	MRI Image (Image set 2)
Entropy	5.5678	4.7367	5.450	4.2583
SD	0.1652	0.1015	0.1644	0.2627

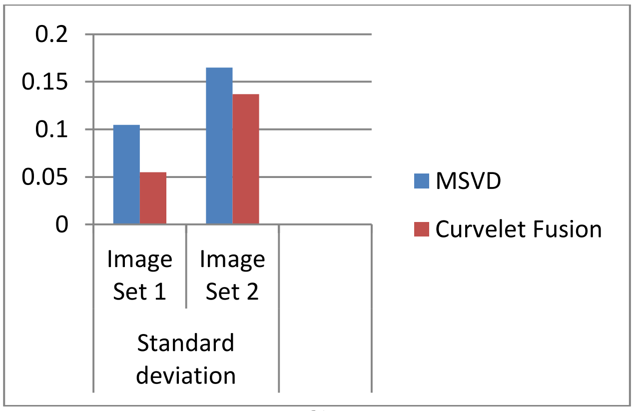
Table IIi: Statistical Analysis of Different Image Fusion Techniques for Input Images

Data Sets	Metric	MSVD	Curvelet fusion
Image set 1	Entropy	6.2884	15.6454
	SD	0.1047	0.0552
	FF	0.0742	0.2329
	CR	0.9910	0.9858
	SSIM	0.9999	0.9999
Image set 2	Entropy	6.6399	15.7360
	SD	0.1659	0.1372
	FF	0.2522	0.2810
	CR	0.9706	0.9895
	SSIM	0.9989	0.9995

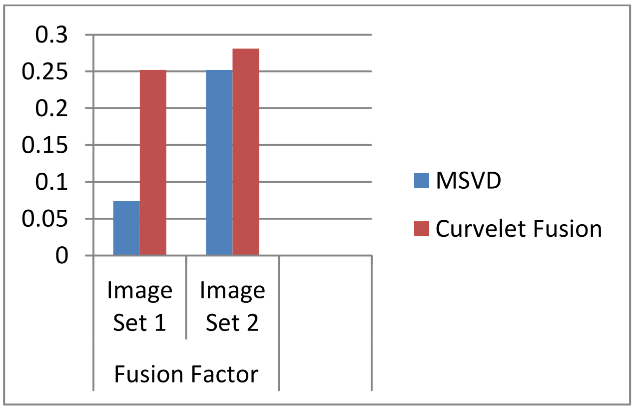
From the Table I and II it is observed that the entropy i.e. the information content is high and the disparity is less for the fused images than for the images without fusion. Thus fused images with high information quality when considered for further processing helps in the better diagnosis of the disease.



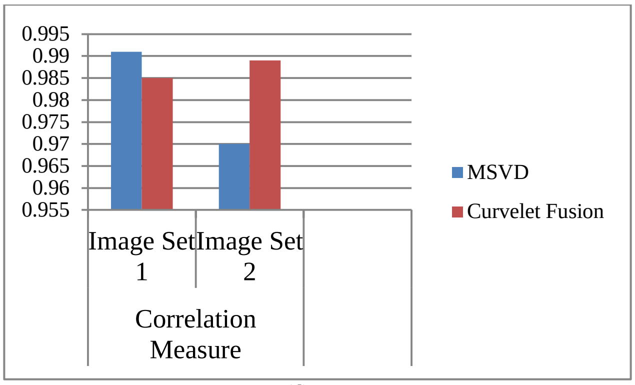
(a)



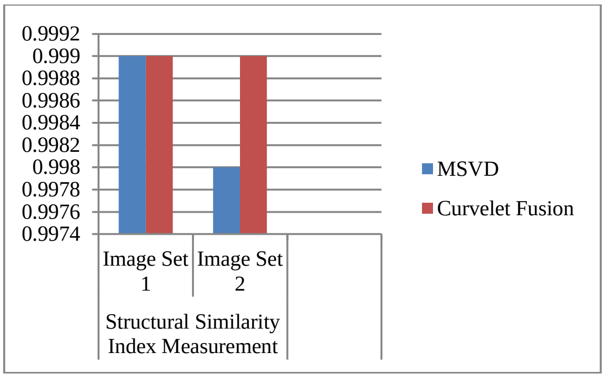
(b)



(c)



(d)

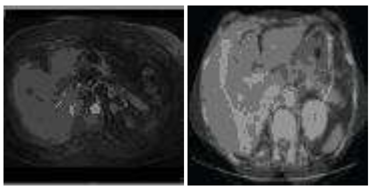


(e)

Fig. 7: Plot of feature values for fused images (a) Entropy (b) SD (c) FF (d) CR (e) SSIM

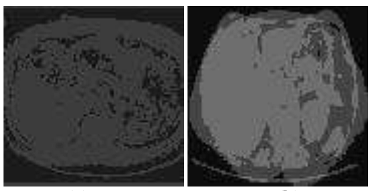
Plots of various feature values for the fused images are represented in Fig.7. From the Table II the value of entropy is high for curvelet fused images which indicates high information content in the fused image. The standard deviation indicates that the images obtained are of high contrast and it is high for MSVD fused images. The correlation measure indicates the feature mapping of both the input images onto the fused image. The SSIM value near to '1' indicates a high degree of similarity between the original image and fused image. Curvelet fused images are considered for further image processing due to its high information content and less disparity.

The fused images are segmented using different segmentation methods. Fig.8(a) and 8(b) represents the output images obtained using K means clustering method. Fig.9(a), 9(b) represents the output images obtained using mean shift segmentation method. Fig.10 (a) and 10(b) represents the output images obtained using normalized cut segmentation methods.



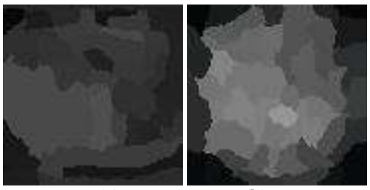
(a) (b)

Fig. 8: Output of K means segmentation method for (a) Image set 1 (b) Image set 2



(a) (b)

Fig. 9: Output of mean shift segmentation method for (a) Image set 1 (b) Image set 2



(a) (b)

Fig. 10: Output of normalized cut segmentation method for (a) Image set 1 (b) Image set 2

The output images show that the K means segmented image not only eliminates noise, which decreases the accuracy of mean shift segmentation and normalized cut segmentation methods, but also improves the performance of segmentation. Mean shift segmentation method produces the phenomenon of over-segmentation which is overcome using K means clustering method.

The performance of the segmented image is analysed using quality metrics like Entropy, PSNR and RMSE as shown in Table III.

Table IIIi: Statistical Analysis Of Different Segmentation Techniques For Input Images

Data Sets	Metric	K means segmentation	Mean shift segmentation	Normalized cut segmentation
Image set 1	Entropy	6.6608	4.8118	3.5903
	PSNR	83.3583	68.8147	67.4954
	RMSE	0.0100	0.0534	0.0621
Image set 2	Entropy	6.8302	5.3962	4.7275
	PSNR	78.9286	70.7858	67.2334
	RMSE	0.0166	0.0425	0.0639

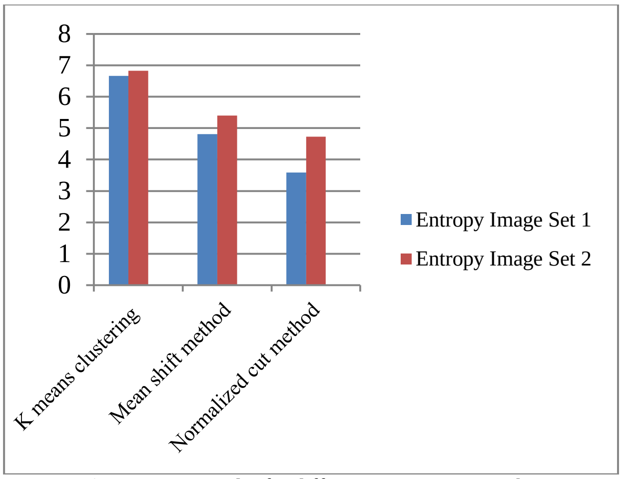


Fig. 11: Entropy plot for different segmentation techniques

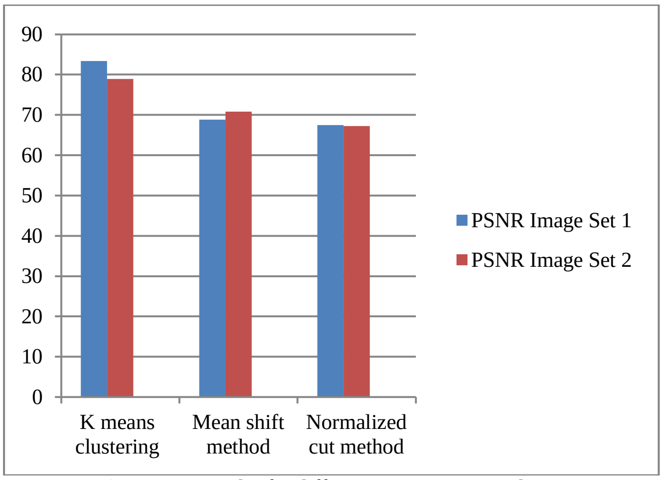


Fig. 12: PSNR plot for different segmentation techniques

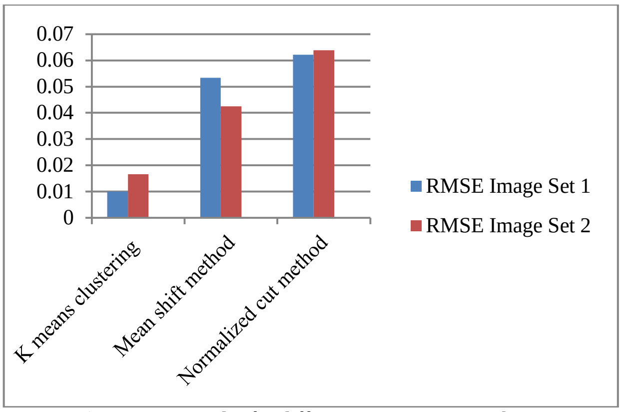


Fig. 13: RMSE plot for different segmentation techniques

Entropy, PSNR and RMSE plots are shown in Fig.11, 12 and 13. The value of entropy is high for K means segmentation method for all the three image datasets, which indicates high information content in the segmented image. The quality for PSNR is high and the value of RMSE is low for K means clustering approach, which indicates that noise power in the segmented image is low and the image quality is high when compared to Mean shift and Normalized cut segmentation method.

5. Conclusions

Fusion helps in merging useful and redundant information from multimodal images into a single image. Two different images are fused by using Curvelet and MSVD fusion methods. The quantitative analysis is performed by comparing various features which indicates that Curvelet fusion method provides better performance with efficient spatial and spectral resolution. A comparative study has been carried out among different segmentation methods like K means clustering, Mean shift and Normalized cut segmentation approaches. Parametric analysis performed for this segmentation methods show that information content and image quality is high for the images obtained using K means clustering approach when compared with other approaches. The proposed scheme can be extended by using image fusion technique such as Ridgelet transform and segmentation techniques like Watershed algorithm, Hop field neural networks etc.

Acknowledgement

The authors express sincere gratitude to NMAMIT, Nitte for the support and providing a pleasant environment to carry out the project work.

References

[1] Pappachen and B. V Dasarathy, "Medical image fusion: A Survey of the State of the Art", Information Fusion, Vol. 19, 2014, pp. 4-19.

[2] Bjoern H. Menze, Andras Jakab, and Stefan Bauer, "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)", IEEE Transactions on Medical Imaging, Vol.34, pp. 1993-2024, 2015.

[3] Arnaldo Mayer, and Hayit Greenspan, "An Adaptive Mean-Shift Framework for MRI Brain Segmentation", IEEE Transactions On Medical Imaging, Vol. 28, pp. 1238-1250, 2009.

[4] Sweta Mehta, and Prof. Bijith Marakarkandy, "CT and MRI Image Fusion using Curvelet Transform", Journal of Information, Knowledge and Research in Electronics and Communication Engineering, vol. 2, Issue 2, pp. 848-852, 2014.

[5] Sugandhi Vij, Dr. Sandeep Sharma, and Chetan Marwaha, "Performance Evaluation of Color Image Segmentation using K Means Clustering and Watershed Technique", International

Conference on Computing, Communication and Networking Technologies (ICCCNT), 2013.

[6] Julio Carballido-Gamio, Serge J. Belongie, and Sharmila Majumdar, "Normalized Cuts in 3-D for Spinal MRI Segmentation", IEEE Transactions on Medical Imaging, Vol. 23, pp. 36-44, January 2004.

[7] Padmavathi K, Dr. Maya V Karki, and Mahima Bhat, "Medical Image Fusion of Different Modalities Using Dual Tree Complex Wavelet Transform with PCA", International Conference on Circuits, Control, Communication and Computing, 2016.

[8] Aakanksha Bahri and Savita Shiwani, "Improved performance of Image Fusion by MSVD", International Journal of Innovative Science and Research Technology, Vol. 1, Issue 6, September 2016.