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Medical image fusion with adaptive shape feature

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ABSTRACT

Medical image fusion is an important task for the retrieval of complementary information from medical images captured by different sensors. To improve the fusion effect, a new medical image fusion method is proposed with wavelet framework. The major contribution of our method is the construction of shape measure using structure tensor. The shape measure describes the amount of the structure information within a local region of the data and is used as an index to devise weight function for averaging. We apply the proposed approach to the fusion of medical images and the experimental results demonstrate the performance of the new method visually and quantitatively.

Key words: Medical image fusion, structure tensor, shape measure, eigen-values, structure tensor

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INTRODUCTION

The goal of image fusion is to combine information from two or more images of a scene into a single composite image. 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. Both CT and MR images are needed to provide different kinds of details. Only fused images can provide information that sometimes cannot be observed in the individual input images [1]. 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 [2] and wavelet methods [3-5], or neural network approach [6-10], have been proposed to construct a new image. But 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. [4,5,11-13]. Some post-wavelet methods have also been used to construct fused image [14].

In this paper, a new adaptive image fusion algorithm based on structure tensor is presented. It uses weighted sum of structure tensors, which describe local geometrical information with its eigen-values and eigenvectors, to make selection rules for image fusion within wavelet multi-resolution framework. The fusion rules for both low frequency and high frequency are based on adaptive technology.

Medical image fusion with shape feature

Local Shape Feature Extraction and Description

Wavelet analysis has been proven to be an efficient tool for a range of image processing, including image fusion. After wavelet decomposition, the approximation information is contained in low frequency sub-bands while detail formation in high frequency sub-bands. Here we adopt the structure tensor as our tool to extract such a feature. For simplicity, we just use u to denote the coefficients at pixel X, regardless of the level number of wavelet decomposition.

Given an image u, the structure tensor is defined as:

$$J_0 = \nabla u \nabla u^T = \begin{pmatrix} u_1^2(\mathrm{X}) & u_1(\mathrm{X})u_2(\mathrm{X}) \\ u(x,y)u_2(\mathrm{X}) & u_2^2(\mathrm{X}) \end{pmatrix}. \quad (1)$$

where T is the transpose. u_1 represents the first order partial derivatives of u along horizontal direction and u_2 along vertical direction. When considering applying a certain weighted sum of neighbor element to smooth original data, we can yield a smoothed structure tensor:

$$J := \begin{pmatrix} J_{11} & J_{12} \\ J_{12} & J_{22} \end{pmatrix} \quad (2)$$

$$= \begin{pmatrix} T(u_1^2(\mathrm{X})) & T(u_1(\mathrm{X})u_2(\mathrm{X})) \\ T(u(x,y)u_2(\mathrm{X})) & T(u_2^2(\mathrm{X})) \end{pmatrix}$$

where T is a smoothing operator. In corner detect, T is defined as Gaussian convolution. See [15] for another nonlinear structure tensor and its applications to other image processing tasks. we introduce a refined filter to construct new nonlinear structure tensor. The nonlocal means (NLM) filtering argued that images contain repeated structures and therefore averaging them will reduce the random noise [16]. For a structure element data, the filtered value $j_{ij}(\mathrm{x})$, is computed as a weighted average of all the pixel in the image

$$j_{ij}(\mathrm{x}) = \sum_{Y \in W} \omega(\mathrm{X},\mathrm{Y}) u_i(\mathrm{Y}) u_j(\mathrm{Y}), i,j = 1,2. \quad (3)$$

The family of weights $\omega(\mathrm{X},\mathrm{Y})$ satisfies the usual conditions $0 \le \omega(\mathrm{X},\mathrm{Y}) \le l$ and $\sum_{Y \in I} \omega(\mathrm{X},\mathrm{Y}) = 1.$ Neighborhood W, which also be named as search window, is defined as a square window centered around a pixel with a certain radius r. The weights $\omega(\mathrm{X},\mathrm{Y})$, which describe the similarity of the two pixel X and Y, are based on the similarity between the neighborhoods N_x and N_y of pixels X and Y respectively. These weights are defined as

$$\omega(X,Y) = \frac{1}{Z(\mathrm{Y})} e^{-d(\mathrm{X},\mathrm{Y})}, \quad (4)$$

where

$$Z(I) = \sum_{J \in I} e^{-\frac{d(X,Y)}{h^2}} \quad (5)$$

In weight function, h acts as a exponential decay control filter parameter and d is a Gaussian weighted Euclidian distance of all the pixels of each neighborhood:

$$d(X,Y) = G_\rho \left\| v(N_X - v(N_Y) \right\|_r^2 \quad (6)$$

where G_ρ is a normalized Gaussian weighting function with zero mean and ρ standard deviation that penalizes pixels far from the center of the neighborhood window.

After smoothed by nonlocal means filter, we can calculate the structure tensor matrix's two orthonormal eigenvectors v1 and v_1 with v_2 parallel to

$$\left(j_{11} + j_{22} - \frac{2 j_{11}}{\sqrt{((j_{11} - j_{22})^2) + 4 j_{12}{}^2}} \right). \quad (7)$$

Two eigen-values are given by

$$\mu_1 = \frac{1}{2}\left[j_{11} + j_{22} + \sqrt{((j_{11} - j_{22})^2) + 4 j_{12}^{\ 2}} \right]. \tag{8}$$

and

$$\mu_2 = \frac{1}{2}\left[j_{11} + j_{22} - \sqrt{((j_{11} - j_{22})^2) + 4 j_{12}^{\ 2}} \right]. \tag{9}$$

Now we discuss the geometrical meaning of the eigen-value and eigen-direction. The vector v_1 indicates the orientation with the highest grey value fluctuations, while v_2 gives the preferred local orientation, the coherence direction. Further more, μ_1 and μ_2 serve as descriptors of local structure. Structure tensor has been successfully used in the field of image processing [15,17]. But till now, only a few literature can be found for a image fusion. In the next section, structure tensor will be adopted to design a fusion rule within wavelet framework.

Reminding that the goal of measure is to describe the abundance of the details and structure, we define a shape measure

$$\phi_{shape} = \begin{cases} \mu_1^{\ 2} & if \quad \mu_2 \geq T_1 \\ 2\mu_1^{\ 2} & if \quad 1 \leq \frac{\mu_1}{\mu_2} \leq 2 \, and \, \mu_1 \leq T_2 \\ (\mu_1 - \mu_2)^2 & else \end{cases} \tag{10}$$

The definition of ϕ_{shape} conveys the local geometrical feature. Note that this shape measure is an supplement to the classical coherence measure defined as

$$\phi_{coherence} = (\mu_1 - \mu_2)^2 . \tag{11}$$

When considering a corner whose two eigen-values may be large, or isotropic structures case characterized by $\mu_1 \cong \mu_2$, two threshold T_1 and T_2 are used to estimate the local geometrical structure.

Image fusion with shape feature

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 pixel, 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 magnitudes 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. The fused coefficients $u(\mathrm{C})$ can be obtained as the weighted average of two source image wavelet coefficients $u(\mathrm{A})$ and $u(B)$:

$$u(\mathrm{C}) = \omega_A * u(\mathrm{A}) + \omega_B * u(B) . \tag{12}$$

where ω_A and ω_B are weights. As weighted coefficients, ω_A and ω_B are positive and $\omega_A + \omega_B = 1$. For low frequency sub-band, we use local energy of gradient (LEOG) to calculate ω_A and ω_B:

$$\omega_A = \frac{LEOG(\mathrm{A})}{LETG(\mathrm{A}) + LEOG(B)} \tag{13}$$

$$\omega_B = \frac{LEOG(\mathrm{B})}{LETG(\mathrm{A}) + LEOG(B)} \tag{14}$$

where $LEOG$ describes the local gradient energy, which can avoid the lost of contrast. For high frequency sub-bands, the weights can be yielded by

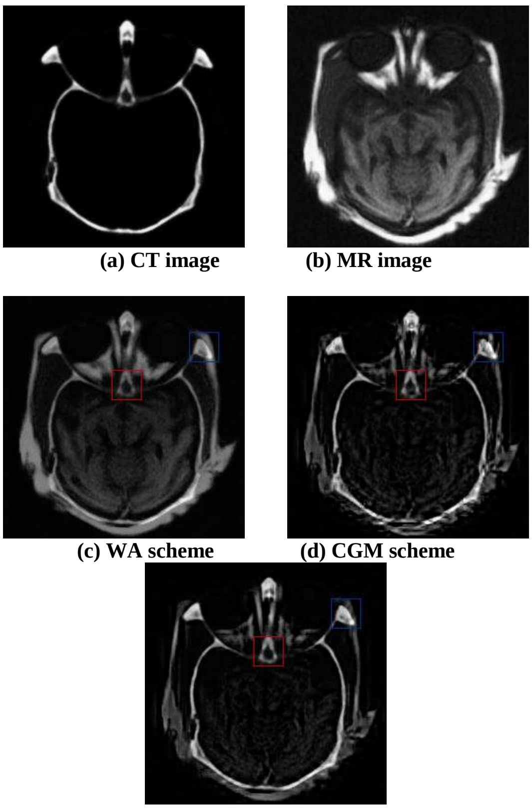
$$\omega_A = \frac{\phi_{shape}(\mathrm{A})}{\phi_{shape}(\mathrm{A}) + \phi_{shape}(B)}\,. \tag{15}$$

$$\omega_B = \frac{\phi_{shape}(B)}{\phi_{shape}(\mathrm{A}) + \phi_{shape}(B)}\,. \tag{16}$$

where $\phi(A)$ is the shape measure defined as (10) for source image A and $\phi(\mathrm{B})$ for source image B.

RESULTS

We have carried out some experiments on medical images to see the performance of the proposed fusion scheme quantitatively and visually. To do a quantitative comparison, Energy of image gradient (EOG) is adopted as performance measure for the purpose of comparing choosing max (CM), weighted average (WA) and choosing gradient max(CGM) fusion scheme. For visual comparisons, fine details of the fused image will be shown with two parts of fused images zoomed, through which we can compare the differences between various methods. In our tests, the same level of decomposition and the same wavelet basis function were used for the four methods, which implies the differences between the fusion results lie in that of the feature extraction. For the same reason, we select $'db3'$ wavelet for three methods in our setting.



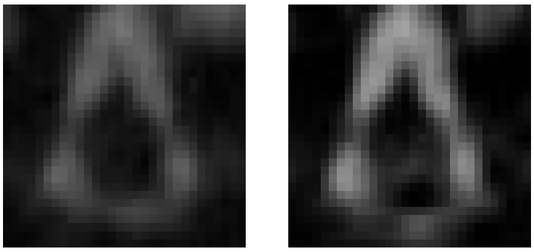
(a) CT image **(b) MR image**

(c) WA scheme **(d) CGM scheme**

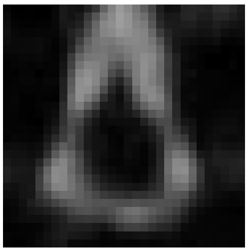
(e) Our scheme

Fig.1: Fusion of Medical Images

Figure 1 demonstrates the fusion results of multi-sensor medical images. Two medical source images, One is CT image and the other is MRI image, come exactly from the same brain area. The fusion results by three schemes are shown in Fig.1.(c)- Fig.1. (e). Though in standard nonlocal mean filter, the search window can be the whole image, it may be time consuming. Therefore, the search window we set is a 11×11 region and the similar window is 7×7. Compared to the AW scheme, the proposed approach produces a better contrast and more details. In the result by CGM, some details are enhanced while some artifacts can be found near edges. 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.2 and Fig.3. As shown in Fig.2, It can be observed that the edge in AW is blurred. The propose scheme and CGM protects edges and more details. However, our scheme produces a more smoothing effect for homogenous region. In Fig.3, we can observe that the contrast in AW is low and hence edges seems be blurred. The fused image of CGM shows some ghost in the left part of the image. In table 1, the data of EOG are presented.

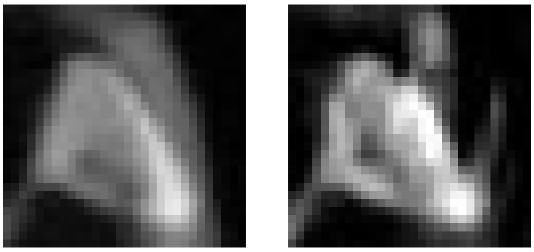


(a) WA scheme (b) CGM scheme

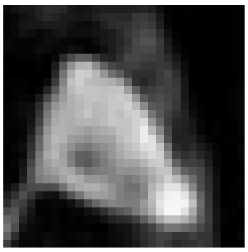


(c) Our scheme

Fig.2: Center Part of the Fusion Results



(a) WA scheme (b) CGM scheme



(c) Our scheme

Fig.3: Right Part of the Fusion Results

Tab.1: Comparison of The EOG Data

	WA	CGM	Our Scheme
CT/MR	3.6763	5.7283	5.8362

CONCLUSION

A new image fusion algorithm based on local structure is presented within wavelet framework. The structure feature is conveyed by the eigen-values of structure tensor. A new index is defined and used to construct fusion rule. The proposed method preserves fine details of medical images and produces a more smoothing homogenous region. Experimental results on real medical images demonstrate the performance of the proposed method.

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