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Research Article

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CT/MRI medical image fusion based on sub-band coefficients selection through curvelet transform method

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ABSTRACT

Medical image fusion plays important roles for accurate clinical diagnosis and pharmacology determination. In this article, the fusion on CT/MRI medical images is carried out based on the curvelet transform due to its high sensitivity to two dimensional edges and curves. After analyzing the sub-band coefficients decomposed from the original images, three methods are put forward to manipulate the transformed coarse and fine scales. Results imply that the maximally selecting the coefficient at every scale from the original images is optimal to achieve more effective fusion than the combined methods as maximal selection at fine scales but weighted averaging or simply averaging coefficients at coarse scales. For the latter two methods, the weighted averaging at coarse scale is better. More MRI information extraction is important for the fusion performance, since the MRI image has more details than CT. The algorithms proposed in this article can be integrated into the multi-modal medical imaging instrument to acquire higher accuracy for clinical and pharmacology decision.

Key words: Medical image fusion, curvelet transform, maximal selection, weighted average, image processing

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INTRODUCTION

Medical images can be acquired from many instruments such as CT (Computerized Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography) and so on **[1]**. Computer assistance in these imaging processes can not be neglected. For example, the built-in computer controls the X-ray tube for CT scanning on different sections of the pathologically changed tissues. Except the X-ray or γ-ray emission control, another essential application of computer is signal processing on the digitalized images **[2-3]**. *Buades* et al. compare several methods for image denoising based on the local smoothing filters, including *Gaussian* filter, anisotropic filter and neighborhood filter. Such denoising achievement is derived from locally averaging the image pixel matrix **[4]**. Regionally processing on medical images is important, i.e. *Hill* et al. review the medical image registration based on spatially rigid or non-rigid methods **[5]**. Watershed is an effective algorithm through locally operating for image segmentation **[6]**. When mapping pixel matrix into high-resolution scales, one image can be transformed into a slice of coefficient matrices in order to respectively represent the coarse and fine information of the image. The redundancy information of medical images can be compressed through manipulating the wavelet transformed coefficients even at three-dimension (3-D) **[7]**. *Yang* et al. also propose an algorithm for image enhancement based on the *Haar* wavelet transform and soft-threshold treatment on the high-frequency sub-bands of the image **[8]**. Other than the wavelet transform, there have several multi-resolution methods also efficient for medical image processing, such as framelet transform, contourlet transform, ridgelet transform, curvelet transform and so on **[9-10]**.

When it comes to the multi-modal images for integrative clinical diagnosis and pharmacology determination, the image fusion is an essential topic in medical image processing field. Namely, the multi-sourced images should be informatively merged together. The easiest method is operated through adding the image pixels, but many defects can not be avoided during direct pixel fusion **[11]**. The fusion operation at transformation scale is a candidate to fuse images with higher accuracy. Wavelet transform is beneficial for fusing information at coarse and fine scale based on the methods such as modulus maxima criteria **[12]**, wavelet pyramid **[13]** and so on. Though wavelet transform is effective to represent the one-dimensional (1-D) piecewise smooth signals, there have limitations for decompose the two dimensional (2-D) lines or curves, whereas the essential features of medical images are embedded in the 2-D edges **[14]**. The novel curvelet transform is consequently applied for compensating such limitations **[15]**. There have several reports on the multi-spectral remote sensing image fusion, though its application on medical image fusion should be further investigated **[16-17]**. In this article, the curvelet transform fusion on CT/MRI image set is focused on, and several fusion strategies are put forward. The fusion effect is quantitatively evaluated by the factors including average gradient, edge intensity and mutual information. The algorithms established in this article can be jointly utilized for multi-modal clinical and pharmacology analysis on the pathologic change.

EXPERIMENTAL SECTION

The two dimensional (2-D) discrete curvelet transform (DCT) on medical image is consisted of the following procedures.

Firstly, the image is decomposed into sub-bands through convolution as

$$\Delta f = P_0 f + \Delta_s f = \Phi_0 * f + \Psi_{2s} * f \,. \tag{1}$$

In which, the first component is related to low-pass treatment on the *f*, and the second component is about band-pass information extraction from *f*. Consequently, the signal *f* has been sub-banded. Secondly, smooth partitions are operated on the band-pass decomposed components, and renormalization on the partitioned segments followed. Finally, ridgelet transform is applied to the segmented squares by representing them with a few of coefficients indexed by scale, orientation and spatial location. Inverse transform on the coefficients can reconstruct the processed images.

The curvelet transform is anisotropy sensitive to discriminate out the 2-D edges in the images. The object of this article is to manipulate the coefficient matrices at every sub-band for medical image fusion. Such fusion scheme is shown in Fig. 1. The selected CT and MRI images have been transformed into many coefficient matrices to represent the information embedded in the images at scales with different resolution.

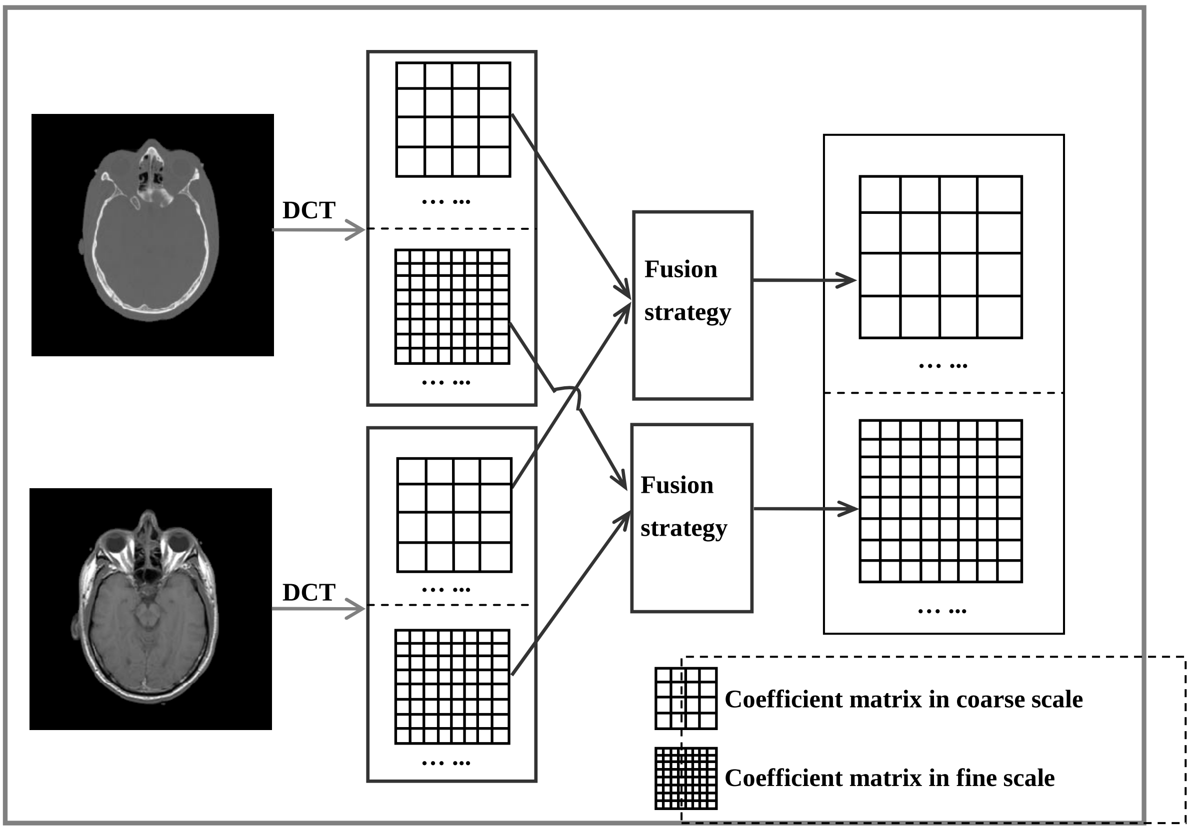


Fig. 1. Fusion scheme of the CT/MRI medical images based on curvelet transform

Since the coarse scales and the fine scales represent different information of the images, there should assign different methods for maximally utilizing the respective information. The fusion methods proposition and evaluation is the major task of this article.

RESULTS AND DISCUSSION

The selected CT and MRI image from the same patient have been spatially registered as shown in Fig. 1. The CT image can scan out the cerebrovascular pathologic change, cerebral hemorrhage, intracranial pressure, and so on. For the MRI image, it is utilized for discriminating the soft tissues to observe the cerebrovascular accident, cerebrovascular tumors etc. CT possesses high spatial resolution but low contrast when scanning soft tissues. Contrarily, MRI has high contrast on soft tissue though low in resolution. The two images are complementary. Fusion of CT/MRI image set is significant from the clinical and pharmacology viewpoints.

CURVELET DECOMPOSED SUB-BANDS ANALYSIS

The coefficients at decomposed scales are different in orientation and spatial location to represent the fragments of the images. In Fig. 2, the coarse and fine information in different scales is graphically exampled.

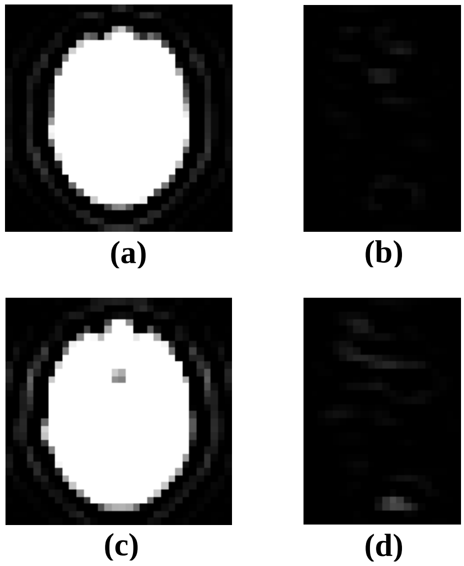


Fig. 2. Curvelet transformed sub-bands, exampled by (a) CT and (c) MRI image at low-frequency scale, and by (b) CT and (d) MRI image at high frequency scale

At low frequency scale, the outer profiles of the CT/MRI images have been segmented out. For the high frequency information, there have edges or curves in a given direction. Every scale is related to a coefficient matrix. And fusion algorithms are designed for fusing the corresponding coefficients. It also should be noticed that more information is embedded in the high resolution scale of MRI image as shown in Fig. 2d, since there have more fragments than that CT in Fig. 2b.

MAXIMUM COEFFICIENT SELECTION FUSION METHOD

The rational method for comparing the information amount embedded in a coefficient is the coefficient value. And the bigger the coefficient is, the more important such coefficient becomes for fusion. Consequently, all the coefficients of CT and MRI image are compared with each other at the same scale. After traversing all the sub-bands, the maximum coefficients are selected out and fused into the corresponding scales.

Such fusion method is present in Eq.(2). Since the curvelet transformed coefficient is complex in format, the absolute values of the coefficients are applied for comparison.

Method 1: $C_F^L(i,j) = Q \times C_1^L(i,j) + (1-Q) \times C_2^L(i,j)$, **(2)**

in which $Q = \{ \begin{matrix} 1 & if\,|C_1^L(i,j)| \geq |C_2^L(i,j)| \\ 0 & if\,|C_1^L(i,j)| < |C_2^L(i,j)| \end{matrix}$

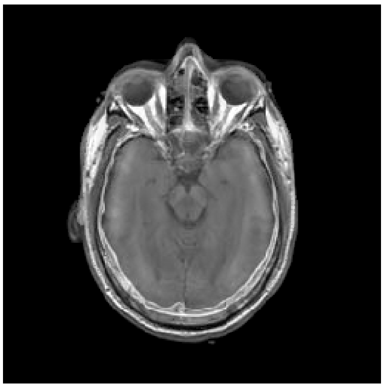


Fig. 3. The fused image based on the *Method 1* through maximally selecting the coefficients

The fused image is shown in Fig. 3. Compared to the original images, there have CT information appeared in the MRI structure. The fused image is more informative.

In order to quantitatively evaluate the fusion effect, three parameters such as average gradient, edge intensity and mutual information are calculated and present in Tab.1. There has distinct improvement for the fused image, i.e. the average gradient has been increased to 4.9318, which is higher than 4.3591 of MRI and 2.3076 of CT. And the edge intensity has been heightened to 50.2508. It implies that more details have been integrated together. In order to discriminate out the information source in the fusion image, the mutual information parameter indicates that the fused image is embedded with more information sourced from MRI image rather than CT. About one-third more information of MRI is appeared in the fused image.

Table 1. Evaluation on original CT/MRI images and the fused image based on Method 1

Image / Parameters	CT image	MRI image	Fused image through Method 1
Average gradient ($\overline{G}$)	2.3076	4.3591	4.9318
Edge intensity (I_E)	23.6800	45.0382	50.2508
Mutual information (M)	0.7969	1.0676	__

Such a deduction can be verified by the sub-band decomposition of the fused image, as shown in Fig. 4. It seems that the decomposed sub-band of the fused image is more similar to that of MRI. Such a phenomenon is ascribed that the MRI image has more details, or in other words has more edges and macrostructures than CT, which is quantitatively verified by its higher edge intensity and average gradient parameters. Such edges are decomposed into every sub-band by the anisotropy seeking from curvelet transform. Consequently, higher fusing weight is acquired by the coefficient in MRI sub-bands.

Fig. 4 Curvelet transform of the fused image at the same sub-band as Fig. 2b and 2d

DIFFERENT TREATMENT ON LOW-FREQUENCY SUB-BANDS

For comparison, the other methods are put forward for treating with the curvelet transformed coefficients. Such methods are based on the observation that more detail information is decomposed into the high-frequency sub-bands, but the coarse information in low-frequency sub-bands are also important to determine the image profile, as shown in Fig. 2. The maximal selection on coefficients in high sub-bands is rational, whereas the fusion method in low sub-bands can be differently operated according to Eq.(3) and Eq.(4).

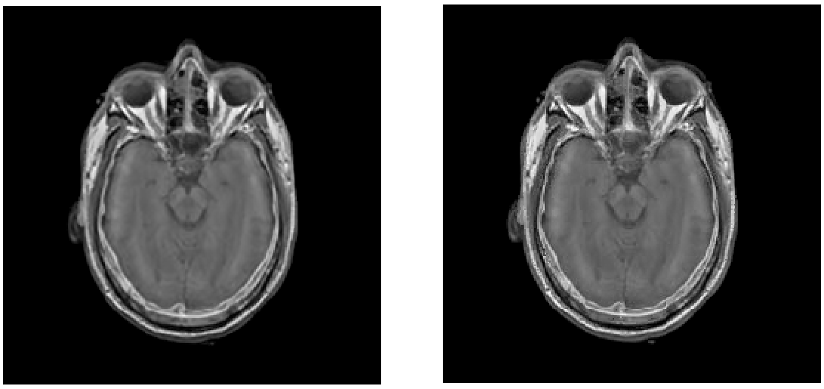
Method 2: $$C_F^L(i,j) = \frac{C_1^L(i,j) + C_2^L(i,j)}{2},$$ **(3)**

in which L∈ low frequency sub-bands.

Method 3: $$C_F^L(i,j) = \frac{C_1^L(i,j)}{C_1^L(i,j) + C_2^L(i,j)} \times C_1^L(i,j) + \frac{C_2^L(i,j)}{C_1^L(i,j) + C_2^L(i,j)} \times C_2^L(i,j),$$ **(4)**

in which L∈ low frequency sub-bands.

The fused images based on the different methods are shown in Fig. 5. When analyzed by the quantitative parameters in Tab. 2, it implies that the weighted averaging on the coarse scale has achieved more effective fusion than the simple averaging method, since average gradient and edge intensity derived from method 3 are remarkably higher than that of method 2. Such a difference is ascribed that the method 3 has extracted more MRI rather than CT information, which is verified through comparing the two mutual information parameters in Tab. 2. MRI has more inner edges and microstructures. Consequently, fusion from method 3 has more details and edges obtained.



(a) **(b)**

Fig. 5. The fused image based on (a) *Method 2* by averaging and (b) *Method 3* by weighted averaging treatment on the coefficients at low-frequency sub-bands, with maximally selection on the coefficients at high-frequency sub-bands

Table 2. Evaluation on the original CT/MRI images and the fused images

Parameters \ Image	Fused by Method 2	Fused by Method 3
Average gradient ($\overline{G}$)	4.5140	4.9355
Edge intensity (I_E)	46.9294	49.8279
Mutual information (*M*) with CT	0.7981	0.7916
Mutual information (*M*) with MRI	1.0501	1.0572

When compared all the three fusion methods, more MRI information are extracted by the method 1 fused image, which achieves the highest edge intensity even though the average gradient is slightly lower than that of the method 2. The method 1 through maximal coefficient selection at all the sub-bands is prior to the latter two methods. For the latter method 2 and method 3, the weighted averaging in method 2 is relatively better.

CONCLUSION

Multi-modal medical image fusion has medical significance. In this article, the curvelet transform method is put forward for such purpose, since curvelet transform can discriminate out the 2-D edges or curves in medical images with higher sensitivity. Three fusion methods are established according to the curvelet transformed coarse or fine sub-bands. After evaluated by quantitative parameters, results indicate that the fusion method based on maximal selection on the coefficient at every corresponding sub-band of the original images is the optimal. And the combined method through weighted averaging at coarse scale and maximal selection at fine scale achieves more informative fusion than the method with simply averaging at coarse scale. More MRI information extraction can improve the fusion performance.

Such proposed algorithms can be integrated into the multi-modal imaging instruments for improving the clinical and pharmacology activities.

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REFERENCES

[1] Y Qiang; YB Ma; JJ Zhao; J Wang, *J. Chem. Pharm. Res.*, **2013**, 5(12), 183-187.
[2] JJ Zhao; YX Liu; MY Qu; Y Qiang, *J. Chem. Pharm. Res.*, **2013**, 5(12), 188-195.
[3] XW Li, *J. Chem. Pharm. Res.*, **2013**, 5(12), 113-117.
[4] A Buades; B Coll; JM Morel, *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, **2005**, 2, 60-65.
[5] DL Hill; PG. Batchelor; M Holden; DJ Hawkes, *Phys. Med. Biol.*, **2001**, 46(3), R1-R45.
[6] V Grau; AUJ Mewes; M Alcaniz; R Kikinis; SK Warfield, *IEEE T. Med. Imaging*, **2004**, 23(4), 447-458.
[7] J Wang; HK Huang, *IEEE T. Med. Imaging*, **1996**, 15(4), 547-554.
[8] Y Yang; Z Su; L Sun, *Electron. Lett.*, **2010**, 46(2), 120-121.
[9] G Bhatnagar; QMJ Wu, *Int. J. Wavelets Multiresolut. Inf. Process.*, **2012**, 10(1), 1250002.
[10] S AlZubi; N Islam; M Abbod, *J. Biomed. Imag.*, **2011**, 2011, 4.
[11] F Luo; BB Lu; CL Miao, *J. Chem. Pharm. Res.*, **2013**, 5(12), 215-220.
[12] GH Qu; DL Zhang; PF Yan, *Opt. Express*, **2001**, 9(4), 184-190.
[13] LF Yu; DL Zu; WD Wang; SL Bao, *J Syst. Eng. Electron.*, **2001**, 12(1), 42-48.
[14] MN Do; M Vetterli, *IEEE T. Image Process.*, **2005**, 14(12), 2091-2106.
[15] JL Starck; EJ Candès; DL Donoho, *IEEE T. Image Process.*, **2002**, 11(6), 670-684.
[16] F Nencini; AGarzelli; S Baronti; L Alparone, *Inform. Fusion*, **2007**, 8(2), 143-156.
[17] S Li; B Yang, *Pattern Recogn. Lett.*, **2008**, 29(9), 1295-1301.