Pixel-Level Image Fusion Using Wavelet Transform

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Abstract

Image fusion is a process to combine information from multiple images of the same scene. The result of image fusion will be a new image which is more suitable for human and machine perception or further tasks of image processing such as image segmentation, feature extraction and object recognition. In this paper we present a wavelet-based image fusion algorithm. The images to be fused are firstly decomposed into high frequency and low frequency bands. Then, the low frequency components are combined by maximum energy rule and high frequency components are combined by variance rule. Finally, the fused image is constructed by inverse wavelet transform. We select four groups of images to simulate, and compare our simulation results with the pixel averaging method and most common wavelet method based on mean-max fusion rule.

1. Introduction

Due to the limitation of depth of focus all the objects in a sensor image are not clear, so multiple images of the same scene with focus on different objects are required each of these images has some important information about the scene but none of them is sufficient in terms of its information content. To understand and acquire the complete information, view the series of images is not an easy task for humans as well as for machine perception.so all these images should be fused to form a single image in such a way that the fused image has better focus on all objects and complete information[1]. Image fusion can be divided into three levels, which are pixel-level fusion, feature-level fusion and decision-level fusion. Almost all image fusion algorithms, from the simplest weighted averaging to more advanced multiscale methods, belong to pixel-level fusion [2].

In pixel-level image fusion, some general requirements are imposed on the fused results: 1) The fusion process should preserve (as far as possible) all salient information in the source images; 2) The fusion process should not introduce any artefacts; 3) The fusion process should be shift-invariant performed [3].

In the field of image fusion, pixel-level fusion becomes the primary method since it can preserve original information of source images as much as possible, and the algorithms are computationally efficient and easy to implement, the most image fusion applications employ pixel level based method[4]. There are three commonly used methods of pixel-level image fusion, including simple image fusion (such as linear weighted average, HPF (high-pass-filter), HIS (intensity hue-saturation), PCA (principal component analysis), etc.), pyramid-based decomposition image fusion (such as Laplace pyramid decomposition, ratio pyramid, etc.) and wavelet transform image fusion, etc. [5]. Recently, wavelet transform becomes an important aspect of image fusion research with the merits of multi-scale and multi-resolution.

This paper is organized as follows: In section 2, the proposed wavelet-based image fusion is introduced. In section 3, experiments on different focus images with the proposed method performed and compared. Finally, conclusion is provided.

2. Proposed wavelet based image fusion technique

2.1. General Procedure of Wavelet Based Image Fusion

The information flow diagram of wavelet-based image fusion algorithm is shown in figure 1. In wavelet image fusion scheme, the source images I1(x, y) and I2(x, y) are decomposed into approximation and detailed coefficients at required level using DWT. The approximation and detailed coefficients of both Images are combined using fusion rule Φ. The fused image If(x, y) could be obtained by taking the inverse wavelet transform (IDWT) as:

$$If(x, y) = IDWT [\Phi \{DWT (I1(x, y), DWT (I2(x, y)))\}] \quad (1)$$

The fusion rule used is vary from simple rule i.e. averages the approximation coefficients and picks the detailed coefficient in each sub band with the largest magnitude to very advance rule described below[6].

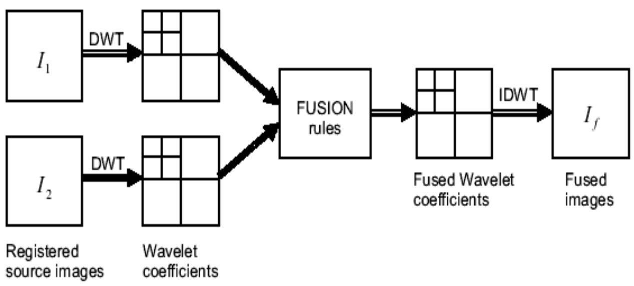


Figure.1 information flow diagram in image fusion scheme using wavelet transforms

2.2. Selection Scheme for Low Frequency Bands

The low frequency band is the original image at the coarser resolution level, which can be considered as a smoothed and subsampled version of the original image. Therefore, most information of the source images is kept in the low frequency band. When the image has more obvious texture features (information) in a certain frequency bands or direction, the corresponding wavelet channel output has larger energy. The bigger energy of corresponding pixel gives the clearer texture feature. Therefore, an energy-based scheme is adopted for low frequency coefficients. The energy of image is described as follows:

$$E = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[f(i,j)\right]^2}{M \times N} \qquad (2)$$

Where f (i, j) represents pixel grey value of point (i, j). M*N is the size of image.
Then the fusion scheme for low frequency bands can be illustrated as the following:

$$f_L(i,j) = \begin{cases} A_L(i,j) & \text{if } E_A \geq E_B \\ B_L(i,j) & \text{else} \end{cases} \qquad (3)$$

$f_L(i,j)$, $A_L(i,j)$, $B_L(i,j)$ respectively represents low frequency coefficient pixel value of fused image, image A, image B at point (i, j). E_A and E_B respectively represent energy of low frequency coefficient of pixel value of image A and image B at point (i, j).

2.3. Selection Scheme for High Frequency Bands

The high frequency bands contain the detail coefficients of an image, which usually have large absolute values correspond to sharp intensity changes and preserve salient information in the image. On the other hand, according to characteristic of HVS it is easy to know that for the high resolution region the human visual interest is concentrated on the detection of changes in contrast between regions on the edges separate these regions. Therefore, a good method for the high frequency bands should produce large coefficients on those edges. Based on the above analysis, we propose a scheme by computing the variance in a neighbourhood to select the high frequency coefficients. The variance of an image is defined as follows

$$\sigma_I(p) = \frac{1}{S \times T}\sum_{s=-S/2}^{S/2}\sum_{t=-T/2}^{T/2}\left(f(i+s, j+t) - mean_I(p)\right)^2 \qquad (4)$$

$$mean_I(p) = \frac{1}{S \times T}\sum_{s=-S/2}^{S/2}\sum_{t=-T/2}^{T/2} f(i+s, j+t) \qquad (5)$$

Where S ×T is the neighboring size and in this paper it is considered as 4×4, meanI(p), σ1(p) denote the mean value and variance value of the coefficients centered at (i, j) in the window of S×T respectively. Then the fusion rule for the high frequency bands can be illustrated as following:

$$f_H(i,j) = \begin{cases} A_H(i,j) & \text{if } \sigma_A \geq \sigma_B \\ B_H(i,j) & \text{else} \end{cases} \qquad (6)$$

$f_H(i,j)$, $A_H(i,j)$, $B_H(i,j)$ respectively represents high frequency (HL,LH,HH) coefficient pixel value of fused image, image A, image B at point (i, j). σ_A and σ_B respectively represent variance of high frequency coefficient of pixel value of image A and image B at point (i, j).

2.4. Procedure of Proposed DWT Based Image Fusion

- To implement two-dimension discrete wavelet decomposition (DWT) to each source image on the level of N, and obtain 3N+1 sub-image.
- Decompose source image A and B's low frequency part $LL_A(i,j)$and $LL_B(i,j)$ into 4×4 sub images and calculate energy using equation (2) and using equation (3) obtain low frequency part of fused image $LL_F(i,j)$.
- Decompose source image A and B's high frequency part $LH_A^K(i,j)$, $HL_A^K(i,j)$, $HH_A^K(i,j)$,$LH_B^K(i,j)$,$HL_B^K(i,j)$, $HH_B^K(i,j)$ into 4×4 sub images and calculate variance of all 4×4 sub images using equation (4) & (5) and using equation(6) obtain high frequency part

of fused image $LH_F^K(i,j)$, $HL_F^K(i,j)$, $HH_F^K(i,j)$ respectively.
K represents decomposition level (K=1,2,3….).

- Finally, using $LL_F(i,j)$, $LH_F^K(i,j)$, $HL_F^K(i,j)$, $HH_F^K(i,j)$, obtain fused image by inverse discrete wavelet transform (IDWT).

3. RESULTS

The proposed method has been tested on several pairs of multifocus images. Four examples are given here to illustrate the performance of the fusion process. And proposed method is evaluated by comparing with most common pixel averaging method and wavelet based method in which weighted averaging rule used for low-frequency coefficient and the rule of selection of maximum value for high frequency coefficient .In all cases the grey value of pixel are scaled between 0 to 255. The source images are assumed to be registered and no pre-processing is performed.

3.1. Objective Evaluation of an Image

In addition to visual analysis, we conducted some quantitive analysis of fused image and three objective criteria are used to compare the fusion results are entropy, standard deviation and root mean square error.

3.1.1. Entropy: Image entropy is an important indicator for measuring the image information richness. The image entropy's value represents the average amount of information which is included by the image. The calculated information entropy can objectively evaluate the amount of information changes. According to principal of Shannon information theory, entropy of an image is defined as Ref. [7]

$$H = \sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij}\log_2 P_{ij} \tag{7}$$

$$p_{ij} = f(i,j) \Big/ \sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j) \tag{8}$$

Where H-Pixel Entropy, L-Image total grayscale
Pi- The i Pixels rate to the image's total ones N
i.e.=Ni/N

3.1.2. Standard deviation (σ): Standard deviation reflects discrete case of the image grey intensity relative to the average. The standard deviation represents the contrast of an image. If the standard deviation is large, then the image grey scale distribution is scattered and the image's contrast is large that more information can be seen. It can be defined as Ref. [7]

$$\sigma = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(F(i,j)-\overline{f}\right)^2}{M\times N}} \tag{9}$$

F (i, j) is the grey value of fused image at point (i, j). $\overline{f}$ is the mean value of grey-scale image fusion. M×N is the size of image.

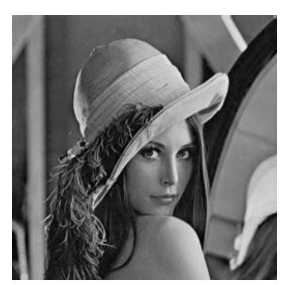
3.1.3. Root mean square error (RMSE): Root mean square error (RMSE) indicates how much error the fused image conveys about the reference image. Hence, lower the RMSE, the better the fused result. The RMSE is defined as ref. [7]

$$RMSE = \left[\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(R(i,j)-F(i,j)\right)^2\right]^{1/2} \tag{10}$$

R (i, j) is ideal reference image, F (i, j) is the fused image, M×N is the size of image

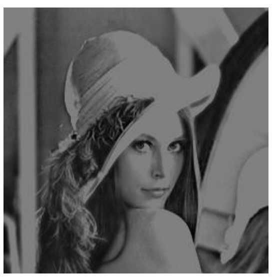
3.2. Visual Analysis of an Image

Experiment is performed on a popular widely used standard image Lena of size 256×256 as shown in Fig.2 (a), which served as ideal reference image here. Then the two other source images are obtained with a Gaussian blurring method as reference [9].Fig.2 (b) is the image blurred on the lower horizontal, Fig.2(c) is the image blurred on upper.



(a)


(b) (c)




(d) (e)

(f)

Figure 2. Simulation results of Lena images. (a) reference Lena image (b)Lena image blurred on the horizontal lower;(c) Lena image blurred on the horizontal upper; (d) fused image by pixel averaging method; (e) fused image by wavelet based mean-max algorithm; (f) fused image by proposed method using 5 level wavelet decomposition;

TABLE 1

Entropy and Standard Deviation of Fig.2 (Lena image)

		ENTROPY	STANDARD DEVIATION	RMSE
Reference image Lena		7.5784	52.3689	-
Horizontally blurred Lena 1		7.5035	48.2143	5.4776
Horizontally blurred Lena 2		7.5246	49.4620	4.9028
Pixel averaging		5.6372	35.4814	8.3216
Wavelet based Mean-max fusion rule	db1	7.4509	48.0642	5.3936
	Sym1	7.4509	48.0462	5.3936
	Coif1	7.4469	47.9500	5.3418
	Bior3.3	7.4466	47.8966	5.3601
	Dmey	7.4466	47.9093	5.3688
	haar	7.4509	48.0642	5.3936s
Proposed method	Db1	7.6071	52.4130	3.4991
	Sym1	7.6071	52.4130	3.4991
	coif1	7.5979	52.1534	3.3547
	Bior3.3	7.6228	52.8679	3.8543
	Dmey	7.5900	52.0523	3.1029
	haar	7.6071	52.4130	3.4991

4. CONCLUSION

In this paper, we present a wavelet-based image fusion, and show the simulation result and objective evaluation. In the process of fusion we gave fusion rule based on energy and variance, which effectively conserved the energy of source images and avoided the loss of useful information. Comparing with the most common algorithm, proposed fusion method gives improved visual effect of fused image and also improved objective parameter such as, entropy, standard deviation and RMSE.

5. References

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