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Original Article

Image Fusion Based on Absolute Maximum Fusion Rule Using Biorthogonal Wavelet Transform

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Abstract: *In computer vision applications, one of the challenging problems is to combine the relevant information from various images of the same scene without introducing artifacts in the resultant image. Because of the different types of sensors are used in image capturing devices and their principle of sensing and also, due to the limited depth of focus of optical lenses used in camera, it is possible to get several images of the same scene providing different information. Therefore, combining different information from several images to get a new improved composite image becomes important area of research.*

This work is related to the development of a system which helps to decompose the different images captured from many sensors from the same, then wavelet coefficients are extracted from that images and these coefficients are combined to form a fused image using Absolute Maximum Fusion Rule. Finally, inverse wavelet transform is used to obtain fused image. This paper focuses on the Pre-processing of Image Fusion.

Keywords: *Image Fusion, Pre-processing of Image Fusion, Multi-focus images, Biorthogonal Wavelet Transform, Fusion Rules.*

I. INTRODUCTION

A. Face Recognition Technology:

Face is a unique feature of a human being. Human faces are nonrigid objects with a high degree of variability in size, shape, color, and texture. The goal of face detection is to efficiently identify and locate human faces regardless of their positions, scales, orientations, poses, and illumination. Any automated system for face and facial gesture recognition will have immense potential in criminal identification, surveillance, missing children retrieval, office security, credit card verification, video document retrieval, and telecommunication.

Facial expressions involve extracting sensitive features (related to emotional state) from facial landmarks such as regions surrounding the mouth, nose, and eyes of a normalized image. Often dynamic image frames of these regions are tracked to generate suitable features.

Figure 1: Face Movements

The location, intensity, and dynamics of the facial actions are important for recognizing an expression. Moreover, the intensity measurement of spontaneous facial expressions is often more difficult than that of posed facial expressions. Face gestures are complex in nature and difficult to recognize.

In computer vision applications, one of the challenging problems is to combine the relevant information from various images of the same scene without introducing artifacts in the resultant image. Because of the different types of sensors are used in image capturing devices and their principle of sensing and also, due to the limited depth of focus of optical lenses used in camera, it is possible to get several images of the same scene providing different information. Therefore, combining different information from several images to get a new improved composite image becomes important area of research.

II. MAIN BODY OF THE PAPER

A. Image Fusion:

1. Image fusion is used to combine relevant information from two or more images of the same scene into a single composite image which is more informative and is more suitable for human and machine perception.

2. Sometimes Texture Identification is not done accurately when images are captured from no. of sensing devices. So, there is requirement of such a technique of identification which can identify texture correctly even when images captured from many sensing devices.

3. Images of the same scene from sensors with different characteristics and different resolution at different time may provide complementary information about the scene. Image fusion is an advanced image processing technology, which could produce a new integrated image while retaining the important feature of these images.

4. This paper makes the modest suggestion that Biorthogonal Wavelet Transform based Image Fusion is such a beneficial technique of image fusion which produces a new integrated image and retaining the important feature of these images.

5. Research into getting a new integrated composite image using image fusion with the help of various wavelet transform methods such as Biorthogonal Wavelet Transform is required and hopes to have inspired others to use image fusion in for effective and accurate face recognition.

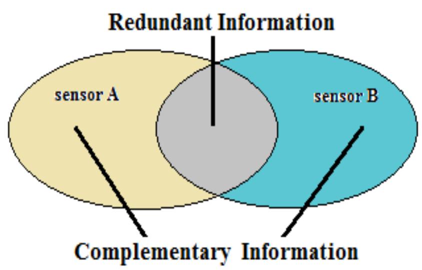


Figure 2: Fusion of Two Images

A primary goal of **Image Fusion** research is to create a system which can combine relevant information from two or more images of the same scene into a single composite image which is more informative and is more suitable for human and machine perception and identifies face images correctly.

Proposed system is used when different images captured from the same scene using sensing devices and decomposed and fused using first some spatial domain methods and then Biorthogonal Wavelet Transform (BWT) in which Absolute Maximum Fusion Rule is used for fusion. Finally, fused images using BWT are compared against that of the spatial domain methods.

The main objective of Seminar is:

- Study of Face Recognition
- Study of Image Fusion Concept
- Study of different requirements and levels of Image Fusion
- Study of different methods of Image Fusion
- Detailed Study of Biorthogonal Wavelet Transform (BWT) based Image Fusion
- Advantages of BWT based Image Fusion
- Study of Application areas of Image Fusion

B. Proposed Method of Biorthogonal Wavelet Transform based Image Fusion:

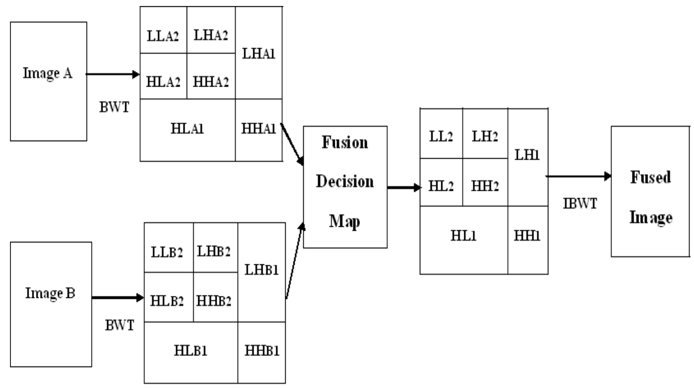


Figure 3: Proposed method of Biorthogonal Wavelet Transform based Image Fusion

The proposed method of image fusion uses the biorthogonal wavelet transform for decomposion and reconstruction of the source images. The overall fusion scheme based on BWT is shown in Figure 3.

Firstly we decompose source images of same scene (can have different focusing and modality) using Biorthogonal wavelet transform (BWT) and then coefficients obtained are merged using absolute maximum selection fusion rule. We have used wavelet and scaling functions used in BWT for decomposition of source images. The selection of proper wavelet for decomposition varies from application to application. No general selection criteria for wavelet and scaling function is available in literature. Although vanishing moment and regularity (smoothness) of wavelet can be considered to decide wavelet function. For image fusion application, selection of wavelet with sufficient vanishing moment is desired. Therefore, we have used biorthogonal filters to get desired number of vanishing moments. The coefficients obtained by decomposition of source images are fused using absolute maximum fusion rule.

C. Image Fusion Methods:

There are different techniques of Image Fusion are available such as:

- Spatial Domain Method
    1. Principal Component Analysis (PCA)
    2. Sharpness Criteria
    3. Linear Fusion
- Wavelet Domain Method

a) Principal Component Analysis

PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension.

It covers standard deviation, variance, covariance, eigenvectors and eigenvalues.

b) Standard Deviation

The Standard Deviation (SD) of a data set is a measure of how spread out the data is. It is the average distance from the mean of the data set to a point". The way to calculate it is to compute the squares of the distance from each data point to the mean of the set, add them all up, divide by n-1 and take the positive square root.

$$s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{(n-1)}}$$

Here, 's' denotes Standard Deviation. Xi is the set of numbers, i = 1 to n.

Example:

Set 1:

X	$(X - \bar{X})$	$(X - \bar{X})^2$
0	-10	100
8	-2	4
12	2	4
20	10	100
Total		208
Divided by (n-1)		69.333
Square Root		8.3266

c) Variance

Variance is another measure of the spread of data in a data set. In fact it is almost identical to the standard deviation.

$$s^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{(n-1)}$$

d) Covariance

Standard deviation and variance only operate on 1 dimension, so that you could only calculate the standard deviation for each dimension of the data set *independently* of the other dimensions. However, it is useful to have a similar measure to find out how much the dimensions vary from the mean *with respect to each other*.

Covariance is such a measure. Covariance is always measured *between* 2 dimensions. If you calculate the covariance between one dimension and *itself*, you get the variance. So, if you had a 3-dimensional data set, (x, y, z) then you could measure the covariance between the x and y dimensions, x and z dimensions and y and z dimensions. Measuring the covariance between x and x or y and y or z and z would give the variance of the x, y, and z dimensions respectively.

$$var(X) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(X_i - \bar{X})}{(n-1)}$$

$$cov(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)}$$

Example:

Covariance matrix for an imaginary 3 dimensional data set, using the usual dimensions x, y and z has 3 rows and 3 columns, and the values are this:

$$C = \begin{pmatrix} cov(x,x) & cov(x,y) & cov(x,z) \\ cov(y,x) & cov(y,y) & cov(y,z) \\ cov(z,x) & cov(z,y) & cov(z,z) \end{pmatrix}$$

e) Eigenvectors

Two matrices can multiply together if they are of same sizes. Consider the two multiplications between a matrix and a vector in Figure 2.3.1 below:

$$\begin{pmatrix} 2 & 3 \\ 2 & 1 \end{pmatrix} \times \begin{pmatrix} 1 \\ 3 \end{pmatrix} = \begin{pmatrix} 11 \\ 5 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 3 \\ 2 & 1 \end{pmatrix} \times \begin{pmatrix} 3 \\ 2 \end{pmatrix} = \begin{pmatrix} 12 \\ 8 \end{pmatrix} = 4 \times \begin{pmatrix} 3 \\ 2 \end{pmatrix}$$

Figure 2.3.1: Example of One Non-eigenvector and One Eigenvector

$$2 \times \begin{pmatrix} 3 \\ 2 \end{pmatrix} = \begin{pmatrix} 6 \\ 4 \end{pmatrix}$$

$$\begin{pmatrix} 2 & 3 \\ 2 & 1 \end{pmatrix} \times \begin{pmatrix} 6 \\ 4 \end{pmatrix} = \begin{pmatrix} 24 \\ 16 \end{pmatrix} = 4 \times \begin{pmatrix} 6 \\ 4 \end{pmatrix}$$

Figure 2.3.2: Example of how a Scaled Eigenvector is still an Eigenvector

In the first example, the resulting vector is not an integer multiple of the original vector, whereas in the second example, the example is exactly 4 times the vector we began with. The vector is a vector in 2 dimensional spaces. The vector $\begin{pmatrix} 3 \\ 2 \end{pmatrix}$ (from the second example multiplication) represents an arrow pointing from the origin, (0, 0) to the point (3, 2). The other matrix, the square one, can be thought of as a transformation matrix. If you multiply this matrix on the left of a vector, the answer is another vector that is transformed from its original position. It is the nature of the transformation that the eigenvectors arise from.

Eigenvectors can only be found for *square* matrices. And, not every square matrix has eigenvectors. All the eigenvectors of a matrix are *perpendicular*, i.e. at right angles to each other, no matter how many dimensions you have. In above example, $\begin{pmatrix} 3 \\ 2 \end{pmatrix}$ is an eigenvector.

f) Eigenvalues

Eigenvalues are closely related to eigenvectors. In above example, the amount by which the original vector was scaled after multiplication by the square matrix was 4. 4 is the *eigenvalue* associated with that eigenvector. Eigenvectors and eigenvalues always come in pairs [5].

g) Image Fusion by PCA

PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this subspace, this component points the direction of maximum variance.

The information flow diagram of PCA-based image fusion algorithm is shown in Figure 2.3.3.

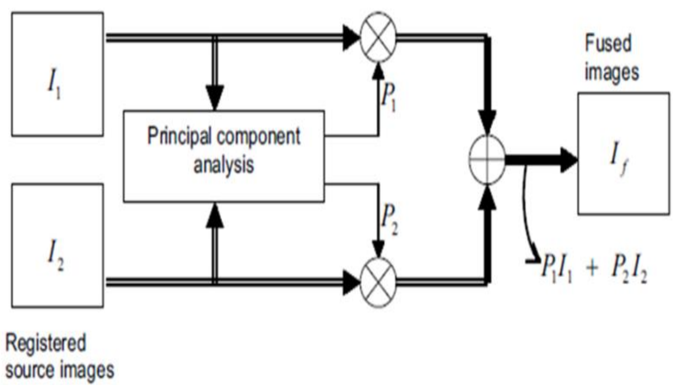


Figure 2.3.3: Information Flow Diagram in Image Fusin employing PCA

The input images (images to be fused) ***I1(x, y)*** and ***I2(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. The eigenvector and eigenvalues for this resulting vector are computed and the eigenvectors corresponding to the larger eigenvalue obtained. The normalized components ***P1*** and ***P2*** (i.e., ***P1*** + ***P2*** = 1) are computed from the obtained eigenvector. The fused image is:

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

- **Applications of PCA**

1. In data of high dimensions, where graphical representation is difficult, PCA is a powerful tool for analyzing data and finding patterns in it.
2. Data compression is possible using PCA.

The most efficient expression of data is by the use of perpendicular components, as done in PCA [3].

- **Sharpness Criteria**

Sharp images contain more details than blurred images. In many situations great variations are present in scene's depth; it is difficult to acquire an image in which all the areas of scene appear sharp. The scene areas which are in-focus will appear sharp and has higher contrast. Areas which are out of focus i.e. in front of or behind the focus plane will be blurred. So the key challenge of image fusion process is to identify the relevant information such as contrast/ high local energy and areas that are having high sharpness from the best-focused images and combine this useful information to create a highly informative image.

A multiresolution transform along with the gradient information of the images is being used to measure the strength and phase coherence which is the deciding factors in measuring sharpness of the image. An image with higher phase coherence and higher strength is considered as sharper and more informative. It is locally adaptive to image's content and sensitive to the blur of each image. To measure the degree of images blur the high-frequency information such as edges and boundaries are usually used as the basis. In general, sharper edges are present in the well-focused images and are expected to have higher frequency content than those that are blurred.

- **Bilateral Gradient based Sharpness Criterion**

Using the image gradients Image structure can be measured effectively. Consider an image of interest ***I(x, y)***. The gradient covariance matrix of a region within an M × N local window is defined as:

$$C = \begin{pmatrix} \sum_w I_x^2(x,y) & \sum_w I_x(x,y) I_y(x,y) \\ \sum_w I_x(x,y) I_y(x,y) & \sum_w I_y^2(x,y) \end{pmatrix}$$

Where, ***Ix(x, y)*** and ***Iy(x, y)*** represent image's gradient at the row and column directions, respectively. The above gradient covariance matrix can be decomposed as:

$$C = VDV^T = (v_1 \ \ v_2) \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} v_1^T \\ v_2^T \end{pmatrix}$$

Where V represents a 2×2 matrix whose column vectors are eigenvectors v1 and v2, D denotes the 2×2 diagonal matrix whose diagonal elements are eigenvalues λ1 and λ2 that correspond to eigenvectors v1 and v2, respectively, and the superscript T denotes the transpose.

The geometrical structure at a pixel in an image can be described by the eigenvalues λ1 and λ2 of the above gradient covariance matrix. Motivated by this, the first criterion is proposed to measure the strength of the image's gradient, which is defined as:

$$A(x, y) = \lambda_1 - \lambda_2$$

On the other hand, local phase coherence is consistent with the perceptual significance of image's characteristics. This has been supported by the physiological evidence that showed high human perception response to signal characteristics with high local phase coherence. Another advantage is the fact that it is insensitive magnitude variations caused by illumination conditions or noise present in image signals. In view of this, the second criterion is to consider the phase coherence of the image's gradient, that is:

$$P(x, y) = -\cos(\theta(x, y) - \overline{\theta}(x, y))$$

Where, $\theta(x, y)$ is the phase information at the position (x, y) and $\bar{\theta}(x, y)$ is the average of phases of the neighboring positions. This measure achieves the maximal value when the local phase coherence is worst, which is usually caused by an edge. Finally, the above two criterions and are jointly considered to develop a bilateral sharpness criterion as:

$$S_{BSC} = A^{\alpha}(x, y) P^{\beta}(x, y)$$

Where, α and β are two factors to adjust contributions of two criterions [4].

- **Wavelet Domain**

Spatial Domain Image Fusion Methods usually produce edge distortions in the fused image. This is well handled by the use of Wavelet Transform based Image Fusion Methods.

3. Analysis

3.1 Block diagram of Preprocessing of Image Fusion System

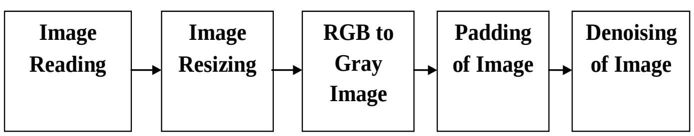


Figure 3.1.1: Block diagram of Preprocessing of Image Fusion System

The proposed method of image fusion uses the biorthogonal wavelet transform for decomposition and reconstruction of the source images. The overall preprocessing of image fusion scheme based on biorthogonal wavelet transform is shown in Figure 3.1.

➢ Image Reading:

Firstly original source images are read.

➢ Image Resizing:

According to different camera, sensing devices of cameras changes, hence, pixel values of images changes. So, if two images of same scene captured from sensing devices, then their pixel values changes, hence images are first resized into a standard format i.e. 256×256.

➢ RGB to Gray Image:

Sometimes there are color images, at that time transforms used for coefficient calculation becomes difficult hence RGB i, e. color to gray image conversion should be required.

➢ Padding of Image:

Images are converted into standard format after resizing, but to remove all the noise contents in the images Median filters are required. Median filters works only on 2×2 matrix element of each 3×3 matrix of each pixel in the image. Hence, corner elements are not taken into account during denoising process. So, padding of image is done, which pads zero's (bydefault) to both sides of two dimensional images.

➢ Denoising of Image:

For image fusion, first denoising of images is required; hence Median filters are required to remove all the noise contents in the images. Median Filters checks that each 2×2 matrix element of each 3×3 matrix of each pixel in the image is 0 or 255 or not. If it is 0 or 255 pixel value, then noise is contained, otherwise not. After removing all the noise content in the images, wavelets transform being used to calculate wavelet coefficients, which are combined to form fused image.

➢ **Proposed Method Algorithm**

Input: Two source images from same scene
Output: Fused Image
Step 1: Read the images
Step 2: Now, resize the images into standard format.
Step 3: Apply functions to convert RGB to Gray Image.
Step 4: Pad zeros at the two dimensions of images.
Step 5: Denoise the images to remove the noise.
Step 6: Wavelet transforms used to calculate wavelet coefficients.
Step 7: Combine the coefficients using Fusion Rules.
Step 8: Inverse wavelet transform is used to obtain fused image.

➢ **Flow Chart of Pre-processing of Image fusion**

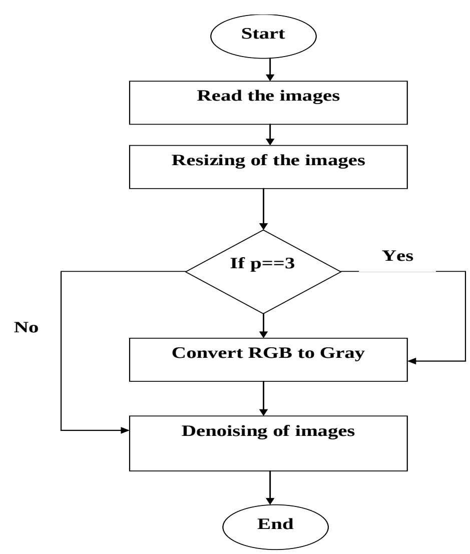
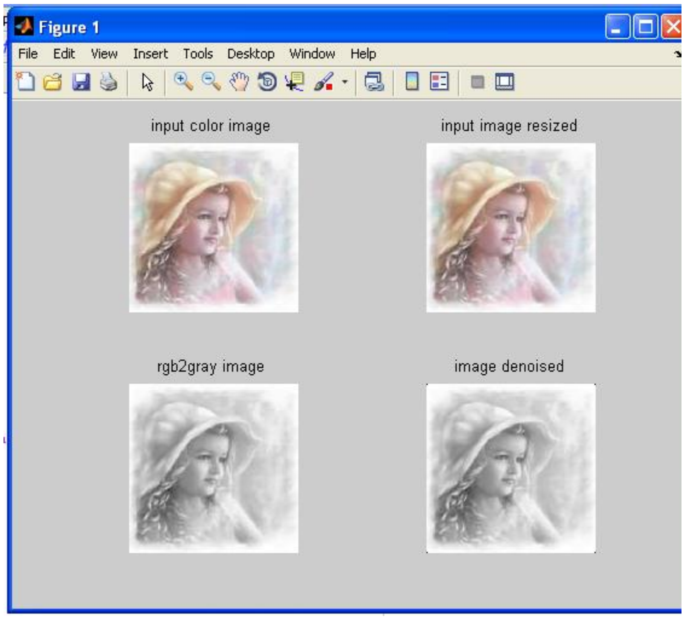


Figure 3.1.2: Flow Chart of Pre-processing of Image Fusion

After pre-processing of image fusion, few results have been observed shown below:



IV. CONCLUSIONS

A. Conclusion

1) This work concludes that, images are read using MATLAB with the help of image processing tools. Images are resized to convert into a standard format as images captured from different sensing devices changes pixels and if color images, then converted to gray image.
2) As images contains noise, so images should be denoised before applying transforms to them. Hence Median filter is used, which denoises the image.
3) When images having standard format, only second element of each matrix element of each pixel in image is check i.e. 0 or 255 or not using median filtering. Hence, corner elements of images are not taken into account. So, first padding zeros to both dimensions of image are done and then median filter removes noise.

4.2 Future Scope

1) Multilevel sensor can be used to capture images of same scene.
2) These multilevel sensor captured images can be fused using several wavelet transform methods.
3) Multimodal image fusion can be explored further using wavelet transform techniques such as BWT.

4.3 Applications

1) Medical Imaging
2) Forensic Science
3) Remote Sensing
4) Cancer staging
5) Surveillance
6) Radiotherapy treatment planning
7) Quantitative assessment of treatment response etc.

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