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Medical Image Fusion with Adaptive Region-based Direction Feature

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Abstract: To improve the medical image fusion effect, a novel method with region-based direction feature is proposed with wavelet transform. The direction information of the source images is extracted by the eigen-values and eigen-vectors of structure tensor of the every source image. The eigen-values are used to devise an index to show the local feature of the image. The index is averaged to yield the weight for adaptive high frequency coefficient fusion. We apply the proposed approach to the fusion of medical images and the experimental results show the performance of the new method.

Key words: Medical image fusion, region information, wavelet decomposition, eigen-values, structure tensor

INTRODUCTION

In the last decade, medical images have been intensively applied in physical and other correlative fields, including clinical diagnosis, pathology analysis and healing examinations etc. Image fusion, whose goal is to combine information from two or more images of a scene into a single composite image, has drawn much more attention of the researchers (Pajares and de la Cruz, 2004). In medical imaging, a positron emission tomography is a functional imaging system displaying the brain activity without anatomical information while a magnetic resonance images provides anatomical information but without functional activity. No single sensor can produce a complete representation of a scene. Both CT and MR images are needed to provide different kinds of details (Piella, 2003). Only fused images can provide information that sometimes cannot be observed in the individual input images. The result of medical image fusion is a new image which is more suitable for human perception and diagnoses by doctors. Various image fusion algorithms, ranging from the simplest weighted averaging to complex multi-resolution pyramid (Kingsbury, 2000) and wavelet methods (Liu *et al*., 2001), or neural network approach (He *et al*., 2011), have been proposed to construct a new image. Recent developments include the emergence of region based techniques, in which the source images are first segmented into a set of regions that constitute the image, followed by the fusion of the corresponding regions (Zribi, 2010). For medical image fusion, wavelet decomposition is still an important tool. The process starts by decomposing the source images into approximation (low-frequency) and detail (high-frequency) sub-bands; so that the features of each image are represented at different scales. Intelligent rules (e.g., choosing max) are then used to fuse the corresponding wavelet coefficients and create a decomposed fused image, followed by an inverse wavelet transform to yield the final fused image. The Discrete Wavelet Transform (DWT) is widely used in image fusion since it captures the features of an image not only at different resolutions, but also at different orientations. The Shift-Invariant DWT and Dual-Tree Complex Wavelet Transform (Kingsbury, 2000) achieve good fusion results with spatial and directional knowledge. Some post-wavelet methods have also been used to construct fused image. A fusion algorithm for multi-modal medical images was proposed based on contourlet transform (Yang *et al*., 2008). The final fusion image is obtained by directly applying inverse contourlet transform to the fused low-pass and high-pass sub-bands which preserve more details in source images and further improve the quality of fused image.

The key step in wavelet-based image fusion is combination rule of wavelet coefficients. As an important tool for describing local geometrical information, structure tensor has been widely used in image smoothing, corner detection, optical estimation and other applications (Brox *et al*., 2006; Li *et al*., 2012).

In this studyr, a new adaptive image fusion algorithm based on Regional Structure Tensor (RST) is presented. It uses weighted sum of structure tensors which describe local geo-metrical information with its eigen-values and eigen-vectors, to make selection rules for image fusion within wavelet multi-resolution framework. The fusion rule considers region-based information as an important link between the nearby pixels.

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WAVELET FRAMEWORK FOR IMAGE FUSION

Wavelet analysis has been proven to be an efficient tool for a range of image processing, including image fusion. The key step in image fusion based on wavelets is that of coefficient combination, namely, the process of merge the coefficients in an appropriate way in order to obtain the best quality in the fused image.

Figure 1 shows a schematic diagram of wavelet framework for image fusion. First, wavelet decomposition is applied to the registration source Image A and Image B, getting low frequency and high frequency components of the image. Second, fusion of the wavelet coefficient is performed according to the characteristics of low frequency and high frequency components, in accordance with their respective fusion algorithm fusion. Low frequency coefficients, in which most of image information is concentrated, are combined with weighted average to yield new coefficients. The critical task in pixel level image fusion is the combination rules for high frequency coefficients which contain an abundance of image edge information. Finally, based on the high frequency and low frequency components, the fused image is reconstructed with the inverse wavelet transform.

IMAGE FUSION WITH REGION-BASED GEOMETRICAL FEATURE

Local geometrical description with structure tenor: In image processing and other applications in computer vision, gradient operator provides the information for local feature, including magnitude and direction. However, the local structure can also be conveyed by structure tensor to obtain more abundant local structure information.

Given an image I(x, y), the structure tensor J_0 is defined as the outer product of gradient vector ΔI:

$$J_0 = \nabla I \nabla I^T = \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix} \quad (1)$$

where, T is the transpose. To consider the information of its neighborhood, J_0 is extended to the linear structure tensor by convoluting of the components of J_0 with a Gaussian kernel K_ρ (Gaussian smoothing):

$$J_\rho = J_0 * K_\rho \begin{pmatrix} j_{11} & j_{12} \\ j_{12} & j_{22} \end{pmatrix} \quad (2)$$

The introduction of the structure tensor is a consequence of the fact that one can only describe the local structure at a point by considering also the data of its neighborhood. The matrix J_ρ has orthonormal eigen-vectors v_1 and v_2 with v_1 paralled to:

$$\left(j_{11} + j_{22} - \frac{2j_{11}}{\sqrt{((j_{11} - j_{22})^2) + 4j_{12}^2}} \right) \quad (3)$$

The corresponding eigen-values are given by:

$$\mu_1 = \frac{1}{2}\left[j_{11} + j_{22} + \sqrt{((j_{11} - j_{22})^2) + 4j_{12}^2} \right] \quad (4)$$

and:

$$\mu_2 = \frac{1}{2}\left[j_{11} + j_{22} - \sqrt{((j_{11} - j_{22})^2) + 4j_{12}^2} \right] \quad (5)$$

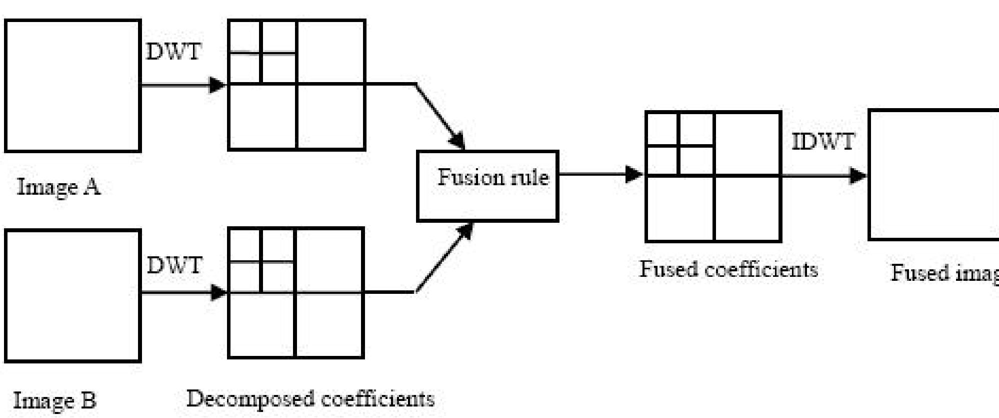

Fig. 1: Wavelet-based image fusion framework

The unit vectors of v_1 and v_2 can be denoted as:

$$V_i = (\cos\theta_i, \cos\theta_i), i = 1, 2$$

By a simple calculation, we can yield:

$$\theta_1 = \frac{1}{2}\arctan\frac{2j_{12}}{j_{11} - j_{22}}, \theta_2 = \theta_1 + \frac{\pi}{2}$$

Now we discuss the geometrical meaning of the eigen-value and eigen-direction. Gaussian convolution with a 2-D function is equivalent to averaging in a region of scale ρ. They describe average contrast in the eigen-directions within a neighborhood of size O(ρ). The vector v_1 indicates the orientation with the highest grey value fluctuations while v_2 gives the preferred local orientation, the coherence direction. The speed of v_1 is $\sqrt{\mu_1}$. Further more, μ_1 and μ_2 serve as descriptors of local structure. Local geometrical structure are characterized by $\mu_1 \cong \mu_2$, straight edges gives $\mu_1 >> \mu_2 = 0$, corner by $\mu_1 \geq \mu_2 >> 0$. Structure tensor has been successfully been used in the field of image processing. Some benefit fields are image denoising and enhance, optic flow estimation, corner detection, texture analysis (Brox *et al.*, 2006; Li *et al.*, 2012). But till now, few literatures can be found for image fusion with structure tensor. Next, structure tensor will be adopted to design a fusion rule within wavelet framework.

To measure the local image structure, coherence of image is measured by:

$$\phi = (\mu_1 - \mu_2)^2 \quad (6)$$

The definition of ϕ conveys the local geometrical feature. The corners and edges produce larger magnitudes of coherence measure.

Image fusion with region-based direction feature: The local direction feature can be extracted by structure tensor and its eigen-values and vectors. However, we need a region and robust feature to construct fusion rules. Two problems motive us to use a averaging of ϕ of the every pixel within a local region. The first problem is the noise which may disturb the original information of the image as well the extracted direction. The second one is that the link between the every pixel should be considered as an important aspect to device fusion rule. To overcome these problems, we adopt a regional averaging direction feature within wavelet-based fusion wavelet framework.

In multi-resolution wavelet fusion framework, every source image is decomposed into its several multi-resolution levels.

In every level four frequency sub-bands, low-low (LL), low-high (LH), high-low (HL) and high-high (HH) are obtained. Three sub-bands, including LH, HL and HH, contain transform values that are fluctuating around zero. The coefficients in these sub-bands provide much high frequency information, including edges and corners. And they should be treated with a fine fusion rule. For LL sub-bands, weighted average is performed for the same level. For LH, HL and HH sub-bands, coefficient combining can be performed by at least two alternatives: averaging and selection.

The larger transform values in these bands correspond to sharper brightness changes and thus to the salient features in the image such as edges, lines and region boundaries. Therefore, a good integration rule is the Choose-max (CM) scheme which means just pick the coefficient with the larger activity level and discard the other. Another combining scheme is the Weighted Average (WA) scheme. To consider the link between the nearby pixels, a region-based gradient approach was proposed for image fusion. In this method, the average gradient magnitudes of a region, instead of a sole gradient magnitude of a single pixel, is adopted to construct weight function for averaging. The new coefficients are obtained by the weighted sum of the region information of the source images.

To preserve more details for fused image, selection rule should be chosen with good feature descriptor. The eigen-value of linear structure tensor conveys local shape information which provides clues for fusion rule design. If c(A) and c(B) are high frequency coefficients of the two source images at a certain level, c(Z) is that of the fused image, our fusion rule is as following:

$$c(Z) = \omega_A * c(A) + \omega_B * c(B) \quad (7)$$

where, ω_A and ω_B are weighted coefficients, μ(A) and μ(B) are the larger eigen-value of their own structure tensor, respectively. As weighted coefficients, ω_A and ω_B are positive and $\omega_A + \omega_B = 1$. Some literature discussed the selection of the weighted coefficients. Here we presented an adaptive method based on the structure tensor as follows:

$$\omega_A = \frac{\frac{1}{n_R}\sum_{p\in R}\phi(A,p)}{\frac{1}{n_R}\sum_{p\in R}\phi(A,p) + \sum_{p\in R}\phi(B,p)} \quad (8)$$

$$\omega_B = \frac{\frac{1}{n_R}\sum_{p\in R}\phi(B,p)}{\frac{1}{n_R}\sum_{p\in R}\phi(A,p) + \sum_{p\in R}\phi(B,p)} \quad (9)$$

where, ϕ(A, p) is the coherence measure in the pixel p defined as Eq. 6. And R denotes a rectangular region of $m\times n$ and $n_R = m\times n$ is the area of R.

EXPERIMENTAL RESULTS

We have conducted some experiments on medical images to see the performance of the proposed fusion scheme quantitatively and visually. The two parts of fused images are also zoomed to show the fine details, through which we can compare the differences between various methods. To do a quantitative comparison, entropy, mean value, standard deviation and mean gradient are adopted as performance measure for the purpose of comparing Weighted Average (WA) and Choosing Gradient Max (CGM) fusion scheme. For visual comparisons, fine details of the fused image will be shown. To show the justice of the comparison, the same level of decomposition and the same wavelet basis function are used for the four methods which imply the difference between the fusion results lie in that of the combination strategies. For the same reason, we select 'db3' wavelet for three methods in our setting.

Figure 2 shows the fusion results of multi-sensor medical images. Two medical source images coming exactly from the same brain area. One is CT image and the

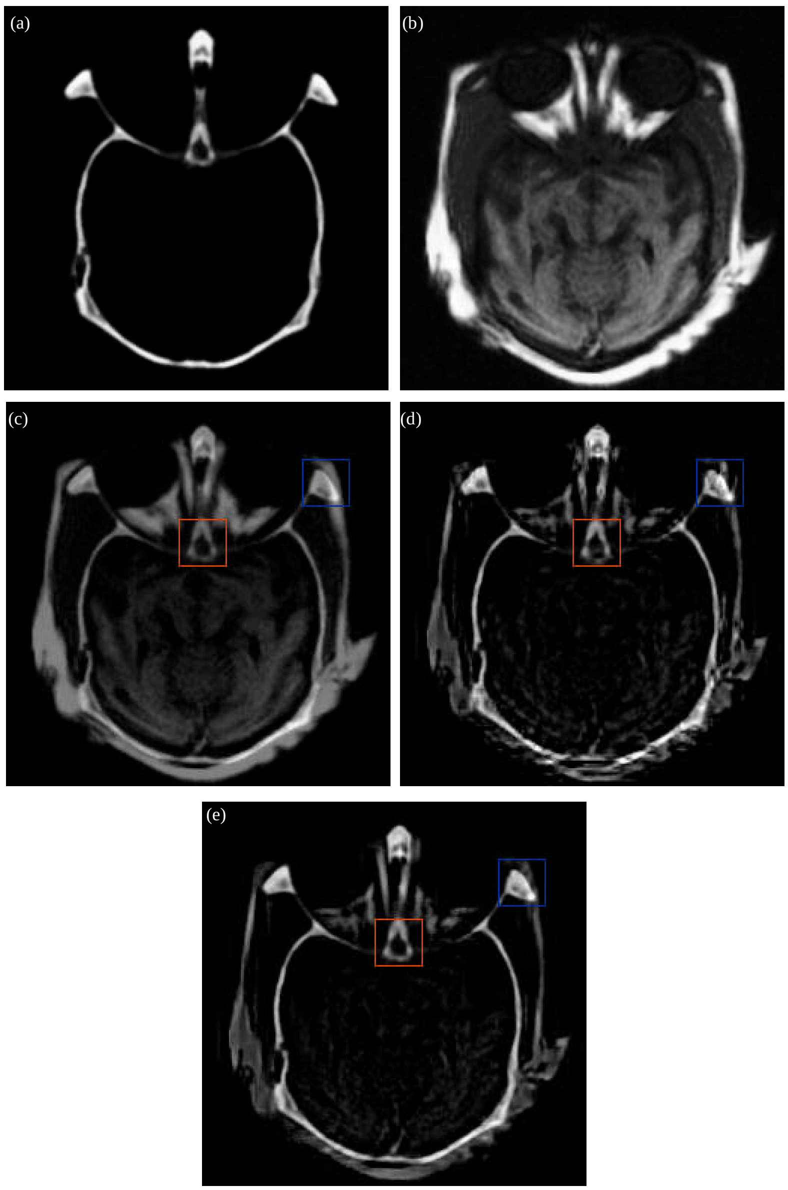

Fig. 2(a-e): Fusion of Medical CT and MR Images, (a) CT image, (b) MR image, (c) WA scheme, (d) CGM and (e) Our scheme

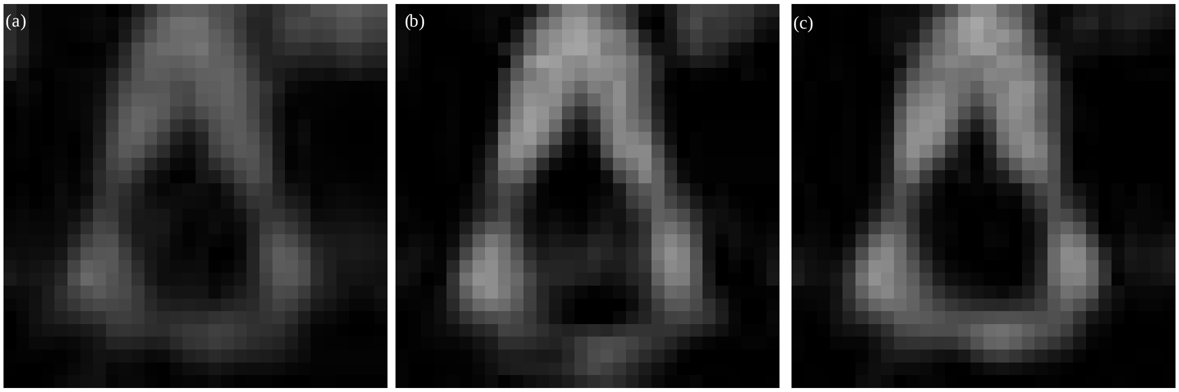

Fig. 3(a-c): Results on four test functions, (a) WA scheme, (b) CGM scheme and(c) Our scheme

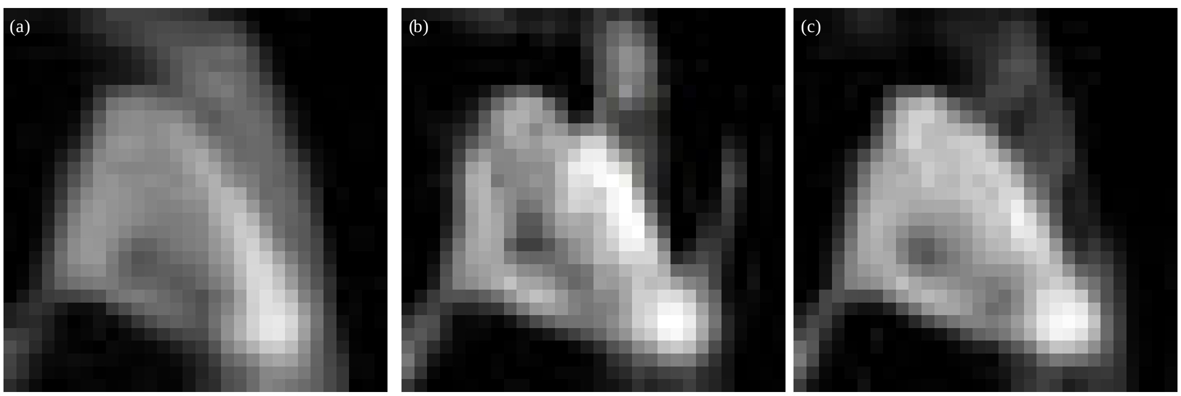

Fig. 4(a-c): Right part of the fusion results, (a) WA scheme, (b) CGM scheme and (c) Our scheme

Table 1: Comparison of The EOG Data

	WA	CGM	Our scheme
Entropy	5.9526	5.6643	5.6879
Mean value	22.0246	22.0695	21.6280
Standard deviation	35.0216	35.3894	35.8422
Mean gradient	3.6763	5.7283	4.5790 x

other is MRI image. The results of the three fusion schemes are shown in Fig. 2c-e. The region size we consider is a 5×5 square for averaging the eigen-value of the structure tensor. The whole image of WA results seems to be a litter lighter than the other results. Two parts of the fused images with different methods which are featured with blue lines and red lines in original fused images, are shown in Fig. 3 and 4. The propose scheme and CGM protects edges and more details. However, our scheme produces a more smoothing effect for homogenous region, as shown in Fig. 3. The artifact can be founded in the fused image of CGM. In Fig. 4, we can find that part of the fused image of CGM is lost. The lost part can be founded in the results of AW and our scheme. It is can be observed that the edges in AW are blurred. In Table 1, the data of three quantitative indexes are presented.

CONCLUSION

A new image fusion algorithm based on direction feature is presented within wavelet framework. The direction feature is conveyed by the eigen-values and eigen-vectors of structure tensor. The coherent measure is adopted and adaptive weighted sum, combined with the region information around the pixel considered. The proposed method preserves fine details of medical images and produces a more smoothing homogenous region. Experimental results on real medical CT/MR images demonstrate the performance of the proposed method.

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