A Comparative Study of various Image fusion Technics

Sunil Sharma

Abstract— Image fusion refers the process of combining multiple images of a scene to obtain a single composite image. The composite image should contain a more useful description of the scene than provided by any of the individual source images. Image fusion is widely used in intelligent robots, stereo camera fusion, medical imaging, and manufacture process monitoring, electronic circuit design and inspection, complex machine/device diagnostics and in intelligent robots on assembly lines.

Here we have consider some image fusion techniques such as averaging, min-max, PCA, brovey, pyramid based and transform based techniques. Various parameters have been considered and varied for all these techniques and found that every algorithm has some advantages and drawbacks. Combination of qualitative and quantitative assessment approach may be the correct way to find out which fusion algorithm is most appropriate for an application.

Index Terms— Image Fusion, Spatial Domain, Frequency Domain Techniques, Wavelets etc.

I. INTRODUCTION

Latest technologies in image capturing devices help us to extract variety of different information from an image. This information can be collectively combined using "fusion" to generate more informative image. Multi-view, multi-modal, multi-temporal and multi-focus are the four ways in which image fusion can be performed [1]. Image Fusion reads several images of the same scene or objects and retrieves important information from them to put it into a single output image. The basic idea is to perform a multiscale transform (MST) on each source image, then construct a composite multiscale representation from these according to some specific fusion rules [2].



Image fusion scheme

There are various image fusion techniques which are classified below.



Image Fusion Techniques Averaging Technique:

It is a well documented fact that regions of images that are in focus tend to be of higher pixel intensity. Thus this algorithm is a simple way of obtaining an output image with all regions in focus. The value of the pixel P (i, j) of each image is taken and added [3]. This sum is then divided by 2 to obtain the average. The average value is assigned to the corresponding pixel of the output image which is given in equation (2). This is repeated for all pixel values.

The fused image K(i,j) is given as

 $K(i, j) = \{X(i, j) + Y(i, j)\}/2$ (1)

Where X (i, j) and Y (i, j) are two input images and K(i,j) is the fused image.

Maximum Selection Scheme:

This scheme just picks coefficient in each subband with largest magnitude. A selection process is performed here wherein, for every corresponding pixel in the input images, the pixel with maximum intensity is selected, and is put in as the resultant pixel of the fused image

$$K(i,j) K(i,j) = Max.[w(I1(x,y)), w(I2(x,y))]$$
(2)

Where I1(x,y), I2(x,y) are the input images.

Minimum Selection Scheme:

This scheme just picks coefficient in each subband with smallest magnitude. A selection process is performed here wherein, for every corresponding pixel in the input images, the pixel with minimum intensity is selected and is put in as the resultant pixel of the fused image [4].

$$K(i,j) K(i,j) = Min.[w(I1(x,y)), w(I2(x,y))]$$
 (3)

% Load two original images: a mask and a bust

load mask; X1 = X;

load bust; X2 = X;

% Merge the two images from wavelet decompositions at level 5

% using db2 by taking two different fusion methods

% fusion by taking the mean for both approximations and details

XFUSmean = wfusimg(X1,X2,'db2',5,'mean','mean');

% fusion by taking the maximum for approximations and the

% minimum for the details

XFUSmaxmin = wfusimg(X1,X2,'db2',5,'max','min');

Principal Component Analysis:

It is a simple non-parametric method of extracting relevant information from confusing data sets. 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 [5]. The origins of PCA lie in multivariate data analysis, it has a wide range of other applications PCA has been called, 'one of the most important results from applied linear algebra and perhaps its most common use is as the first step in trying to analyses large data sets.



PCA process flow

The input images $I_1(x, y)$ 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 [6]. The normalized components P_1 and P_2 are computed from the obtained eigenvector. The fused image is given by equation,

 $I_{f}(x,y)=P_{1}I_{1}(x,y)+P_{2}I_{2}(x,y)$ (4)

coeff = pca(X) coeff = pca(X,Name,Value) [coeff,score,latent] = pca(X) [coeff,score,latent,tsquared] = pca(X) [coeff,score,latent,tsquared,explained,mu] = pca(X)

Brovey:

It is also known as the color normalization transform because it involves a red-green-blue (RGB) color transform method. The Brovey transformation was developed to avoid the disadvantages of the multiplicative method. It is a simple method for combining data from different sensors. It is a combination of arithmetic operations and normalizes the spectral bands before they are multiplied with the panchromatic image [7]. It retains the corresponding spectral feature of each pixel, and transforms all the luminance information into a panchromatic image of high resolution.

 $Red = (band1/\Sigma band n)* High Resolution Band$ $Green = (band2/\Sigma band n)* High Resolution Band$ $Blue = (band3/\Sigma band n)* High Resolution Band$ High resolution band = PAN(5)

Pyramid:

A pyramid based fusion comprises of a number of images at different scales which together represent the original image. Every pyramid based image fusion has three stages. Number of levels 'L' of pyramid is pre decided based on the size of the image.

The image reduction process involves lowpass filtering and downsampling the image pixels. The image expansion process involves upsampling the image pixels and lowpass filtering. You can also use this block to build a Laplacian pyramid.

A pyramid structure contains different levels of an original image. These levels are obtained recursively by filtering the lower level image with a low-pass filter [8]. We first make a Gaussian pyramid by filtering each level of image using a low pass filter and do the down sampling. As the level goes up, the image is getting smaller and smaller.

The matlab code is as follows:

function LLk = Lk(k,address)

International Journal of Engineering and Technical Research (IJETR) Volume-2011, January-June 2011

Now, we do the reconstruction part to reconstruct the original image using the first level of Laplacian pyramid and the filtered, upsampled version of (k+1)-th level of Gaussian pyramid [9].



Pyramid Flow chart

plot:: Pyramid(br, $[b_x, b_y, b_z]$, $\langle tr \rangle$, $[t_x, t_y, t_z]$, $\langle a = a_{min} ... a_{max} \rangle$, options)

- I1 = impyramid(I, 'reduce');
- I2 = impyramid(I1, 'reduce');
- I3 = impyramid(I2, 'reduce');

There are three stages in which stage one is repeated 'L' times, original image is convolved with a predefined filter of the corresponding method and a pyramid is formed for that level. Input images are then decimated to half their sizes. In second stage, using the final decimated input matrices a new image matric is generated either by selecting minimum or maximum or taking average [10]. Third stage is repeated 'L' times wherein input image matrix is un-decimated and then convolved with the transpose of the filter used in stage one.

Conclusion:

I have compared various image fusion method based on a Gaussian mixture distortion model. The results showed the advantages of pyramid approach in some cases. We also have studied the effect of the settings (number of Laplacian pyramid levels, the size of local analysis window). Generally speaking, using more Laplacian pyramid levels can be beneficial but this comes at the cost of increased complexity. In practice, we have found there is not much difference between the fused results obtained using a different number of pyramid levels if a sufficient number of levels is used (5 in our experiments). The local analysis window should be small enough so that the parameters are indeed constant in the window, but it should be large enough to contain enough sensor data to estimate the parameters reliably. In cases we considered, we found a 5×5 or 3×3 window size is a good choice.

References

[1] L.A. Klein, "Sensor and Data Fusion Concepts and Applications," SPIE Optical Engineering Press, Tutorial Texts, Vol. 14, pp.132-139, 1993.

[2] Shutao Li, "Image Fusion with Guided Filtering", IEEE Transactions On Image Processing, Vol. 22, No. 7, July 2013

[3] E. Waltz and J. Llinas, *Multisensor Data Fusion*. Artech House, Boston, MA, 1990.

[4] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proc. IEEE*, vol.

85, no. 1, pp. 6-23, Jan. 1997.

[5] P. K. Varshney, "Multisensor data fusion," *Electronics & Communication Engineering Journal*, vol. 9, pp. 245-253, Dec. 1997.

[6] J. K. Aggarwal, *Multisensor Fusion for Computer Vision*. Springer Verlag, 1993.

[7] L. A. Klein, Sensor and Data Fusion Concepts and Applications. SPIE, 1993.

[8] D. D. Ferris Jr., R. W. McMillan, N. C. Currie, M. C. Wicks, and M. A. Slamani, "Sensors for military special operations and law enforcement applications," *Proc.*

SPIE, vol. 3062, pp. 173-180, 1997.

[9] M. A. Slamani, L. Ramac, M. Uner, P. K. Varshney, D. D. Weiner, M. G. Alford, D. D.

Ferris Jr., and V. C. Vannicola, "Enhancement and fusion of data for concealed weapons

detection," Proc. SPIE, vol. 3068, pp. 8-19, 1997.

[10] M. R. Franklin, "Application of an autonomous landing guidance system for civil and

military aircraft," Proceedings of SPIE, vol. 2463, pp. 146-153, 1995