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Image Fusion Techniques for the Assessment of Multi-focus Ultrasound Placenta using Quality Metrics

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Abstract

The innovation of applications such as Medical Imaging, Microscopic Imaging, Computer Vision, Remote Sensing, and Robotics rely exclusively on the successful fusion of images acquired from different modalities or instruments. Images of the same modality taken simultaneously from different places under different conditions are fused together to generate a single image with information content from both the images. Such a type of fusion is called multi-view image fusion that has been discussed in this study. The transverse abdominal scan taken with the right side of the maternal abdomen appears on the left side of the monitor, whereas, the maternal left side appears on the right of the monitor. Image fusion aims at combining multi-view ultrasound images of the placenta into a single image to obtain relevant information from the source images using the fusion technique. The resultant fusion image combines the richness of information from all the source images. The findings of this study point toward the improved performance of Wavelet image fusion in comparison to the image averaging and PCA methods. The information entropy is comparatively better when the images are fused using Wavelet. The mutual information obtained is relatively good signifying a richness of information. The Wavelet decomposed images when subject to image fusion increase the quality of information in the images. Thus, the essential features that characterize the placenta can be extracted. The boundary information and structural details are preserved without the introduction of other inconsistencies to the image. The Spatial Frequency, Fusion Mutual Information, Entropy, Peak Signal to Noise Ratio, and Root Mean Square Error prove to be good evaluators of fusion methods suitable for ultrasound of placenta images. Among these measures, Entropy seems to be an enhanced indicator of the performance of fusion methods.

Keywords: images, quality metrics, placenta, ultrasound, image fusion, multi-focus, diabetes mellitus, wavelets, ultrasound.

Introduction

A combination of several images or a few of their distinct features to form a single image represents the process of image fusion. This can be performed at different levels of information representation. Four different levels are eminent; they are Signal, Pixel, Feature, and Symbolic levels. At present, the results of image fusion in areas such as Remote Sensing and Medical Imaging are primarily intended towards easier and enhanced interpretation for presentation and human observation. Hence, the perception of fused images is of vital importance while evaluating the different fusion schemes. Some generic requirements that can be imposed on the fusion results are as follows:

- The fused image should preserve all relevant information contained in the input images as close as possible
- The fusion process should not introduce any artifacts or inconsistencies that may divert or mislead the subsequent image processing steps or the human observer
- The fused image should suppress to the maximum possible level all irrelevant features and noise

Literature Survey

Ultrasound imaging is an ideal non-invasive diagnostic tool often preferred in imaging modality due to its ability to provide continuous real time images without the risk of ionization radiation, at a significantly lower cost. The final image of the ultrasound image scanner [1] is the basis for diagnostic decisions. Hence, the quality of the scanner should be of high precedence. Nevertheless, like all other imaging modalities, ultrasound imaging is also vulnerable to a number of artifacts that degrade the image quality. Gestational Diabetes Mellitus is defined as a degree of glucose intolerance with onset [2] or first recognition of pregnancy. Normal placental function is vital for a healthy pregnancy outcome as well as maternal, fetal, childhood and adult health. Abnormal placental function may result in a compromised pregnancy creating pathology for the fetus and mother in a similar way. Ultrasound examination of the placenta [3] is often considered secondary to the fetus by expectant parents and sonographers alike. Generally, image fusion methods can be categorized into two [4] groups: Spatial domain fusion and Transform domain fusion. Fusion techniques incorporate the simplest method of pixel averaging to more complicated methods such as Principal Component Analysis and Wavelet transform fusion. Approaches towards image fusion can be distinctly defined, depending on whether the images are fused in the spatial domain, or transformed into another domain and their transforms fused[5,6]. In a region-based multi-focus image fusion algorithm using spatial frequency and genetic algorithm, the source image is divided into blocks, and then, the corresponding blocks with higher [7] spatial frequency value are selected to construct the resultant fused image. GA is brought forward to decide the appropriate sizes of the block. Though the selection [8] of block-size by using differential evolution algorithm enhanced the self-adaptation of the fusion method, it still requires more computational time. Selection of the focused patches [9] from the source images by using a belief propagation algorithm is also complicated and time-consuming. The problem of multi-focus image fusion is transformed into a problem of choosing the sparse features [10] of the sparse matrices to form a feature space. An optimal subdivision of blocks of the sparse matrices is obtained by using a quad tree structure to inhibit the blocking artifacts. The resultant fused image is constructed by integrating the focused regions of the source images that are detected by the local sparse feature of the blocks. A metric for the objective evaluation of image fusion performance, that does not necessitate any reference image, is proposed in [11]. Assessing the clinical quality of ultrasound images are of paramount significance. The various image quality measures usually used for objective evaluation are Mean Squared Error (MSE), Signal to Noise Ratio (SNR), and Peak Signal to Noise Ratio (PSNR) [12]. Performance of the fusion algorithm is measured using the amount of information in image features that are carried from the source image to the fused image. This amount is derived through mutual information. An approach for estimating the 4-D joint probability distribution has also been suggested which is utilized in MI calculation. The existing metrics for evaluation of image fusion algorithms are usually based on the measurement of the transfer of a feature (e.g., edges, amount of information) from the source images into the fused image [13].

Ultrasound is one of the most extensively used modalities in medical imaging. Various streams including cardiology, obstetrics, gynecology, abdominal imaging, etc. regularly use Ultrasound imaging. In principle, the ultrasound system [14] focuses sound waves along a given scan line so that the waves constructively add together at the desired focal point. Figure 1 represents [15] the schematic diagram of a typical clinical ultrasound beam.

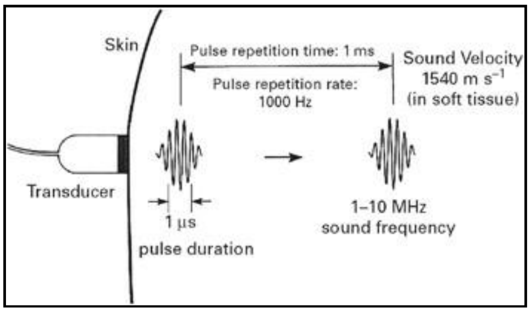


Figure 1: Schematic diagram of a typical clinical ultrasound beam

Ultrasound measurements play a considerable role in obstetrics as a precise means in estimating the fetal age. Several parameters [16] are used as aging parameters, the most important of which are the bi-parietal diameter (BPD), occipital-frontal diameter (OFD), head circumference (HC) and femur length (FL). The tissues of interest need to reflect sufficient ultrasound energy; this in turn limits the method to soft tissues, fluids and small calcifications preferably close to the surface of the body and are unobstructed by bony structures.

Ultrasounds are generally engaged in abdominal and pelvic examinations. In obstetrics, fetal head size and fetal length are used as measures to determine fetal maturity and health, while spinal morphology can be used to identify the presence of abnormalities such as spina bifida.

An ultrasound examination of the pelvis can be done using the B-mode ultrasound scanner. Scans undergone during the course of pregnancy can be broken down into those done in early pregnancy (from six to fourteen weeks of gestation), mid-pregnancy (from fourteen to twenty six weeks of gestation), and late pregnancy (from twenty six to forty weeks of gestation). During the later stages of gestation, the fetus in the uterus hides the placenta and hence becomes difficult to capture in the ultrasound. The placenta needs to be screened [17] in the initial stages, so that miscarriages due to GDM can be avoided. The standard common obstetric diagnostic mode is 2D scanning.

Grading of the placenta can be done through ultrasound by observing and analyzing the calcification aspects of the placenta. Table 2.2 below gives the sonographic characteristics [18] of placenta at various grades. A grade 3 placenta, for example, is normal at 40 weeks. But if too many calcifications are seen early in pregnancy, it indicates that the placenta is aging too rapidly. This can happen due to presence of high blood pressure and diabetes. If the placenta is found to have advanced calcifications in the early stages of pregnancy, the fetus needs to be periodically evaluated for growth, to ensure that it is getting the required supply of vital nutrients.

Principle of Image Fusion

Image fusion is the process wherein two or more images are combined together to form a single image that retains the important features from each of the original images. Images acquired from different instrument modalities or capture techniques of the same scene or objects often require a fusion of images. In this paper, the multi-view of the ultrasound images of the placenta is subject to image fusion by applying image averaging; principle component analysis and Wavelet transform techniques using fusion rules. Figure 3 portrays the multi-view of the ultrasound placenta complicated by GDM. The applications differ from one another in using the fusion rules.

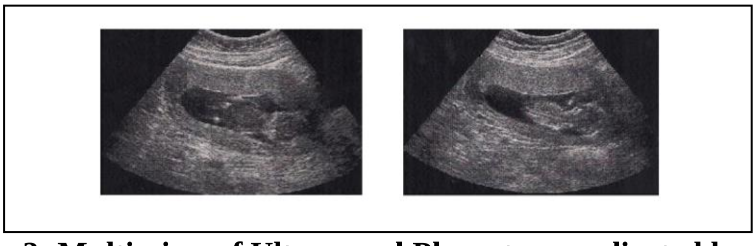


Figure 3: Multi-view of Ultrasound Placenta complicated by GDM

Image fusion aims at improving the quality of the ultrasound images of placenta to make it suitable for diagnostic purposes. The framework of image fusion technique carried out in this work is illustrated in Figure 4.

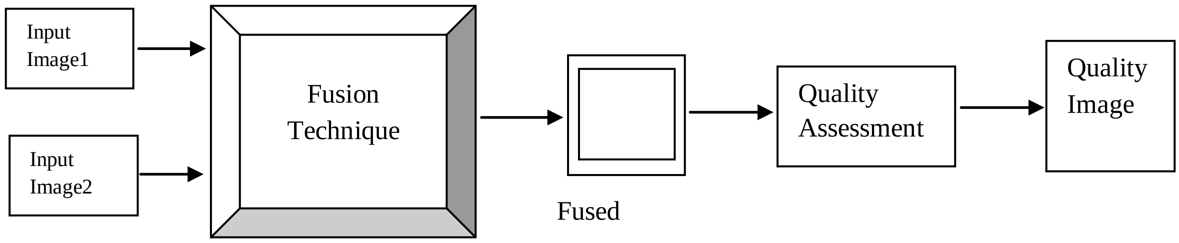


Figure 4: A framework of image fusion techniques

Image Fusion Techniques

There are many approaches to fusion techniques. Discussed below are the primarily used techniques, such as:

1. Fusion Techniques based on Averaging

A basic and straight forward technique through which fusion is achieved by a simple averaging of corresponding pixels in each input image using:

$$I_f(x,y) = (I_1(x,y) + I_2(x,y))/2 \qquad \text{(Eq.1)}$$

2. Fusion Techniques based on Principal Component Analysis

The Principal Component Analysis (PCA) involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. An optimal and compact description of the data set is thereby computed. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular to the first. Within this subspace, the component points to the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also called as Karhunen-Loeve transform or the Hotelling transform. PCA is a general statistical technique that transforms multivariate data with correlated variables into data with uncorrelated variables. A univariate measure uses a single image, whereas a bivariate measure is a comparison between two images. The new variables are obtained as linear combination of the original variables where the input images to be fused is arranged in two column vectors. The Eigen vectors corresponding to the larger Eigen value is obtained and the normalized components are computed from the obtained Eigen vectors.

PCA Algorithm

Arrange source images in two-column vectors. The steps to be followed to project this data into 2-D subspaces are as follows:

1. Organize the data into column vectors. The resulting matrix Z is of dimension *2*X*n*.
2. Compute the empirical mean along each column. The empirical mean vector M_e has a dimension of *1X2*.
3. Subtract the empirical mean vector M_e from each column of the data matrix Z. The resulting matrix X is of dimension 2Xn.
4. Find the covariance matrix C of X i.e. Cov(X).
5. Compute the Eigen vectors V and Eigen value D of C and sort them by decreasing Eigen value. Both V and D are of dimension *2X2*.
6. Consider the first column of V which corresponds to larger Eigen value to compute P_1 and P_2 as:

$$P_1 = \frac{V(1)}{\sum V} \qquad \text{(Eq.2)}$$

$$P_2 = \frac{V(2)}{\sum V} \qquad \text{(Eq.3)}$$

The fused image is represented as:

$$I_f(x,y) = P_1 I_2(x,y) + P_2 I_2(x,y) \qquad \text{(Eq.4)}$$

3. Fusion based on Wavelet Transform Techniques

The two dimensional Wavelet transform has become one of the standard tools for image fusion. The later technique has been employed in this research. The Wavelet image fusion works by merging the Wavelet decompositions of two original images using fusion methods, applied to approximation coefficients and detail coefficients. The Wavelet transform partitions the original image into low frequency and high frequency components. The low frequency coefficients reveal the approximate feature of the image. It contains the main outline information of the image. It is an approximate image of the original image at specific dimensions. Most of the information and energy of the image is included in this. The high frequency coefficients reflect the detail of the luminance change which corresponds to the edge information of an image. It is crucial to contain both the edge information as well as the outline information of the input image in the fused image. The fusion should certainly preserve detailed information like high frequency and give prominence to the outline information in the target image. The two images must be of the same size and color map.

$$I_f(x,y) = fusion\, rule\, \{WT(I_1(x,y)), WT(I_2(x,y))\} \qquad \text{(Eq.5)}$$

where,

$I_1(x, y)$ = input image1 (transverse scans)
$I_2(x, y)$ = input image 2 (longitudinal scans)
$I_f(x, y)$ = image fused using the fusion rule
WT = Wavelet transforms

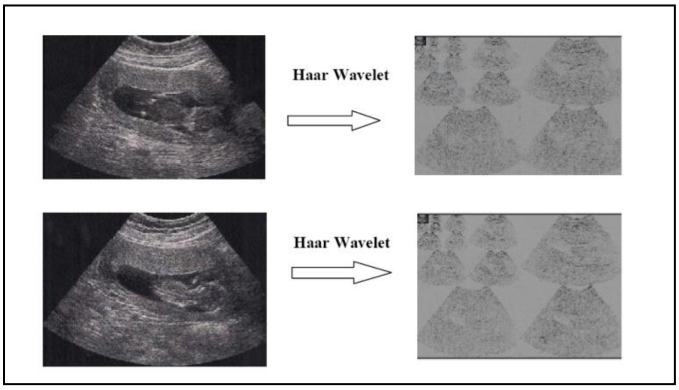


Figure 4: Haar Wavelet Decomposition of multi-view (longitudinal and transverse) ultrasound placenta image

In the Wavelet image fusion scheme, the source images $I_1(x, y)$ and $I_2(x, y)$ are decomposed into approximation and detailed coefficients at required levels using Haar Wavelet. The approximation and detailed coefficients of both the images are combined using fusion rule as represented by [17] Eq. 4. The fused image $I_f(x, y)$ is obtained by taking the inverse Wavelet transform. The fused image is then used for further analysis. For the next level of decomposition, the decomposed ultrasound images of the placenta are used as input. Corresponding information is found in each of the fused images that are different from the original images.

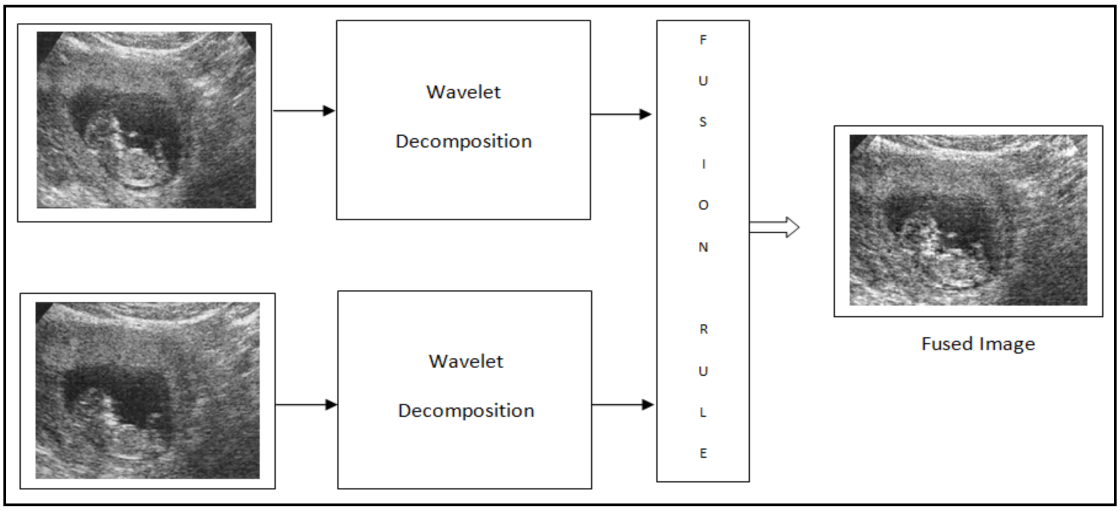


Figure 4: Transverse scans of placenta (10 weeks Gestational Age) image re-constructed using Wavelet Image Fusion

Experimental Results

The performance analysis of various fusion techniques are recorded in Table 1 and Table 2. The finding of this work is to show that the performance of Wavelet image fusion is better when compared to image averaging and PCA methods. This is clearly shown in Figure 5.

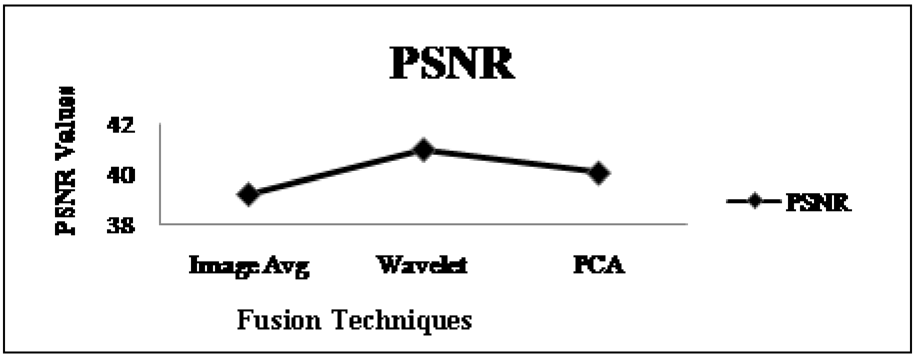
Table 1 Performance Assessment of Various Fusion Techniques using Peak signal to noise ratio, mean square error, root mean square error, normalized absolute error, normalized cross correlation, structural content and fusion mutual information of 15 weeks Gestational Age

Fusion Techniques	PSNR	MSE	RMSE	NAE	NCC	SC	FMI
Image Averaging	39.1725	7.8673	2.8049	0.0923	0.9764	1.0271	1.8706
Wavelet	40.9709	5.1999	2.2803	0.0637	1.0066	0.9782	4.625
PCA	40.0335	6.4525	2.5402	0.0768	1.0019	0.9826	4.2678

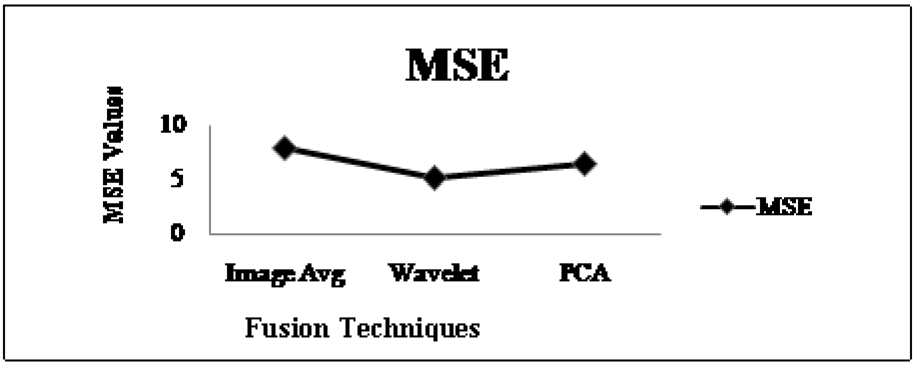
Table 2 Performance Assessment of Various Fusion Techniques using fusion entropy, mean, standard deviation, average difference, signal to noise ratio and spatial frequency of 15 weeks Gestational Age.

Fusion Techniques	STDF	Entropy H	Mean F	AD	SNR	SF
Image Averaging	29.6438	6.2384	88.4785	-0.1009	39.1725	-0.006
Wavelet	33.2047	6.6184	89.6649	-0.4963	40.9709	3.4182
PCA	33.0031	6.5281	89.5115	-0.4452	40.0335	-0.0044

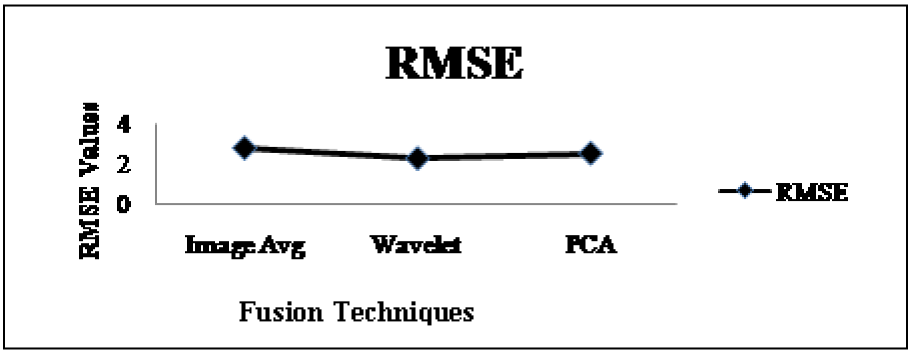
Figure 5 (a), (e), (g), (j), and (l) show an increase in the values for Wavelet image fusion technique in comparison with Image Averaging or PCA. The PSNR, NCC, FMI, ENT, SF, RMSE, MSE, NAE, SC and AD prove to be efficient in the evaluation of the fusion methods suitable for ultrasound of placenta images. SF, FMI, ENT, PSNR, RMSE seem better indicators to the performance of the fusion methods.



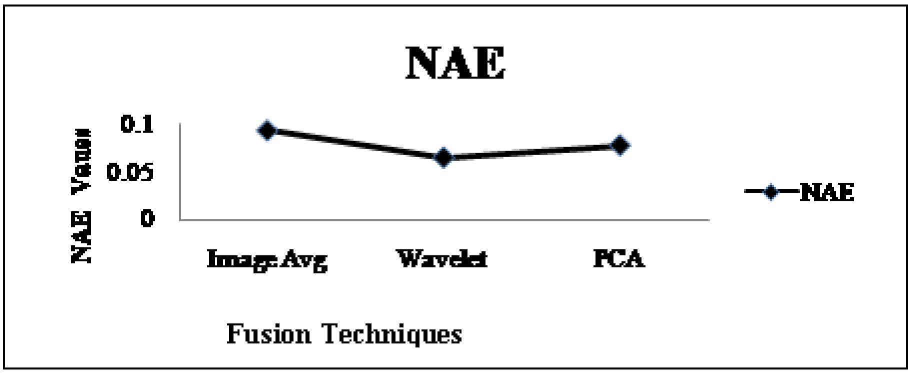
(a)


MSE
MSE Values
10
5
0
Image Avg
Wavelet
PCA
Fusion Techniques
MSE

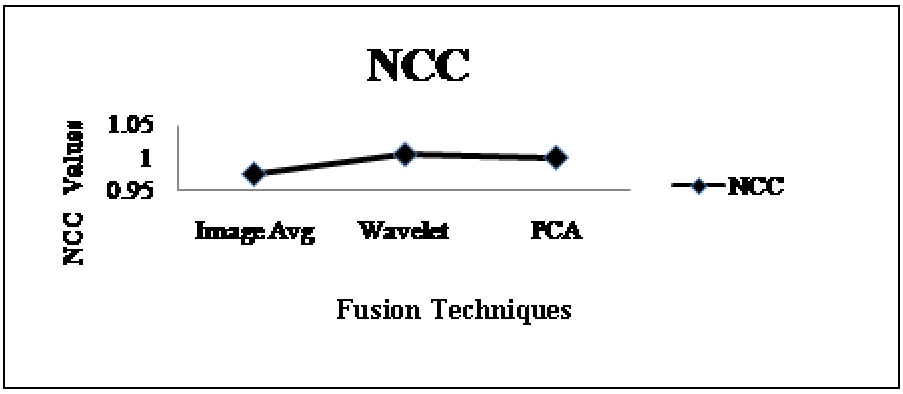
(b)


RMSE
RMSE Values
4
2
0
Image Avg
Wavelet
PCA
Fusion Techniques
RMSE

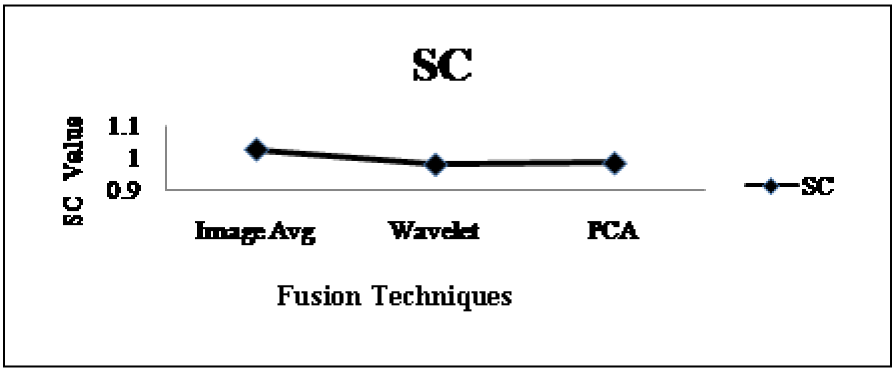
(c)


NAE
NAE Values
0.1
0.05
0
Image Avg
Wavelet
PCA
Fusion Techniques
NAE

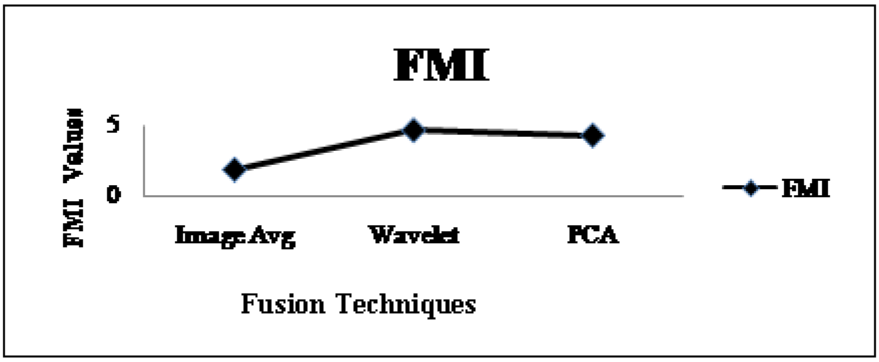
(d)


NCC
NCC Values
1.05
1
0.95
Image Avg
Wavelet
PCA
NCC
Fusion Techniques

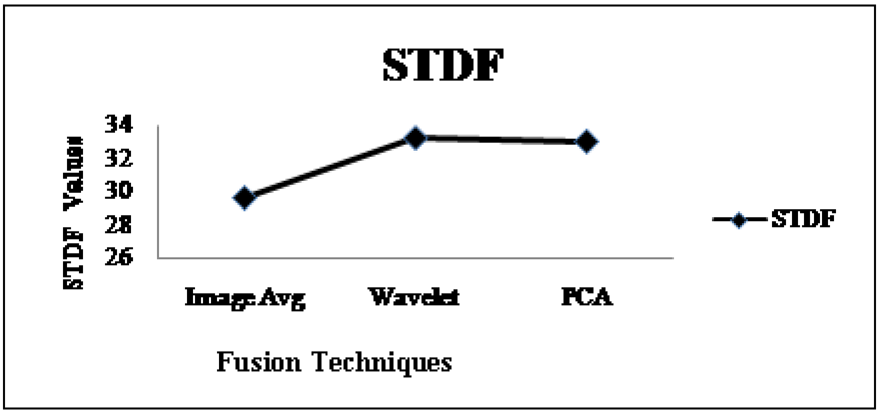
(e)


SC
SC Value
1.1
1
0.9
Image Avg
Wavelet
PCA
SC
Fusion Techniques

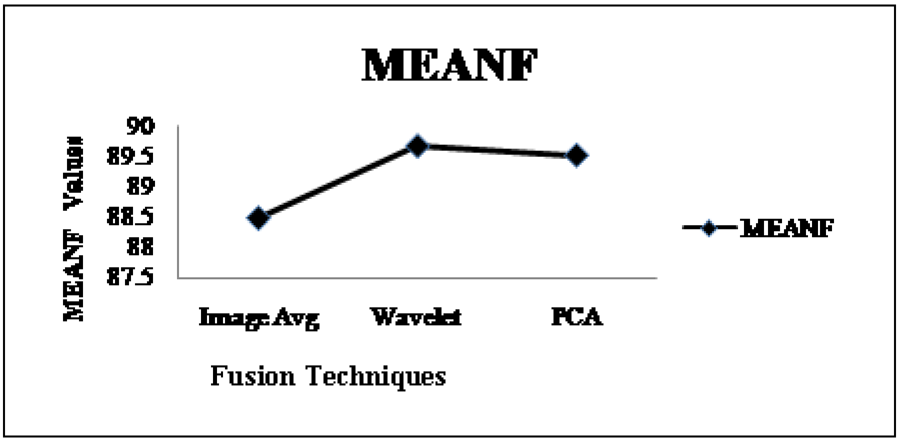
(f)


FMI
FMI Values
5
0
Image Avg
Wavelet
PCA
FMI
Fusion Techniques

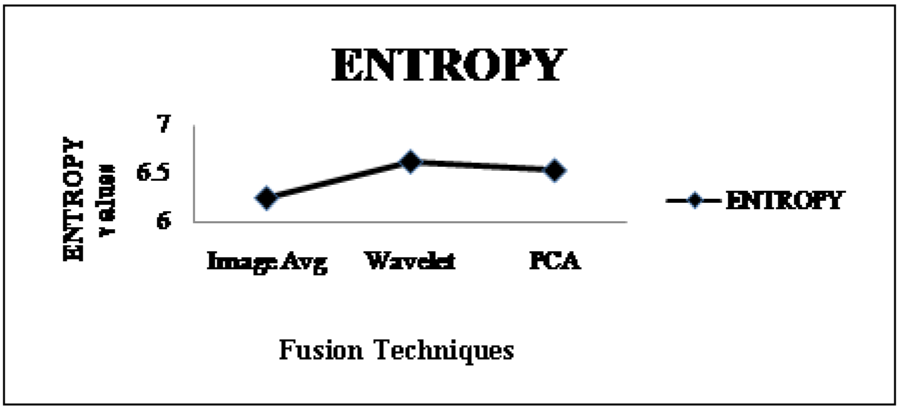
(g)


STDF
STDF Values
34
32
30
28
26
Image Avg
Wavelet
PCA
Fusion Techniques
STDF

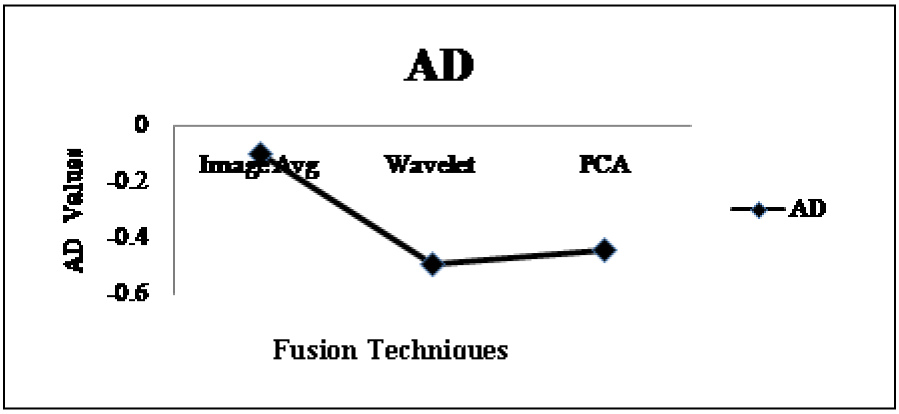
(h)


MEANF
MEANF Values
90
89.5
89
88.5
88
87.5
Image Avg
Wavelet
PCA
Fusion Techniques
MEANF

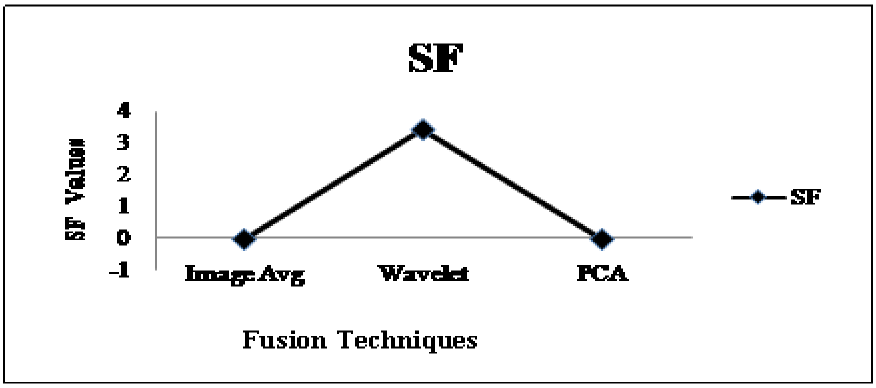
(i)


ENTROPY
ENTROPY Values
7
6.5
6
Image Avg
Wavelet
PCA
Fusion Techniques
ENTROPY

(j)



(k)



(l)

Figure 5: Quality Measures for various fusion techniques using entropy, mean, standard deviation, average difference, signal to noise ratio, spatial frequency, PSNR, RMSE, NAE, NCC and SC of 15 weeks Gestational Age((a) – (l))

Conclusion

This research has used image quality measures like Entropy, Mean, SD, FMI, NCC, RMSE, PSNR, SC, SF, NSE and AD to analyze the fused image. The findings of this study point toward the improved performance of Wavelet image fusion in comparison to the image averaging and PCA methods. The information entropy is comparatively better when the images are fused using Wavelet. The mutual information obtained is relatively good signifying a richness of information. A useful image is identified based on the execution of quality measures on the images. Based on the above mentioned findings, it is clearly shown that the Wavelet decomposed images when subject to image fusion increase the quality of information in an image. This in turn helps in precisely extracting the essential features that illustrate the placenta. It further preserves the boundary information and structural details without introducing any other consistencies to the image. The Spatial Frequency, Fusion Mutual Information, Entropy, Peak Signal to Noise Ratio, and Root Mean Square Error prove to be good evaluators of fusion methods suitable for ultrasound of placenta images. Among these measures, Entropy seems to be an enhanced indicator of the performance of fusion methods.

List of Abbreviations

SC – Structural Content
NCC – Normalized Cross Correlation
SF – Spatial Frequency
RMSE – Root Mean Square Error
PSNR – Peak Signal to Noise Ratio
FMI – Fusion Mutual Information
SD – Standard Deviation
NAE – Normalized Absolute Error
AD – Absolute Difference
PCA – Principle Component Analysis

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BIOGRAPHICAL SKETCH

G.Malathi received the Ph.D. degree in Computer Science in 2013. She is currently an Associate Professor in School of Computer Science and Engineering. Her research interests are image processing and BigData. She has published many papers in International and National Journals. She has also authored a chapter of a Book.