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Medical image fusion based on statistical modeling

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Abstract. For improving the imaging quality and increasing the clinical applicability, a novel approach to multimodal medical image fusion is proposed based on statistical modeling in contourlet transform domain. Firstly, the coefficients of the approximate subband are modeled as a Gaussian mixture distribution, and fused by a new rule using the weighted average of a posterior probability. Then, the coefficients of the detail subbands are modeled by generalized Gaussian distribution, and a selection rule is used for fusion based on the estimated parameters and the matching measure. Finally, an effectively fused image is achieved through inverse contourlet transform. The experimental results show that, compared with existing approaches, the proposed method can make the fused image have better performance, and provide more valuable diagnostic information.

1. Introduction

Due to the practical limitation of medical imaging modality, each source image sensor usually captures different significant information from the same target. In order to make practitioners easily obtain comprehensive and reliable understanding, or meet the requirements of subsequent medical image processing tasks, it is necessary to effectively fuse the related multi-source images. Currently, medical image fusion has been widely applied to medical diagnosis, monitoring and analysis [1,2].

In pixel level context, medical image fusion approaches include that of spatial domain and multiscale transform domain, respectively [3]. Usually, the fusion methods based on transform domain can fully utilize image characteristics of the spatial frequency locality, and obtain better fusion effect [1-3]. Specially, the fusion methods combining multiscale statistical modeling have received a great deal of attention. Burt firstly proposes a statistical fusion algorithm based on saliency measure and matching measure [4]. Achim proposes a fusion method based on generalized Gaussian and alpha-stable modeling[5]. Loza presents a fusion method of multimodal medical image based on non-Gaussian statistical modeling[6]. Howlader proposes a statistical medical image fusion algorithm based on Bayesian maximum posterior probability [7]. Generally speaking, these methods based on wavelet statistical modeling have better effect of image fusion. However, due to the lack of rich directionality, the fusion performance remains to be further improved. In comparison, the contourlet transform can optimally describe the geometric directional information of natural images [8]. Therefore, its statistical subband modeling is used for the image fusion in this paper.

Recently, the multimodal medical image fusion methods based on contourlet transform have aroused extensive attention. Bhatnagar proposes a novel fusion method based on the activity measure and the directive contrast [9]. Yang proposes a fusion scheme based on generalized Gaussian distribution modeling and weight maps [10]. Luo proposes a new fusion method based on hidden Markov model [11]. Considering that any medical image can be regarded as a random distribution
implementation, thus the fusion methods using statistical probability modeling may obtain better performance. In recent years, some researchers have made preliminary explorations [10-12].

In this paper, a new fusion method is proposed based on joint modeling in contourlet domain. Specifically, the approximate subband coefficients are modeled as Gaussian mixture distribution (GMD), and fused by using the weighted average of a posterior probability; the detail subband coefficients are modeled by generalized Gaussian distribution (GGD), and the fusion rules of the selection and weighted average are used based on distribution parameters and matching measure.

2. Contourlet transform and Its Approximate Subband Modeling

The contourlet transform includes the multiscale transform and the multidirectional transform. The multiscale transform is achieved by the Laplacian pyramid (LP), and the directional transform of the multiscale detail subbands is implemented by the directional filter bank (DFB). Specifically, the LP firstly decomposes input image into a approximate subband and a detail subband. Then, the multiscale decomposition procedure is iterated after the approximate subband followed by downsampling by 2 in each dimension. Finally, every detail subband image of the LP is further decomposed by a DFB into $2^n$ directional subband images, where $n$ is the level number of the directional decomposition.

In this paper, the approximate subband coefficient $x$ with the multimodal distribution can be modeled as the GMD, and its mixture probability density function is represented as

$$p(x | \theta) = \sum_{m=1}^{K} \omega_m p(x | \mu_m, \sigma_m^2)$$

where $\omega_m$, $m=1,2,\ldots,K$ denotes the weighted coefficient of the component; $K$ is the number of mixture components, $\sum_{m=1}^{K} \omega_m = 1$ , and $K = \text{5}$ is adopted in all the following experiments; $\theta = \{\omega_1, \mu_1, \sigma_1^2, i=1,2,\cdots,K\}$ represents the parameter set of GMD model. Usually, the parameters are estimated according to the expectation maximization (EM) method.

3. Image fusion method based on jointly statistical modeling

The multimodal medical source images are firstly decomposed by contourlet transform. Then, the approximate subband coefficients are modeled as finite GMD and fused according to the weighted average. The choice of the weight adopts our proposed posterior probability of the coefficients. Meanwhile, the detail subband coefficients are modeled as GGD [13], and fused by using the selection and weighted average rule which is based on the refined Burt method. Specifically, the adopted image fusion approach in this paper is described as follows.

Assuming that the source images are A and B, the fused image is C.

1) The source images A and B are respectively decomposed by contourlet transform into the approximate subband and the detail directional subbands.

2) The fusion rule for the approximate subband coefficients adopts the weighted average of a posterior probability. The $5 \times 5$ sliding window is used to traverse the approximate subband of the source image. The central pixel coefficient of each window determines the fusion weight according to a posterior probability. Namely, for the approximate subbands of the source images A and B, firstly GMD density functions $p(x | \theta_A) = p(x | A)$ and $p(y | \theta_B) = p(y | B)$ are respectively estimated for the central coefficients $x_i$ and $y_i$, $i=1,2,\cdots,N$ in every window, where $N$ is the total number of approximate coefficients; then, the class posterior probabilities

$$P(A | z) = \frac{p(x | A)p_i(z)}{p(x | A)p_i(z) + p(y | B)p_i(z)}$$

and

$$P(B | z) = \frac{p(y | B)p_i(z)}{p(x | A)p_i(z) + p(y | B)p_i(z)}$$

of the corresponding fused central coefficients $z_i$, $i=1,2,\cdots,N$ are respectively computed, where $p_i(x) = x_i / (x_i + y_i)$ and $p_i(y) = y_i / (x_i + y_i)$ are the prior probabilities of the
central coefficients in the \(i\)th window of the source images \(A\) and \(B\), respectively; finally, the central coefficient in every window of the fused image \(C\) is obtained by using weighted average, namely

\[
z_i = P(A_i | x_i) x_i + P(B_i | y_i) y_i, \quad i = 1, 2, \ldots, N
\]  

(2)

3) The fusion rule of the detail directional subband coefficients uses the selection and weighted average method. Assuming that some detail directional subbands corresponding to \(A\) and \(B\) are \(X\) and \(Y\), respectively. The \(11 \times 11\) sliding window is adopted. For each of the sliding windows,

(1) the variance parameter of GGD model for the detail directional subband coefficients is estimated according to the refined Newton–Raphson iterative algorithm [13].

(2) determine the salience measure \(\sigma_x^2\) and \(\sigma_y^2\), which are equal to the estimated variance of the detail directional subband coefficients, respectively.

(3) compute matching measure

\[
M = \sigma_x^2 + \sigma_y^2
\]

where \(\sigma_x\) and \(\sigma_y\) denote the covariance of \(X\) and \(Y\).

(4) compute fusion weights \(W_{\text{max}}\) and \(W_{\text{min}}\) according to the relationship between matching measure \(M\) and threshold \(T\); if \(M \geq T\), then \(W_{\text{max}} = 0.5 + (1 - (1 - M) / (1 - T))\) and \(W_{\text{min}} = 1 - W_{\text{max}}\), otherwise \(W_{\text{max}} = 1\) and \(W_{\text{min}} = 0\); in this paper, each threshold selection is carried out based on the optimal fusion performance.

(5) compute and determine the coefficients of the fused detail directional subbands, namely

\[
D_{\text{c}}(m,n) = W_{\text{max}} D_{\text{X}}(m,n) + W_{\text{min}} D_{\text{Y}}(m,n) \quad \text{if } \sigma_x^2(m,n) \geq \sigma_y^2(m,n)
\]

\[
D_{\text{c}}(m,n) = W_{\text{min}} D_{\text{X}}(m,n) + W_{\text{max}} D_{\text{Y}}(m,n) \quad \text{if } \sigma_x^2(m,n) < \sigma_y^2(m,n)
\]

(3)

where \(D_{\text{c}}(m,n)\), \(D_{\text{X}}(m,n)\) and \(D_{\text{Y}}(m,n)\) represent the coefficients of the source images and fused image in the central position \((m,n)\) of the sliding window, respectively.

4) Reconstruct every fused contourlet subband coefficient, and generate the final fusion image.

4. Experimental Results

The experiments are conducted in two aspects. The modeling accuracy for approximate subband and detail subbands is firstly evaluated through the experimental effect of histogram fitting, then the subjective and objective performance are compared with the existing image fusion methods.

The subjective performance evaluation is based on the visual effect of the fused images. Without requiring a reference image, the objective evaluation adopts the well-known information entropy (\(E\)), standard deviation (\(\text{STD}\)), and \(Q\)-index (\(Q_{\text{AB}}\))[1, 9]. Among them, the greater the entropy, the more abundant the image information; the larger the STD value, the clearer the fused image; and the larger \(Q_{\text{AB}}\) value shows that the edge details of source images are better preserved.

4.1. GMD modeling for approximate subband coefficients

The contourlet approximate subband can be modeled as finite GMD. In order to compare and verify the modeling accuracy, the estimated GMD probability density curve is used for fitting the approximate subband histogram. In all the experiments below, contourlet transform is decomposed into three levels. The experimental result is shown in Figure 1. Figure 1(a) is the MRI source image, and Figure 1(b) depicts the statistical modeling result. It can be seen from Figure 1(b) that, the approximate subband histogram has a distinct multimodal distribution shape, and its statistical property can be accurately fitted by the estimated GMD.

4.2. GGD modeling for detail directional subband coefficients

Every contourlet detail subband distribution can adopt GGD modeling[13]. The parameter estimation accuracy of GGD model is also evaluated through the effect of histogram fitting. The modeling result for the first directional subband in the first level is also depicted in Figure 1. Figure 1(c) is the CT source image, and Figure 1(d) represents the GGD modeling result. It can be seen from Figure 1(d)
that, the histogram of the detail subband presents a single peak mode, and the distribution estimation is also more accurate.

![Figure 1. Statistical modeling of subbands](image)

4.3. Comparisons with existing image fusion methods

Two different modal medical images, namely MRI and CT images with the size of 256×256 are selected as source images [2], as shown in Figure 1(a) and Figure 1(c), respectively.

Firstly, the experimental results are evaluated from the visual effect, as shown in Figure 2(a)-(f). For comparison, we respectively adopt the weighted average method in discrete wavelet transform domain (DWT-W), the weighted average method in contourlet domain (Con-W), the method using the weighted average for approximate subband and GGD modeling for detail subbands in DWT domain (DWT-W-GGD, \( T=0.1 \)), the method using the weighted average for approximate subband and GGD modeling for detail subbands in contourlet domain (Con-W-GGD, \( T=0.3 \)), the method using GMD modeling for approximate subband and GGD modeling for detail subbands in DWT domain (DWT-GMD-GGD, \( T=0.1 \)), and the proposed method using GMD modeling for approximate subband and GGD modeling for detail subbands in contourlet domain (the proposed method, \( T=0.3 \)). It can be seen from Figure 2 that, our proposed approach obtains better visual effect on the contrast, definition and artifact, therefore is more conducive to rational medical diagnosis.

![Figure 2. Visual effect of medical image fusion based on different methods](image)

The objective performance of medical image fusion is respectively evaluated by the information entropy, standard deviation and \( Q_{AB/F} \), as shown in Table 1. It can be seen from table data that, the performance achieved by our proposed approach is obviously better than that of the other methods.

| Methods           | E      | STD     | \( Q_{AB/F} \) |
|-------------------|--------|---------|----------------|
| DWT-W             | 0.0012 | 18.7596 | 0.5768         |
| Con-W             | 0.0012 | 18.7600 | 0.6130         |
| DWT-W-GGD         | 0.3334 | 18.7872 | 0.7130         |
| Con-W-GGD         | 0.3332 | 20.9750 | 0.7133         |
| DWT-GMD-GGD       | 0.3581 | 30.7660 | 0.7379         |
| the propose method| 0.5195 | 31.4354 | 0.7680         |

5. Conclusion

In contourlet transform domain, the performance of image fusion can be effectively improved by using statistical modeling. To this end, a new multimodal medical image fusion approach is proposed in this paper based on joint modeling in contourlet domain. Its innovations include that, the approximate
subband coefficients are modeled by finite GMD, and fused by using a novel weighted average of a posterior probability; every detail subband coefficients are modeled by GGD, and fused based on distribution parameters and matching measure. The experimental results show that the proposed method effectively improves the performance and visual effect of multimodal medical image fusion.

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References
[1] Du, J., Li, W., Lu, K., Xiao, B. (2016) An overview of multi-modal medical image fusion. Neurocomputing, 215: 3–20.
[2] James, A.P., Dasarathy, B.V. (2014) Medical image fusion: a survey of the state of the art. Information Fusion, 19: 4-19.
[3] Li, S., Kang, X., Fang, L., et al. (2017) Pixel-level image fusion: A survey of the state of the art. Information Fusion, 33: 100-112.
[4] Burt, P.J., Kolczynski, R.J. (1993) Enhanced image capture through fusion. In: Fourth International Conference on Computer Vision. Berlin. pp. 173-182.
[5] Achim, A., Loza, A., Bull, D., et al. (2008) Statistical modeling for wavelet-domain image fusion. Image Fusion, 2008: 119-138.
[6] Loza, A., Bull, D., Canagaraiia, N., Achim, A. (2010) A non-Gaussian model-based fusion of noisy image in the wavelet domain. Computer Vision and Image Understanding, 114: 54-56.
[7] Howlader, T., Jhohura, F.T., Rahman, S.M.M. (2013) A novel statistical image fusion rule for noisy source images. In: 59th ISI World Statistics Congress. Hong Kong. pp. 3630-3635.
[8] Do, M.N., Vetterli, M. (2005) The Contourlet transform: an efficient directional multisresolution image representation. IEEE Transactions on Image Processing, 14: 2091-2106.
[9] Bhatnagar, G., Wu, Q., Liu, Z. (2015) A new contrast based multimodal medical image fusion framework. Neurocomputing, 157: 143-152.
[10] Yang, G., Li, M., Chen, L., et al. (2015) The nonsubsampled contourlet transform based statistical medical image fusion using generalized Gaussian density. Computational and Mathematical Methods in Medicine, 2015: 1-13.
[11] Luo, X., Zhang, Z., Zhang, B., Wu, X.. (2017) Contextual information driven multi-modal medical image fusion. IETE Technical Review, 34: 598-611.
[12] Zhang, H., Luo, X., Wu, X., et al. (2014) Statistical modeling of multi-modal medical image fusion method using C-CHMM and M-PCNN. In: 22nd International Conference on Pattern Recognition. Stockholm. pp. 1067-1072.
[13] Qu, H., Peng, Y., Sun, W. (2007) Texture image retrieval based on Contourlet coefficient modeling with generalized Gaussian distribution. In: the 2nd International Conference on Advances in Computation and Intelligence. Wuhan. pp.493-502.