Image Fusion Based on Consistency Checking and Salience Match Measure

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Abstract—— **Image fusion is process of merging two or more images to get more informative image than any of the source image. Image fusion combines registered images to produce a high quality fused image with spatial and spectral information. In this paper we proposed image fusion based on multiresolution wavelet transform using consistency checking and salience match measure rule for low and high frequency bands fusion. Medical image fusion has been used to improve the information content in fused image. Medical images like computed tomography (CT) and magnetic resonance (MR) are fused to provide more information for diagnoses. This work covers medical and multi focus image fusion based on wavelet transform. In order to evaluate result statistical parameters like root mean square error (RMSE) and peak signal to noise ratio (PSNR) are used and results compared with other fusion methods.**

Keywords— **Image fusion, Wavelet transform, RMSE, PSNR.**

I. INTRODUCTION

Image fusion produces a single image from a set of input images so that fused image describes the scene better than any of single image means source image. Image fusion is an important research topic in many related areas such as computer vision, image processing automatic object detection, remote sensing, robotics, and medical imaging. The fast development of the technique of sensors, micro-electronics, and communications requires more attention on information fusion. Several situations in image processing require high spatial and high spectral resolution in a single image. For example, the traffic monitoring system, satellite image system, and long range sensor fusion system all use image processing. Image fusion has wide application domain in Medicinal diagnosis. Image fusion provides the possibility of combining different sources of information.

Many techniques for image fusion have been proposed in the literature. Arithmetic fusion algorithms are the simplest methods for fusion, and sometimes effective. Arithmetic fusion algorithms produce the fused image pixel by pixel, as an arithmetic combination of the corresponding pixels in the input images. The simplest way of image fusion is to take the average of the two images pixel by pixel but it results in contras reduction. The various image fusion methods include high-pass filter (HPF), brovey transform (BT), principal component analysis (PCA), intensity-hue-saturation (IHS), pyramidal transform [1], and wavelet transform [2-4].

II. WAVELET TRANSFORM

Wavelet transform has been greatly used successfully in many areas, such as texture analysis, data compression, feature detection, and image fusion. To decompose two-dimensional signals such as two-dimensional gray-scale image signals into different resolution levels wavelet transform can be used for a multi resolution analysis. The original concept and theory of wavelet based multi resolution analysis came from mallat [7]. Wavelet transforms provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution or lower frequency band, and higher frequency bands. Discrete wavelet transform (DWT), applies a two-channel filter bank (with down sampling) iteratively to the low-pass band (initially the original signal). The wavelet representations consist then of the high pass bands obtained at each step and low-pass band at the lowest resolution. This transform is invertible and non-redundant. The DWT is a spatial-frequency decomposition that provides a flexible multi resolution analysis (MRA) of an image. In one dimension the basic idea of the wavelet transform is to represent the signal as a superposition of wavelets. If a discrete signal is represented by $f(t)$, the wavelet decomposition is then

$$f(t) = \sum_{m,n} c_{m,n} \Psi_{m,n}(t), \qquad (1)$$

Where, $\Psi_{m,n}(t) = 2^{-m/2}\Psi[2^{-m}t - n]$, m and n are integers. Here choices of Ψ such that $\Psi_{m,n}(t)$ constitutes an orthonormal basis, so that the wavelet transform coefficients can be obtained by an inner calculation:

$$c_{m,n} = \langle f, \Psi_{m,n} \rangle = \int \Psi_{m,n}(t) f(t) dt \qquad (2)$$

A scaling function ϕ is needed, together with the dilated and translated version of it, $\emptyset_{mn}$, in order to develop a multi resolution analysis. According to the characteristics of the scale spaces spanned by ϕ and, the signal f (t) can be

decomposed in its coarse part and details of various sizes by projecting it onto the corresponding spaces. Therefore, the approximation coefficients $a_{m,n}$, of the function f at resolution 2^m and wavelet coefficients $c_{m,n}$ can be obtained:

$$a_{m,n} = \sum_k h_{2n-k} a_{m-1,k} \quad \text{(3)}$$

$$c_{m,n} = \sum_k g_{2n-k} a_{m-1,k} \quad \text{(4)}$$

Where, h_n is a low pass FIR filters and g_n is related high pass FIR filter. To reconstruct the original signal the analysis filters can be selected from a biorthogonal set which have a related set of synthesis filters. These synthesis filters h' and g' can be used to perfectly reconstruct the signal using the reconstruction formula

$$a_{m-1,l}(f) = \sum_n \left[h'_{2n-1} a_{m,n}(f) + g'_{2n-1} c_{m,n}(f) \right] \quad \text{(5)}$$

Equations (3) and (4) are implemented by filtering and down sampling. Conversely equation (5) is implemented by an initial up sampling and a subsequent filtering.

The 2-D wavelet transform can be considered as a straightforward extension of 1-D case by separately filtering and down sampling in the horizontal and vertical directions. After one stage of processing, an image will be decomposed into four frequency bands: low–low (LL), low–high (LH), high–low (HL), and high–high (HH). By recursively applying the same scheme to the LL subband multiresolution decomposition can be achieved. Therefore, a DWT with *J* decomposition levels will have *M* = 3 * *J*+1 such frequency bands. It should be noted that for a transform with *K* levels of decomposition, there is always only one low frequency band, the rest of bands are high frequency bands in a given decomposition level.

III. IMAGE FUSION USING WAVELET TRANSFORM

In image fusion based on wavelet transform the source images are decomposed in rows and columns by low-pass (L) and high-pass (H) filtering and subsequent down sampling at each level to get approximation (LL) and detail (LH, HL and HH) coefficients. Scaling function is associated with smooth filters or low pass filters and wavelet function with high-pass filtering. Various fusion rules are then applied on the wavelet coefficients of low and high frequency bands. We have presented salience match measure rule for low frequency band fusion and consistency checking rule for high frequency band fusion. Figure 1 shows schematic diagram of wavelet based fusion procedure.

Detailed fusion steps based on wavelet transform can be summarized below:
1. Take registered input images.
2. These images are decomposed into wavelet transformed images, respectively, based on wavelet transformation. The transformed images with J-level decomposition will include one low-frequency portion (low band) and 3*J*

high-frequency portions (low-high bands, high-low bands, and high-high bands).
3. The transform coefficients of different portions or bands are performed with a certain fusion rule. Here we proposed consistency checking rule for high frequency bands fusion and salience match measure rule for low frequency band fusion.
4. The fused image is constructed by performing an inverse wavelet transform based on the combined transform coefficients from Step 3.
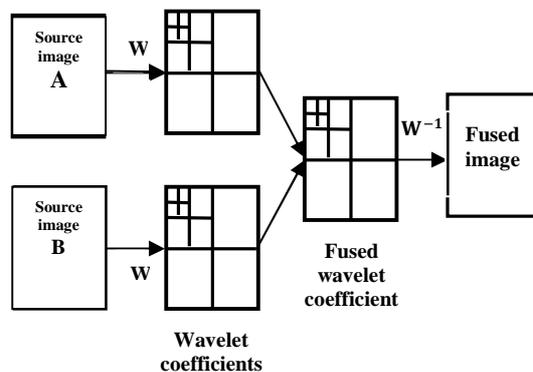

Fig 1. Image fusion using wavelet transform

A. Consistency checking rule:

The first one is to construct a decision mask, which can be done with:

$$\text{Decision} = \text{abs}(L_1) > \text{abs}(L_2)$$

Here L1 and L2 are coefficients of source images. Decision is a matrix of the same size of L1 and L2, which contains 1's and 0's if the source selected to construct the fused level or not selected to construct fused level respectively. This binary map is subject to consistency verification. Result can be obtained after applying a two dimensional convolution between a padded version of the original decision mask and an averaging 3x3 or 5x5 template, followed by a rounding operation.

B. Salience match measure rule:
a. Salience measure:

It is the degree of saliency of each coefficient in *L*1 and *L*2 (i.e. its importance to image fusion at hand). The saliency should increase when features are in focus or it should give emphasis on the contrast difference. The fact that human visual system is highly sensitive to local contrast changes (edges). Compute the activity as a local energy measure.

$$a_i^k(x, y) = \sum_{\Delta n \in w} | L_i^k(x + \Delta n, y + \Delta n)|^2 \quad \text{(6)}$$

Where, k is decomposition level, i is input image in this case images A and B, and W is a finite local window of size 1X1, 3X3 or 5X5.

b. Match measure:

To quantify the degree of similarity between the sources match measure is used. Precisely $m^k(x, y)$ reflects the resemblance between L_A and L_B. The match measure tells where the sources are different and to what extent they differ. We can use this information to appropriately combine them. In our algorithm it is defined as a normalized correlation average over neighborhood of the samples as shown in equation (7). Where W being window of size either $1x1$ $3x3$ or $5x5$ centered at the origin.

$$m^k(x,y) = \frac{2\sum L_A^k(x + \Delta n, y + \Delta n).L_B^k(x + \Delta n, y + \Delta n)}{a_A^k(x,y) + a_B^k(x,y)} \quad (7)$$

c. Decision Map:

It is the core of the combination algorithm. The actual combination of the coefficients of the various sources is governs by its output and it controls the weights to be assigned to each source coefficients. The conventional approach is to assign a weight which is directly proportional to the saliency measure. But this has a contrast reduction effect in images which have opposite contrast. It actually assumes that at a point only one of the source images is a valid choice. The ultimate solution is to apply a selection rule which considers the match measure which is proposed by Burt [5]. At points where the source images are different the combination selects the most salient component. At location where they are similar, we average the source components. The averaging provides stability and reduces noise. In this case it is computed as shown in equation 4 where T is decision threshold, T=0.85 for this experiment.

$$d^k(.) = \begin{cases} T \\ \quad \text{If } m^k(.) \leq T \& a_A^k(.) > a_B^k(.) \\[6pt] 1\text{-}T \\ \quad \text{If } m^k(.) \leq T \& a_A^k(.) > a_B^k(.) \\[6pt] 1/2 + 1/2\left(\frac{1-m^k(.)}{1-T}\right) \\ \quad \text{If } m^k(.) > T \& a_A^k(.) > a_B^k(.) \\[6pt] 1/2 - 1/2\left(\frac{1-m^k(.)}{1-T}\right) \\ \quad \text{If } m^k(.) > T \& a_A^k(.) \leq a_B^k(.) \end{cases} \quad (8)$$

d. Combination Map:

The actual combination of the transform coefficients of the sources is described by combination map. In weighted average the weights are determined from the decision map.

$$L_F^K(.) = d^k(.).L_A^k + (1 - d^k(.)).L_B^k \quad (9)$$

In our work we have proposed consistency checking rule for high frequency band fusion and salience match measure rule for low frequency band fusion.

We have compared wavelet transform with pyramidal transform with use of statistical parameters.

IV. RESULT EVALUATION

There are two methods for evaluation of fusion result, which are subjective evaluation and objective evaluation. Subjective evaluation is based on the knowledge and experience of vision, and it is very easy. However, it is lack of objectivity and different people will come to a different conclusion. In order to the quantitative analysis, we make use of statistical parameters to evaluate the fusion result, which are Root mean square error and Peak signal to noise ratio.

A. Root Mean Square Error:

The root mean square error s given by:

$$\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}[R(i,j) - F(i,j)]^2 \Big/ M \times N} \quad (10)$$

Where, $R(i, j)$ is original image (or one of the source images) and $F(i, j)$ is the fusion result. M and N are the dimensions of the images to be fused, the smaller the value of the RMSE, the better the fusion performance.

B. Peak signal to noise ratio:

Peak signal to noise ratio can be given as follow:

$$PSNR = 10 \times \log((f_{max})^2/RMSE^2) \quad (11)$$

Where, f_{max} is maximum gray scale value of the pixels in fused image, the higher the value of the PSNR, the better the fusion result.

Figure 2 and Figure 3 shows results for medical (CT scan and MRI images) and multi focus images respectively.

Table I Quantitative Analysis (For a and b Source Images)

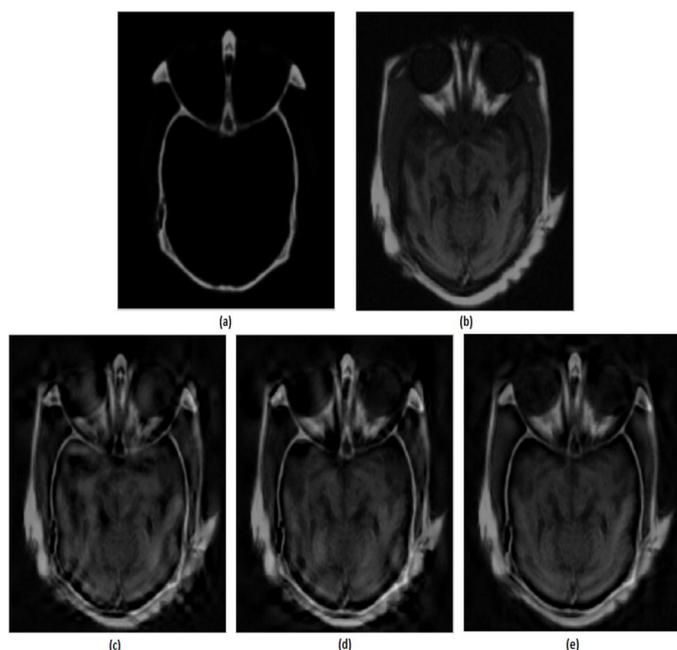|		Methods		
	Parameters	**Pyramidal transform (Contrast)**	**Pyramidal transform (laplacian)**	**Wavelet transform**
W.R.T. MR image	**RMSE**	51.6699	39.1687	38.9969
	PSNR	30.9984	32.2014	32.2205
W.R.T. CT image	**RMSE**	72.9294	18.5017	17.1182
	PSNR	29.5018	35.4587	35.7962

Fig. 2. (a), (b) source images (a.gif, b.gif), fused image using (c) Pyramidal transform (contrast), (d) Pyramidal transform (laplacian), (e) Wavelet transform.

Table II Quantitative Analysis (For S1 and S2 Source Images)

		Methods		
	Parameters	**Pyramidal transform (contrast)**	**Pyramidal transform (laplacian)**	**Wavelet transform**
W.R.T. s1.jpg image	**RMSE**	19.0718	19.0786	18.9221
	PSNR	35.3269	35.3253	35.3611
W.R.T. s2.jpg image	**RMSE**	13.8279	13.8499	13.7428
	PSNR	36.7232	36.7163	36.7500

In this work we have covered quantitative analysis for medical and multi focus images. The evaluation factors include Root Mean Square Error and Peak Signal to Noise Ratio. Table 1 and Table 2 shows evaluation results, wavelet transform gives better performance in terms of RMSE and PSNR.
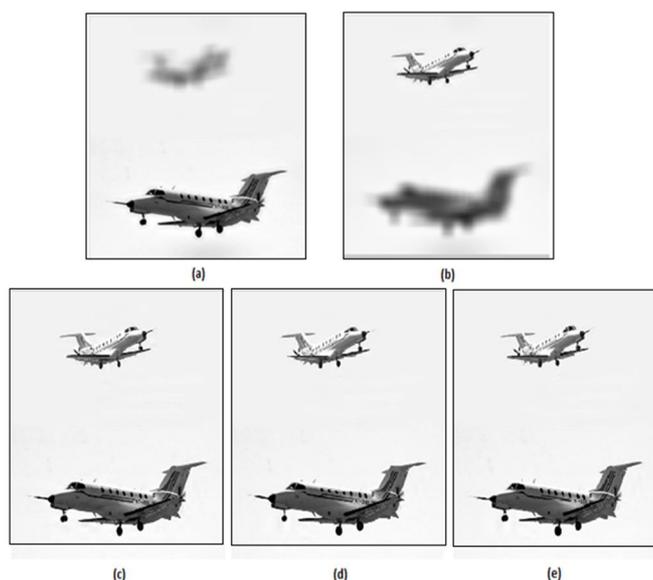

Fig. 3. (a), (b) source images (s1.gif, s2.gif), fused image using (c) Pyramidal transform (contrast), (d) Pyramidal transform (laplacian), (e) Wavelet transform.

V. CONCLUSIONS

We have presented wavelet fusion method using salience match measure rule for low frequency band fusion and consistency checking for high frequency band fusion. Compared with pyramidal transform by using statistical parameters. Proposed algorithm represents better performance for medical and multi focus images.

REFERENCES

[1] HU Xue-long, SHEN Jie, "An algorithm on image fusion based on median pyramid", *Microelectronics & Computer*. vol.25, no.9, pp.165-165, Sept., 2008.

[2] KiranParmar, Rahul K Kher, Falgun N Thakkar, "Analysis of CT and MRI Image Fusion using Wavelet Transform", *IEEE International Conference on Communication Systems and Network Technologies*, pp. 124 -127, May 2012.

[3] HongboWu and Yanqiu Xing, "Pixel-based Image Fusion Using Wavelet Transform for SPOT and ETM+Image", *IEEE International Conference on Progress in Informatics and Computing(PIC)*,Vol. 2,Dec.2010, pp.936–940.

[4] Yong Yang, Dong Sun Park, Shuying Huang, Zhijun Fang, Zhengyou Wang, "Wavelet based Approach for Fusing Computed Tomography and Magnetic Resonance Images", *Control and Decision Conference (CCDC '09), Guilin, China*, pp 5770-5774, 17-19 June, 2009.

[5] Burt, P. J., Kolczynski, R. J., "Enhanced image capture through fusion", *Proceedings of the 4th International Conference on Computer Vision,* pp. 173-182, 1993.

[6] SahooTapasmini, MohantySankalp, SahuSaurav, "Multifocus image fusion using variance based spatial domain and Wavelet Transform", *International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT)*, pp. 48 – 51, 2011.

[7] S. Mallat, *A Wavelet Tour of Signal Processing*, Academic Press, 2nd edition, 1999.

[8] J. Wenjun Chi, Sir Michael Brady, Niall R. Moore and Julia A. Schnabel, "Fusion of Perpendicular Anisotropic MRI Sequences", *IEEE Int. Symp.on Biomedical Imaging (ISBI 2011)*, Chicago, pp 1455-1458, March 30 – April 2 2011.