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IMAGE FUSION USING FRACTIONAL LOWER ORDER MOMENTS

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ABSTRACT

Image Fusion is a process of integrating complementary information from multiple images of the same scene such that the resultant image contains a more accurate description of the scene than any of the individual source images. A method for fusion of multifocus images is presented. First, multifocus images are decomposed using a discrete wavelet transform (DWT). Then an algorithm is proposed in the multiscale wavelet domain to develop a novel fusion rule based on fractional lower order moments. The experimental results on several pairs of multifocus images indicate that the proposed algorithm is superior to an existing algorithm by achim et al., in terms of spatial frequency (SF), fusion quality measure (Q_W), edge information preservation ($Q^{AB/F}$) and various other image quality metrics. The performance of the proposed algorithm is also compared with simple average and Principal Component Analysis (PCA) techniques.

KEYWORDS: Image Fusion, Moments, Principal Component Analysis, Wavelet Transform

INTRODUCTION

Multi-sensor image fusion (MIF) [1, 3] is a technique to combine the registered images to increase the spatial resolution of acquired low detail multi-sensor images and preserving their spectral information. Of late MIF has emerged as a new and promising research area. The benefiting fields from MIF are: Military, remote sensing, machine vision, robotic, and medical imaging, etc. Some generic requirements could be imposed on the fusion scheme: (a) the fusion process should preserve all relevant information contained in the source images, (b) the fusion process should not introduce any artifacts or inconsistencies which would amuse the human observer or following processing stages, and (c) irrelevant features and noise should be suppressed to a maximum extent. The problem that MIF tries to solve is to merge the information content from several images (or acquired from Different imaging sensors [15]) taken from the same scene in order to accomplish a fused image that contains the finest information coming from the original images. Hence, the fused image would provide enhanced superiority image than any of the original source images. Dependent on the merging stage, MIF could be performed at three different levels viz. pixel level, feature level and decision level. In this paper, pixel-level-based [2] MIF is presented to represent a fusion process generating a single combined image containing an additional truthful description than individual source image.

FUSION ALGORITHMS

The details of wavelets and PCA algorithm and their use in image fusion along with simple average fusion algorithm are described in this section.

Image Fusion by Simple Average

This technique is a basic and straight forward technique and fusion could be achieved by simple average of corresponding pixels in each input image as:

$$I_f(x,y) = \frac{I_1(x,y) + I_2(x,y)}{2} \tag{1}$$

Principal Component Analysis

The PCA [6] involves a mathematical procedure that transforms a number of correlated variables into fewer number of uncorrelated variables called principal components. 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. The first principal component is taken to be along the direction with the maximum variance and the second principal component is constrained to lie in the subspace perpendicular of the first. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on.

PCA Algorithm

The two source images are arranged in two-column vectors. Steps followed to project this data into a 2-D subspace are:

Step 1: Arrange the data into column vectors. The resulting matrix Z is of dimension $2\ X\ n$.

Step 2: Compute the empirical mean along each column. The empirical mean vector M_e has a dimension of $1\ X\ 2$.

Step 3: Subtract the empirical mean vector M_e from each column of the data matrix Z. The resulting matrix X is of dimension $2\ X\ n$.

Step 4: Find the covariance matrix C of X and mean of expectation using formulae

$$C = XX_T \tag{2}$$

Mean of expectation = $\mathrm{cov}(X)$ (3)

Step 5: Compute the eigenvectors V and eigenvalue D of C and sort them by decreasing eigen value. Both V and D are of dimension $2\ X\ 2$.

Step 6: Consider the first column of V which corresponds to larger eigenvalue to compute P_1 and P_2 as:

$$P_1 = \frac{V(1)}{\sum V} \text{ and } P_2 = \frac{V(2)}{\sum V} \tag{4}$$

Image Fusion by PCA

The input images (images to be fused) $I_1(x,y)$, $I_2(x,y)$ 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. Eigenvector and eigenvalues for this resulting vector are computed and the eigenvectors corresponding to the larger eigenvalue is obtained. The normalized components P_1, P_2 (i.e., $P_1 + P_2 = 1$) using eq. (4) are computed from the obtained eigenvector. The fused image is:

$$I_f(x,y) = P_1 I_1(x,y) + P_2 I_2(x,y) \tag{5}$$

Lower Order Moments

The paper is organized as follows: In Section 2, we provide some necessary preliminaries on alpha-stable processes with a special emphasis on bivariate models. Section 3 describes our proposed algorithm for wavelet-domain image fusion, which is based on fractional lower order moments. Section 4 compares the performance of our proposed algorithm with the performance of other current wavelet-based fusion techniques applied on two pairs of test images. Finally, in Section 5 we conclude the paper with a short summary.

Alpha-Stable Distributions

This section provides a brief, necessary overview of the alpha-stable statistical model used to characterize wavelet coefficients of natural images. Since our interest is in modeling wavelet coefficients, which are symmetric in nature, we restrict our exposition to the case of symmetric alpha-stable distributions. For detailed accounts of the properties of the general stable family, we refer the reader to [11] and [12].

Univariate S α S Distributions

The appeal of S α S distributions as a statistical model for signals derives from two main theoretical reasons. First, stable random variables satisfy the stability property which states that linear combinations of jointly stable variables are indeed stable. Second, stable processes arise as limiting processes of sums of independent identically distributed (i.i.d.) random variables via the generalized central limit theorem. The S α S distribution [14] lacks a compact analytical expression for its probability density function (pdf). Consequently, it is most conveniently represented by its characteristic function

$$\varphi(w) = \exp(j\delta w - \gamma |w|^{\alpha}) \tag{6}$$

Where a is the characteristic exponent, taking values 0 < α < 2, δ (-∞ < δ <∞) is the location parameter, and -y (-y > 0) is the dispersion of the distribution. For values of a in the interval [1, 2], the location parameter δ corresponds to the mean of the S α S distribution, while for 0 < α < 1, δ corresponds to its median. The dispersion parameter a determines the spread of the distribution around its location parameter δ , similar to the variance of the Gaussian distribution. The characteristic exponent α is the most important parameter of the S α S distribution and it determines the Characteristic exponent a is, the heavier the tails of the S α S density. This implies that random variables following S α S distributions with small characteristic μ exponents are highly impulsive. One consequence of heavy tails is that only moments of order less than a exist for the non-Gaussian alpha-stable family members. As a result, stable laws have infinite variance. Gaussian processes [13] are stable processes with α = 2 while Cauchy processes result when α = 1.

Bivariate Stable

Distributions Much like univariate stable distributions, bivariate stable distributions are characterized by the stability property and the generalized central limit theorem [3]. The characteristic function of a bivariate stable distribution has the form

$$\varphi(w) = \begin{cases} \exp(jw^T\delta - w^T A w) \; for \; \alpha = 2 \\ \exp(jw^T\delta - \int_s |w^T s|^{\alpha} \mu(ds) + j\beta_{\alpha}(w)) \; for \; 0 < \alpha < 2 \end{cases} \tag{7}$$

Where

$$\beta_\alpha(w)=\begin{cases}\tan\frac{\alpha\pi}{2}\int_s |w^T s|^\alpha \, sign|w^T s|\mu(ds)\ for\alpha\neq 1, 0<\alpha<2\\ \int_s w^T s\log|w^T s|\mu(ds)\ for\alpha=1\end{cases}\tag{8}$$

and where $\omega=(\omega 1,\omega 2),|\omega|=\sqrt{\omega_1^2+\omega_2^2}$,

S is the unit circle, the measure a(.) is called the spectral measure of the a-stable random vector and A is a positive semi definite symmetric matrix. Unlike univariate stable distribution, bivariate stable distributions form a nonparametric set being thus of much more difficult to describe. An exception is the family multidimensional isotropic stable distributions whose characteristic function has the form

$$(\omega_1,\ \omega_2) = \exp(j(\delta_1\omega_1+\delta_2\omega_2)-\gamma|\omega|\alpha)\tag{9}$$

The distribution is isotropic with respect to the location point (δ_1, δ_2). The two marginal distributions of the isotropic stable distribution are Sα S with parameters (δ_1, γ, α) and (δ_2, γ, a). Since our further developments are in the framework of wavelet analysis, in the following we will assume that (δ_1, δ_2) = (0, 0). The bivariate isotropic Cauchy and Gaussian distributions [10] are special cases for α = 1 and α = 2, respectively.

PROPOSED FUSION METHOD

The proposed multifocus image fusion process is accomplished by the following steps:

Step 1: Decompose the test images into sub bands. The set of images to be fused are analyzed by means of the wavelet transform.

Step 2: For each subband pair (except the lowpass residuals):

- Estimate neighborhood dispersions of the test images Υ_{X1} , Υ_{X2} using equations

$$E(Y)=\frac{\alpha-1}{\alpha}C_e+\frac{\log\gamma}{\alpha}\tag{10}$$

Where C_e = 0.5772166…. is the Euler constant, and Variance of the variable Y is given by

$$E([Y-E(Y)]^2)=\frac{\pi^2}{12}\frac{\alpha^2+2}{\alpha^2}\tag{11}$$

- Compute neighborhood symmetric covariation coefficient $Corr_\alpha(X_1,X_2)$

$$Corr_\alpha(X_1,X_2)=\lambda_{X_1,X_2}\lambda_{X_2,X_1}=\frac{[X_1,X_2]_\alpha[X_2,X_1]_\alpha}{[X_1,X_1]_\alpha[X_2,X_2]_\alpha}$$

- Calculate the fused coefficients using the formulae

$Y=W_1X_1+W_2X_2$ Where W_1 and W_2 are found by as follows: (Assume the threshold value of the image as T).

If $Corr_{\alpha} \leq T \ then \ W_{\min} = 0 \ and \ W_{\max} = 1$

else if $Corr_{\alpha} > T \ then$

$$W_{\min} = 0.5 - 0.5\frac{1 - Corr_{\alpha}}{1 - T} \ \& \ W_{\max} = 1 - W_{\min}$$

If $\Upsilon_{X1} > \Upsilon_{X2}$ then $W_1 = W_{max}$ and $W_2 = W_{min}$

else $W_1 = W_{min}$ and $W_2 = W_{max}$

Step 3: Calculated the average coefficients in low pass residuals. Averaging provides a way to average multiple video frames to create a more stable image.

This module can be used to eliminate pixel vibrations or high frequency image changes.

Step 4: Reconstruct the fused image from the processed subbands and the low pass residuals.

EXPERIMENTAL RESULTS

The proposed method has been tested on several pairs of multifocus images. Five examples are given here to illustrate the performance of the fusion process. The source images are assumed to be registered. The first example is shown in Figure 1. Figure 1(a) and (b) are two multifocus images with different distances towards the camera, and only half part of the clock in either image is in focus. Figure 1(e) is the fusion result by using the proposed method. Figures. 1(c)-(d) are the fused images by using simple average method [5], principal component analysis method (PCA) respectively. The fused results using Average and PCA are worse than that of our proposed method. For further comparisons, few objective criteria are used to compare the fusion results. Comparison between Fusion algorithms based on objective strategies are shown in Table 1.

Entropy (H)

Entropy is used to measure the information content of an image. Entropy is sensitive to noise and other unwanted rapid fluctuations. An image with high information content would have high entropy. It is defined as:

$$H = -\sum_{i=0}^{L} h_{I_f}(i) \log_2 h_{I_f}(i) \tag{12}$$

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

Standard Deviation (SD)

$$\sigma = \sqrt{\sum_{i=0}^{L} (i - \bar{i})^2 h_{I_f}(i)}, \ \bar{i} = \sum_{i=0}^{L} i h_{I_f} \tag{13}$$

Where $h_{I_f}(i)$ is the normalized histogram of the fused image $I_f(x, y)$ and L number of frequency bins in the histogram. Standard deviation is composed of the signal and noise parts. This metric would be more efficient in the absence of noise. It measures the contrast in the fused image. An image with high contrast would have a high standard deviation.

Spatial Frequency (SF)

Spatial Frequency [16] criterion is $SF = \sqrt{RF^2 + CF^2}$

Where $RF\ and\ CF$ are row and column frequency of the fused image and are given as:

$$RF = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=2}^{N}[I_f(x,y) - I_f(x,y-1)]^2} \tag{14}$$

$$CF = \sqrt{\frac{1}{MN}\sum_{y=1}^{N}\sum_{x=2}^{M}[I_f(x,y) - I_f(x-1,y)]^2} \ \ldots \tag{15}$$

This frequency in spatial domain indicates the overall activity level in the fused image. A larger Spatial Frequency implies better quality the fused image.

Mutual Information (MI)

It is a metric defined as the sum of *MI* [16] between each source image and the fused image. Considering the two source images *X* and *Y* and a fused image *Z*

$$I_{Z,X}(z,x) = \sum_{z,x} P_{Z,X}(z,x)\log\frac{P_{Z,X}(z,x)}{P_Z(z)P_X(x)} \tag{16}$$

$$I_{Z,Y}(z,y) = \sum_{z,y} P_{Z,Y}(z,y)\log\frac{P_{Z,Y}(z,y)}{P_Z(z)P_Y(y)} \tag{17}$$

Where P_X, P_Y and P_Z are the probability density functions in the images *X*, *Y* and *Z* respectively. $P_{Z,X}$ and $P_{Z,Y}$ are the joint probability density functions. Thus the image fusion performance mutual information can be defined as

$$MI = I_{Z,X}(z,x) + I_{Z,Y}(z,y) \tag{18}$$

Thus *MI* measures the degree of dependence of two images. The larger the value, the better the fusion result.

Fusion Quality Measure (Q_W)

Fusion quality measure Q_W [17] is defined as: Considering the two source images *X* and *Y* and a fused image *Z*

$Q_W(X,Y,Z) = \frac{1}{|W|}\sum_{w\in W}(\lambda_X(w)Q_0(X,Z\mid w) + \lambda_Y(w)Q_0(Y,Z\mid w))$ Where $\lambda_X(w) = \frac{S(X\mid w)}{S(X\mid w) + S(Y\mid w)}$ denote the local weight of image *X* which indicates the relative importance of image *X* compared to image *Y*. The larger $\lambda_X(w)$ the more weight is given to image *X*. $S(X\mid w)$ denote some saliency of image *X* in window *w*. It should reflect the local relevance of image *X* within the window *w*, and it may depend on contrast, variance, or entropy. In a similar fashion $\lambda_Y(w)$ is computed.

Where Q_0 is the overall image quality index, computed by averaging all local local quality indices:

$$Q_0(X,Z) = \frac{1}{|W|}\sum_{w\in W} Q_0(X,Y\mid w) \tag{19}$$

Where *W* is the family of all windows and |W| is the cardinality of *W*.

Image quality index Q_0 is defined as

$$Q_0 = \frac{4\sigma_{XY}\overline{X}\,\overline{Y}}{(\overline{X}^2 + \overline{Y}^2)(\sigma_X^2 + \sigma_Y^2)} \quad \ldots \quad (20)$$

$\overline{X}$ denote the mean of X , σ_X^2 is variance of X and σ_{XY} is the covariance of X and Y.

Edge Information Preservation Metric ($Q^{AB/F}$)

$Q^{AB/F}$ is edge information preservation value [18] and takes between 0 to 1.

CONCLUSIONS

In this paper, a new method for multifocus image fusion based on Fractional Lower Order Moments is presented. Different image fusion performance metrics have been evaluated. Experimental results on several pairs of multifocus images have demonstrated the superior performance of the proposed fusion scheme.

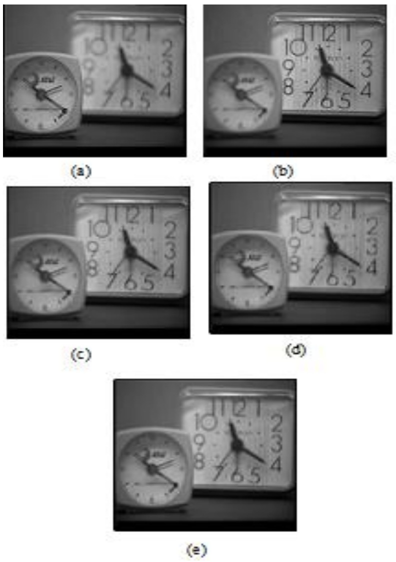

Figure 1: Example 1 (a) Clock 1 (b) Clock 2 (c) Fused Image by Simple Average (d) Fused Image by PCA (e) Fused Image by Proposed Method

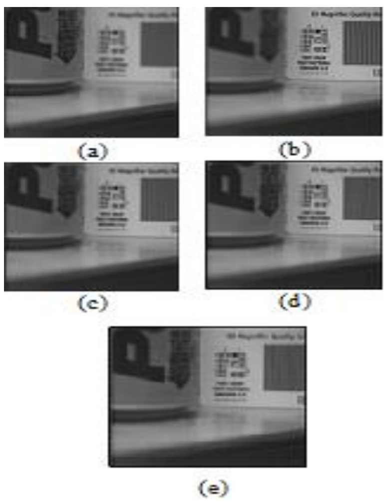

Figure 2: Example 2 (a) Pepsi 1 (b) Pepsi 2 (c) Fused Image by Simple Average (d) Fused Image by PCA (e) Fused Image by Proposed Method

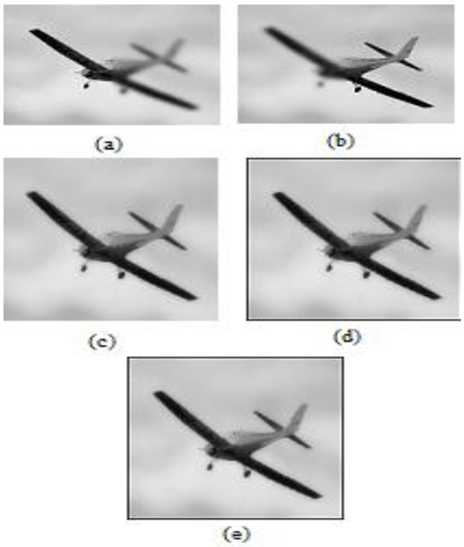

Figure 3: Example 3 (a) Plane 1 (b) Plane 2 (c) Fused Image by Simple Average (d) Fused Image by PCA (e) Fused Image by Proposed Method

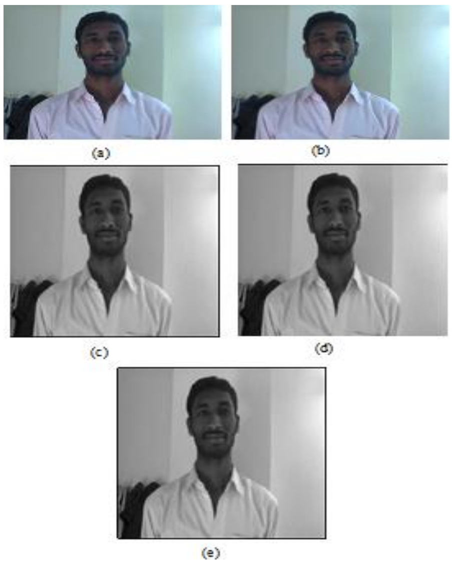

Figure 4: Example 4 (a) TR1 (b) TR2 (c) Fused Image by Simple Average (d) Fused Image by PCA (e) Fused Image by Proposed Method

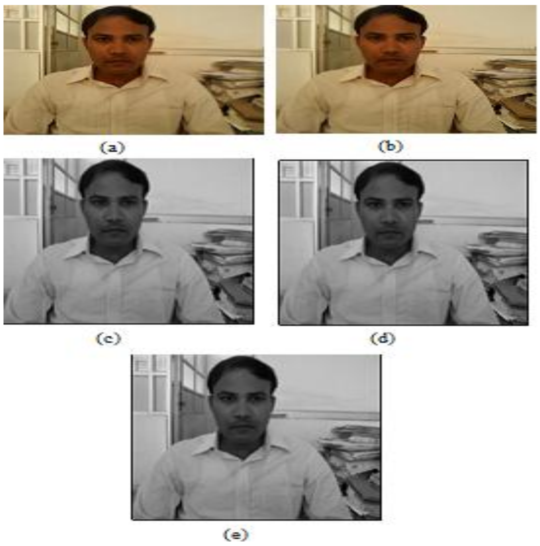

Figure 5: Example 5 (a) TT1 (b) TT2 (c) Fused Image by Simple Average (d) Fused Image by PCA (e) Fused Image by Proposed Method

Table 1: Performance Evaluation Metrics to Evaluate Image Fusion Algorithms for Figures 1-5

Image	Method	Quality Measures					
		Entropy	Standard Deviation	Spatial Frequency	Mutual Information	$Q^{AB/F}$	Q_W
Clock	Average	7.2481	0.1934	6.1851	1.4248	0.5859	1
	PCA	7.2656	0.1934	6.1882	1.4239	0.5867	1
	Proposed Method	7.2792	0.1940	10.6227	1.3619	0.4937	1
Pepsi	Average	7.0805	0.1725	9.6653	1.5474	0.6321	0.9933
	PCA	7.0880	0.1725	9.6384	1.5456	0.6281	0.9934
	Proposed Method	7.1586	0.1751	16.9665	1.4506	0.4627	0.9737
Plane	Average	6.2620	0.1771	3.7431	0.7344	0.6161	0.9775
	PCA	6.2631	0.1771	3.7404	0.7343	0.6156	0.9773
	Proposed Method	6.2769	0.1792	8.0667	0.7001	0.4591	0.9639
TR	Average	7.1521	0.2010	4.5831	1.3585	0.7773	0.0056
	PCA	7.1521	0.2010	4.5832	1.3585	0.7773	0.0055
	Proposed Method	7.1641	0.2016	8.1275	1.3183	0.6644	0.1135
TT	Average	7.3357	0.1892	8.7909	1.5185	0.6852	0.9913
	PCA	7.3357	0.1892	8.7903	1.5185	0.6851	0.9913
	Proposed Method	7.3635	0.1916	17.0619	1.3498	0.5314	0.9900

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