ISSN:0975-9646

Jincy Kuriakose et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (4) , 2014, 5944 - 5949

Image Fusion Using Kuwahara Filter

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***Abstract*— This paper proposes an efficient method for image fusion using Kuwahara filter, which is used for edge-preserving noise removal of images. Source images are fused by weighted average using the weights computed from the detail images that are extracted from the source images using Kuwahara filter. The performance of this method has been verified on several pairs of multifocus and multisensor images and compared with the existing methods visually. It is found that, none of the methods have shown consistence performance for all the performance measures. But as compared to them, the proposed method has shown good performance in most of the cases. Further, the visual quality of the fused image by the proposed method is superior to other methods.**

Keywords*— *Kuwahara, image Fusion, PCA, Detail image, Multi focus, Multi sensor

I. INTRODUCTION

Image fusion means the combining of two images into a single image that has the maximum information content without producing details that are non-existent in the given images. With rapid advancements in technology, it is now possible to obtain information from multi source images to produce a high quality fused image with spatial and spectral information. Image Fusion is a mechanism to improve the quality of information from a set of images. Important applications of the fusion of images include remote sensing, medical imaging, computer vision robotics and microscopic imaging.

Information fusion can be achieved at any level of image information representation. Similar to other forms of information fusion, image fusion is usually performed at one of the three different processing levels: signal, feature, and decision. Signal level image fusion, also known as pixel level image fusion, represents fusion at the lowest level, which defines the process of fusing visual information associated with each pixel from a number of registered images into a single fused image. As the pixel-level fusion is part of the much broader subject of multi-focus and multisensory information fusion, it has attracted many researchers in the last two decades [2-5]. Object level image fusion, also called feature level image fusion, fuses feature, object labels, and property descriptor information that have already been extracted from individual input images [6]. Finally, the highest level, decision or symbol-level image fusion represents fusion of probabilistic decision information obtained by local decision makers operating on the results of feature level processing on the image data produced from individual sensors [7].

Image fusion methods can be broadly classified into spatial domain and frequency domain fusion. Spatial image fusion work by combining the pixel values of the two or more images. Principal Component analysis (PCA) IHS (intensity hue saturation) and High pass filtering methods fall in the spatial domain fusion techniques. The simplest is averaging the pixel values of the input images. In frequency domain methods the image is first transferred into frequency domain. It means that the Fourier Transform of the image is computed first. All the Fusion operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. In the transform domain method the multiscale decomposition of the images is done and the composite image is constructed by using the fusion rule. Then inverse multiscale transform is applied to achieve the fused image. Image Fusion can be applied in every field where images are ought to be analyzed for example, microscopic imaging, robotics, medical image analysis, analysis of images from satellite, computer vision, remote sensing Application etc.

Because of limitations in the system, generally one image of a complex scene does not contain enough information. It is difficult to get all the objects in focus in a single image due to limited depth of focus by optical lens of a CCD camera. But, a series of images obtained by progressively shifting the focal plane through the scenery can be fused with a best fusion rule to produce an image with a quasi-infinite depth of field. This gives rise to the problem of multi-focus image fusion. Similarly, the images obtained by CCD camera give information only in visible spectrum whereas Infrared (IR) camera in IR spectrum, and hence, the multispectral data from different sensors often present complementary information about the region surveyed, scene or object. In such scenarios, image fusion provides an effective method to enable comparison, interpretation, and analysis of such data, as the fused image facilitates improved detection and unambiguous localization of a target (represented in IR image) with respect to its background (represented in the visible image). Hence, the fusion of IR and visual images is gaining momentum in surveillance applications. A suitably fused representation of IR and visible images provides a human operator a more complete and accurate mental representation of the perceived scene, which results in a larger degree of situational awareness. Likewise in medical imaging, the MRI image shows brain tissue anatomy, whereas CT scan image provides details about bony structures. The integration of these medical images of different modalities into one image with the merits of both source images provides both anatomical and functional information, which is important for planning surgical procedure. The aim is to achieve better situation assessment and/or more rapid and accurate completion of a predefined task than would be possible using any of the sensors individually. In the literature, it has been defined as the synergistic combination of different sources of sensory information into a single representational format [1].

II. LITERATURE SURVEY

A. Simple Average based Image Fusion

It is a very basic technique for image fusion. Image fusion could be achieved by simple averaging corresponding pixels in each input image as follows:

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

This is the simplest method of image fusion. The main disadvantage of this method is that it does not give guarantee to have a clear objects from the set of images.

B. Select Maximum

The greater the pixel values the more in focus the image. Thus this algorithm chooses the in-focus regions from each input image by choosing the greatest value for each pixel, resulting in highly focused output. The value of a pixel of each image is taken and compared to each other. The greatest pixel value is assigned to the corresponding pixel. Compared to average method, it results in highly focused image output obtained from the input images.

It is affected by blurring effect which directly affect on the contrast of the image

C. PCA Algorithm

PCA transform is a statistical method which transforms a number of correlated variables into a number of uncorrelated variables called principal components; this property can be used in image fusion. The most straightforward way to build a fused image of several input images is performing the fusion as a weighted average of all input images. The optimal weighting coefficients, with respect to information content can be determined by a principal component analysis (PCA) of all input intensities. By performing a PCA of the covariance matrix of input intensities, the weightings for each input image are obtained from the eigen vector corresponding to the largest eigen value. It is easy to implement and it increases the PSNR ratio also. PCA helps to reduce redundant information and highlight the components with biggest influence so as to increase the peak-signal-to-noise ratio. PCA is widely used in pattern matching and data compression by expressing the data in a way to highlight the differences and similarities without much loss of information. The PCA is also called as Hotelling transform or Karhunen-Loève transform.

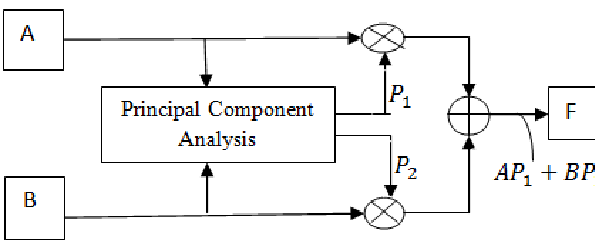


Figure 1 PCA Image Fusion

The steps involved in PCA Fusion are:

• The data should be organized into column vector. Let R be the resulting column vector of dimension 2xN.

• Next, empirical mean should be calculated along each column. The dimension of Empirical mean is 1x2.

• Subtract Mean from each column of R. The resulting matrix X has dimension 2xN.

• Find covariance C of matrix X.

• Consider first column of Eigen vector which correspond to larger Eigen value to compute normalized component P1 and P2.

The disadvantage of this method is that it may produce spectral degradation.

D. Laplacian Pyramid

In this method, a “pattern selective” approach is implemented for image fusion, so that the composite image is constructed not a pixel at a time, but a feature at a time. A pyramid decomposition is performed on each source image, and then integrate all these decompositions to form a composite representation, and finally the fused image is reconstructed by performing an inverse pyramid transform. The first step is to construct a pyramid for each source image Then using feature selection decision, fusion is implemented for each level of the pyramid. There are two modes of the combination: selection and averaging. In the averaging case, source patterns are averaged for reducing the noise. In the selection method the most salient component pattern from the source images are copied while less salient patterns are discarded. Averaging is used where the source images are similar and selection is used where the source images are distinctly different. Laplacian pyramid image fusion has mainly five steps 1) checking images size 2) pyramid level construction 3) pyramid level fusion 4) final level analysis 5)fused image reconstruction [14]. Some main advantages of pyramid transform are:

i) Provides information on sharp contrast changes. Human visual system(HVS) is especially sensitive to these sharp contrast changes.

ii) Provides both spatial and frequency domain localization.

The Laplacian pyramid based image fusion techniques generate fused images with blocking artifacts in the regions where the multi-sensor data are significantly different. In contrast, the wavelet transform based approach produces more naturally fused images

E. Wavelet Fusion

Wavelet transform can be applied to image decomposition and reconstruction [11-13]. Wavelet transforms provide a framework in which an image is decomposed, with each level corresponding to a coarser resolution band.

The wavelet transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale. The L-L band contains the average image information whereas the other bands contain directional information due to spatial orientation. Higher absolute values of wavelet coefficients in the high bands contains salient features such as edges or lines.

The wavelets-based approach is appropriate for performing fusion tasks for the following reasons:-

(1) It is well suited to manage the different image resolutions as it is a multi scale (multi resolution) approach. It is useful in many image processing applications including the image fusion.

(2) The discrete wavelets transform (DWT) allows the image decomposition in different kinds of coefficients preserving the image information. Such coefficients from different images can be appropriately combined to obtain new coefficients so that the information in the original images is collected appropriately.

(3) Once the coefficients are merged the final fused image can be achieved by taking the inverse discrete wavelets transform (IDWT). Thus the information in the merged coefficients is also preserved.

Distortion of the spectral information is minimized compared to the standard methods. In general, as a typical feature level fusion method, wavelet-based fusion could evidently perform better than convenient methods in terms of minimizing color distortion and denoising effects. It has been one of the most popular fusion methods in remote sensing in recent years, and has been standard module in many commercial image processing softwares, such as ENVI, PCI, ERDAS. Problems and limitations associated with them include:

(1) Its computational complexity compared to the standard methods;

(2) Spectral content of small objects often lost in the fused images;

(3) It often requires the user to determine appropriate values for certain parameters (such as thresholds).

The development of more sophisticated wavelet-based fusion algorithm (such as Curvelet, Ridgelet and Contourlet transformation) could improve the performance results, but these new schemes may cause greater complexity in the computation and setting of parameters.

III. PROPOSED METHOD

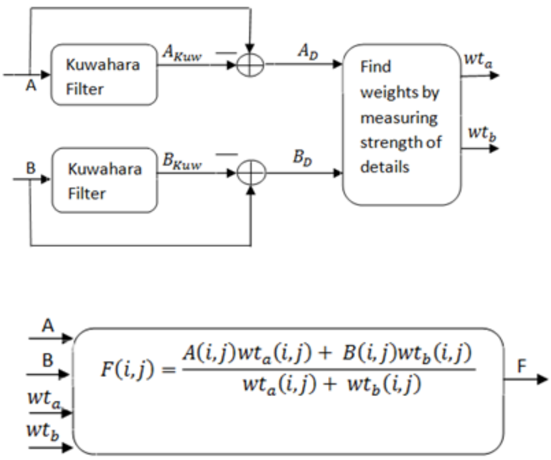


Figure 2 Kuwahara Image Fusion Block Diagram

The proposed image fusion algorithm directly fuses two source images of a same scene using weighted average. The proposed method differs from other weighted average methods in terms of weight computation and the domain of weighted average. Here, the weights are computed by measuring the strength of details in a detail image obtained by subtracting Kuwahara output from original image. The weights thus computed are multiplied directly with the original source images followed by weight normalization. The block diagram of the proposed scheme is shown in Fig. 2 for two source images A and B.

A. Review of the Kuwahara Filter

The Kuwahara filter is a non-linear smoothing filter used in image processing for adaptive noise reduction. Most filters that are used for image smoothing are linear low-pass filters that effectively reduce noise but also blur out the edges. However the Kuwahara filter is able to apply smoothing on the image while preserving the edge.

Let us consider a gray scale image I(x,y) and a square window of size 2a + 1 centered around a point (x,y) in the image. This square can be divided in to four smaller square regions Q1, Q2, Q3 and Q4; each of which will be

$$Q_1(x,y) = [x, x+a]\ X\ [y, y+a]$$
$$Q_2(x,y) = [x-a, x]\ X\ [y, y+a]$$
$$Q_3(x,y) = [x-a, x]\ X\ [y-a, y]$$
$$Q_4(x,y) = [x, x+a]\ X\ [y-a, y]$$

where X is the cartesian product. It must be noted that pixels located on the borders between two regions belong to both regions so there is a slight overlap between sub regions.

The arithmetic mean $\mathrm{m}_i(x,y)$ and standard deviation $\sigma_i(x,y)$ of the four regions centered around a pixel (x,y) are calculated and used to determine the value of the central pixel. The output of the kuwahara filter $\phi(x,y)$ for any point (x,y) is then given by:

$$\phi(x,y) = \begin{cases} \mathrm{m}_1(x,y) & if\ \sigma_1(x,y) = \min_i \sigma_i(x,y) \\ \mathrm{m}_2(x,y) & if\ \sigma_2(x,y) = \min_i \sigma_i(x,y) \\ \mathrm{m}_3(x,y) & if\ \sigma_3(x,y) = \min_i \sigma_i(x,y) \\ \mathrm{m}_4(x,y) & if\ \sigma_4(x,y) = \min_i \sigma_i(x,y) \end{cases}$$

That is, a symmetric square neighborhood around each pixel of a gray level image is divided in four square sub regions and the value of the central pixel is replaced by the gray level average over the most homogeneous sub region, i.e., the sub region with the lowest standard deviation.

This means that the central pixel will take the mean value of the area that is most homogenous. The location of the pixel in relation to an edge plays a great role in determining which region will have the greater standard deviation. If for example the pixel is located on a dark side of an edge it will most probably take the mean value of the dark region. On the other hand should the pixel be on the lighter side of an edge it will most probably take a light value. On the event that the pixel is located on the edge it will take the value of the smoother, least textured region. The fact that the filter takes into account the homogeneity of the regions ensures that it will preserve the edges while using the mean creates the blurring effect.

The detail image, obtained by subtracting Kuwahara output from the respective original image, for image A and B is given by $A_D = A - A_{KUW}$ and $B_D = B - B_{KUW}$ respectively. In multi focus images, unfocused area in image A will be focused in image B and the application of Kuwhara on image B will blur the focused area more compared to that of unfocused area in image B. This is because the unfocused area in image A anyway looks blurred with almost similar gray values in that area. Now, the idea is to capture most of the focused area details in detail image B_D such that these details can be used to find the weights for image fusion using weighted average. Similarly, in multi-sensor images, the information in image B is absent in image A and the application of Kuwahara on image B will blur the information in image B. This is because, as the information in A is absent, the gray levels in that region have similar values thereby making the kernel as Gaussian. Kuwahara has blurred the focused area keeping the unfocused area as it is and the details in the focused area have been captured in the detail images. Now, these detail images are used to find the weights by measuring the strength of details.

B. Pixel-based fusion rule

Fusion rule proposed in Shah et al. [8] is discussed here for completeness to compare the performance of proposed method. Here, the weights are computed using statistical properties of a neighborhood of detail coefficient instead of wavelet coefficient as in Shah et al. [8]. A window of size w × w around a detail coefficient $A_D(i,j)$ or $B_D(i,j)$ is considered as a neighborhood to compute its weight. This neighborhood is denoted as matrix X. Each row of X is treated as an observation and column as a variable to compute unbiased estimate $C_h(i,j)$ of its covariance matrix [9], where i and j are the spatial coordinates of the detail coefficient $A_D(i,j)$ or $B_D(i,j)$.

$$covariance(X) = [(X - E[X])\,(X - E[X])^T]$$

$$C_h(i,j) = \frac{\sum_{k=1}^{w}(x_k - \bar{x})\,(x_k - \bar{x})^T}{(w-1)}$$

where x_k is the kth observation of the w-dimensional variable and $\bar{x}$ is the mean of observations. It is observed that diagonal of matrix $C_h(i,j)$ gives a vector of variances for each column of matrix X. Now, the eigenvalues of matrix $C_h(i,j)$ is computed and the number of eigenvalues depends on size of $C_h(i,j)$. Sum of these eigenvalues are directly proportional to horizontal detail strength of the neighbourhood and are denoted as HdetailStrength [8]. Similarly, an unbiased covariance estimate $C_v(i,j)$ is computed by treating each column of X as an observation and row as a variable (opposite to that of $C_h(i,j)$), and the sum of eigenvalues of $C_v(i,j)$ gives vertical detail strength VdetailStrength. That is,

$$HdetailStrength(i,j) = \sum_{k=1}^{w} eigen_k \ of\ C_h(i,j)$$

$$VdetailStrength(i,j) = \sum_{k=1}^{w} eigen_k \ of\ C_v(i,j)$$

where $eigen_k$ is the kth eigenvalue of the unbiased estimate of covariance matrix. Now, the weight given to a particular detail coefficient is computed by adding these two respective detail strengths. Therefore, the weight depends only on the strength of the details and not on actual intensity values.

$$wt(i,j) = HdetailStrength(i,j) + VdetailStrength(i,j)$$

After computing the weights for all detail coefficients corresponding to both the registered source images, the weighted average of the source images will result in a fused image.

If wt_a and wt_b are the weights for the detail coefficients A_D and B_D belonging to the respective source images A and B, then the weighted average of both is computed as the fused image using the equation:

$$F(i,j) = \frac{A(i,j)wt_a(i,j) + B(i,j)wt_b(i,j)}{wt_a(i,j) + wt_b(i,j)}$$

C. Performance Measures

1) Average Pixel Intensity (API)

It measures the average pixel values in the fused image. It measures an index of contrast.

$$API = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} f(i,j)}{mn}$$

where f (i, j) is pixel intensity at (i, j) and mxn is the size of the image

2) Standard Deviation(SD)

This performance measure is more efficient in the absence of noise. Standard deviation measures the contrast in the fused image. An image with high contrast would have a high standard deviation.

$$\sigma = \sqrt{\sum_{i=0}^{L}(i - \bar{\imath})^2 h_{If}(i)}, \ldots \ \bar{\imath} = \sum_{i=0}^{L} i h_{If}$$

where $h_{If}(i)$ is the normalized histogram of the fused image and L is number of frequency bins in histogram.

3) Entropy(EN)

Entropy is the amount of information contained in a signal. The first person who introduced entropy to quantify the information was Shannon. If the value of entropy becomes larger after fusion, it indicates that information increases and the fusion performances are thus improved. The entropy evaluation of an image can be done as

$$E = -\sum_{i=0}^{L-1} p_i log_2 p_i$$

where L is the total of gray levels, *pi* is the probability distribution of each level.

4) Normalized Cross Correlation (Corr)

Normalized cross correlation is used to find out similarities between fused image and registered image. The correlation coefficient measures the similarity or closeness in small size structures between the original and the fused images. It can vary between -1 and +1.Values close to +1 indicate that they are highly similar while the values close to -1 indicate that they are highly dissimilar. It will be less than one when the dissimilarity increases. The ideal value is one when the reference and fused are exactly alike.

$$NCC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} * B_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{n}{A_{ij}}^2}$$

5) Spatial frequency (SF)

It measures the overall information level in the regions (activity level) of an image and is calculated as:

$$SF = \sqrt{RF^2 + CF^2} \text{ where } RF = \sqrt{\frac{\sum_i\sum_j(f(i,j)-f(i,j-1))^2}{mn}}$$

$$CF = \sqrt{\frac{\sum_i\sum_j(f(i,j)-f(i-1,j))^2}{mn}}$$

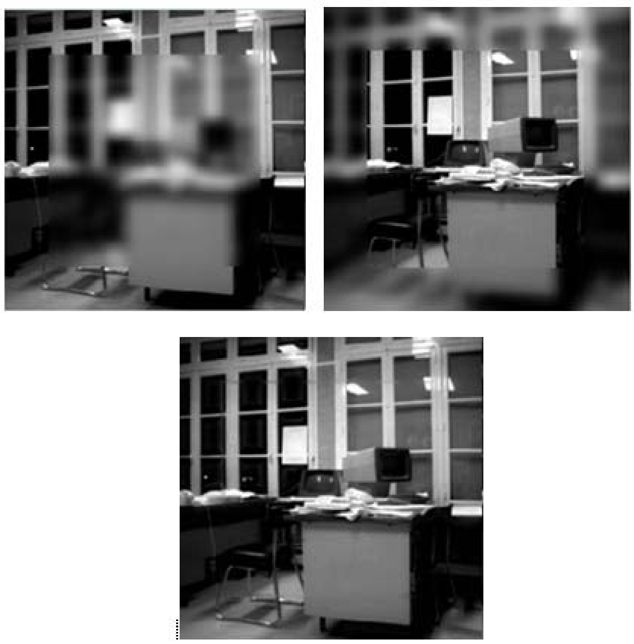
6) Average Gradient (AG)

It measures the degree of sharpness and clarity and it is calculated as:

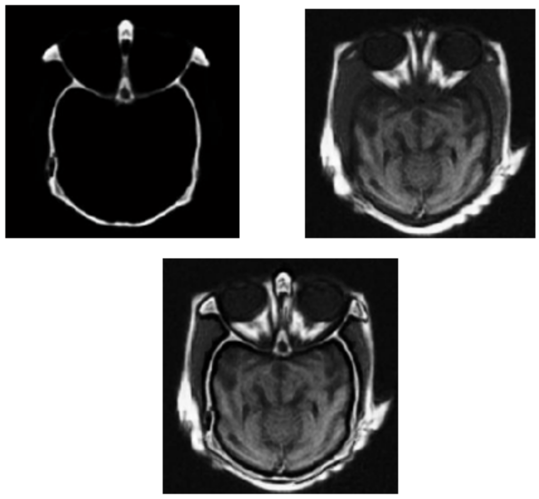
$$AG = \frac{\sum_i\sum_j((f(i,j)-f(i+1,j))^2 + (f(i,j)-f(i,j+1))^2)^{1/2}}{mn}$$

IV. EXPERIMENTAL RESULT

Experiments were carried out on various standard test pairs of multifocus, medical and IR–visible images provided by online resource for research in image fusion. Due to lack of space, fusion performance comparison is given only for two standard test pairs, namely multifocus (office) and medical (MRI). Fused image by the proposed method is compared with different methods discussed above.



Method	API	SD	EN	Corr	SF	AG
Avg	72.63	47.38	6.14	0.970	10.98	5.87
Max	81.47	63.91	6.70	0.969	18.31	10.20
PCA	80.37	59.42	7.52	0.976	14.22	8.34
CBF	81.35	64.89	7.42	0.964	24.67	13.27
DCT	80.87	**66.02**	7.43	0.965	23.92	12.82
DCT&LP	80.44	64.91	7.03	0.953	22.42	13.10
Kuwahara	**82.14**	65.74	**7.58**	**0.986**	**25.06**	**14.21**



Method	API	SD	EN	Corr	SF	AG
Avg	31.80	32.93	5.79	0.60	9.62	5.16
Max	49.69	55.68	6.75	0.65	18.68	10.06
PCA	51.83	54.17	6.58	0.54	13.74	7.64
DCT	32.08	48.82	6.62	0.65	19.72	10.69
DCT&LP	31.51	50.11	6.64	**0.67**	21.67	10.73
Kuwahara	**55.42**	**57.86**	**6.77**	0.65	**21.79**	**11.53**

CONCLUSION

In this paper, it was proposed to use detail images extracted from the source images by Kuwahara for the computation of weights. These weights, thus computed by measuring the strength of horizontal and vertical details, are used to fuse the source images directly. Several pairs of multisensor and multifocus images are used to assess the performance of the proposed method. Through the experiments conducted on standard test pairs of multifocus and medical images, it was found that the proposed method has shown superior/similar performance in most of the cases as compared to other methods in terms of quantitative parameters and in terms of visual quality, it has shown superior performance to that of other methods.

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