



Enhancing Image Fusion – Pseudo Colour Multi-Scale Approach

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Abstract: The existing system approach concentrates on the colour fusion of both day and night imagery's, but they are less naturalistic for images containing regions that differ significantly in the coloured content. Even though colour mapping methods matches the statistical properties of the both day and night images, the accuracy of the colouring is very much depended on how well target and source images matches. To achieve accuracy, of colouring and naturalistic fusion this method uses a multi-scale scheme for image fusion using EM algorithm and pseudo colour-transfer algorithm. The fusion algorithm accomplishes YUV space. The Y component is obtained from the result of IR and visible image fusion, by which the original images are fused in non sub sampled contour let domain by using EM algorithm. U and V components come by a ratio of local to global divergence of the IR and visible image. The experimental result demonstrate that a better fusion performance with compare to traditional colour image fusion methods, which meets the requirement of accuracy colouring and naturalistic colour fusion.

Keywords: EM - Expectation and Maximization algorithm. NSCT - Non sub sampled contour let transformation algorithm, SAGE – Space Alternating Generalized Expectation Maximization, PCA - Principal Component Analysis, FSD - Filter Subtract Decimate.

I. INTRODUCTION

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or, a set of characteristics or parameters related to the image. Most image processing techniques involve treating the image as a two-dimensional signal and applying standard signal processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. The acquisition of images is referred to as imaging.

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions digital image processing may be modelled in the form of multidimensional systems.

A. Overview :

An image may be defined as a two-dimensional function, where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y , and the intensity values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are called picture elements,

image elements, pels, and pixels. Pixel is the term used most widely to denote the elements of a digital image.

B. Image Processing:

Image processing is a physical process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image or the characteristics of an image.

The most common type of image processing is photography. In this process, an image is captured using a camera to create a digital or analog image. In order to produce a physical picture, the image is processed using the appropriate technology based on the input source type.

In digital photography, the image is stored as a computer file. This file is translated using photographic software to generate an actual image. The colours, shading, and nuances are all captured at the time the photograph is taken the software translates this information into an image. Image processing is a physical process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image or the characteristics of an image.

C. Classification:

The Image Processing Toolbox software defines four basic types of images. That is given bellow. These image types determine the way MATLAB interprets data matrix elements as pixel intensity values.

- a. **Binary Images:** In a binary image, each pixel assumes one of only two discrete values: 1 or 0. A binary image is stored as a logical array.

b. Indexed Images: An indexed image consists of an array and a colour map matrix. The pixel values in the array are direct indices into a colour map. By convention, this documentation uses the variable name *X* to refer to the array and map to refer to the colour map.

The colour map matrix is an *m*-by-3 array of class double containing floating-point values in the range [0,1]. Each row of map specifies the red, green, and blue components of a single colour. An indexed image uses direct mapping of pixel values to colour map values. The colour of each image pixel is determined by using the corresponding value of *X* as an index into map.

A colour map is often stored with an indexed image and is automatically loaded with the image when you use the `imshow` function. After you read the image and the colour map into the MATLAB workspace as separate variables, you must keep track of the association between the image and colour map. However, you are not limited to using the default colour map—you can use any colour map that you choose.

c. Gray scale Images: A gray scale image (also called gray-level) is a data matrix whose values represent intensities within some range. MATLAB stores a gray scale image as individual matrix, with each element of the matrix corresponding to one image pixel. By convention, this paper uses the variable name *I* to refer to gray scale images.

The matrix can be of class `uint8`, `uint16`, `int16`, `single`, or `double`. While gray scale images are rarely saved with a colour map, MATLAB uses a colour map to display them. For a matrix of class `single` or `double`, using the default gray scale colour map, the intensity 0 represents black and the intensity 1 represents white. For a matrix of type `uint8`, `uint16`, or `int16`, the intensity `intmin(class(I))` represents black and the intensity `intmax(class(I))` represents white.

d. True colour Images: A true colour image is an image in which each pixel is specified by three values — one each for the red, blue, and green components of the pixel's colour. MATLAB store true colour images as an *m*-by-*n*-by-3 data array that defines red, green, and blue colour components for each individual pixel. True colour images do not use a colour map. The colour of each pixel is determined by the combination of the red, green, and blue intensities stored in each colour plane at the pixel's location.

Graphics file formats store true colour images as 24-bit images, where the red, green, and blue components are 8 bits each. This yields a potential of 16 million colours. The precision with which a real-life image can be replicated has led to the commonly used term true colour image.

D. Applications:

a. Digital camera images: Digital cameras generally include dedicated digital image processing chips to convert the raw data from the image sensor into a colour-corrected image in a standard image file format. Images from digital cameras often receive further processing to improve their quality, a distinct advantage that digital cameras have over film cameras. The digital image processing typically is executed by special software programs that can manipulate the images in many ways.

b. Intelligent transportation systems: Digital image processing has wide applications in intelligent transportation systems.

c. Film: Westworld (1973) was the first feature film to use digital image processing to pixel photography to simulate an android's point of view.

E. Proposed Approach:

In this paper, the two images are fused one is IR image and one is visible image which will be converted to grey scale first. The fusion is done by the EM algorithm. Later pseudo colour is applied to the fused image using the NSCT algorithm. The EM based algorithm is used for colour transferring from high resolution image to the lower resolution image is used, to get more accuracy and naturalistic output image.

A new multi scale scheme for image fusion is presented using EM algorithm and pseudo colour transfer algorithm for IR and visible images. By using multi scale scheme of approach the performance of the fusion can be improved, objective performance metric and accuracy with which visual information is transferred from the source image to the fused image, better fusion performance is achieved with more “naturalistic”.

II. LITERATURE SURVEY

Before building the system the above consideration are taken into account for developing the proposed system. As two of the most commonly used image sensors in night-vision for military applications [1], infrared (IR) and visible light cameras have their own advantages and limitations due to the physical differences between the image formation processes.

To make the colouration of false-colour images appear more natural [2], Reinhard et al. introduced a method that enabled the transfer of colours from one image to another. In the correlated principal component colour space derived from a large ensemble of hyper spectral images of natural scenes, the first order statistics of natural colour images (manually selected target scenes with chromatic properties presumed similar to the source scene) are transferred to the multi-band night-vision images (source scenes). Subsequently, Toet[3] demonstrated that Reinhard's method could be adapted to transfer the natural colour characteristics of daylight imagery into multi-band night vision images. Essentially, Toet's natural colour mapping method matches the statistical properties (i.e., mean and standard deviation) of the night-vision imagery to that of a natural daylight colour image (manually selected as the “target” colour distribution).

However, this particular colour mapping method colours the image regardless of scene content, and thus the accuracy of the colouring is very much dependent on how well the target and source images are matched. Specifically, Toet's method weights the local regions of the source image by the “global” colour statistics of the target image, and thus will yield less naturalistic results (e.g., biased colours) for images containing regions that differ significantly in their coloured content. Another drawback of this “global-colouring” method (referred to Toet's colour mapping) is that the scene matching between source and target is performed manually. This paper adapts a new image fusion method of multi resolution decomposition to night imagery

fusion. A new multi-scale scheme for colour image fusion is presented using EM algorithm and colour transfer algorithm for IR and visible image. The colour fusion algorithm implements in YUV colour space. The Y component is obtained from the result of IR and visible image fusion, by which the original images are fused in non sub sampled contour let domain by using EM algorithm. U and V components come from the original images by simple arithmetical operation. The V component is enhanced by a ratio of local to global divergence of the IR image. The experiment results demonstrate by real image data that the proposed scheme can achieve better fusion performance than the traditional colour image fusion methods.

A. Multi-Scale Colour Image Fusion:

In recent years, colour image fusion is becoming a more and more important research field and lots of novel false colour fusion approaches have been developed to fuse IR and visible images. Appropriately false-coloured night-time imagery is often helpful for human observers improving their performance, for instance, on scene classification and reaction time tasks. Inappropriate colour mappings can be detrimental to human performance. One of the possible reasons is lack of physical colour constancy. Ideally, a colour rendering method will produce night-vision imagery with a 'naturalistic', as well as stable, colour appearance. On the other hand, if the night time imagery is (automatically) rendered with natural colours, users should be able to readily recognize and identify objects.

To make the colouration of false-colour images appear more natural, Reinhard *et al*[3], introduced a method that enabled the transfer of colours from one image to another. In de correlated principal component colour space derived from a large ensemble of hyper spectral images of natural scenes, the first order statistics of natural colour images (manually selected target scenes with chromatic properties presumed similar to the source scene) are transferred to the multi-band night-vision images (source scenes). Subsequently, Toet[4] demonstrated that Reinhard's method could be adapted to transfer the natural colour characteristics of daylight imagery into multi-band night vision images. Essentially, Toet's natural colour mapping method matches the statistical properties (i.e., mean and standard deviation) of the night-vision imagery to that of a natural daylight colour image (manually selected as the "target" colour distribution). Specifically, Toet's method weights the local regions of the source image by the "global" colour statistics of the target image, and thus will yield less naturalistic results (e.g., biased colours) for images containing regions that differ significantly in their coloured content. Another drawback of this "global-colouring" method (referred to Toet's colour mapping) is that the scene matching between source and target is performed manually.

This method adapts a new image fusion method of multi resolution decomposition to night imagery fusion[5]. A new multi-scale scheme for colour image fusion is presented using EM algorithm and colour transfer algorithm for IR and visible image. The colour fusion algorithm implements in YUV colour space. The Y component is obtained from the result of IR and visible image fusion, by which the original images are fused in non sub sampled contour let domain by using EM algorithm. U and V components come from the

original images by simple arithmetical operation. The V component is enhanced by a ratio of local to global divergence of the IR image. The experiment results demonstrate by real image data that the proposed scheme can achieve better fusion performance than the traditional colour image fusion methods.

Colourfulness is defined as the attribute of a visual sensation according to which the perceived colour of an area appears to be more or less chromatic [6]. Recently, an efficient metric for calculating colourfulness is proposed by Hasler, which is simple in computing and well correlated (95.3%) with subjective judgments.

B. Image Fusion Methods:

- a. **Maximum/minimum selected method:** A selection process if performed here wherein, for every corresponding pixel in the input images, the pixel with maximum/minimum intensity is selected, respectively, and is put in as the resultant pixel of the fused image
- b. **Principal Component Analysis Algorithm:** Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a "shadow" of this object when viewed from it's (in some sense) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced.

- c. **Laplacian Pyramid method:** The Laplacian pyramidal method is identical to FSD pyramid except for an additional low pass filtering performed with 2^*W . All the other steps are followed as in FSD pyramid.
- d. **Ratio Pyramid:** The Ration pyramidal method is also identical to FSD pyramid except for, in the decomposition phase, after low pass filtering the input image matrices; the pixel wise ratio is calculated instead of subtraction as in FSD.
- e. **Filter-subtract-decimate (FSD) method:** A filter-subtract-decimate (FSD) method for analyzing the frequency spectrum of an n-dimensional information component, defined by respective level-values of certain samples of an applied temporal-signal sample stream, into at least one band pass sub-spectrum and a

remnant sub-spectrum, where n is a given integer having a value of at least one, said certain samples of said applied sample stream defining each of said n-dimensions of said information component with a particular relatively high sample density.

f. Morphological pyramid method: This algorithm utilizes mathematical morphology for pyramidal[7] coding of colour images. We obtain lossy colour image compression by using Block Truncation Coding at the pyramid levels to attain reduced data rates. The pyramid approach is attractive due to low computational complexity, simple parallel implementation, and the ability to produce acceptable colour images at moderate data rates.

g. DWT with DBSS (2,2) method: It is well known that the discrete Wavelet Transform (DWT)[8] results in a shift variant signal representation, i.e. a shift of the input signal yields a nontrivial modification of the transformation coefficients. When applied to pixel-level image fusion, this result in a shift dependent fusion scheme.

The Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function (also called father wavelet) which generates an orthogonal multi resolution analysis. In general the Daubechies wavelets are chosen to have the highest number.

h. DWT with Haar based fusion: The Haar wavelet [9] is a certain sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an ortho normal function basis. The Haar sequence is now recognized as the first known wavelet basis and extensively used as a teaching example in the theory of wavelets.

C. Fusion by EM Algorithm:

a. EM algorithm based Lowest Frequency Band Fusion [10]: Before the proposed EM method is applied to the low frequency band, the image model should be defined as:

$$\bar{S}_N(\bar{X},j)=\alpha(X,j) \bar{S}_N(F,j)+\beta(X,j)+\varepsilon(X,j)$$

Where $\mathbf{X} = \mathbf{A}$ or \mathbf{B} , represents the source image index; j denotes the pixel location in low frequency band. $S_N(\mathbf{X}, j)$ denotes the low frequency band of the X image at the j^{th} pixel; $S_N(\mathbf{F}, j)$ represents the optimally fused low frequency band at the j^{th} pixel that is a parameter to be estimated. $\alpha(X, j)=+1$ or 0 is sensor selectivity factor. $\beta(X, j)$ is the bias of image which reflects the mean of the low frequency image. $\varepsilon(X, j)$ is the ran dom noise which is modelled by a K-term mixture of Gaussian probability density functions (pdf). That is,

$$f_{\varepsilon}(X,j)(\varepsilon(X,j))=\sum_{k=1}^K \lambda_{k,x}(j) \frac{1}{\sqrt{2\pi\sigma_{k,x}^2(j)}} \exp\left(-\frac{\varepsilon(X,j)^2}{2\sigma_{k,x}^2(j)}\right)$$

Where $\lambda_{k,x}(j)$ is the weights of the K term Gaussian distribution. $\sigma_{k,x}^2(j)$ is the variance of the distribution.

The fusion process of multiple images is in fact estimation true scene $S_N(\mathbf{F}, j)$. The estimation process is performed in a neighbourhood region of j . The region size

must be carefully chosen to be large enough to allow good estimation but small enough to allow our assumptions to be reasonable. Here, we choice a size 5X5 region. In the small region, we assume the model parameters $\beta(j)$, $(\lambda_{k,l}(j)\sigma_{k,l}^2(j))$ and α_i is constant. Here, we perform the EM fusion process on the lowest frequency part. At the beginning of the recursive process, it is necessary to normalize the image data.

$$I_i^*(j)=(I_i(j) - \mu)/H$$

Where I_i^* and I_i is the normalized image and source image; μ is the mean of the source image; H is the gray level, it is defined as the highest gray value of the source image.

The recursive process is derived from the SAGE algorithm [11], similar to the development in [12]. When the parameters converged to a fixed range, we can calculate the true scene:

Where the dumthis variable l is the scalar in the region sized 5X5, surrounding the j^{th} pixel in the source images; $g_{k,i,l}(I_i(l))$ is the condition probability density in the term of the i^{th} sensor and the k^{th} term of K-term mixture of Gaussian probability density function. It is obtained by perform EM algorithm. For more detail of EM algorithm, we can look up the reference [12].

$$S^*(l)=\frac{\sum_{i=1}^q \sum_{k=1}^K \alpha_i^q \frac{g_{k,i,l}(I_i(l))}{\sigma_{k,i}^2}}{\sum_{i=1}^q \sum_{k=1}^K \alpha_i^q \frac{g_{k,i,l}(I_i(l))}{\sigma_{k,i}^2}}$$

b. High Frequency Band Fusion: For the high frequency band models the low-level image information processing in a way that resembles principal components of the early retinal process [13]. A quantitative estimation of this important information can be provided by the measure of uncertainty in pixel-to-neighbours interaction. Two sources of such uncertainty must be considered: luminance uncertainty and topological uncertainty.

$$PI_x(m,n) = C(m,n).I(m,n)$$

Where $PI_x(m,n)$ indicate the important information of the steerable pyramid coefficient, the subscript X denote source images. It means the source image is image A when $\mathbf{X} = \mathbf{A}$. $C(m, n)$ is the absolute value of steerable pyramid coefficient and also reflects the luminance uncertainty; $I(m, n)$ denotes the topological uncertainty.

$$C(m,n) = |w_x(m,n)|$$

Where $w_x(m, n)$, is the high frequency coefficient neglect the subscript that denote the scale as Figure.1. Considering the relationship of neighbourhood coefficients, the sign of the high frequency coefficient is decided firstly.

$$sign(m,n) = sign(w_x(m,n))$$

If the high frequency coefficient is equal to or greater than zero, then sign is one, otherwise sign is zero.

$$I(m,n) = P_x(m,n). (1 - P_x(m,n))$$

Where $p_x(m, n)$, is probability to find surrounding coefficients in the same state (sign) as the central coefficient at position (m, n) .

Then, fusion selective pattern:

$$w_F(m,n) = \begin{cases} w_A(m,n)PI_A \geq PI_B & (m,n) \in E \\ w_B(m,n) & \text{Otherwise} \end{cases}$$

Where A is the source image A, B is the source image B and F is the fused image F.

III. SYSTEM DESIGN

A. System Architecture:

The schematic diagram of linear image fusion is shown in Figure1. The source IR and visible images are firstly fused by false colour fusion and then the colour transfer technology is applied to obtain a natural final fused image. Different false colour fusion approaches and different colour spaces can be utilized in the scheme. In this paper, we implement the false colour fusion and colour transfer step in YUV space, where Y denotes luminance, U stands for difference between blue and luminance, and V stands for difference between red and luminance.

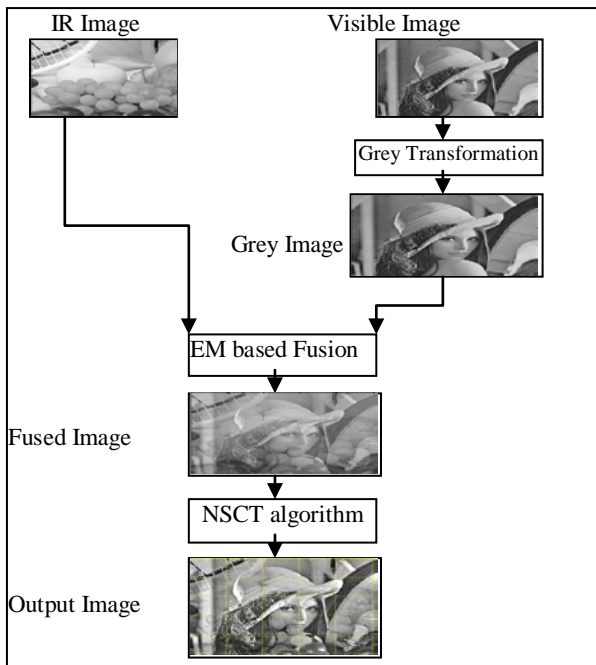


Figure 1: The Colour Image Fusion Framework

The transform from RGB space to YUV space is written as:

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.1471 & -0.2888 & 0.4359 \\ 0.6148 & -0.5148 & -0.1000 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

The transform from YUV space to RGB space is written as:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1.13983 \\ 1 & -0.39465 & -0.580060 \\ 1 & 2.03211 & 0 \end{bmatrix} \begin{bmatrix} Y \\ U \\ V \end{bmatrix}$$

The false colour fusion in YUV space is carried out as:

$$\begin{cases} Y = EM(V_{is}, IR) \\ U = V_{is} - IR \\ V = IR - V_{is} \end{cases}$$

Where V_{is} and IR stand for visible image and IR image respectively and $EM(V_{is}, IR)$ denoted the Vis and IR image is fused by EM operator.

B. Data Flow Diagram:

The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system

in terms of the input data to the system, various processing carried out on these data, and the output data is generated by the system.

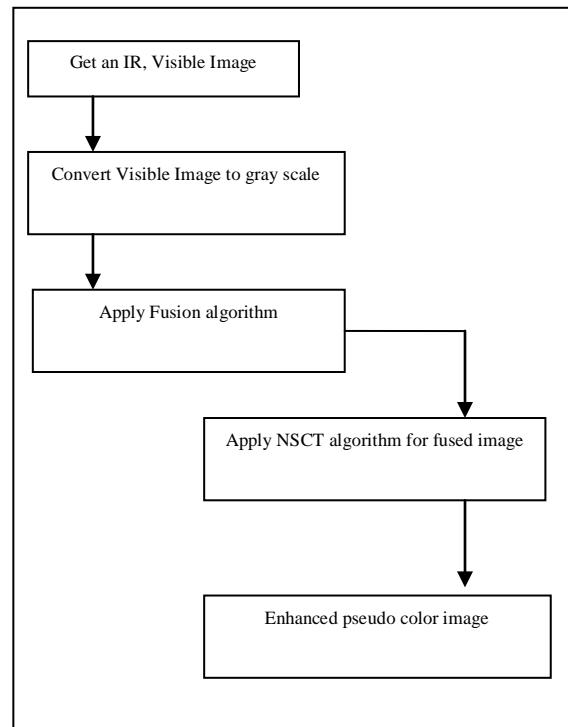


Figure 2: Flow diagram

C. System Implementation:

a. Modules:

- Load the images which are low resolution and high resolution
- Apply colour fusion
- Save the fusion image and image data

IV. IOOUTPUT RESULT AND ITS DESCRIPTION

The result analysis can be made by the following output results in thispaper.

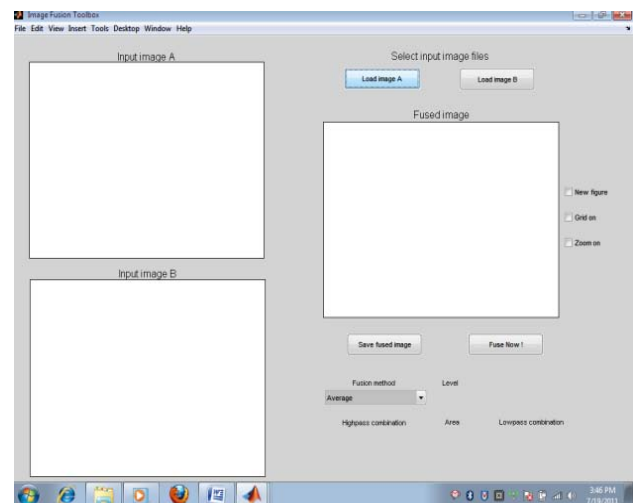


Figure 3: This shows the output result in the GUI form.

This above figure shows the first output result in this paper when executing main program in MATLAB. This is the graphical user interface (GUI) result. This is designed by using the visual basics in MATLAB. This GUI helps the

user to insert or accept the input images and to see their result. This mainly includes the textbox, checkbox, Drop Down button, these are all design is made over this GUI interface.

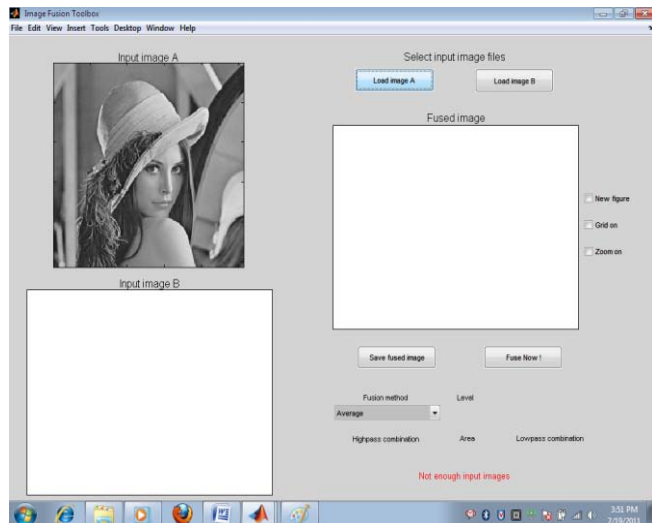


Figure 4: Loading the input image A that is, the low resolution image.

In this paper first we accept the Low resolution image i.e Image A. by reading the values of this input image in the matrix form that is YUV. That is by using the MATLAB program. Input image values will be stored as matrix A, the image A is loaded by browsing option where actually user is stored their images.

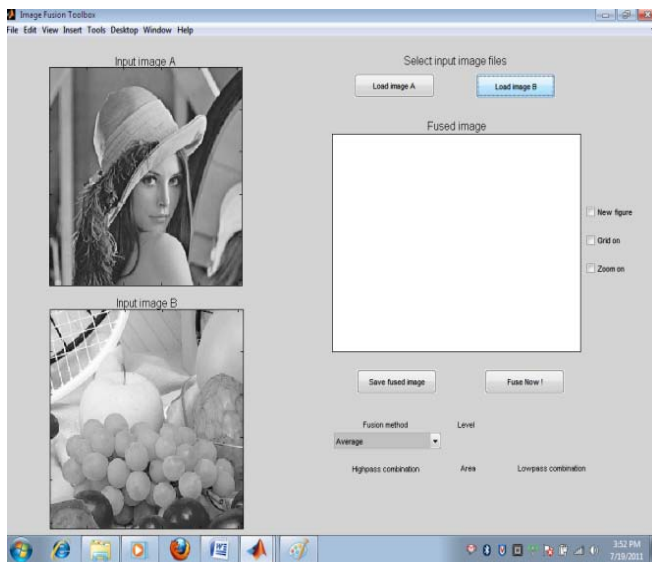


Figure 5: Loading the input image B that is, the high resolution image.

In this paper secondly we accept the high resolution image i.e. Image B. by reading the values of this input image in the matrix form that is YUV. That is by using the MATLAB program. Input image values will be stored as matrix B, the image B is loaded by browsing option where actually user is stored their images. But important thing is the size of the must be same. If the size is not same then fusion cannot be done. We get the message not enough image size, in the red line in the fuse now option button. But another important is here the high resolution image will convert into gray scale image when we load.

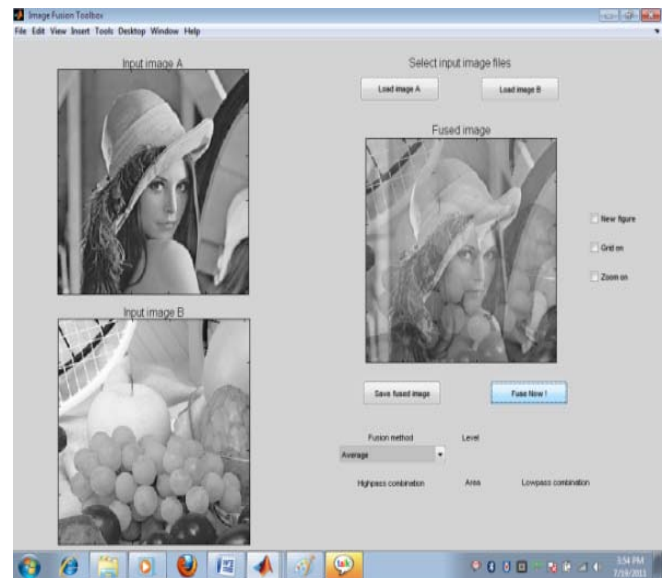


Figure 6: This shows the fused image output in the average method

This figure shows the final output result. After loading both the images by using the algorithm we fuse the both the image. Here we can analyze that matrix A values and matrix B values in the YUV format for the fusion. Where the image a value is low resolution values. That is it includes the some negative values as compared with RGB standard values. That is EM algorithm that provides the values of YUV of image B will be added or transferred to the image A . and Finally we get the matrix C i.e. image C that is fused image.

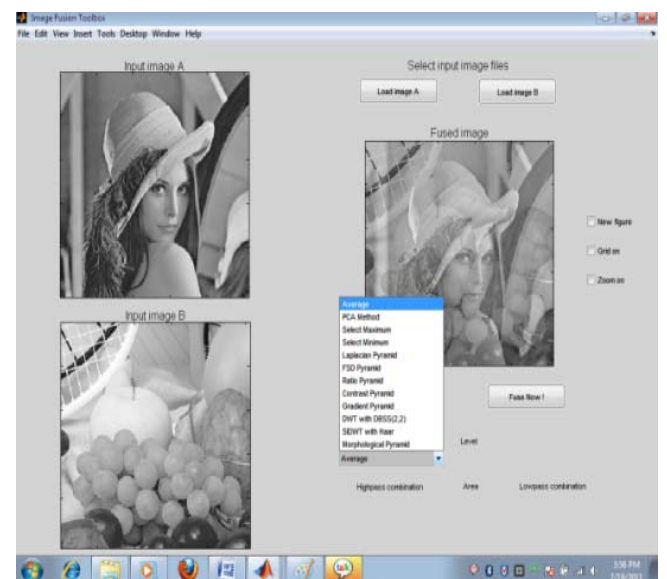


Figure 7: This shows the different methods for fusion of image.

This output figure represents the different fusion methods and these methods can be applied for the fused image that shows the output image in different methods by dropdown button. This method helps to analyze the figure in different way. Those methods will link to the main program by MATLAB.

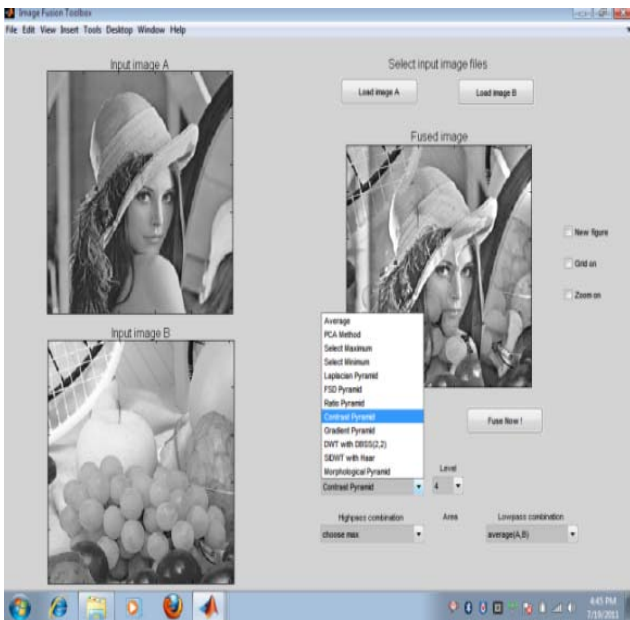


Figure 8: Fused output result is showed when selecting the contrast pyramid method.

This output result is helpful to analyze the method of contrast pyramid. That is used to increase the contrast of the fused image. That helps to get the clarity and accuracy of image will be analyzed.

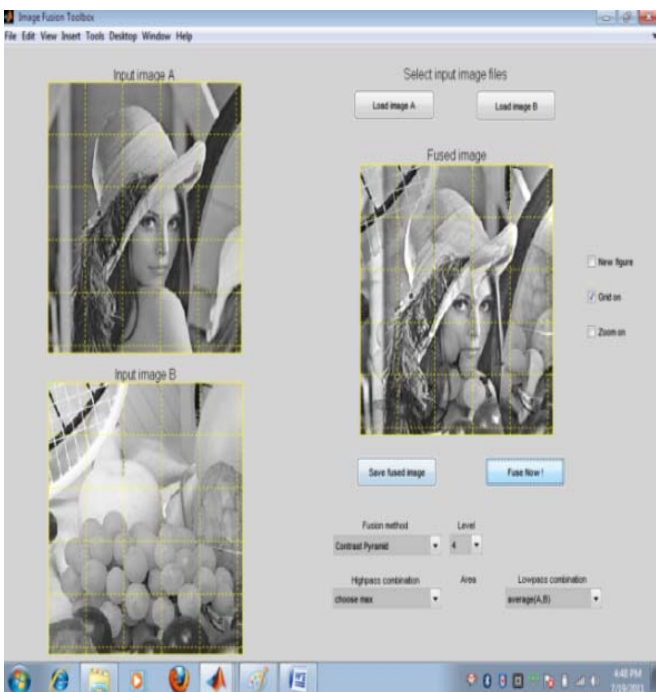


Figure 9: This shows the result image in the Grid on view.

This is shows the Grid view to analyze the image pixels in different sections which is fused. And also the surrounding of image can be covered by choosing the option grid on option from the GUI. And also the zoom on option will gives the output result in zoom way.

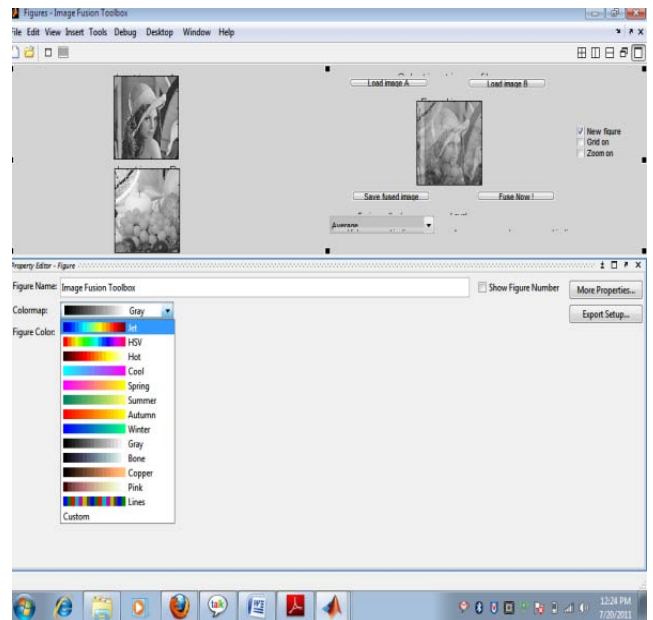


Figure 10: This resulted output image can be saved as new figure by changing its different colour maps

This is the image fusion toolbox options that provides the change can be made to the image by colour map and figure colour. When we select the fused image as new figure option and by choosing the edit menu we can change the colour of the fused image.

V. CONCLUSION

In this paper a Pseudo Colour Multi-Scale approach scheme is done for image fusion for IR and visible images by using the EM algorithm and fusion methods. By this paper we conclude that, by using image fusion methods, the accuracy of fusion can be met and also from the EM algorithm we meet the image fusion is more naturalistic than other methods. The experiment results demonstrate by real image data that the proposed scheme can achieve better fusion performance than the traditional colour image fusion methods.

VI. FUTURE WORK

We can extend for multiple images as input and one output. And also in future different methods can be implementing for the accuracy and more naturalistic fusion results.

VII. REFERENCES

- [1]. A. Toet, E. M. Franken, Perceptual evaluation of different image fusion schemes, *Displays* 24 (2003) 25–37.
- [2]. A. Toet, J.K. IJspeert, Perceptual evaluation of different image fusion schemes, in: I. Kadar (Ed.), *Signal Processing, Sensor Fusion, and Target Recognition X*, The International Society for Optical Engineering, Bellingham, WA, 2001, pp. 436 - 441.
- [3]. A. Toet, Natural colour mapping for multiband nightvision imagery, *Information Fusion* 4 (2003) 155 - 166.
- [4]. E. Reinhard, M. Ashikhmin, B. Gooch, P. Shirley, Colour transfer between images, *IEEE Computer Graphics and Applications* 21 (5) (2001) 34 - 41.

- [5]. Xydeas. C.S, Petrovic. V, Objective image fusion performance measure, [J], Electronics Letters, v36, n 4, p. 308-309, 2000.
- [6]. Hasler, D., Suesstrunk, S. “Measuring colourfulness for natural images”, Proc. IS&T/SPIE Electronic Imaging 2003: Human Vision and Electronic Imaging VIII, SPIE, 87-95, 2003.
- [7]. Wei. Chen and Scott T. Acton “Morphological Pyramids For Multiscale Edge Detection”. [Courtesy of http://viva.ee.virginia.edu/publications/c_morphpyramid.pdf]
- [8]. R. R. Hoffman, A. B. Markman, Interpreting remote sensing imagery: human factors, CRC Press (2001) 137-182.
- [9]. William F. Herrington, Jr., Berthold K.P. Horn, and Ichiro, Masaki,” Application of the Discrete Haar Wavelet Transform to image fusion for nighttime driving”, Intelligent Vehicles Symposium, 2005. Proceedings. IEEE Conference 2005. Courtesy of <http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=1505114>]
- [10]. Gang Liu, Guohong Huang, “Colour Fusion Based on EM Algorithm for IR and Visible Image”, 2010 IEEE, p.253-258.
- [11]. Fessler. J. A, Hero. A. O, Space-alternating generalized expectation-maximization algorithm, [J], IEEE Trans. Signal Processing, v. 42, n. 10, p. 2664- 2677, (Oct. 1994).
- [12]. Blum. R. S, Kozick. R. J, and Sadler. B. M, An adaptive spatial diversity receiver for non-Gaussian interference and noise, [J], IEEE trans. Signal Processing, Aug, v 47, n 8, p. 2100-2111, (1999).
- [13]. Diamant. E, Single Pixel Information Content, [C], Proceedings of SPIE, v 5014, p. 20-24. (2003).