A project report on

ENHANCED IMAGE RESTORATION THROUGH FUSION: BLUR ROI APPROACH

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In

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Submitted by:

Pramod Kumar Tiwari

(2K15/ISY/13)

Under the guidance of

Dr. O.P. Verma

(Professor, Department of Computer Science and Engineering, DTU)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

Bawana Road, Delhi-110042

Certificate

This is to certify that **Pramod Kumar Tiwari (2K15/ISY/13)** has carried out the major project entitled "**Enhanced Image Restoration Through Fusion: Blur ROI Approach**" in partial fulfillment of the requirement for the award of Master of Technology Degree in Information System during session 2015-2017 at Delhi Technical University.

The major project bonafide piece of work carried out and completed under my supervision and guidance. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

Dr. O.P. Verma

Professor

Department of Computer Science and Engineering

Delhi Technical University

Delhi - 110042

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Pramod Kumar Tiwari

Roll No. 2K15/ISY/13

M.Tech (Information System)

Department of Computer Science and Engineering

Delhi Technical University

Abstract

Image fusion is the technique of joining two or more images for best conditional awareness. Fusing process takes the important feature from one image and combines with best feature of other images. This experiment present a pixel level image fusion of multi-focus images based on the two-stage fuzzy fusion. In this approach, we first applied two different fusion approaches on the input image, and then applied fuzzy fusion approach on the output of the previous stage. Performance of this approach, output of fusion image is degraded where focused area in source image and good to blur area of source image. Blur are two types: defocus blur which is caused by imaging systems and motion blur caused by the relative motion between camera and objects. The proposed approach is applicable on the defocused blur images, images are taken in the focused and blur region segmentation by Local Binary Pattern (LBP) based and then find intersection blur region of source image, then finally applied two stage fuzzy fusion approach on blur region. And output of fusion result is combined to focused area of source images. The experiment result of proposed approach is enhances image quality compare to other available fusion approach.

Content

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Overview: Image Fusion

With the development of multiple types of sensors such as chemical sensors, remote sensors, on board satellites and more data have become available for scientific researches. As the volume of data grows, need to combine data gathered from different sources to extract the most useful information. Different terms such as data analysis, data integrating have been used. Since early 1990's, "Data fusion" has been widely used.

- Data fusion is a process dealing with data and information from multiple sources/sensors to achieve refined/improved information for decision taking.
- Image fusion is the combination of two or more different view angle images to form a new image by using a certain algorithm.
- Image fusion is the process of combining information from two or more images of a scene into a single image that is more informative and decision making.

Generally speaking, data fusion is the information of a specific scenario acquired by two or more sensors at the same time or separate times is combined to generate the scenario; those are not obtainable from a single sensor. The data fusion and image fusion in the hole-part relationship, image fusion is part of data fusion. Image fusion has most important algorithms to use the very big volume of data those are received by different sources. Multiple image fusion seeks to collect the information from multiple sources to achieve more informative data that information is not possible from a single source.

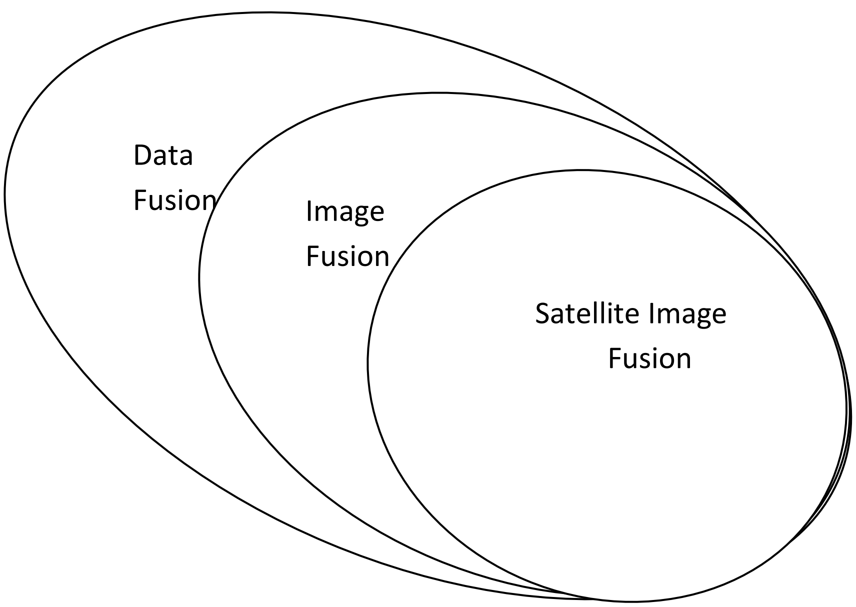


Fig.1. Illustration of relationship of data fusion and image fusion

Image fusion is the process of combining information from two or more images of a same scene into a single composite image that is more suitable visualization and decision making. Image fusions are wildly applied in many areas such as medical and military areas etc. In military applications image fusion used in navigation and surveillance systems.

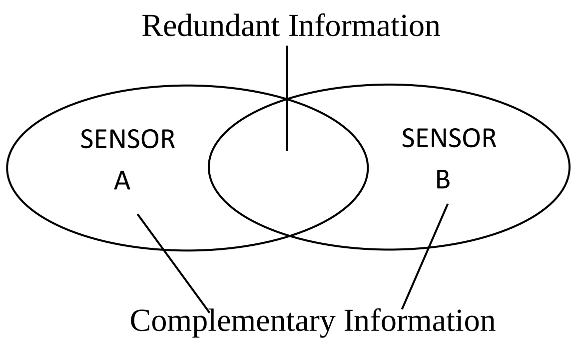


Fig. 2 Image Fusion Concept

The fuzzy logic approach [1] is combined the two or more images from different sensors and enhance to better navigations. Sensor fusion is used extensively in military applications and it is attracting the attention in army research and development.

1.2 Fusion Categories

The basic fusion strategy is the acquisition or gaining feature from different images. In other words, it's combination of image together. Figure 3 illustrates of the different categories of the fusion.

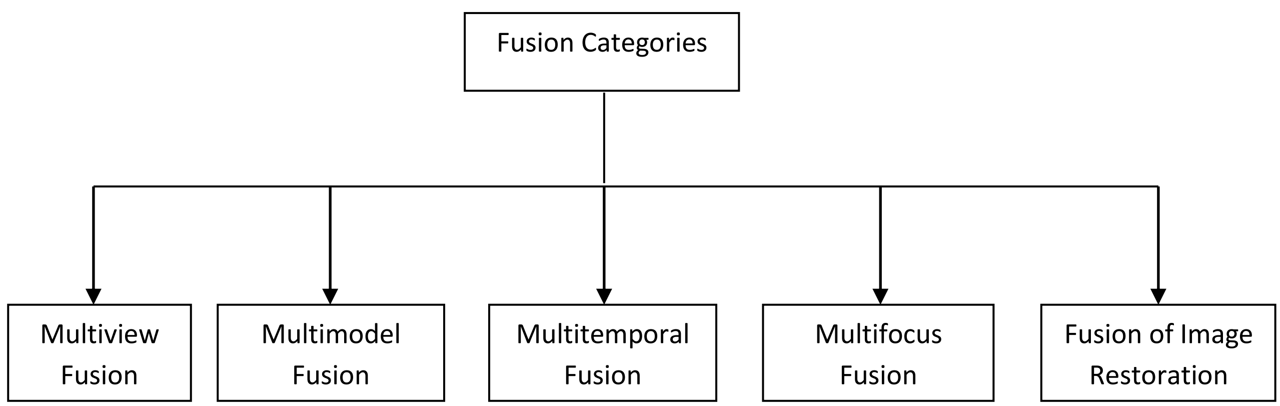


Fig. 3: Categories of Image fusion

1.2.1 Multiview Fusion

If two or more than two image of same modality on same time but different location of different view angle and these images taken as source image for fusion process, this fusion process known as multiview fusion.

Goal: This is given the combined information from different view angle.

1.2.2 Multimodel Fusion

If two or more than two image of different modality on same time or different time such as PET, CT, MRI and these images taken as source image for fusion process, this fusion process known as multimodel fusion.

Goal: This is given the specific information or stress on point of different mode and decrease the amount of data,

1.2.3 Multitemporal Fusion

If two or more than two image of same scene or same mode at different time and these images taken as source image for fusion process, this fusion process known as multitemporal fusion.

Goal: This is given the detection of change in source images.

1.2.4 Multifocus Fusion

If the original image divided in different part and in each part atleast one focus area, these focus area combined together or these images region taken as source image for fusion process, this fusion process known as multitfocus fusion.

Goal: This is given the highly focus images.

1.2.5 Fusion of Image Restoration

If the source image consists of focus part and blurs part and these blur part (degradation part of image) is removed or overcome by fusion process, this fusion process known as fusion of image restoration.

Goal: This is given the high resolution or highly focus image from several low resolution images.

1.3 Categorization of image fusion techniques

Image fusion is generally applied at three different level such as pixel level, feature level and decision level. Figure 4 illustrates of the concept of the four different fusion stages.

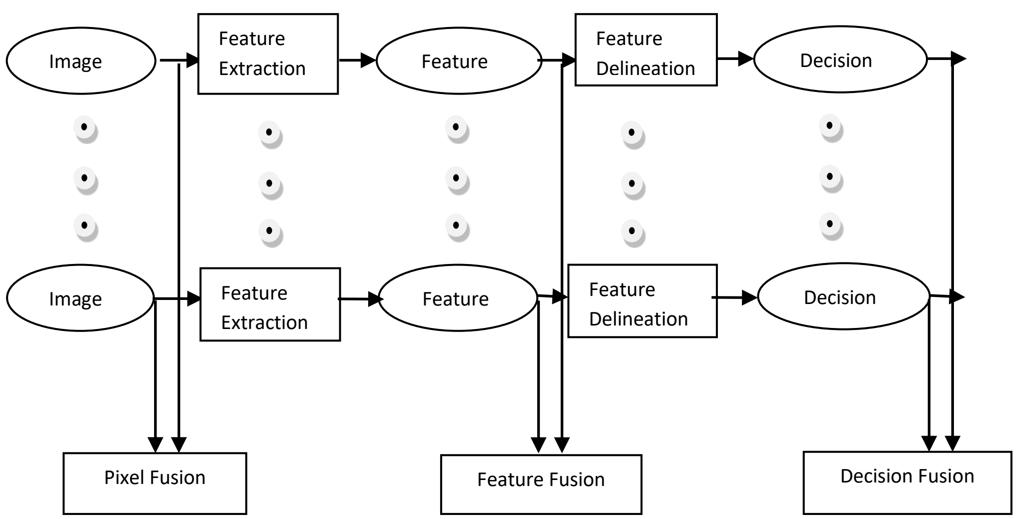


Fig. 4. An overview of categorization of the Image fusion Technique

1.3.1 Pixel Level Image Fusion

Pixel-level image fusion is applied on individual pixel. It's find a fused image where information combining with each pixel is determined from a corresponding pixels location in source images.

Pixel level fusion is join the raw data from two or more than two source images into a single image. In pixel level fusion the fused pixel is calculated from a set of input image pixels.

1.3.2 Feature Level Image Fusion

Feature-level image fusion required to find out of objects in the various data sources received information. It required finding the features which are depending on pixel intensities, edges and other various environments. These similar features from input images are fused and construct the output feature.

In other word, Feature level fusion requires the finding of various features from the different source image before features are merged together for construct fused information.

1.3.3 Decision Level Image Fusion

Decision-based image fusion is consists of combining information at a higher level of abstraction results, combines the results from multiple algorithms to find a final fused decision level image fusion.

Decision-level fusion takes sensor information fusion, those are preliminary determinate. In decision level fusion the multiple algorithms results are combining together and find a final fused decision level fused image.

In signal-level image fusion, signals from various source/sensors are together and create a new signal with enhanced signal-to noise ratio. In the Pixel-level image fusion takes place directly at the every pixel location of source image. The pixel level is calculated by intensity values of every pixel in source images and taken as the corresponding intensity value of the pixel in output image. The image fusion approaches in sensor image are principal component analysis fusion [2], wavelet transform (WT) fusion [3], multiplicative fusion, additive fusion [4], and fuzzy fusion [5]. Comparison of various methods with fuzzy logic, this is fused various regions of the image, depending on the focused and blur region of the target. The fuzzy logic approach result in output images with higher intensity focused region and low pixel intensity regions. The various of images required for taking the complete information of single object, so we fused multiple input images to one output image.

The multi sensor image fusion systems are widely increasing the importance of various applications such as military and civilian. A single sensor only provides the limited feature about the environment or the specific object, but multiple sensors are given the sufficient useful information specific object or environment. The heterogeneous sensors also are combined using image fusion methods to obtain more detailed information about the environment. Thus, the benefits of multi-sensor image fusion systems are to more suitable for machine learning and enhance visibility of the object with compare as received the visibility stage of single sensor image fusion system.

1.4 Local Binary Pattern

In last few years, Local Binary Patterns (LBP) widely increases the interest in computer vision and image processing. The local binary pattern has refines local structures of images by comparing the each pixel with its eight neighborhood pixels in 3*3 neighboring scenario. The most effective feature of Local Binary Pattern is its tolerance regarding highly fluctuating in intensity value and it's also a computational simplicity. LBP was initially applied for texture analysis but now a day it has been extensively explored in various areas, such as, biomedical and image analysis, remote sensing, face image analysis, environment modeling, image retrieval and video retrieval, visual inspection, motion analysis.

In recent years, the one of most important and successful applications in LBP-based approach is facial image analysis. Facial image analysis is aroused increasing interest to research topic in computer vision, biometric identification, human-computer interaction, security, surveillance and computer animation etc. Local Binary Pattern has been exploited in the different tasks of facial representation such as face detection, facial expression analysis, face recognition, classification.

Defocus blur and motion blur is very common in images capturing in optical imaging systems. It is mostly undesirable, but in somewhere this is intentionally by artistic. The purpose of separate of blurred and non-blurred regions segmentation in defocus blur also utilized the concept of Local Binary Patterns (LBP).

1.5 Thesis Objective and Scope

Two-stage fuzzy fusion (TSFF) [6] method that joins two or more than two images without increased the complexity. The proposed approach is also enhancing the fusion outputs of other approaches. In first stage input images are joined using additive and multiplicative image fusion approach. In second stage fuzzy fusion approach is applied on the output of the first stage fusion. The output of two-stage fusion, an enhanced fused image with highly focused region is produced. But Output is degraded in focused region of source image and enhance in blur region of source image. For increasing the performance of two-stage fuzzy fusion approach, we segment the blurred and non-blurred regions in single image. Our described method only works on the defocus (out-of-focus) blur and provides useful high-level focus region and blur region. These blur regions is applied in image fusion for enhancing visualization of result of two state fuzzy fusion.

1.6 Thesis Outline

The rest of the thesis is outlined in this section. In Second chapter, the background of image fusion and the background of defocused segmentation are discussed. Third chapter discusses the different approach of image fusion and blur region segmentation. Fourth chapter discusses the implementation of two stage image fusion and LBP blur segmentation. In Fifth chapter discuss on experiment results and evaluation criteria. Finally, discussion with conclusion and the scope for the future work in chapter six.

Chapter 2
Literature Survey

2.1 Image Fusion

In during previous years, it has been very frequently used in various areas such as object recognition, area surveillance object detection and enhancement of visibility. Hall and Llinas give an introduction on multi-sensor data fusion [7], in 1997. In 1998, another review article on multiple sensors data fusion techniques [8] and in this paper discussed the image fusion methods, concepts, and various applications of multi-sensor image fusion. After that, the image fusion has widely increase attention. And another scientific paper on image fusion has been basically focused on finding more application areas and improving fusion quality. Vijayaraj explained the concepts of various image fusions in remote sensing applications [9]. In recently, the few papers have been focused on provides the history, developments, and the current state of image fusion, but current development of multi-sensor data fusion on the base of blur region segmentation has not been discussed in detail.

During the previous two to three decades, there are several image fusion algorithms are proposed. The many of these algorithms are based on the pixel based image fusion and some are feature based. Among the various image fusion techniques, the widely used methods include principal component analysis (PCA), different arithmetic combination (Averaging, Additive, Multiplicative methods), multi-resolution analysis-based wavelet transform methods and Artificial Neural Networks (ANNs), etc.

2.2 Defocus Segmentation

The resultant of -of-focus optical imaging system is the defocus blur in an imaged. In the image construction process, there are some circle of confusion because in between light radiating from points on the focus plane are mapped to a point in the sensor and light from a point outside the focus plane illuminates a non-point region on the sensor. When this circle becomes large enough to be perceived by human eyes then resulted in defocus blur.

Many blur detection techniques are available on edge sharpness information. But here are cannot distinguish the blurred/non-blurred image regions or the type of image blurs in edge sharpness based methods. The local sharpness measurement is most commonly seen approach for defocus segmentation. In last two decades, there are many works in this area and most of them can be found quality assessment. These applications in single image only require a single sharpness value. Some image structures used the complex wavelet transform domain.

The aim of this thesis is to explore the two stage image fusion process for increase the visibility for blurred image. But exploration of blur region is required to image segmentation in blur and non-blur region, therefore we explore the blur region detection technique such as local binary pattern (LBP) based. The local binary pattern blur detection technique is one of the mostly used techniques in blur region segmentation.

Chapter 3
Various Approaches of Image Fusion and Blur Segmentation

3.1 Overview

Image fusion is a process to join the information from two or more than two images of a same scene and construct into a single image those have more information and is more visible. The blur segmentation is the separation of focus and non-focus region in the image. Here are various image fusion approach explained in the section 3.2 and in section 3.3 explained the blur segmentation technique.

3.2 Image Fusion Approaches

3.2.1 Arithmetic Image Fusion

In the arithmetic image fusion, require mathematical calculation on every pixel on source image and construct the fused image. Here are various technique explained in this section under arithmetic image fusion.

3.2.1.1 Pixel Level Average Image Fusion

This technique is a very simple and straight forward technique, for fused image do the simple averaging of corresponding pixel of source images. The equation as:

$$I(i,j) = \frac{I_1(i,j)+\cdots+I_n(i,j)}{n} \tag{1}$$

Where, I_1 to I_n is the input images.

3.2.1.2 Pixel Level Weighted Average Method

In this method, we have added some weight in input image and perform as same pixel level average method. Here is also for fused image do the simple averaging of corresponding pixel of source images with multiply of some assigned weight. The equation for pixel level weighted average method as:

$$I(i,j) = \frac{W_1 * I_1(i,j)+\cdots+W_n I_n(i,j)}{n} \tag{2}$$

Where, W_1 and W_n are the weights those are assigned with input images.

3.2.1.3 Select Maximum/Minimum Method

Maxima

The greater pixel values are exist where highly focus region in image. So, in this algorithm select the highly pixel intensity regions from each input image by choosing the highest pixel value for each pixel comparison with other source images pixel value, resulting in more focused fused image. The intensity value of the pixel I (i, j) of each image is taken and compared with other input image corresponding pixel intensity value, chose the max pixel value among them and take place on same pixel location value of fused image. The equation as:

$$I(i,j) = \max\{I_1(i,j), \dots, I_n(i,j) \qquad (3)$$

Where, I_1 to I_n is the source images

Minima

The lowest pixel values are exist where low focus region in image. So, in this algorithm select the lowest pixel intensity regions from each input image by choosing the lowest pixel value comparison with other source images pixel value, resulting in fused image. The intensity value of the pixel I (i, j) of each image is taken and compared with other input image corresponding pixel intensity value, chose the min pixel value among them and take place on same pixel location value of fused image. The equation as:

$$I(i,j) = \min\{I_1(i,j), \dots, I_n(i,j) \qquad (4)$$

Where, I1 to In is the source images

3.2.1.4 Multiplication Method

The multiplicative image fusion improves the detection, visualization and localization of the targets. The value of the pixel location I (m, n) of each image is taken and multiplied with others. This result is rooted by n (number of input image) to find the actual of pixel value of location I (m, n), and this is repeated for all pixel location of image values. Equation for multiplicative image fusion as:

$$I(m,n) = \sqrt[n]{I_1(m,n) * \dots \dots * I_n(m,n)} \qquad (5)$$

Where, n is the number of input images

3.2.2 Fuzzy Based Image Fusion

The fuzzy logic image fusion algorithm for pixel level using the process of membership functions, rules and difuzzification for the image fusion process.

Algorithm:

- First the image 1 and image 2 in variable M1 and M2 with size of (i1, j1) and (i2, j2) respectively.

- These images converted in to gray image if originally in RGB mode and each pixel value is in the range from 0-255.

- Compare the both images are same size (i1 == i2 & j1 == j2), if not then select the portion, which are the same size.

- Convert the matrix in column form row*column.

- Define the type and number of membership functions for all source images by applying membership functions. Input images pixel value (0 to 255) is converted into the membership function.

- Define the fuzzy rules for source images membership value, which compute the one output membership value from two input membership value.

- Finally applied the defuzzification process on output membership value, those are computed in previous step. In defuzzicication process is converted intensity pixel value (0 to 255) from the membership values.

- Then convert the column form to row*column matrix form and construct the output fused image.

3.2.4 PCA Based Image Fusion

Principal component analysis (PCA) is a well-known scheme for various applications such as extraction of feature and reduction of dimensions and it is widely used in image fusion process. The algorithm for PCA based fusion as fallow:

Algorithm:

- The input image matrixes are converted from data to column vectors.
- Then find out the empirical mean (M_e) of each column for all source images.
- Subtracting the empirical mean vector (M_e) from all column of the data matrix. The result is X.
- Compute the covariance matrix C = cov(X).
- Compute the eigenvectors V and eigenvalue D

$$P_1 = \frac{V(1)}{\sum v} \quad \text{and} \quad P_2 = \frac{V(2)}{\sum v} \tag{6}$$

- The equation for fused image is:

$$I(i,j) = P_1 I_1(i,j) + P_2 I_2(i,j) \tag{7}$$

3.2.5 WT Based Fusion

The algorithm of image fusion using discrete wavelet transform has the following steps those are applicable to image fusion method:

- Read the input images.
- Convert to Gray scale image, if they in RGB.
- Convert into the double precision format for accurate calculation.
- Compute the discrete wavelet transform of all input images (figure 5).

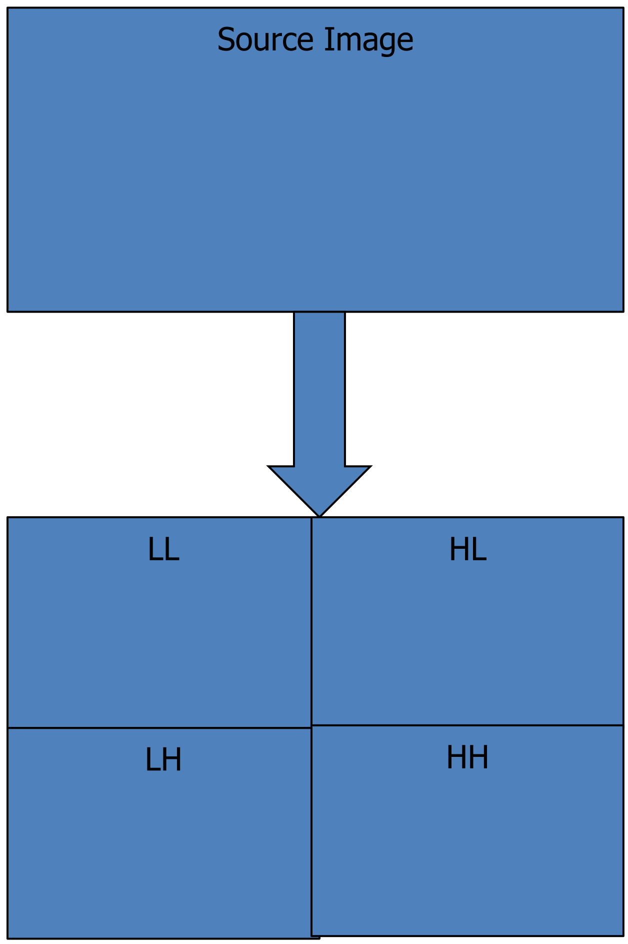


Fig. 5: Image conversion to DWT

- Let for first image OUT bands be HH_a, HL_a, LH_a, LL_a and for the second image is HH_b, HL_b, LH_b, LL_b.
- For fusion have two option
- **Option 1:** Image fusion using Maximum Pixel replacement

$$HH_f = \max(HH_a, HH_b) \tag{8}$$

$$HL_f = \max(HL_a, HL_b) \tag{9}$$

$$LH_f = \max(LH_a, LH_b) \tag{10}$$

$$LL_f = \max(LL_a, LL_b) \tag{11}$$

- **Option 2**: Image Fusion using Pixels Averaging

$$HH_f = \frac{HH_a + HH_b}{2} \tag{12}$$

$$HL_f = \frac{HL_a + HL_b}{2} \tag{13}$$

$$LH_f = \frac{LH_a + LH_b}{2} \tag{14}$$

$$LL_f = \frac{LL_a + LL_b}{2} \tag{15}$$

- We find the new coefficient is HH_f, HL_f, LH_f and LL_f.
- Compute the inverse discrete wavelet transform.

And then we construct the fused image.

3.3 Blur Segmentation Approaches

There are two type of blur exists in the many digital images such as defocus blue and motion blur and various approaches available for detection of these blur. The some important approaches explain in this section.

3.3.1 Singular Vector Feature

The Singular value decomposition (SVD) is most important techniques in linear algebra. The SAD is applied to different computer science area.

Suppose **M** is $m \times n$ matrix and its singular value decomposition representation of **M**

$$M = U \sum V^* \tag{16}$$

Where, **U** is $m \times m$, unitary matrix or orthogonal matrices

Σ is a diagonal $m \times n$ matrix

V is a $n \times n$ orthogonal matrices.

$\mathbf{V}^*$ is the transpose of the $n \times n$ orthogonal matrix, $\mathbf{V}$, thus also a orthogonal matrices.

The image can be decomposed into multiple ranks 1 matrix as follows:

$$I = \sum_{i=1}^{n} \mu_i x_i {y_i}^t \quad (17)$$

Where, x_i is the column vector of U, y_i, is the column vector of V and μ_i is the diagonal terms of $\sum$.

Compute blue degree T as:

$$T = \frac{\sum_{i=1}^{k} \mu_i}{\sum_{i=1}^{n} \mu_i} \quad (18)$$

Where, μ_i is represents the singular value that is calculated in patch of local image for all image pixel, k is the highest significant singular value and n is all singular values.

This feature is representing the ration between them and the blurred image areas have a more blur degree than threshold value compared with clear image regions value. The image region will be classified, if $\beta 1$ is larger than a threshold then this is blurred region, otherwise, it will be consider a non-blurred region.

3.3.2 Wavelet Based Histogram

The gradient histograms should be applied as determined features for non-blurred and blurred regions of images. Perform three steps for feature extraction in gradient histograms such as wavelet decomposition of the all source image, calculate the wavelet gradient map and then finally construct the gradient histograms.

For the decomposition of source image:

- Initially apply low-pass filter and high-pass filters on image rows for extracting the image variations in horizontally.
- Same filters is used to the columns on previous results for extracting diagonal and vertical changes.
- Compute vertical, horizontal and diagonal wavelet maps and one approximation map (LL) after applied wavelet transform on previous step output.

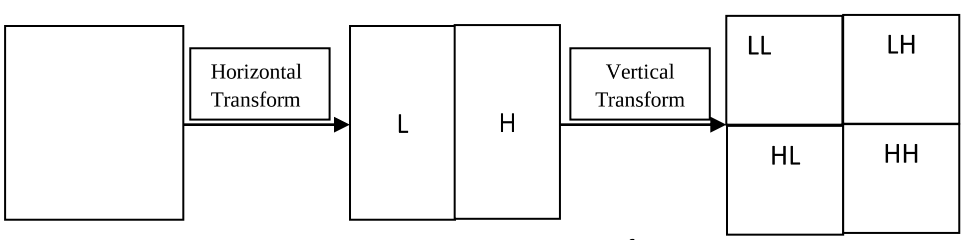


Fig. 6: DWT of Image

- In the second step, we construct a wavelet gradient map by obtaining the sum of vertical (HL) wavelet map and horizontal (LH) wavelet maps.

$$grad[i,j] = LH[i,j] + HL[i,j] \tag{19}$$

Where, i and j are the pixel location of the corresponding wavelet coefficients of HL wavelet and LH wavelet maps.

Finally, construct a histogram of wavelet gradient map grad[i,j], those are represents the extracted features. The heavy tailed distributions of gradient histograms in blur region images compare to non blur region.

3.3.3 Local Binary Pattern

The local binary pattern (LBP) is one of most accurate blur detection technique and this will explain in chapter 4.

Chapter 4
The Proposed System

4.1 Overview

The proposed fusion approach is exploring the properties of the arithmetic image fusion methods to produce a high quality combined image. In fusion, the two different fusion methods, such as additive and multiplicative image fusion method are applied on the input images; the fuzzy fusion is explored on the two output images those are resulted from the first fusion stage. In the second stage of the two stage fuzzy fusion approach, the two images are normalized and then converted into membership values based on the membership functions (MFs), where the degree of membership of each input pixel to a fuzzy set is determined. The fusion results are then converted back into pixel values from the membership value using the de-fuzzification process.

Before doing the fusing process, our main aims to segmentation of focus and blur region in a single image. Several blur detection algorithms are available, such as singular value decomposition (SVD) [10], wavelet based histogram and support vector machines [11], local binary pattern (LBP) [12]. In this experiment use the local binary patterns for the segmentation of focus and blur region in a input or source images.

4.2 LBP Based Blur Region Segmentation

Local binary pattern (LBP) have been widely used in digital image processing and a successful for computer vision problems such as texture segmentation, face recognition, background subtraction and recognition. The LBP operator produce a each image pixel with decimal numbers, called Local Binary Patterns or LBP codes. In LBP code (fig 7), each pixel value is comparison with its 3x3 neighborhood by comparison with center pixel value; the result is 0 if center pixel value is less than neighbor pixel value otherwise is 1.

N_b1	N_b2	N_b3
N_b8	n_c	N_b4
N_b7	N_b6	N_b5

Fig. 7: LBP code of 3x3 neighborhood

Where, n_c is the intensity value of center pixel location and N_b1 to N_b8 is the intensity value of neighbor pixels in 3x3 neighborhood.

The resulted binary numbers are known to as Local Binary Patterns or LBP codes.

2	5	3
6	5	7
0	2	9

Threshold

0	1	0
1		1
0	0	1

Fig 8: Example of LBP Operator

In fig (8), the center pixel (x_c, y_c) value is 5 and compared with clockwise rotation from pixel (x_c-1, y_c-1) value 2. The computed binary code is 01011001 and 70 is resulted value after converted to decimal. Formally, given a pixel at (x_c, y_c), the resulting LBP code is defined as:

$$LBP_{P,R}(X_c, Y_c) = \sum_{P=0}^{P-1} s(i_{n}, i_c) 2^P \tag{20}$$

With $$s(x) = \begin{cases} 1, & x \geq T_{LBP} \\ 0, & x < T_{LBP} \end{cases}$$

Where, i_c and i_n are respectively pixel values of the central pixel and neighbor pixels in the circle neighborhood with a radius R, and T_{LBP} is a threshold value. The threshold T_{LBP} controls the sensitivity of sharpness. By increasing T_{LBP}, the metric becomes less sensitive to sharpness. A rotation invariant version [12] of LBP can be achieved by performing the circular bitwise right shift and resulted code is uniform if it is contained maximum two bitwise transitions from 0 to 1 or 1 to 0.

Here are 10 possibilities cases where n_c is the intensity value of center pixel:

type 0

0	0	0
0	n_c	0
0	0	0

type 1

1	0	0
0	n_c	0
0	0	0

type 2

1	1	0
0	n_c	0
0	0	0

type 3

1	1	1
0	n_c	0
0	0	0

type 4

1	1	1
0	n_c	1
0	0	0

type 5

1	1	1
0	n_c	1
0	0	1

type 6

1	1	1
0	n_c	1
0	1	1

type 7

1	1	1
0	n_c	1
1	1	1

type 8

1	1	1
1	n_c	1
1	1	1

type 9

0	1	0
1	n_c	1
1	1	0

Fig. 9: Various possibility of LBP code

Type 0: 00000000 (0 transitions (uniform)); type 1: 10000000 (1 transition (uniform)); type 2: 11000000(1 transition (uniform)); type 3: 11100000(1 transition (uniform)); type 4: 11110000(1 transition (uniform)); type 5: 11111000(1 transition (uniform)); type 6: 11111100(1 transition (uniform)); type 7: 11111110(1 transition (uniform)); type 8: 11111111(0 transition (uniform)); type 9: 01010111(more than 2 transition (non-uniform)). According to study of around 50 image, the type 6-9 are more effective to find out blur region, image compare to ground truth. The sharpness metric exploits these observations:

$$m_{LBP} = \frac{1}{N}\sum_{i=6}^{9} n(LBP_{8,1}^{riu2} i) \tag{21}$$

Where, $n(LBP_{8,1}^{riu2} i)$ is the number of rotation invariant uniform 8-bit LBP pattern for type i = 6 to 9, and N is the total number of pixels in the selected patch (in all source image, above equation repeated for 3 patch) which serves to normalize the metric so that $m_{LBP} \in [0,1]$.

4.3 Two Stage Image Fusion Approach:

The proposed two stage image fusion approach exploring the properties of the arithmetic image fusion approach to find a more clearly composite image. Most commonly image fusion referred methods in arithmetic are additive and multiplicative; those are applied in first stage of two stage image fusion approach and in the second stage, the fuzzy logic method is used for fusion process on first stage fusion output image.

4.3.1 First Stage

The arithmetic image fusion methods, such as additive fusion and multiplicative fusion, were proposed to improve image fusion. It is a well-known fact that image regions are in more focused in higher pixel intensity value. So, this algorithm is a simple way to finding out most focus regions in output image.

The value of the pixel location I (m, n) of every image is taken and addition together. This sum is then divided by 2 (number of the input image) to find the average of the pixel intensity value of location I (m, n), and this is repeated for all pixel location of the input images. The additive image fusion is given as:

$$I(m,n) = \frac{\{I_1(m,n)+I_2(m,n)\}}{2} \tag{22}$$

Where, I_1 and I_2 are the input images.

The multiplicative image fusion improves the detection, visualization and localization of the targets. The intensity value of the pixel location I (m, n) of every image is taken and multiplied with others. This result is rooted by 2 (number of the input image) to find the actual intensity value of a pixel location I (m, n), and this is repeated for all pixel location of the input images. The equation for multiplicative image fusion as:

$$I(m,n) = \sqrt{\{(I_1(m,n) * I_2(m,n))\}} \tag{23}$$

Where, I_1 and I_2 are the input images.

4.3.2 Second Stage

The fuzzy fusion stage is the second stage of two stage image fusion approach. In this stage the images pixel value are converted from set of predefined MFs into membership values, and the degree of MFs for each input pixel to a fuzzy set is determined using fuzzification process. Next, fusion operators are applied to the fuzzification output.

4.3.2.1 Fuzzification

The system has two inputs of a differently focused area in images. The system has divided into 7 membership functions for intensity value 0 to 255. Where 0 is referred for black and 255 referred the white.

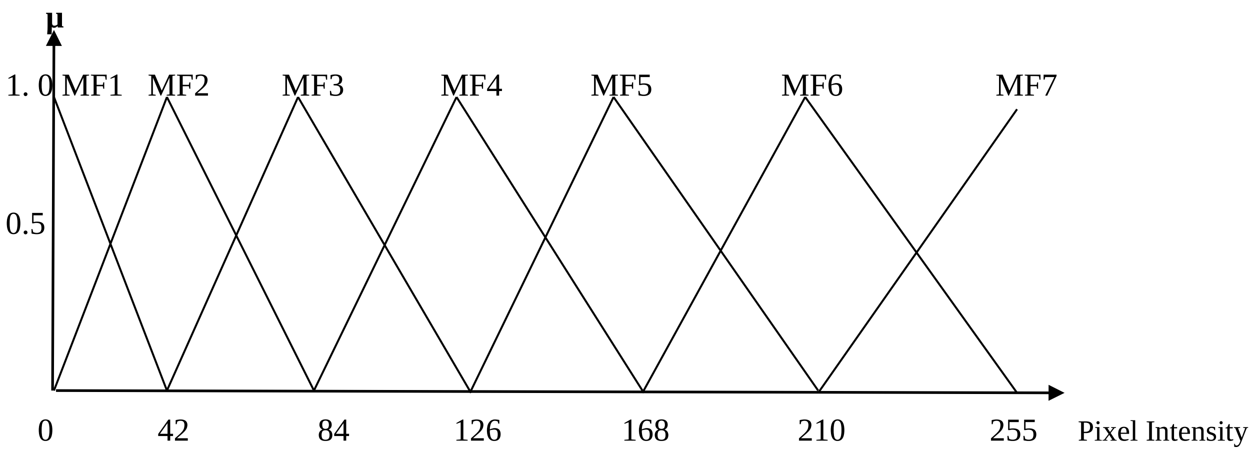
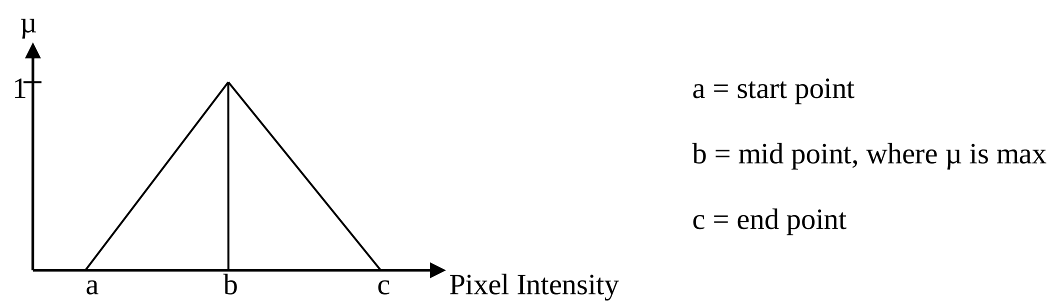


Fig 10: Membership Functions (MFs) for fuzzification

The triangular fuzzification [13] method is used for calculating the membership value of each pixel intensity value. The triangular method is measure by equation (5):



$$\mu(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & x > c \end{cases} \tag{24}$$

In equation (5), x is defining the intensity value of pixel and μ(x) is defining for membership value of pixel x.

4.3.2.2 Fuzzy Rule

A fuzzy rule is used for calculating the output membership value from the input membership values. The system has 49 rules for computing the membership value shown in fig.?, where I1_MF1 – I1_MF7 (line) represent the membership value of image 1, I2_MF1 – I2_MF7 (x-axis) represent the membership value of image 2 and y-axis (1-7) represent the membership value of output.

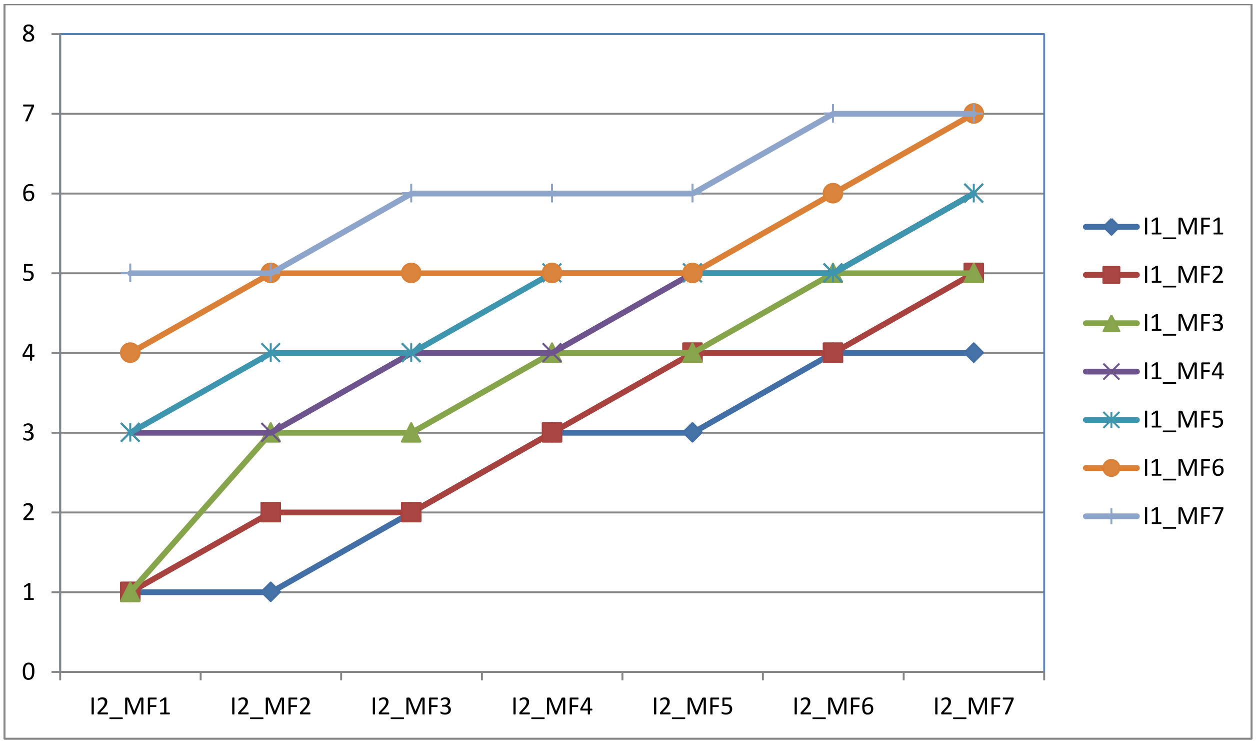


Fig 11: Fuzzy Rules for Defuzzification Process

The fuzzy rules defined in other word as follows:

1. If intensity value of image 1 in MF1 and intensity value of image 2 in MF1 for same pixel location then fused image intensity value in MF1.
2. If intensity value of image 1 in MF1 and intensity value of image 2 in MF2 for same pixel location then fused image intensity value in MF1.

3. If intensity value of image 1 in MF1 and intensity value of image 2 in MF3 for same pixel location then fused image intensity value in MF2.
4. If intensity value of image 1 in MF1 and intensity value of image 2 in MF4 for same pixel location then fused image intensity value in MF3.
5. If intensity value of image 1 in MF1 and intensity value of image 2 in MF5 for same pixel location then fused image intensity value in MF3.
6. If intensity value of image 1 in MF1 and intensity value of image 2 in MF6 for same pixel location then fused image intensity value in MF4.
7. If intensity value of image 1 in MF1 and intensity value of image 2 in MF7 for same pixel location then fused image intensity value in MF4.
8. If intensity value of image 1 in MF2 and intensity value of image 2 in MF1 for same pixel location then fused image intensity value in MF1.
9. If intensity value of image 1 in MF2 and intensity value of image 2 in MF2 for same pixel location then fused image intensity value in MF2.
10. If intensity value of image 1 in MF2 and intensity value of image 2 in MF3 for same pixel location then fused image intensity value in MF2.
11. If intensity value of image 1 in MF2 and intensity value of image 2 in MF4 for same pixel location then fused image intensity value in MF3.
12. If intensity value of image 1 in MF2 and intensity value of image 2 in MF5 for same pixel location then fused image intensity value in MF4.
13. If intensity value of image 1 in MF2 and intensity value of image 2 in MF6 for same pixel location then fused image intensity value in MF4.
14. If intensity value of image 1 in MF2 and intensity value of image 2 in MF7 for same pixel location then fused image intensity value in MF5.
15. If intensity value of image 1 in MF3 and intensity value of image 2 in MF1 for same pixel location then fused image intensity value in MF2.
16. If intensity value of image 1 in MF3 and intensity value of image 2 in MF2 for same pixel location then fused image intensity value in MF3.
17. If intensity value of image 1 in MF3 and intensity value of image 2 in MF3 for same pixel location then fused image intensity value in MF3.
18. If intensity value of image 1 in MF3 and intensity value of image 2 in MF4 for same pixel location then fused image intensity value in MF4.
19. If intensity value of image 1 in MF3 and intensity value of image 2 in MF5 for same pixel location then fused image intensity value in MF4.
20. If intensity value of image 1 in MF3 and intensity value of image 2 in MF6 for same pixel location then fused image intensity value in MF1.
21. If intensity value of image 1 in MF3 and intensity value of image 2 in MF7 for same pixel location then fused image intensity value in MF1.
22. If intensity value of image 1 in MF4 and intensity value of image 2 in MF1 for same pixel location then fused image intensity value in MF3.

23. If intensity value of image 1 in MF4 and intensity value of image 2 in MF2 for same pixel location then fused image intensity value in MF3.
24. If intensity value of image 1 in MF4 and intensity value of image 2 in MF3 for same pixel location then fused image intensity value in MF4.
25. If intensity value of image 1 in MF4 and intensity value of image 2 in MF4 for same pixel location then fused image intensity value in MF4.
26. If intensity value of image 1 in MF4 and intensity value of image 2 in MF5 for same pixel location then fused image intensity value in MF5.
27. If intensity value of image 1 in MF4 and intensity value of image 2 in MF6 for same pixel location then fused image intensity value in MF5.
28. If intensity value of image 1 in MF4 and intensity value of image 2 in MF7 for same pixel location then fused image intensity value in MF6.
29. If intensity value of image 1 in MF5 and intensity value of image 2 in MF1 for same pixel location then fused image intensity value in MF3.
30. If intensity value of image 1 in MF5 and intensity value of image 2 in MF2 for same pixel location then fused image intensity value in MF4.
31. If intensity value of image 1 in MF5 and intensity value of image 2 in MF3 for same pixel location then fused image intensity value in MF4.
32. If intensity value of image 1 in MF5 and intensity value of image 2 in MF4 for same pixel location then fused image intensity value in MF5.
33. If intensity value of image 1 in MF5 and intensity value of image 2 in MF5 for same pixel location then fused image intensity value in MF5.
34. If intensity value of image 1 in MF5 and intensity value of image 2 in MF6 for same pixel location then fused image intensity value in MF5.
35. If intensity value of image 1 in MF5 and intensity value of image 2 in MF7 for same pixel location then fused image intensity value in MF6.
36. If intensity value of image 1 in MF6 and intensity value of image 2 in MF1 for same pixel location then fused image intensity value in MF4.
37. If intensity value of image 1 in MF6 and intensity value of image 2 in MF2 for same pixel location then fused image intensity value in MF4.
38. If intensity value of image 1 in MF6 and intensity value of image 2 in MF3 for same pixel location then fused image intensity value in MF5.
39. If intensity value of image 1 in MF6 and intensity value of image 2 in MF4 for same pixel location then fused image intensity value in MF5.
40. If intensity value of image 1 in MF6 and intensity value of image 2 in MF5 for same pixel location then fused image intensity value in MF5.
41. If intensity value of image 1 in MF6 and intensity value of image 2 in MF6 for same pixel location then fused image intensity value in MF6.
42. If intensity value of image 1 in MF6 and intensity value of image 2 in MF7 for same pixel location then fused image intensity value in MF7.

43. If intensity value of image 1 in MF7 and intensity value of image 2 in MF1 for same pixel location then fused image intensity value in MF5.
44. If intensity value of image 1 in MF7 and intensity value of image 2 in MF2 for same pixel location then fused image intensity value in MF5.
45. If intensity value of image 1 in MF7 and intensity value of image 2 in MF3 for same pixel location then fused image intensity value in MF6.
46. If intensity value of image 1 in MF7 and intensity value of image 2 in MF4 for same pixel location then fused image intensity value in MF6.
47. If intensity value of image 1 in MF7 and intensity value of image 2 in MF5 for same pixel location then fused image intensity value in MF6.
48. If intensity value of image 1 in MF7 and intensity value of image 2 in MF6 for same pixel location then fused image intensity value in MF7.
49. If intensity value of image 1 in MF7 and intensity value of image 2 in MF7 for same pixel location then fused image intensity value in MF7.

Case: Suppose image 1 intensity value is 30 and image 2 is 40 of corresponding pixel location.

(a) The intensity value 30 is lies in Mf1 and Mf2, (i) for Mf1 the membership value μ(30) = 0.2857 and (ii) for Mf2 μ(30) = 0.7142.
(b) The intensity value 40 is also lies in Mf1 and Mf2, (i) for Mf1 the membership value μ(40) = 0.0476 and (ii) for Mf2 μ(40) = 0.9523.

For this intensity value consideration, this is lies in four rules:

Rule 1: If membership value of image 1 in Mf1 and image 2 in Mf1, then output in Mf1.
μ(mf2) = min (0. 2857, 0. 0476) = 0. 0476.

Rule 2: If membership value of image 1 in Mf1 and image 2 in Mf2, then output in Mf1.
μ(mf2) = min (0. 2857, 0. 9523) = 0. 2857.

Rule 3: If membership value of image 1 in Mf2 and image 2 in Mf1, then output in Mf1.
μ(mf2) = min (0. 7142, 0. 0476) = 0. 0476.

Rule 4: If membership value of image 1 in Mf2 and image 2 in Mf2, then output in Mf2.
μ(mf3) = min (0. 7142, 0. 9523) = 0. 7142.

This process is fallows for every pixel of input images.

4.3.2.3 Defuzzification

The fusion results are then converted back into pixel values from the membership values using defuzzification. CENTROID method is used for the defuzzification. The equation (25) for centroid method as:

$$x^* = \frac{\int \mu(x) * x \, dx}{\int \mu(x) dx} \tag{25}$$

Where, $\mu(x)$ is the fused (output) membership value, x is the corresponding intensity value and x^* is the fused intensity value.

i.e. the fused intensity value of input 30 and 40 intensity value is: 33.6363

After the conversion of pixel value in defuzzification, these pixel values are used for fuse image pixel value and construct the fused image. Fused image is more enhance in visualization, and more informative, fused image in more useful in decision making and surveillance in military purpose.

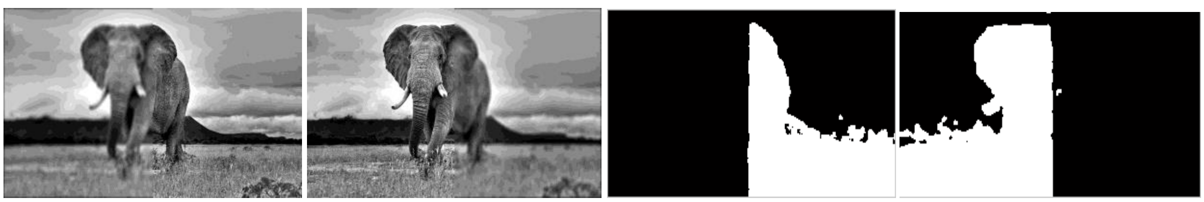
Chapter 5
Experiment Results and Evaluations

5.1 Experiment Result

The performance of the proposed approached is evaluated on the basis of three experiments.

Experiment 1:

Fusion performed on two elephant image. The every image has some focus region and blur region.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig 12: (a) Elephant image (right focus). (b) Elephant image (left focus). (c) LBP segmentation of right focus elephant image. (d) LBP segmentation of left focus elephant image. (e) Composite focused/blur. (f) 2-stage fuzzy fusion of blur region. (g) LBP fuzzy fusion. (h) Reference image

The Fig. (12) shown the LBP fuzzy fusion approach, Fig. 12(b) and Fig. 12(d) are resulted of LBP segmentation in focus and blur region of Fig. 12(a) and Fig. 12(c) respectively. Fig. 12(e) is the composite focus/blur (white/black) regions and Fig. 12(f) is resulted of two stage fuzzy fusion of blur regions. Fig. 12(h) is the final result of LBP fuzzy fusion.

The different image fusion approaches on elephant image are shown in Fig. (13).

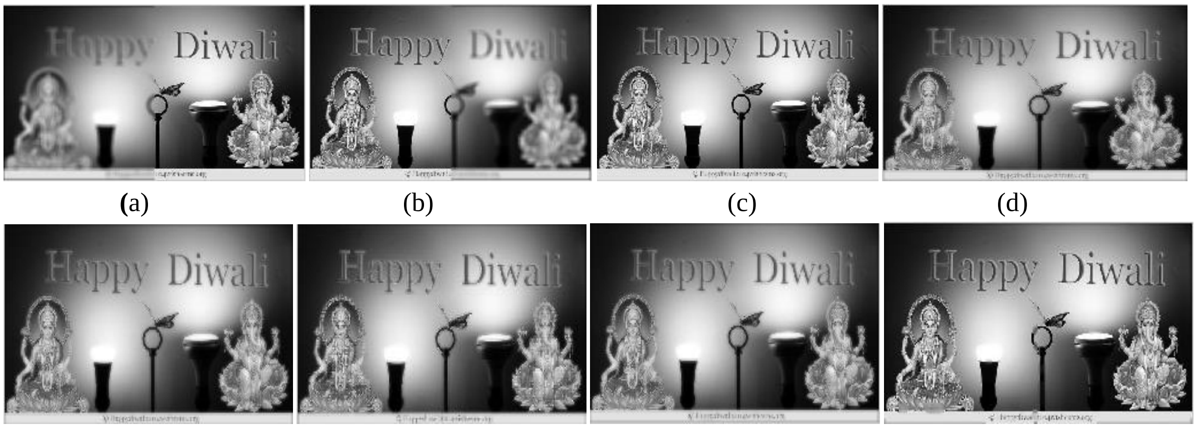
(a) (b) (c) (d)

Fig 13: (a) PCA. (b) WT. (c) 2-stage fuzzy fusion. (d) Fuzzy fusion

The resulted fusion images are Fig. 13(a) by PCA fusion, Fig. 13(b) by WT fusion, Fig. 4(13) by 2 stage fusion approach and Fig 13(d) by fuzzy fusion.

Experiment 2:

The different image fusion processes on diwali image are shown in fig. 14.



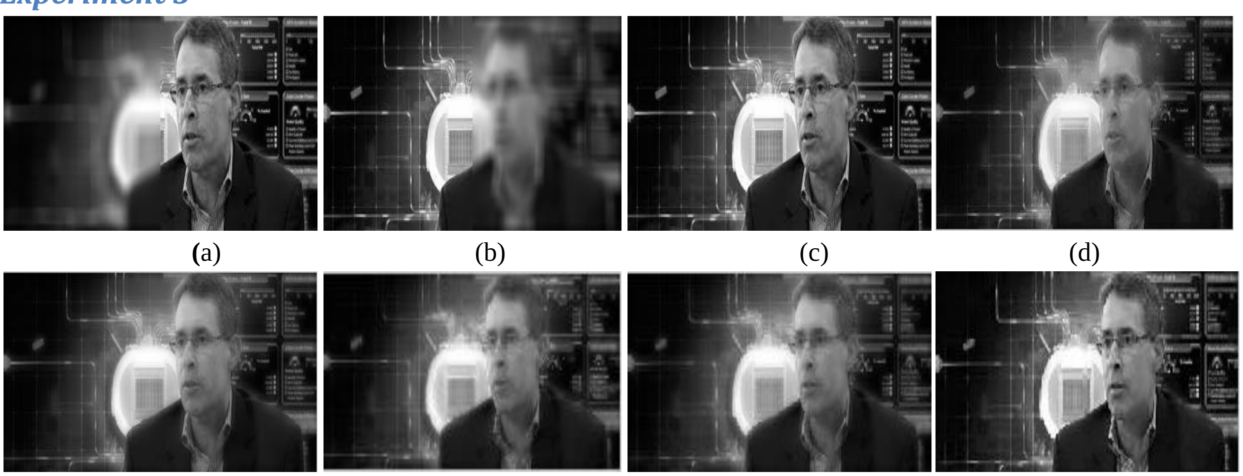
(a) (b) (c) (d)

(e) (f) (g) (h)

Fig 14: (a) Diwali image (right focus). (b) Diwali image (left focus). (c) Reference image. (d) Fuzzy fusion output. (e) PCA output. (f) WT output. (g) 2-stage fuzzy fusion output. (h) LBP fuzzy fusion output.

In experiment 2, the resulted fusion images are fig 14(d) by fuzzy fusion, fig. 14(e) by PCA fusion, fig. 14(f) by WT fusion, fig. 14(g) by 2 stage fusion approach and our proposed fusion approach (LBP Fuzzy Fusion) has resulted in fig. 14(h), those are fused blur part region.

Experiment 3



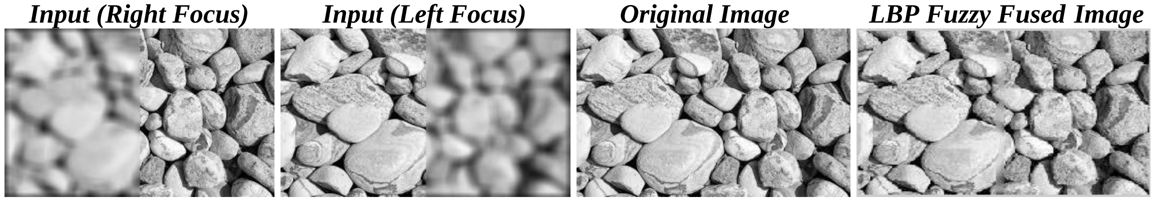
(a) (b) (c) (d)

(e) (f) (g) (h)

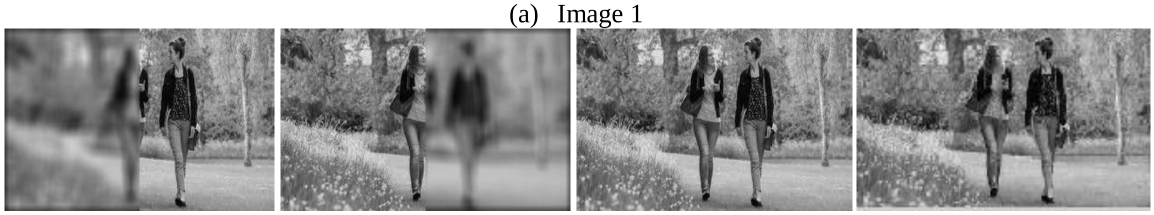
Fig 15: (a) Face image (right focus). (b) Face image (left focus). (c) Reference image. (d) Fuzzy fusion output. (e) PCA output. (f) WT output. (g) 2-stage fuzzy fusion output. (h) LBP fuzzy fusion output.

The LBP fuzzy fusion approach is also applied on various images are shown in fig. 16.

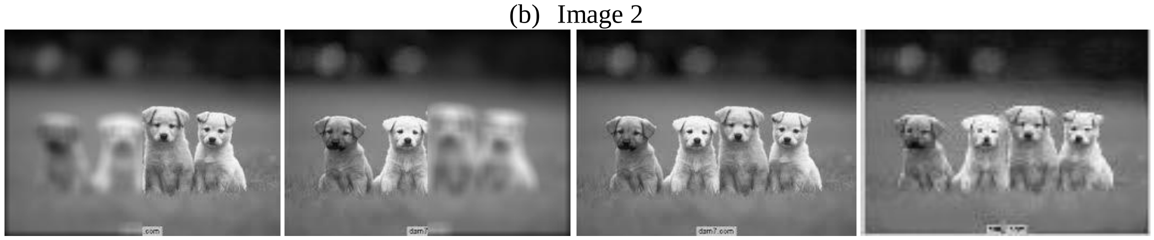
Input (Right Focus) ***Input (Left Focus)*** ***Original Image*** ***LBP Fuzzy Fused Image***



(a) Image 1

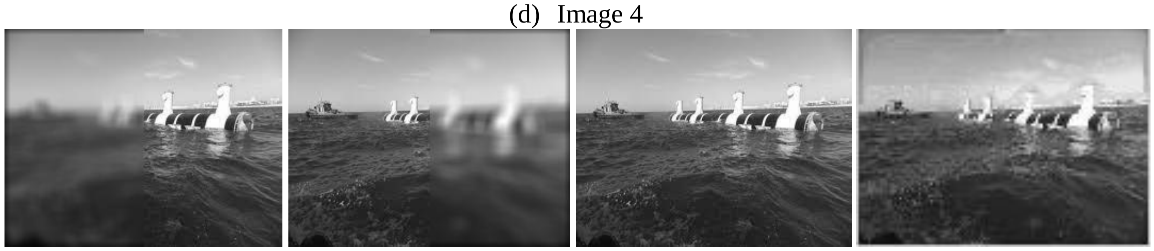


(b) Image 2

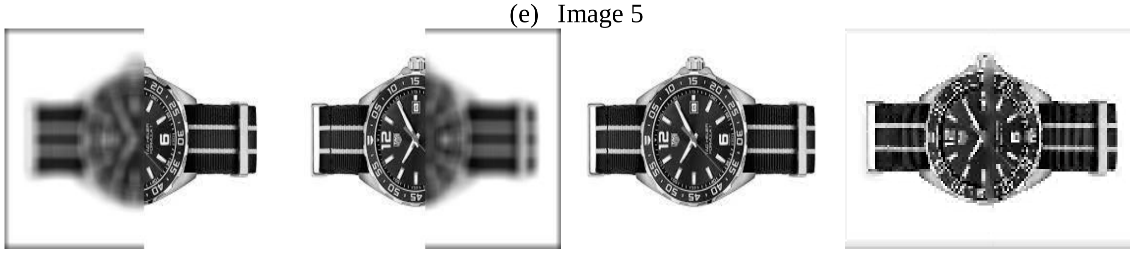


(c) Image 3

(d) Image 4



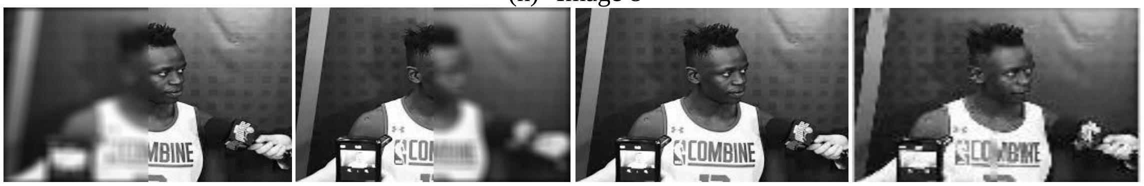
(e) Image 5



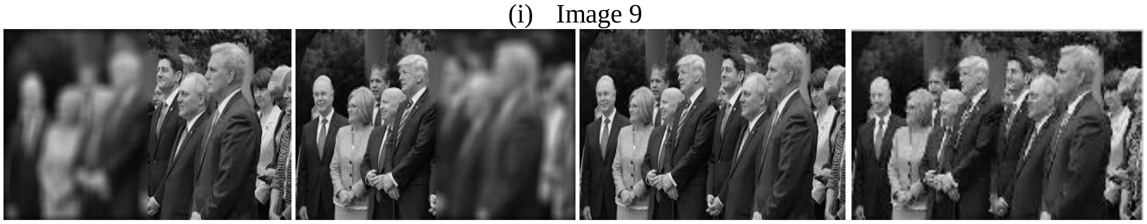
(f) Image 6

(g) Image 7

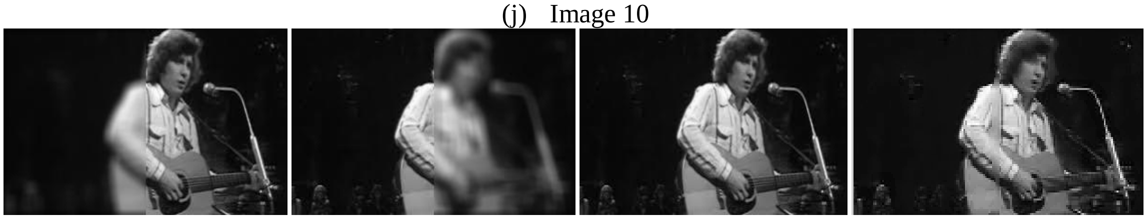
(h) Image 8



(i) Image 9

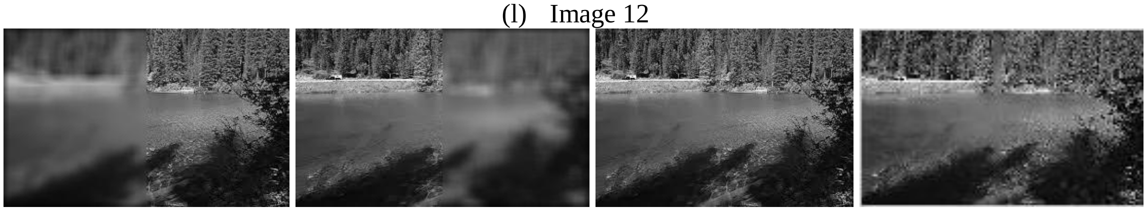


(j) Image 10

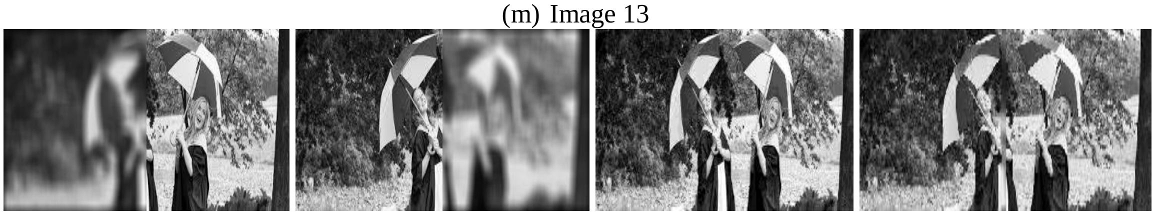


(k) Image 11

(l) Image 12



(m) Image 13



(n) Image 14

Fig 16: Result of LBP Fuzzy Fusion for various images

5.2 Evaluation Criteria

Image qualities have a very great significant for various image processing applications. In this experiment, various evaluation parameters are used to evaluate the quality of the fused image, such as root mean square error [14], peak signal to noise ratio [15], spatial frequency [5], image quality index and correlation coefficient [1].

5.2.1 Root Mean Square Error (RMSE)

The root mean square error (RMSE) find out the amount of change in per pixel during to the enhancement processing and also find the error differences between reference image and fused image. The RMSE measure by equation (26):

$$RMSE = \sqrt{\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N}(R(k,l) - F(k,l))^2} \quad (26)$$

Where, R is a reference image and F is the fused image.
If we don't have the reference image, then the RMSE is computed by.

$$R_1 = \sqrt{\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N}\left(I_1(k,l) - F(k,l)\right)^2} \quad (27)$$

Here, R_1 is computed for input image I_1.

Similarly, R_2 is computed for 2^{nd} input image.

$$R_2 = \sqrt{\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N}(I_2(k,l) - F(k,l))^2} \quad (28)$$

Then, value is compute by:

$$RMSE = \frac{R_1 + R_2}{2} \quad (29)$$

The smaller RMSE value indicates the good fusion quality.

5.2.2 Image Quality Index (IQI)

Index Quality Index measures the similarity between the reference image and fused image and range of value in between -1 to 1. The IQI value of 1 indicate that the reference and fuse images are similar. IQI is measure by equation (30):

$$IQI = \frac{m_{ab}}{m_a m_b} * \frac{2\bar{x}\bar{y}}{\bar{x}^2+\bar{y}^2} * \frac{2m_a m_b}{{m_a}^2+{m_b}^2} \quad (30)$$

Where, $\bar{x}$ and $\bar{y}$ are a means value of image 1 and image 2, m_a and m_b are the variance of image 1 and image2, m_{ab} is a covariance of image 1 and image 2.

5.2.3 Correlation Coefficient

The Correlation Coefficient (CC) given to the measure of how to close reference and fused image. The equation for CC is given as:

$$CC = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (31)$$

Where, x_i and y_i are the intensity value i^{th} pixel of image 1 and image 2 respectively, $\bar{x}$ and $\bar{y}$ are the mean value of image 1 and image 2.

5.2.4 PSNR (Peak Signal to Noise Ratio):

PSNR block measures the peak signal-to-noise ratio and this ratio is between two images. This ratio is used for quality measurement between the original image and a reconstructed image. The higher value of the PSNR is resulted in the good fusion algorithm and computed by this formula:

$$PSNR = 10 * \log_{10}[\frac{L^2}{MSE}] \tag{32}$$

Where, MSE is the mean square error and L is the max possible pixel value (i.e. 8-bit image, L=255).

5.2.5 Spatial Frequency

Spatial frequency monitored the overall activities performed on the image. The row frequency and column frequencies (eq(14) and eq(15)) are calculated first before calculation of the spatial frequency of the image, the equation for RF & CF respectively:

$$RF = \sqrt{\frac{1}{MN}\sum_{m=0}^{m-1}\sum_{n=1}^{n-1}[F(m,n) - F(m,n-1)]^2} \tag{33}$$

$$CF = \sqrt{\frac{1}{MN}\sum_{m=1}^{m-1}\sum_{n=0}^{n-1}[F(m,n) - F(m-1,n)]^2} \tag{34}$$

Where, M is the number of rows and N is the number of columns and F (m, n) is a fused image.

The spatial frequency (SF) of fused image is calculated as:

$$SF = \sqrt{RF^2 + CF^2} \tag{35}$$

The large activity level performed in the image is indicating by the large value of spatial frequency. And large value represents the more visibility of fused image.

These evaluation parameters values are shown in table I, table II and table III for the experiment 1, experiment 2 and experiment 3 respectively.

Parameter / **Fusion Approach**	*RMSE*	*IQI*	*CC*	*PSNR*	*Spatial Frequency*
Fuzzy Logic	12.2771	0. 97434	0. 97678	26.2829	15.7977
PCA Fusion	10.98	0.97921	0.98136	27.3528	14.0997
WT Fusion	12.4236	0.97353	0.97528	26.2799	18.7833
2 Stage Fusion	10.98	0.97921	0.98136	27.3528	14.0997
LBP Fuzzy Fusion (Proposed)	**7.3617**	**0.99142**	**0.99158**	**30.8252**	**27.0028**

Table I: Evaluation parameters of different fusion approach for experiment 1

Parameter / Fusion Approach	*RMSE*	*IQI*	*CC*	*PSNR*	*Spatial Frequency*
Fuzzy Logic	14.9255	0.97922	0.98119	24.6862	18.2493
PCA Fusion	13.3378	0.98317	0.98522	25.6631	18.8017
WT Fusion	15.4919	0.97736	0.97918	24.3627	21.3478
2 Stage Fusion	13.3378	0.98317	0.98522	25.6631	16.8017
LBP Fuzzy Fusion (Proposed)	**7.7141**	**0.99481**	**0.99489**	**30.4191**	**31.5703**

Table II: Evaluation parameters of different fusion approach for experiment 2

Parameter / Fusion Approach	*RMSE*	*IQI*	*CC*	*PSNR*	*Spatial Frequency*
Fuzzy Logic	12.9218	0. 9766	0. 97925	25.9384	16.3645
PCA Fusion	11.838	0.98023	0.98266	26.6992	14.0384
WT Fusion	13.137	0.97562	0.97772	25.7698	17.8548
2 Stage Fusion	11.838	0.98023	0.98266	26.6992	14.0384
LBP Fuzzy Fusion (Proposed)	**4.0589**	**0.99782**	**0.99758**	**35.9967**	**26.5787**

Table III: Evaluation parameters of different fusion approach for experiment 3

The evaluation parameters values are shown in table IV for the Fig. (16).

S.No.	***RMSE***	***IQI***	***CC***	***PSNR***	***Spatial Frequency***
(a)	6.7507	0.99416	0.99416	31.5779	43.3982
(b)	4.1596	0.99574	0.99574	35.7838	29.2553
(c)	5.3677	0.9947	0.99472	33.5691	15.5621
(d)	7.2299	0.99329	0.99329	30.9822	52.2106
(e)	6.206	0.99533	0.99546	32.3086	21.5747
(f)	9.1216	0.99516	0.99529	28.9634	48.1129
(g)	5.3315	0.99512	0.99514	33.6279	26.3058
(h)	7.3466	0.99065	0.99068	30.8431	40.0029
(i)	6.7281	0.99516	0.99518	31.6069	30.1758
(j)	4.4645	0.99682	0.99682	35.1693	33.9144
(k)	5.3895	0.99557	0.99645	33.5339	17.3524
(l)	6.0582	0.99576	0.99576	32.518	41.0294
(m)	5.2288	0.99283	0.99294	33.7968	40.8008
(n)	6.277	0.99628	0.99628	32.2097	47.2978

Table IV: Evaluation parameters of LBP Fuzzy fusion approach for various images Fig. 16(a-n)

The proposed method is evaluated on the computed results (table I, table II & table III) and it is compared with fuzzy logic, PCA fusion, WT fusion and 2 stage fusion methods on the basis of the evaluation parameters.

(i) The RMSE value of proposed method is smaller as compared to others fusion method.
(ii) The IQI value of proposed method is most near to 1.
(iii) The CC value is also most near to 1.

(iv) The PSNR value of proposed method is maximum as compared to others fusion method.

(v) The spatial frequency value is also maximum.

According to performance analysis, it can be concluded that the proposed method is a more suitable method for image enhancement.

Chapter 6
Conclusion and Future Work

In this experiment, the potentials of image fusion using LBP based fuzzy fusion and other popular fusion approaches has been explored along with image clarity and quality assessment evaluation measures. The experimental results clearly show that the proposed LBP based fuzzy fusion logic for image fusion gives a considerable improvement for many assessment parameters.

This fuzzy method can further be improved and optimized by using other blur/focus segmentation algorithms, which one better as compare to the LBP based defocus segmentation and segmented the motion and defocus blur instead of defocus blur segmentation for the possibility of errors as compare to the proposed LBP based fuzzy fusion approach. So, the use of such methods for motion blur segmentation in image fusion will be examined in the future activities.

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