The Study and Comparative Analysis of Multi-Focus and Medical Image Fusion Techniques for Visual Sensor Networks

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Abstract - ***Image processing techniques primarily focus upon enhancing the quality of an image or a set of images and to derive the maximum information from them. Image Fusion is such a technique of producing a superior quality image from a set of available images. It is the process of combining relevant information from two or more images into a single image where in the resulting image will be added informative and complete than any of the given input images. A lot of research is being done in this field encompassing areas of Computer Vision, Automatic object detection, Image processing, parallel and distributed processing, Robotics and remote sensing. This project is a detailed study performed over a set of image fusion algorithms regarding their implementation which explains the theoretical and implementation issues of the 10 image fusion algorithms considered and the experimental results of the same. The fusion algorithms were assessed based on the study and development of some image quality metrics. This is the study and implementation of a set of 8 image quality metrics that were developed for assessing the image fusion algorithms implemented and developed using Mat Lab. The Project finally concludes with an assessment made on the various image fusion algorithms, identifying the Gradient Pyramid Fusion algorithm and Haar Wavelet based fusion algorithm as the most efficient algorithms of the lot. The experimentation was performed based on the readings produced by the different image quality metrics. The credibility of the assessment based on the image quality metrics was cross verified with an assessment made by five respondents, selected in random, based on their visual perception of the fused images.***

Key Words: *Principal Component Analysis (PCA) , Signal to Noise Ratio (PSNR) , Mean Square Error (MSE),Normalized Cross Correlation (NCC), Normalized Absolute Error (NAE), Filter Subtract Decimate (FSD) Pyramid.*

1. Introduction

Image Fusion [16] is a process to develop the quality and enhancement of information from a set of different images. From this process of image fusion the good quality information from each of input images is fused together to shape a resulting image, which has feature better than any of given input images. To achieve this process by applying a series of operations on the images that would produce the good and quality information in each of the image prominent fusion techniques. The resulting image is produced by combining such magnified information from the given input images into a resultant output image. This project involves the study and implementation of the 10 algorithms of Image Fusion. This project also required the development of the 8 Image Quality Measurement parameters to evaluate the quality of the fused images in comparison to a sample perfect image for a known pair of input images. In turn to assess the Credibility of the metrics, a visual quality based assessment was also performed and the same compared with the assessment made with the help of image quality metrics. The implementation including the GUI was developed using MATLAB. The project was been tested and validated with multi focal images captured using digital camera. The developed Image Metrics were use full to evaluate the quality in the fused image in contrast with the perfect input image.

2. Literature survey

Haghighat et al. [1] has illustrated the purpose of image fusion technique is to combine information from numerous images of the similar vision in order to carry only the valuable information. The DCT (discrete cosine transform) based methods of vision fusion are further suitable and time-saving in real-time system based principles of unmoving image or video. Haghighat et al. has given a more suitable approach for fusion of multi-focus images with respect variance designed in DCT domain.

Lui et al. [2] has proposed that image fusion is a important step for image mosaic in given blurred images. Fusion algorithms influence the visual effect and feature of the mosaic imagery straightforwardly. An AWC (adaptive weighted coefficients) method for image fusion has been projected. An AWC algorithm can fine-tune weighted coefficients adaptively alongside with changes of the selection and shape of the overlapping image regions.

Cao et al. [3] has projected that multi focus image fusion deals through a stack of imagery with the intention of multiple focus point which retrieve better image with all desired objects in the analysis full focused. Multi focus noisy image fusion method using the contour let transform has been proposed in this paper. Utilize the captured directional values of image by the contour let transform, the directional window are used to determine the fusion weight of image.

Pei et al. [4] has proposed the improved DWT (discrete wavelet transform) based vision fusion method, after go through the principles and methodology of the discrete wavelet framework. These algorithms can capably mixture the deserved information of the entire source image retrieve from the multi sensor device. It is the combination of two or more images into one derived image that is more reliable and correct.

Haozheng et al. [5] image fusion is one of the important best enhancement methods of data fusion. This uses mixture multi-vision information in one vision to one picture which is better suitable to human figure and computer image or adapt to further vision processing methods, such as target identification and extraction. Discussion was carried on the image fusion techniques based on wavelet transformation method. Firstly, this paper gives the basic theory of multi-focus image fusion methods. The theory of wavelet analysis and includes its fast arithmetic is shown here; from here on it gives the image fusion process based on singe wavelet. Getting on by means of the single wavelet, it presents some superior wavelet as multi-wavelet, multi-band wavelet, including their theories and that sums of decomposition and reconstruction. In the same time, this is applicable for the multi-band multi wavelet in the vision fusion with the wavelet fusion betterment thought.

Mohamed et al. [6] image fusion is process of which combining the data from two or more source input images from the same analysis to produce one single image containing added accurate details of the vision than of the given input source images. In many image fusion techniques like averaging fusion method, principle component analysis fusion method and different types of Pyramidal Fusion Transforms, DCT(Discrete cosine transform), Discrete Wavelet Transform(DWT) special frequency Components are the largest part universal approaches. In this paper multi-focus image fusion is used as a case study purpose and also features all these issues in multiple vision fusion techniques.

Albuquerque et al. [7] has discussed that image focus process is a property closely related to vision quality and analysis. For some images it is not possible to get a clear focus in all regions at the same time, so an alternative method is to use image fusion technique to merge images with different focus taken at different time into one with all the better focused regions in input images. There are two image fusion methods in the frequency domain that are dependent on focus- DCT and spatial frequency approach. The algorithms divide the image into fixed size of blocks to decide which image should be identified and selected to comprise the final output result.

Parmar et al. [8] has analyzed that medical image fusion technique has been used to get useful contents and data from multimodality medical images. This process of developing the image content by fusing imagery like CT (computer tomography) and MRI (magnetic resonance imaging) images are used, MRI provide improved information on soft tissue whereas CT gives enhanced information about denser tissue images. Fast Discrete Curve let Transform using Wrapper algorithm method based image combination technique has been developed, analyzed and validated with Wavelet based mixture Technique. Fusion of imagery in makes use of different resolutions ideas, intensity and by different ideas helps physicians to dig out the features that may not be usually visible in a single image by different modalities components.

Desale et al. [9] has proposed image fusion technique is process adding the related data from a set of input images, into a single output image, where in the resulting fused image will have better information compared to all the given input images. This paper also illustrated the Formulation, Algorithm Process Flow Diagrams of principal Component Analysis, Discrete Cosine Transform and Discrete Wavelet Transform related image fusion method. The output results are also given in tabulated & output picture format for comparison of above techniques. The PCA & DCT are conventional fusion methods which have a lot of drawbacks, whereas DWT based methods are added favorable as they give better results for image fusion technique. This article also proposes, two algorithms based on DWT are proposed, they are, pixel averaging and maximum pixel replacement methods.

2.1 Objective

By conducting the review it has been found that the most of the existing literature has neglected at least one of the following.

1. As most of the existing methods are based upon therefore it may results in some color artifacts which may reduce the performance of the transform based image fusion methods.
2. It is also initiate the problem of the uneven illuminate has also been neglected in the most of existing work on combination.
3. The DWT based image fusion techniques are more appropriate and time-saving in real-time application systems via DWT based multi-focused images methods. In this dissertation a well-organized approach for fusion of medical and multi-focal images based on DWT domain is presented.

3. METHODOLOGY: IMAGE FUSION TECHNIQUES

3.1 Basic Image Fusion Methods

The three basic image fusion [10] methods mainly carry out a very fundamental operation like pixel selection process, addition, subtraction and averaging of pixels. These techniques are not constantly effective but are at time significant based on the kind of image which is under consideration. Below are some of the three basic image fusion technique methods studied and developed in this project is as follows:

3.1.1 Average Fusion Method

Image Fusion in addition with similar circumstances, the most basic idea is to average the pixel intensities of the corresponding pixels to get the fused image of set of images. The fused image formed by this process to show both the good and the bad information from the input set of images. From this averaging operation, both the good and the bad information are minimizing arriving at an averaged image output. This method does not actually fuse the images perfectly. Here we calculate the average intensity pixel value of every equivalent pixel of the input pair of images.

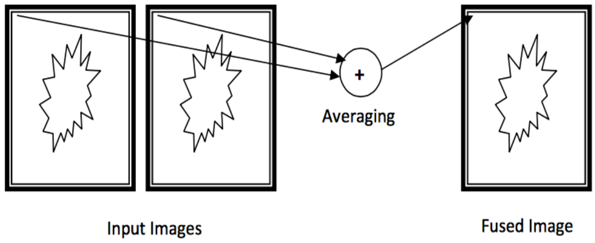

Fig 3.1: Pixel intensities at each position (m,n) are averaged to obtain the (m,n) pixel of the image fused

This process is continued similarly with both Maximum and Minimum Fusion Methods. In Selection of Image Pixels like averaging method, instead of averaging every equivalent pixel, a selection process is performed in these methods. The law of choice is self given by the name of the method, of each equivalent pixel of the input images, the pixel which is having maximum and minimum intensity is selected and is place in as the resultant pixel of the image fused.

3.2 Principal Component Analysis (PCA) Algorithms

PCA [11] is a vector space transform mainly used to decrease multidimensional data sets to lower dimensions for image analysis. PCA is the simplest and useful for the eigenvector-based multivariate image analyses, because its function is to reveal the inner structure of data in a balanced way. If the multivariate dataset is observed as set of coordinate in a high-dimensional information space, PCA supply the user with a two dimensional picture, a shadow of that object when looked from its mainly informative viewpoint of object. This dimensionally-reduced image of the data is the ordination diagram of the 1st two principal axes of the data, which when combined with metadata (such as gender, location etc) can rapidly reveal the main factors underlying the structure of data. PCA is especially useful for taming collinear data; where multiple variables are co-correlated (which is routine in multivariate data) regression-based techniques are unreliable and can give misleading outputs, whereas PCA will combine all collinear data into a small number of independent (orthogonal) axes, which can then safely be used for further analysis.

The PCA algorithm looks into scaling the pixel values of the images with a weight. The algorithm can be summarized as the following:

1. Generate the column vectors, in that sort, from the given input pair of input images matrix.
2. Calculate the covariance matrix of two column vectors created in step one.
3. The diagonal elements of the 2x2, the covariance vector that contains the variance of every one of the Column vector with itself, correspondingly.
4. Find Eigen values and also Eigen vectors of the calculated covariance matrix.

5. Standardize the column vector equivalent to the better Eigen value by dividing every one element with mean of the Eigen vector found.
6. The value of the standardize Eigen vector take action as the weight values that are correspondingly multiplied with every pixel of the input pair of images.
7. Sum of the two scaled matrices calculate in step 6 is the output fused image matrix.

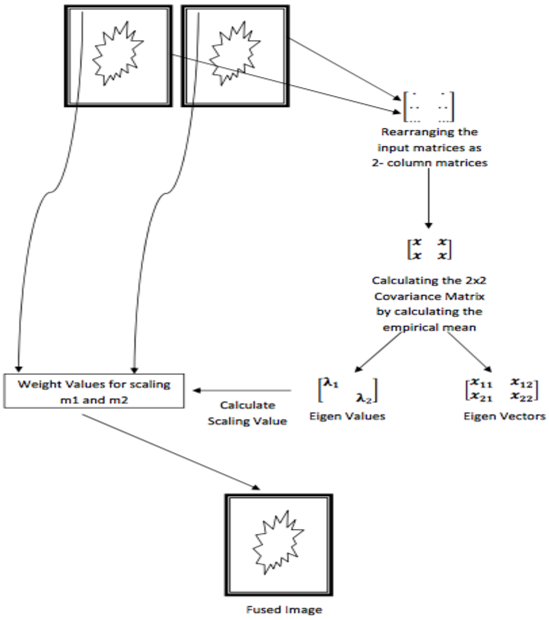

Fig 3.2: The input image pixels at positions (m,n) being scaled with the weights calculated using PCA algorithm, producing the Fused Image pixels (m,n).

3.3 Pyramidal Fusion Algorithms

Pyramid transform proved to be a very efficient method for the same. An image pyramid which is having a set of low pass or band pass copies of a given image, every copy on behalf of pattern information of a dissimilar scale patterns. A Gaussian pyramid is the series of images in which each member of the sequence is the low pass filtered side of the previous version. At each level of fusion by means of pyramid transform, this pyramid will be half the size of pyramid as compared to preceding level and the higher levels that will focus on the lower level spatial frequencies. The fundamental idea is to generate the pyramid transforms of the fused image as of the pyramid transformation of the source input images and then output fused image is getting by taking inverse pyramidal transform method.

There are various types of pyramid transforms. Some of the pyramids transforms considered in the project are as the following:

- Filter Subtract Decimate Pyramid
- Laplacian Pyramid
- Ratio Pyramid
- Morphological Pyramid

Typically, each pyramid transform is having three major phases:

- Decomposition phase
- Formation of the initial image for decomposition.
- Recomposition

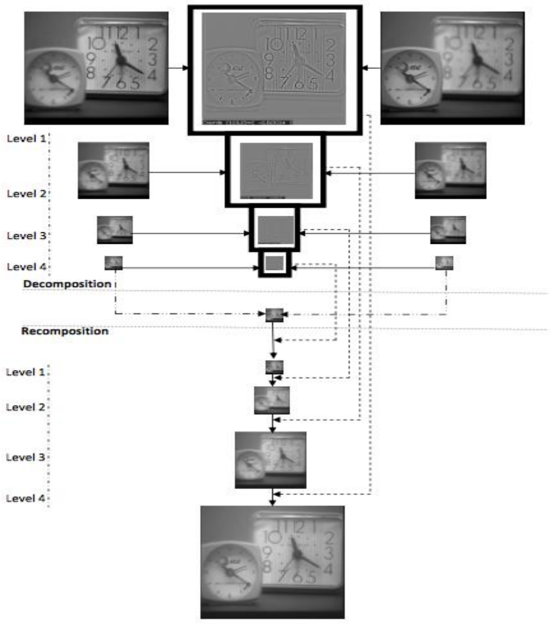

Fig 3.3: Pyramid Transform description with an example.

3.3.1 Laplacian Pyramid Fusion

The Laplacian pyramid can be understood based on the generic flow diagram of the steps involved as shown below. The stepwise description of the algorithm follows the same.

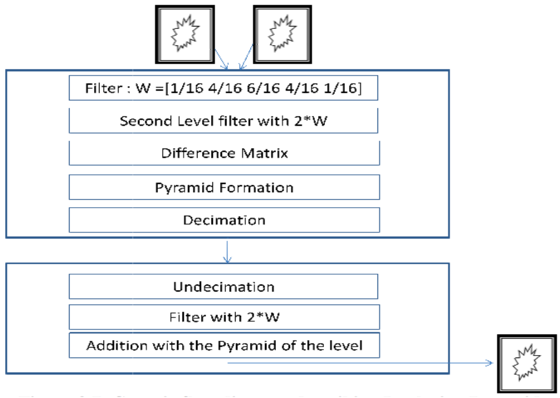

Fig 3.4: Generic flow diagram describing Laplacian Pyramid Fusion

1. Considering the pair of input image matrices as M1 and M2 respectively.
2. A single dimensional filter mask is generated as W = [1/16 4/16 6/16 4/16 1/16]
3. The level of fusion (decomposition and recomposition) is decided upon. Both the decomposition part and the recomposition part are iteratively executed "level" number of times.

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4. Decomposition

a. The image matrices are filtered (convolved) vertically and filter mask generated, producing the filtered image matrices G1 and G2 respectively

b. An additional level of filtering is performed over G1 and G2 producing filtered matrices G11 and G22.

c. The difference matrix is calculated for both the (M1-G11) and (M2-G22). The difference between the original image matrices and the second level of filtered image matrices.

d. The Pyramid of this level of decomposition is generated using any of the three algorithms below:

i. Select Maximum
ii. Burt's Method
iii. Lis Method

e. The pyramid thus formed is retained for the level as E[level].

f. The images are decimated to half the size and the decomposition steps are iterated "level" number of times.

5. The finally decimated pair of images M1 and M2 is manipulated as one of the following, producing X matrix.

a. Average M1 and M2
b. Select Maximum in M1 and M2
c. Select Minimum in M1 and M2

6. Recomposition

a. Matrix X obtained in step 5 is undecimated by alternatively padding zero columns and rows.

b. The undecimated matrix is filtered (convolved) with the doubly scaled filter mask W.

c. The filtered matrix is added upon with the retained pyramid of the level E[level].

d. The matrix generated in step c will act as the input matrix X to the next level of recomposition.

e. Recomposition steps are performed "level" number of time, eventually undecimating the matrices in each level, obtaining the fused image matrix of the original size at the end of the final level.

3.4 Discrete Wavelet Transform Algorithms

A Discrete Wavelet Transform (DWT) [12] in several wavelet transform by which the wavelets are unconnectedly sampled. The first DWT was proposed by the Hungarian mathematician Alfred Haar. For an input represent by a list of $2n$ numbers, the Haar wavelet change may be measured to basically pair up input values, storing the difference values and passing the resultant sum. This method is stable recursively, pairing up the sums to give the next scale: finally resulting in 2n-1 differences and one final sum value. This straightforward DWT illustrate the popular properties of wavelets in general. First, it is capable of performed in $O(n)$ operations; next, it captures not only a thought of the frequency contents of the input image, by resulting it at dissimilar scales, but also in order content i.e. the period at which these frequencies are occurred. Combined, these two characteristics make the Fast wavelet transforms (FWT), an alternate to the conventional Fast Fourier Transform (FFT).

The most usually used set of discrete wavelet transforms was calculated by the Belgian scientist Ingrid Daubechies. This author's idea is related on the use of reappearance relations to produce gradually finer discrete samplings of an implicit look after wavelet function; every resolution is double that of the previous scale value. Daubechies derives a family of wavelets, the initial of which is the Haar wavelet. Awareness in given field has detailed since then, and a lot of variations of Daubechies' original wavelets were manipulated and developed

The DWT of a signal x is designed by carried it through a series of filter methods. Basically the samples are passed all the means of a low pass filter with this impulse response g processed in a convolution of the two different variables.

$$y[n] = (x * g[n]) = \sum_{k=-\infty}^{\infty} x[k]g[nk] \tag{3.1}$$

The signal is also decomposed at the same time by means of a high-pass filter h. The outputs formulates the feature coefficients (from the high-pass filter) and estimated coefficients (from the low-pass).This is important that the two filters are linked to each other and also they are familiar as a quadrature mirror component filter. Since half the frequencies of the signal contain now been removed, half the samples can be detached according to Nyquist's rule. The filter outputs values are again subsampled by 2.

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \tag{3.2}$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \tag{3.3}$$

This decomposition has been halved the time resolution because only half of every filter output characterize the signal strength. On the further hand, each output has semi of the frequency band of given input so that the frequency resolution must been doubled here.

With the sub sampling operator ↓,

$$(y{\downarrow}k)[n]=y[kn] \tag{3.4}$$

the above summation can be written more briefly.

$$Y_{low}=(x*g){\downarrow}2 \tag{3.5}$$

$$Y_{high}=(x*h){\downarrow}2 \tag{3.6}$$

However calculating a total convolution $x * g$ with subsequent down sampling that has waste calculation time. The Lifting method is an derived here where these both computations are discussed and interrelated.

3.4.1 DWT with Haar based Fusion

The Haar wavelet [13] is the first recognized wavelet and was proposed in 1909 by Alfred Haar. Haar uses these functions to give an illustration of a countable orthonormal scheme for the space of square-integral functions on the real time line. As a particular case of the Daubiches wavelet is known as D2. The Haar wavelet is also the simplest possible wavelet transform method. The drawback of the Haar wavelet is that it is not continuous and as a result not differentiable as compared to Dubechies (2,2) [14] Method.

Applying the Haar Wavelet transform on the input images to fuse them together is mentioned stepwise as below steps:

1. Considering the pair of input image matrices as M1 and M2 respectively.
2. One of the most relevant parts in a wavelet method is the selection and generation of the filter. In this wavelet method with Haar, mainly two filters are generated, say, F1 and F2.
3. The main component in F1 will be the values 0.5, 0.5
4. The main component in F2 will be the values 0.5, -0.5.
5. The filters F1 and F2 are padded with zeros for computational purpose in three parts.
6. The first part would have 2^ (level-2) number of zeros padded.
7. The second part would have 2^ (level-1)-1 number of zeros padded.
8. The third part will have the maximum between (1 and 2^ (level-2)) number of zeros padded.
9. Thus, the filters will be of the form F1 = [I part 0.5 II part 0.5 III part] and F2 = [I part 0.5 II part -0.5 III part]
10. The level of fusion (decomposition and recomposition) is decided upon. Both the decomposition part and the recomposition part are iteratively executed "level" number of times.
11. Decomposition
    a. The input image matrices of the input level M1 and M2 are filtered as 4 bands each say (A1, A2, A3, A4) and "(B1, B2, B3, B4) in that order.
    b. Calculate M11 and M12 by filtering (convolving) M1 with F1 and F2 filters correspondingly.
    c. A1 is calculated by filtering M11 with F1 filter.
    d. A2 is calculated by filtering M11 with F2 filter.
    e. A3 is calculated by filtering M12 with F1 filter.
    f. A4 is calculated by filtering M12 with F2 filter.
    g. Similarly B1, B2, B3 and B4 are calculate for M2 in the case of M1 imagery levels.
    h. Three set of coefficient matrices are formed in this wavelet transform method, say E1, E2 and E3.
    i. E1 is calculated with respect to A1 and B1; E2 is calculated with respect to A2 and B2; E3 is calculated with respect to A3 and B3 using either of the following methods,
        i. Select Maximum
        ii. Burts' Method
        iii. Lis Method.
    j. The coefficient matrices of the level are retained as E1 [level], E2 [level] and E3 [level] respectively.
    k. The matrices A4 and B4 will respectively act as the input image of the next level of decomposition as M1 and M2.
12. The A4 and B4 matrices obtained in the final level of decomposition are manipulated as one of the following, producing X matrix.
    a. Average M1 and M2
    b. Select Maximum in M1 and M2
    c. Select Minimum in M1 and M2
13. The recomposition process makes use of reversed filters F1 and F2 wherein the column order of the filters are reversed, making the first element the last and so on.
14. Recomposition
    a. Row wise filtering is performed in steps b, c, d and e.
    b. Input matrix X to this level of recomposition is filtered with F1 filter producing X1.
    c. X2 is calculated by filtering co-efficient matrix E1 [level] with F2 filter.
    d. X3 is calculated by filtering co-efficient matrix E2 [level] with F1 filter.
    e. X4 is calculated by filtering co-efficient matrix E3 [level] with F2 filter.
    f. Column wise filtering is performed in steps g and h.
    g. Filtered matrix Z1 is calculated by filtering (convolving) added matrices (X1 +X2) with F2 filter.
    h. Filtered matrix Z2 is calculated by filtering added matrices (X3 + X4) with F1 filter.
    i. Here (Z1+Z2) will act as the input to next intensity of recomposition and finally act as Fused output image matrix at the final level of the process.

4. RESULTS AND DISCUSSIONS

4.1 Image Quality Metrics

Image Quality is a feature of an image that measures the supposed to help in image degradation (characteristically, compared to a similar or perfect input image). Imaging fusion systems may bring in some amount of distortion or artifact in the signal, so that quality estimation is an important problem of identification. There are numerous techniques and metrics that can be calculated without bias and automatically it is evaluated by a computer program. As a result, they can be divided as Full Reference Methods (FR) and No-Reference Methods (NR). In FR method image quality evaluation methods, the value of a test input image is evaluated by validating it with a reference image that is understood to have a perfect quality image. NR metrics attempt to evaluate the quality of an image not including any of the reference to original input one.

The image quality indices try to figure out the some or the combination of the various factors that determine the quality of the image. Some of the critical factors that the image quality metrics try to project are:
Sharpness, Noise, Colour Accuracy, Distortion, Exposure Accuracy, Colour, Artifacts

Mean Square Error	$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(x_{j,k} - x'_{j,k}\right)^2$
Peak Signal to Noise Ratio	$PSNR = 10\log\frac{(2^n-1)^2}{MSE} = 10\log\frac{255^2}{MSE}$
Normalized Cross-Correlation	$NK = \sum_{j=1}^{M}\sum_{k=1}^{N} x_{j,k}\cdot x'_{j,k} \Big/ \sum_{j=1}^{M}\sum_{k=1}^{N} x_{j,k}^2$
Average Difference	$AD = \sum_{j=1}^{M}\sum_{k=1}^{N}\left(x_{j,k} - x'_{j,k}\right) \Big/ MN$
Structural Content	$SC = \sum_{j=1}^{M}\sum_{k=1}^{N} x_{j,k}^2 \Big/ \sum_{j=1}^{M}\sum_{k=1}^{N} {x'_{j,k}}^2$
Maximum Difference	$MD = Max\left(\left\lvert x_{j,k} - x'_{j,k}\right\rvert\right)$
Normalized Absolute Error	$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\lvert A_{ij} - B_{ij}\rvert\right)}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij}\right)}$
Structural Similarity Index Metric	$SSIM = mean\left(\left(2\times\mu_1\mu_2 + C_1\right)\cdot*\left(2\times\sigma_{12} + C_2\right)\cdot/\left(\left(\mu_1^2+\mu_2^2+C_1\right)\cdot*\left(\sigma_1^2+\sigma_2^2+C_1\right)\right)\right)$

Table 1: Image Quality Metrics

4.2 Sample Fused Images

Here, the input images consist of a pair of Aero-planes; either of them remain of the images blurring the other respectively. These are typically called multi-focus input images.

Fig 4.1: Input Images (Airplanes)

Fig 4.2: Fused Image by Average and Maximum Method

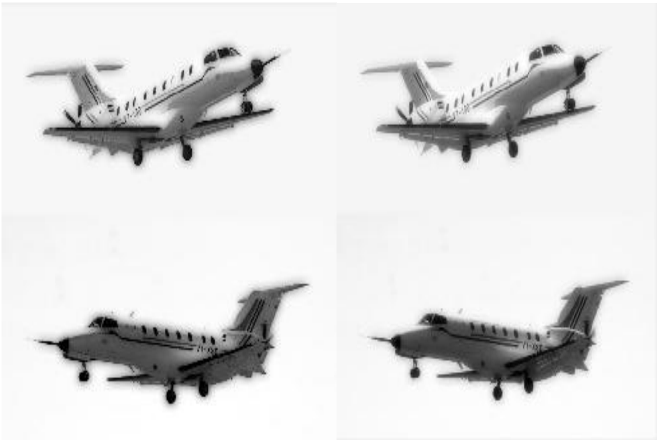

Fig 4.3: Fused Image by Minimum and PCA Method

Fig 4.4: Fused Image by Laplacian Pyramid and Filter Subtract Decimate Pyramid Fusion

Fig 4.5: Fused Image Ratio and Morphological Pyramid Method

Fig 4.6: Fused Image by DWT with Haar and DBSS (2, 2) Method

Here, the input images are a pair of medical images, with one of them being a CT scan and the other being MR scan.

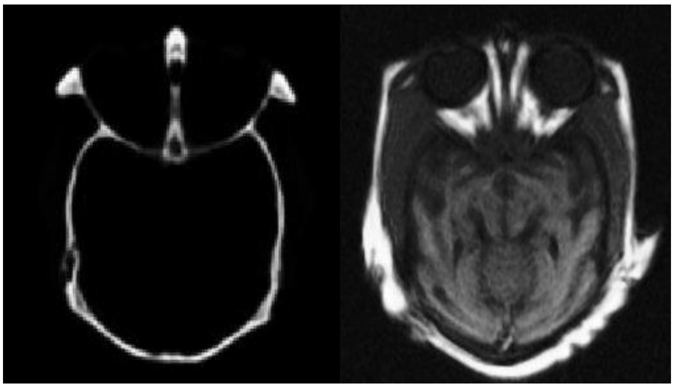

Fig 4.7: Input Images (Medical)

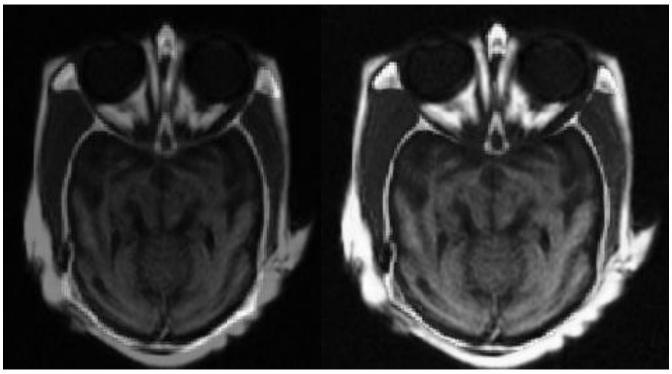

Fig 4.8: Fused Image by Average Maximum Method

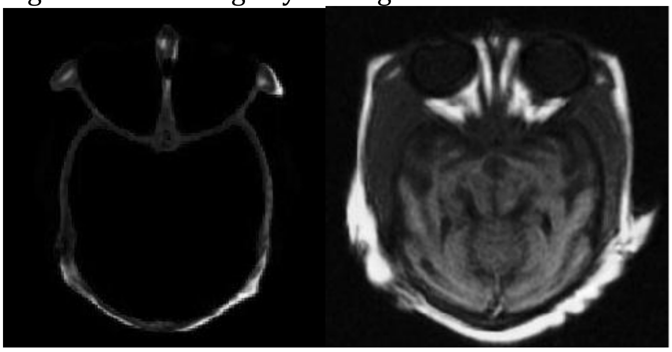

Fig 4.9: Fused Image by Minimum and PCA Method

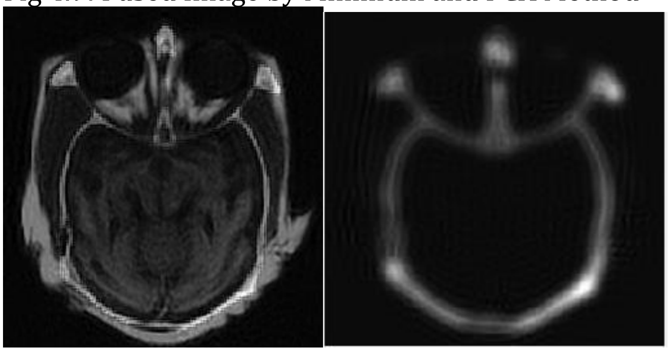

Fig 4.10: Fused Image by Laplacian Pyramid and Filter Subtract Decimate Pyramid Fusion

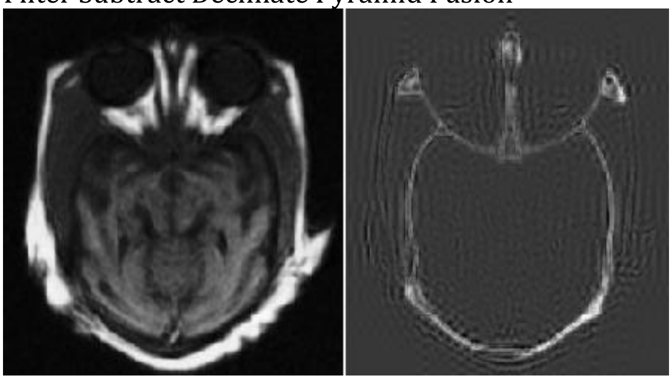

Fig 4.11: Fused Image Ratio and Morphological Pyramid Method

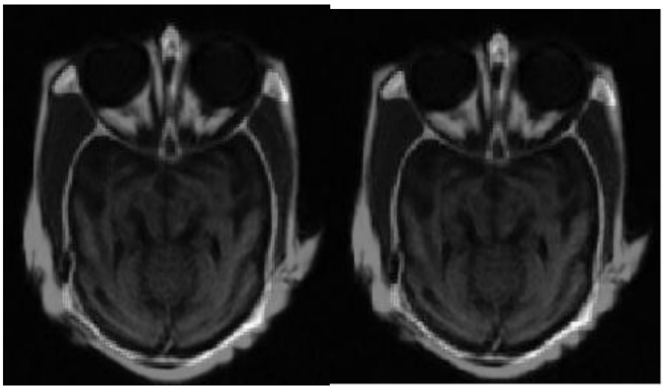

Fig 4.12: Fused Image by DWT with Haar and DBSS (2, 2) Method

4.3 Inference

Now that the sample set of input images are fused, the quality of the same have to be assessed based on the image metrics discussed previously. In the previous section, the image metric reading for each of the fused image using various fusion methods was shown. To assess the quality of the fused image produced by the various fusion methods, the various image metric readings for each fusion method are ranked.

We have discussed two sets of input and fused images in this report. The 10 fused images produced in each set are applied upon with the 8 image metric and the readings recorded. Therefore, for each set, there are 3 image metrics applied on the 10 fusion methods. The readings of an image metric for each of the fusion methods are ranked. Thus each set would produce 2 rank lists for the 10 fusion methods. The 3 rank lists are put together to bring up an overall rank list for the image set.

Likewise, the same process is repeated for all the two sets of input and fused images. So, finally we arrive upon three overall ranking lists for the 10 fusion methods. The two ranking lists are combined together to bring up the final ranking for each of the image fusion algorithm. Here, the inference is made based on three sets of input and fused images. It would be a better picture if more such set of images are considered.

Set 1: Considering the first set of images (pair of Aero-planes), the following table summarizes the various image metric reading for the images fused with various fusion algorithms.

Metrics / Fusion Method	SC	AD	MD	MSE	PSNR	SSIM	NCC	NAE
1.Average	1.0023	-0.0195	106.5	119.96	62.95	0.9213	0.997	0.00072
2.Maximum	0.9758	-4.2543	213	227.87	56.53	0.9185	1.007	0.00069
3.Minimum	1.0254	4.2152	190	251.99	55.53	0.9240	0.9992	0.00075
4.PCA	1.0023	-0.0194	106.68	120.38	62.918	0.9213	0.9997	0.00072
5.Laplacian Pyramid	1.0053	0.41297	176	0.4429	60.0921	0.9213	1.0002	0.00235
6.FSD Pyramid	0.00032	0	0	0	-18.960	0.4376	2.2159	1.2158
7.Ratio Pyramid	0.00031	0	0	0	-19.306	0.4290	2.3671	1.367
8.Morphological Pyramid	0.0050	0.4806	159	0.4890	58.0213	0.92388	0.9990	0.00406
9.Haar Wavelet	1.0023	-0.0195	106.5	119.96	62.952	0.9213	0.9997	0.00072
10.DBSS (2, 2) Wavelet	0.0049	0.3045	95	0.3320	62.952	0.9213	0.9997	0.00072

Table 4.2: Image Metric reading for the various fusion methods for images of Set 1.

Set 2: Considering the Second set of images(MRI and CT Scans), the following table summarizes the various image metric reading for the images fused with various fusion algorithms.

Metrics / Fusion Method	SC	AD	MD	MSE	PSNR	SSIM	NCC	NAE
1.Average	2.7725	22.5144	127.5	1600.44	37.044	1	1	.0023
2.Maximum	0.8507	-5.3426	255	5744.10 1	24.266	0.999	1	.0023
3.Minimum	18.95	50.37	243	657.67	45.93	1	1	0.012
4.PCA	1.1055	2.4842	240.93	5714.9	24.31	.999	1	.0023
5.Laplacian Pyramid	1.253	0.9960	131	0.876	37.0043	1	1	.0025
6.FSD Pyramid	.0766	.9960	159	.9432	40.25	1	1	.0027
7.Ratio Pyramid	.00765	.0130	28	.03949	9.671	.9993	1	.0022
8.Morphological Pyramid	.5771	.9960	255	.9874	47.88	1	1	.003
9.Haar Wavelet	2.7725	22.51	127.5	1600.44	37.04	1	1	.0023
10.DBSS (2, 2) Wavelet	.09974	.9960	122	.8816	37.044	1	1	.0023

Table 4.3: Image Metric reading for the various fusion methods for images of Set 2

In the following table, we combine the rank lists of the three sets of images to arrive at the overall ranking of the various image fusion methods based on visual perception of 5 people selected in random.

	Set 1 Rank	Set 2 Rank	Rank Total	Overall Rank
1.Average	2	6	8	3
2.Maximum	8	10	18	7
3.Minimum	6	7	13	10
4.PCA	3	5	8	5
5.Laplacian Pyramid	5	1	6	2
6.FSD Pyramid	9	9	18	9
7.Ratio Pyramid	10	8	18	8
8.Morphological Pyramid	7	2	9	6
9.Haar Wavelet	1	3	4	1

Table 4.4: Overall ranking for the based on the visual perception of 5 people selected in random

4.4 ImFus GUI Toolkit

ImFus [15] -as it is called, the image fusion toolkit was developed using Visual C++ 6.0 provided with a Graphical User Interface. This section tries to explain the GUI of the toolkit and the options for setting the parameters involved in the various image fusion algorithms implemented.
The following is a sample empty GUI window of the ImFus toolkit.

ImFus GUI ToolKit

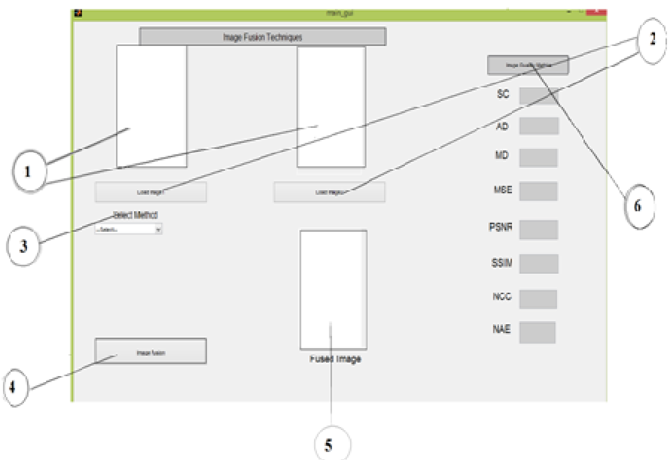

Figure 4.13: Imfus GUI Toolkit

5. CONCLUSIONS

The ten image fusion techniques were implemented using Mat lab. The fusion was performed on two sets of input pair of images. The fused images were verified for their quality based on a perfect image in each of the sets. From these total of ten image fusion techniques, three very basic fusion techniques were Averaging fusion Method, Maximum and Minimum Selection Method, PCA, four pyramidal methods are FSD Pyramid, Laplacian Fusion Pyramid, Ratio Fusion Pyramid and Morphological Fusion Pyramid Methods and two of basic wavelet methods are Haar and DBSS(2,2) Wavelet Methods. By the means of the 8 image metrics developed – AD, MSE, PSNR, SC, NCC, MD, NAE and SSIM. Haar Wavelet method was assessed the better algorithm compared to other algorithms, Laplacian Pyramid Fusion is second best algorithm. The assessment based on the 8 image metrics readings saw that the fused images produced by Ratio Pyramid Method and Morphological Pyramid Method were the most inferior in quality with respect to the perfect images considered in each of the two sample pairs of input images.

The finding and conclusion here may not be the perfect one. The inference will be more concrete if the experiments are performed extensively on many more set of input images and a perfect image. On the more sample data the experiments are performed upon, the better accurate would be the conclusion. Another fact is that though the fusion algorithms were able to be assessed for multi focal and Medical (MRI and CT) input image pairs, the same was not performed on Satellite images due to unavailability of perfect images in the public domain.

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REFERENCES

[1]. Haghighat, Mohammad Bagher Akbari, Ali Aghagolzadeh, and Hadi Seyedarabi. “Real-time fusion of multi-focus images for visual sensor networks”.published in Machine Vision and Image Processing (MVIP), 2010 6th Iranian, pp. 1-6. IEEE, 2010.
[2]. Liu, Haifeng, Mike Deng, Chuangbai Xiao, and Xiao Xu. “Image fusion algorithm based on adaptive weighted coefficients”. Submitted in Signal Processing (ICSP), 2010 IEEE 10th International Conference on, pp. 748-751. IEEE, 2010.
[3]. Cao, Jian-zhong, Zuo-feng Zhou, Hao Wang, and Wei-hua Liu. “Multifocus Noisy Image Fusion Algorithm Using the Contourlet Transform”. Published in Multimedia Technology (ICMT), 2010 International Conference on, pp. 1-4. IEEE, 2010.

[4]. Pei, Yijian, et al. "The improved wavelet transform based image fusion algorithm and the quality assessment".Submitted in Image and Signal Processing (CISP), 2010 3rd International Congress on. Vol. 1. IEEE, 2010.

[5]. Ren, Haozheng, Yihua Lan, and Yong Zhang. "Research of multi-focus image fusion based on M-band multi-wavelet transformation". Published in Advanced Computational Intelligence (IWACI), 2011 Fourth International Workshop on, pp. 395-398. IEEE, 2011.

[6]. Mohamed, M. A., and B. M. El-Den. "Implementation of image fusion techniques for multi-focus images using FPGA". Submitted in Radio Science Conference (NRSC), 2011 28th National, pp. 1-11. IEEE, 2011.

[7]. Albuquerque, Hugo R., Tsang Ing Ren, and George DC Cavalcanti. "Image Fusion Combining Frequency Domain Techniques Based on Focus". Published in Tools with Artificial Intelligence (ICTAI), 2012 IEEE 24th International Conference on. Vol. 1. IEEE, 2012.

[8]. Parmar, K., & Kher, R. (2012, May). "A comparative analysis of multimodality medical image fusion methods". In Modelling Symposium (AMS), 2012 Sixth Asia (pp. 93-97). IEEE.

[9]. Desale, Rajenda Pandit, and Sarita V. Verma. "Study and analysis of PCA, DCT & DWT based image fusion techniques". Submitted in Signal Processing Image Processing & Pattern Recognition (ICSIPR), 2013 International Conference on, pp. 66-69. IEEE, 2013

[10]. http://en.wikipedia.org/wiki/Image_fusion

[11]. Lindsay I Smith, "A Tutorial on Principal Component Analysis",http://www.cs.otago.ac.nz/cosc453/student_tutorials/principal_components.pdf

[12]."DiscreteWaveletTransform",http://en.wikipedia.org/wiki/Discrete_wavelet_transform

[13]."HaarWavelet",http://en.wikipedia.org/wiki/Haar_wavelet

[14]."DaubechiesWavelets",http://en.wikipedia.org/wiki/Daubechies_wavelet

[15]. FuseTool – An Image Fusion Toolbox for Matlab 5.x ..http://www.metapix.de/toolbox.htm

[16]. www.imagefusion.org

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