Comparison on Various Pixel based Image Fusion Techniques

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Abstract--- As the optical lenses in Charged Couple devices (CCD) have limited depth-of focus, it is regularly impossible to obtain an image in which all relevant objects are in focus. To achieve all interesting objects in focus, several CCD images, each of which contains some part of the objects in focus, are required. If multiple images of the same scene are available, this can be achieved by image fusion. Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. The objective in image fusion is to reduce uncertainty and minimize redundancy in the output while maximizing relevant information particular to an application or task. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics. Fusion techniques include in this paper are simplest method of pixel averaging to more complicated methods such as principal component analysis and wavelet transform fusion. Main focus of this paper to perform comparative analysis on various pixel based image fusion techniques on the basis of various performance metrics, in order to check the quality of a fused image.

Keywords: Image Fusion, Multifocus Image, Simple Pixel Method, Principal Component Analysis, Discrete Wavelet Transform

I. INTRODUCTION

Information is used in many forms to solve problems and examine conditions. When multiple source information is combined, it is essentially used to derive or gather more reliable information. However, there is usually a point of withdrawing returns after which more information provides little improvement in the final result. Which information and how to combine it is an area of research called data fusion. In many cases, the problem is not well defined when data is collected. Large amounts of information are hard to organize, evaluate, and utilize. Less information giving the same or a better answer is desirable. Data fusion attempts to combine data such that more information can be evaluated from the combined sources than from the separate sources. Data fusion techniques combine data and related information from connected databases, to achieve improved accuracy.

Due to imperfections of imaging devices (optical degradations, limited resolution of CCD sensors) and instability of the observed scene (object motion, media turbulence), acquired images are often blurred, noisy and may exhibit insufficient spatial and/or temporal resolution. Such images are not suitable for object detection and recognition. Reliable detection requires improving the original image. If multiple images of the same scene are available, this can be achieved by image fusion. Image fusion is the process that combines information from multiple images of the same scene [1]. These images may be captured from different sensors, acquired at different times, or having different spatial and spectral characteristics. The objective of the image fusion is to retain the most desirable characteristics of each image. The actual fusion process can take place at different levels of information representation; a generic categorization is to consider the different levels as, signal, pixel, feature and symbolic level [5].

A. Preprocessing of Image Fusion

Two images taken in different angles of scene sometimes cause distortion. Most of objects are the same in appearance but the shapes change a little. At the beginning of fusing images, we have to make sure that each pixel at correlated images has the connection between images in order to fix the problem of distortion, for this image registration plays an important role. The role of registration methods is to restrain large and complex geometric distortions. Image registration in general is a process of transforming two or more images into a geometrically equivalent. So the fusion process can be made more efficient in order to get better fused result.

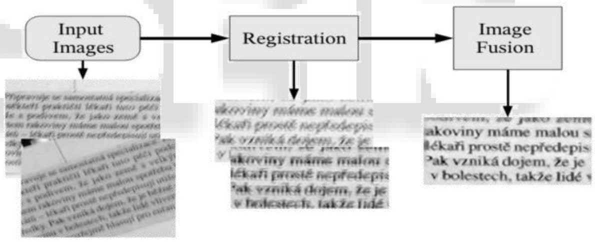


Fig. 1: Image Registration process

After registration, resampling is done to adjust each image that are about to fuse in order to have same dimension.

Fig. 2: Preprocessing of image fusion [1].

After resampling, each image will be of the same size. Several interpolation approaches can be used, to resample the image; the reason is that most approaches we use are all pixel-by-pixel fused. Images with the same size will be easy for fusing process. After the re-sampling, fusion algorithm is applied. Sometimes we have to transfer the image into different domain, sometimes haven't depending on the algorithm. Inverse transfer is necessary if image has been transferred into another domain. Fig 2. Shows preprocessing steps of image fusion.

B. Pixel Based Image Fusion

With the improvement of new imaging sensors arises the need of a meaningful combination of all imaging sources. The actual fusion process can take place at different levels of information representation; a generic categorization is to consider the different levels as signal, pixel, feature and symbolic level. The goal of pixel-level image fusion can broadly be defined as: to represent the visual information present in any number of input images, in a single fused image without the introduction of distortion or loss of information. The main advantage of pixel level fusion is that the original measured quantities are directly involved in the fusion process. Furthermore, algorithms are computationally efficient and easy to implement and shows better results. However, pixel level fusion algorithms require the input images to be co-registered. The main aim of pixel level fusion is to average the input images. Averaging reduces sensor noise but it also reduces the contrast of the complementary features. More robust algorithms for pixel level fusion such as weighted average, transform based approach.

In pixel-level image fusion, some generic requirements can be added in the fusion result. The fusion process should posses all relevant information of the input imagery. The fusion scheme should not introduce any artifacts or inconsistencies which would divert the human observer or following processing stages. The fusion process should be shift and rotational invariant, i.e. the fusion result should not depend on the location or orientation of an object the input imagery.

II. VARIOUS PIXEL BASED FUSION TECHNIQUES

A. Pixel Averaging Method

This is the simplest approach, where intensity of the output pixel is the average intensity of all the corresponding pixels from the input images. Due to the averaging operation, both the good and the bad information are minimized, arriving at a mean image. Performance of this method is not as good as it will miss out most important details from the input images. The averaging method can be calculated by:

$$I_f = \frac{I_1(x,y)+I_2(x,y)}{2} \qquad (2.1)$$

B. Select Pixel Maximum

In this method, the pixel with maximum intensity from the corresponding spatial locations from all the images to be fused is selected as the resultant pixel of the fused output image. The advantage of this method over averaging method is that there is no compromise made over the good information available in the input images. But the disadvantage is that it considers only the higher pixel intensity as the better information ignoring all other values.

C. Select Pixel Mininmum

This is similar to the select maximum method but with the difference, it considers only the pixel with lowest intensity value and ignores all other values. This method also has the disadvantage of either completely considering an information or discarding it fully. Authors suggested that the images with dark shades would generate a good fused image with this method.

D. Principal Component Analysis

Principal component analysis [2][3][7][8] is a vector space transform, which is used to reduce dimensionality. PCA is the simplest true eigenvector-based multivariate analysis. PCA involves ways for identifying and to show patterns in data, in such a way as to highlight their similarities and differences, and thus reduce dimension without loss of data. In this method first the column vectors are extracted, from respective input image matrices. The covariance matrix is calculated. Diagonal elements of covariance vector will contain variance of each column vector. The Eigen values and the vectors of covariance matrix are calculated. Normalize column vector corresponding to larger Eigen value by dividing each element with mean of Eigen vector. Those normalized Eigen vector values act as the weight values and are multiplied with each pixel of input image. Sum of the two scaled matrices are calculated and it will be the fused image matrix. The information flow diagram of PCA-based image fusion algorithm is shown in Fig 3. The input images (images to be fused) $I_1(x, y)$ and $I_2(x, y)$ are arranged in two column vectors and their empirical means are subtracted. The resulting vector has a dimension of n x 2, where n is length of the each image vector. Compute the eigenvector and eigenvalues for this resulting vector are computed and the eigenvectors corresponding to the larger eigenvalue obtained [8]. The fused image is:

$$I_f(x,y) = P_1 I_1(x,y) + P_2 I_2(x,y) \qquad (2.2)$$

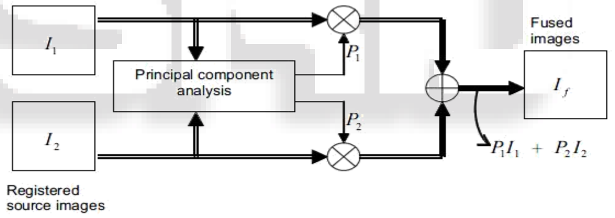


Fig. 3: Information flow diagram in PCA [8].

Let the source images (images to be fused) be arranged in two-column vectors. The major steps followed to convert data into 2-D subspaces are [8]:

- Organize the data into column vectors. The resulting matrix Z is of dimension 2 x n.
- Compute the empirical mean along each column. The empirical mean vector M_e has a dimension of 1 x 2.
- Subtract the empirical mean vector M_e from each column of the data matrix Z. The resulting matrix X is of dimension 2 x n.
- Find the covariance matrix C of X i.e. $C=XX_T$ mean of expectation = cov(X).
- Compute the eigenvectors V and eigenvalue D of C and sort them by decreasing Eigen-value. Both V and D are of dimension 2 x 2.
- Consider the first column of V which corresponds to larger eigenvalue to compute P_1 and P_2 as:

$$P_1 = \frac{V(1)}{\sum V} \;\; \& \;\; P_2 = \frac{V(2)}{\sum V} \qquad (2.3)$$

E. Discrete Wavelet Transform

Wavelet transforms are linear transforms whose basis functions are called wavelets. The wavelets used in image fusion can be classified into many categories such as orthogonal, bi-orthogonal. Although these wavelets share some common properties, each wavelet has a different image decompression and reconstruction characteristics that lead to different fusion results. They are not shift invariants and consequently the fusion methods using dwt lead to unstable and iridescent results. For the case of image sequences the fusion process should not be dependent on the location of an object in the image and fusion output should be stable and consistent with the original input sequence. To make the DWT shift invariant we use haar wavelet transform. Haar wavelets are real, orthogonal and symmetric. The Haar wavelet [10] mother wavelet function $\psi(t)$ can be described as:

$$\psi(t) = \begin{cases} 1\,, 0 \le t < 0.5, \\ -1, 0.5 \le t < 1, \\ 0, \text{Otherwise} \end{cases} \tag{2.4}$$

and its scaling function described as:

$$\phi(t) = \begin{cases} 1, 0 \le t \le 1, \\ 0, \ \text{Otherwise} \end{cases} \tag{2.5}$$

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations.

The information flow in one level of 2-D image decomposition is shown in Fig 4 .Wavelet individually filters and down samples the 2-D data (image) in the vertical and horizontal direction. The input (source) image is I(x, y) filtered by low pass filter L and high pass filter H in horizontal direction and then down sampled by a factor of two (keeping the alternative sample) to create the coefficient matrices $I_L(x,y)$ and $I_H(x,y)$. The coefficient matrix $I_L(x,y)$ and $I_H(x,y)$ are both low pass and high pass filtered in vertical direction and down sampled by a factor of two to create sub bands (sub images) $I_{LL}(x,y)$, $I_{LH}(x,y)$, $I_{HL}(x,y)$, $I_{HH}(x,y)$[8].

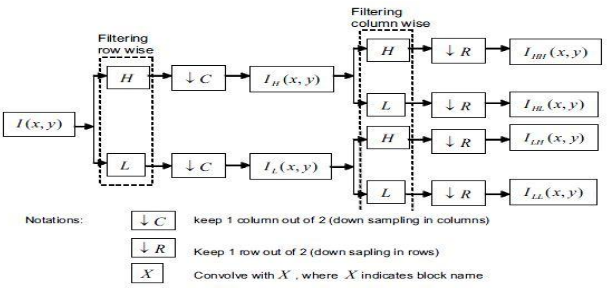


Fig. 4: One level of 2-D image decomposition [8].

The $I_{LL}(x,y)$, contains the average image information corresponding to low frequency band of multi scale decomposition. It can be considered as smoothed and sub sampled version of the source image I(x, y). Portion represents the approximation of source image I(x, y). Where $I_{LH}(x,y)$, $I_{HL}(x,y)$,and $I_{HH}(x,y)$ are detailed sub images which contain directional (horizontal, vertical and diagonal) information of the source image I(x,y), due to spatial orientation.

Inverse 2-D wavelet transform is used to reconstruct the image I(x,y), from sub images $I_{LL}(x,y)$, $I_{LH}(x,y)$, $L_{HL}(x,y)$, and $L_{HH}(x,y)$ as shown in Fig 5. This involves column up sampling (inserting zeros between samples) and filtering using low pass L and high pass filter H for each sub images. Row up sampling and filtering with low pass filter L and high pass filter H of the resulting image and summation of all matrices would construct the image I(x, y).

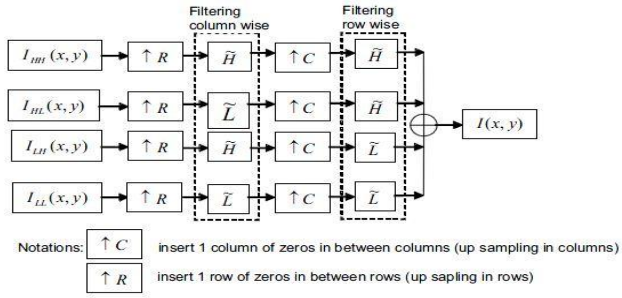


Fig. 5: One level of 2-D image reconstruction [8].

The information flow diagram of wavelet- based image fusion algorithm is shown in Fig 6. In wavelet image fusion method the source images $I_1(x,y)$ and $I_2(x,y)$, are decomposed into approximation and detailed coefficients at necessary level using DWT. The approximation and detailed coefficients of both images are combined using fusion rule f. The fused image (I_f (x,y)) be obtained by taking the inverse discrete wavelet transform (IDWT) as:

$$I_f(x,y) = \text{IDWT} [\ \text{Ø}\{ \text{DWT} (I_1(x,y)), \text{DWT} (I_2(x,y)) \}] \tag{2.6}$$

The fusion rule used in this paper is selecting maximum pixel value to select high frequency coefficient.

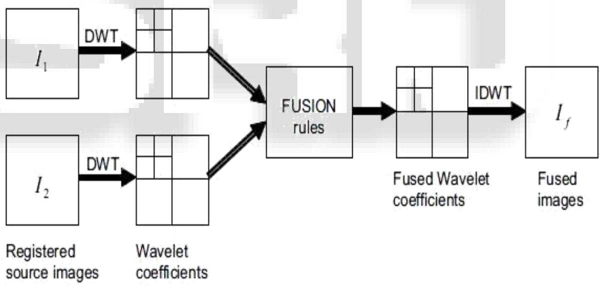
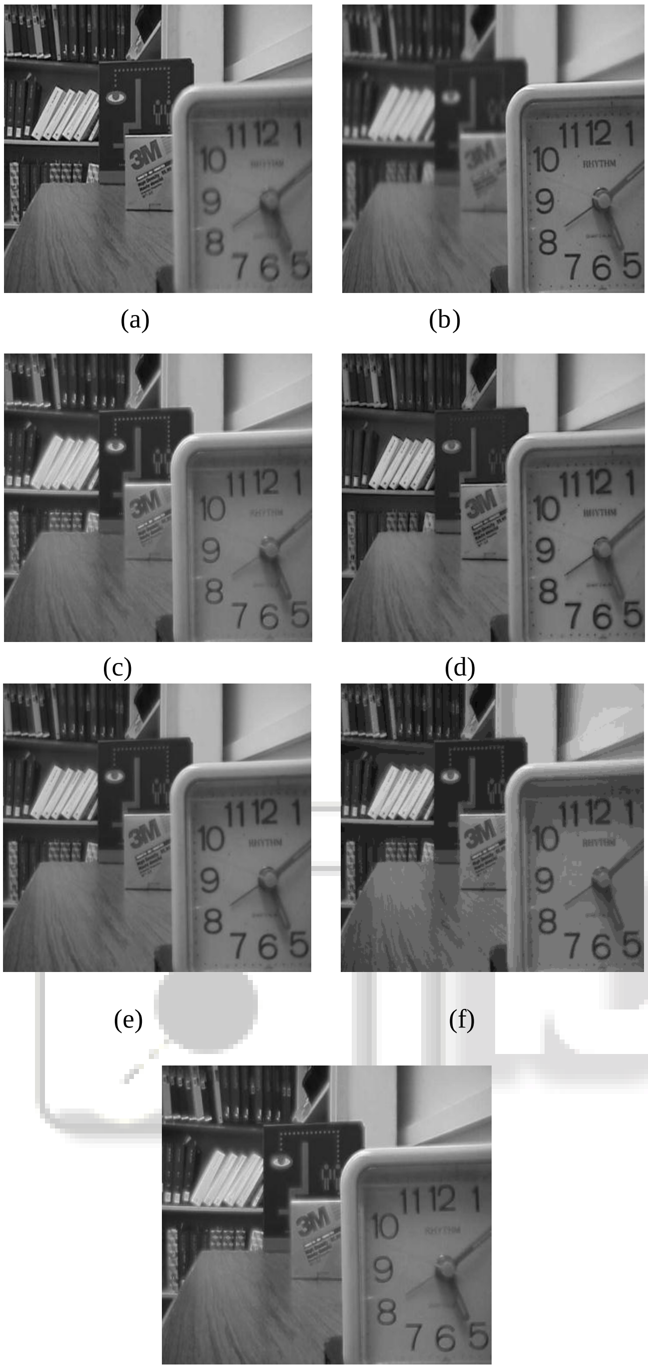


Fig. 6: Information flow diagram of image fusion [8].

III. EXPERIMENTAL RESULTS

In the experiment we have used multifocus images for fusion process. Another consideration is that image used is registered image. The test images are a pair of clock images, which contain multiple objects at separate distance from camera as shown in Figs. (a) and (b) . The fusion methods implemented in this paper are Pixel maximum, Pixel Averaging Method, Pixel Minimum Method, Principal Component Analysis (PCA), and Discrete Wavelet Transform (DWT). The quality assessment criteria implemented in this paper are Entropy and Standard Deviation. As we know bigger the Entropy is, the richer the information contained is, the pictures quality is better. Standard Deviation measures the contrast in the fused image. An image with high contrast would have a high standard deviation [3][10]. So the higher the standard deviation of a fused image is higher the contrast of an image, so the visibility of an fused image is enhanced.



(a) (b) (c) (d) (e) (f) (h)

Fig. 7: (a) Input image 1; (b) Input image 2; (c) Fused image by Pixel Maximum; (d) Fused image by Pixel Minimum; (e) Fused image by Pixel Averaging; (f) Fused image by PCA; (h) Fused image by DWT.

Sr No.	Methods	Entropy	Standard deviation
1	Pixel Maximum	7.1818	44.4902
2	Pixel Minimum	7.1802	44.9837
3	Pixel Averaging	7.1890	44.0560
4	PCA	7.1946	44.1033
5	DWT	7.1965	45.0438

Table. 1: Comparative Analysis Of Various Fusion Techniques.

IV. CONCLUSION AND FUTURE WORK

From the results it is clear that DWT method shows better fused results as compared to various other pixel based fusion techniques implemented. As shown in table I, DWT method posses larger entropy as well standard deviation value as compare to other fusion techniques implemented. So the fused image obtained by the DWT method posses better quality as compare to other methods implemented.

Though DWT shows better result, but disadvantage method is that the fused image has less spatial resolution. In order to improve fusion quality, combination of DWT with other pixel based techniques can be used.

REFRENCES

[1] R.J.Sapkal, S.M.Kulkarni, "Image Fusion based on Wavelet Transform for medical application," International Journal of Engineering Research and Applications, Vol. 2, Issue 5, September- October 2012.
[2] Shih-Gu Huang, "Wavelet for Image Fusion," National Taiwan University.
[3] Jiang Tao, Ji Dabin , Han Jinfang, "Comparison Study of Different Fusion methods based on Remote Sensing Image," 3rd International Congress on Image and Signal Processing, ©2010 IEEE.
[4] Young Yang* "A Novel DWT Based Multi-Focus Image Fusion Method" 2011 International conference on Advance Engg.
[5] Vladimir S. Petrovic, "Multisensor Pixel-level Image Fusion," feb-2001.
[6] Ramesh, K.P.; Gupta, S.; Blasch, E.P., "Image fusion experiment for information content," Information Fusion, 2007 10th International Conference on , vol., no., pp.1,8, 9-12 July 2007.
[7] Sruthy, S.; Parameswaran, L.; Sasi, A.P., "Image fusion technique using DT- CWT," Automation, Computing, Communication, Control and Compressed Sensing, 2013 International Multi-Conference on , vol., no., pp.160,164, 22-23 March 2013.
[8] V.P.S. Naidu and J.R. Raol, "Pixel-level Image Fusion using Wavelets and Principal Component Analysis," Defence Science Journal, Vol. 58, No. 3, May 2008, pp. 338-352.
[9] S. S. Bedi, Rati Khandelwal, "Comprehensive and Comparative Study of Image Fusion technique," International Journal of Soft Computing and Engineering (IJSCE), March 2013.
[10] S. Vasuki, S. Gandhimathi, S. Manicka Vinodhini, "Comparative Analysis of Wavelets for Fusion Application," International Conference on Emerging Technology Trends on Advanced Engineering Research (ICETT'12).
[11] Paresh Rawat, Sapna Gangrade, Pankaj Vyas, "Implementation of Hybrid Image Fusion Technique Using Wavelet Based Fusion Rules," (IJCTEE), 2011.
[12] Gonzalo Pajares∗, Jesus Manuel de la Cruz, "A wavelet-based image fusion tutorial," Pattern Recognition(2004).

