

Multimodality medical image fusion based on multiscale geometric analysis of contourlet transform[☆]

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ABSTRACT

As a novel multiscale geometric analysis tool, contourlet has shown many advantages over the conventional image representation methods. In this paper, a new fusion algorithm for multimodal medical images based on contourlet transform is proposed. All fusion operations are performed in contourlet domain. A novel contourlet contrast measurement is developed, which is proved to be more suitable for human vision system. Other fusion rules like local energy, weighted average and selection are combined with “region” idea for coefficient selection in the lowpass and highpass subbands, which can preserve more details in source images and further improve the quality of fused image. The final fusion image is obtained by directly applying inverse contourlet transform to the fused lowpass and highpass subbands. Extensive fusion experiments have been made on three groups of multimodality CT/MR dataset, both visual and quantitative analysis show that comparing with conventional image fusion algorithms, the proposed approach can provide a more satisfactory fusion outcome.

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1. Introduction

Medical imaging is taking on an increasingly critical role in healthcare. Technological advances in medical imaging in the past two decades have enabled radiologists to quickly acquire images of the human body and its internal structures with unprecedented resolution and realism. X-ray computed tomography (CT) has become popular because of its ability to visualize dense structures like bones and implants with less distortion, but it cannot detect physiological changes. Normal and pathological soft tissue are better visualized by magnetic resonance (MR) image, and the positive electron tomography (PET) provides better information on blood flow and flood activity with low spatial resolution [1]. In medical diagnosis, treatment planning and evaluation, the complementary information in images of different modalities is often needed. For example, combined PET/CT imaging can concurrently visualize anatomical and physiological characteristics of the human body. In oncology, they are used to view tumor activity in conjunction with anatomical references, allowing physicians to better understand the effects of cancer treatment. Combined PET/CT imaging is also very useful in organ diagnosis, where tumor boundaries can be difficult to discern.

Therefore, the multimodality medical image fusion has been emerging as a new and promising research area in recent years [2,14,13]. Image fusion aims at integrating information from multiple modality images to obtain a more complete and accurate description of the same object. It provides easy access to the PET/CT/MRI images at the same location where reading from all other modalities is done, allowing radiologists to quickly and efficiently report PET/CT/MRI studies.

So far, extensive researches have been made on image fusion technique, and various fusion algorithms for medical image have been developed. Depending on the merging stage, common image fusion schemes can be classified into three categories: pixel level, feature level, and decision level. Medical image fusion usually employs the pixel level fusion techniques. The most well-known algorithms include principal component analysis (PCA) [9], Brovey transform method and Laplacian pyramid (LP)/contrast pyramid (CP) filtering [16]. Since image features sensitive to human visual system exist in different scales, multiresolution analysis is more suitable for image fusion. The development in wavelet analysis provides a potential solution [10,17]. Numerous wavelet-based image fusion algorithms have been proposed. Wavelet can be seen as an optimal tool for analyzing one-dimensional (1-D) piecewise smooth signals, however, it has serious limitations in dealing with high dimensional signal like images. In natural images, discontinuity points are typically positioned along object boundaries and smooth edges. As a tense-product of 1-D wavelet, two-dimensional (2-D) separate wavelet is only good at isolating the discontinuities at object edges, but cannot detect the smoothness along the edges. On the other hand, 2-D separable wavelet

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decomposes image in only three directional highpass subbands, namely, vertical, horizontal and diagonal, which means that wavelet can only capture limited directional information. So wavelet-based fusion scheme cannot preserve the salient features in source images very well and will probably introduce some artifacts and inconsistency in the fused results.

Recently, a theory for high dimensional signals called multi-scale geometric analysis (MGA) has been developed. Several MGA tools were proposed, such as ridgelet (Candes, 1998) [5], curvelet (Donoho, 1999) [15] and bandelet (Mallat, 2000), etc. In 2001, contourlet [7] was pioneered by Do and Vetterli as the latest MGA tool. Contourlet is a “true” 2-D sparse representation for 2-D signals like images. The overall result of contourlet transform is a sparse image expansion expressed by contour segments, so it can capture 2-D geometrical structures in visual information much more effectively than traditional multiresolution analysis methods.

In this paper, a novel pixel-level fusion algorithm for multi-modality medical image based on contourlet transform is developed. Region-based contourlet contrast, local energy and weighted averaging are incorporated as the fusion rules. Experimental results show that the proposed contourlet-based fusion algorithm provides an effective way to enable more accurate analysis of multimodality images.

2. Contourlet construction

Do and Vetterli found that to obtain a sparser representation for 2-D piecewise smooth functions in R^2 , an effective method is to utilize a double filter bank scheme [6], that is, first apply a multiscale decomposition to capture point discontinuities; and then perform a local directional decomposition to synthesize the nearby edge points into independent contour segments. With a rich set of basis oriented at various directions and scales, contourlet can effectively capture the intrinsic contours and edges in natural images whose traditional multiresolution analysis methods are difficult to handle. Figs. 1 and 2 depict the block structure and frequency partition of contourlet transform, here 8-direction directional decomposition is applied in the finest scale, subbands 1–4 correspond to the mostly horizontal directions, while subbands 5–8 correspond to the mostly vertical directions. Contourlet offers a much richer subband set of different directions and shapes, which helps to capture geometric structures in images much more efficiently.

In the first stage of contourlet transform, the LP [4] is used for subband decomposition. As shown in Fig. 3, the input image x is first lowpass filtered by filter H and then downsampled to produce a coarse approximation c . It is then interpolated and passed through the synthesis filter G . The resulting image is subtracted from the original image x to obtain the bandpass image d . This process can be iterated repeatedly on the coarser version of the image c . It can be seen that the LP decomposition at each step generates a sampled lowpass version of the original image and the difference between the original and the prediction, resulting in a bandpass high frequency image. Therefore, the $L^2(R^2)$ space is decomposed into a series of subspace with increasing resolutions:

$$L^2(R^2) = V_{j_0} \oplus \left(\bigoplus_{j=j_0}^{\infty} W_j \right) \quad (1)$$

where V_{j_0} is the approximation subspace at the scale 2^{j_0} , W_j is the detail in the finer scale 2^{j-1} . In the LP, each subspace W_j is spanned by a frame $\{\mu_{j,n}(t)\}_{n \in \mathbb{Z}^2}$ that utilizes a uniform grid on R^2 of intervals $2^{j-1} \times 2^{j-1}$.

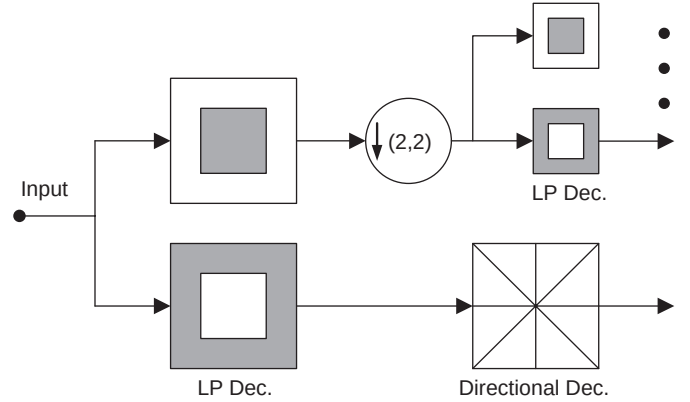


Fig. 1. Block diagram of contourlet transform.

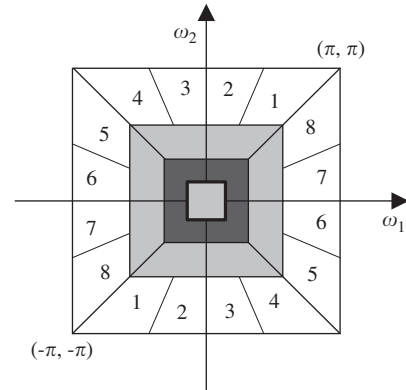


Fig. 2. Frequency partition of contourlet transform.

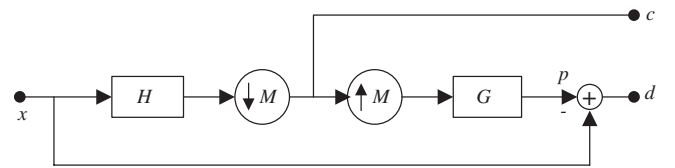


Fig. 3. Construction of LP.

Directional filter bank (DFB) [3] is used in the second stage to link the edge points into linear structures, which involves modulating the input image and using quincunx filter banks (QFB) with diamond-shaped filters. A l -level tree-structured DFB is equivalent to a 2^l parallel channel filter bank with equivalent filters and overall sampling matrices as shown in Fig. 4. The equivalent analysis and synthesis filters are denoted using H_k and G_k , $0 \leq k < 2^m$, corresponding to the subbands indexed as shown in Fig. 2.

A l -level DFB generates a perfect directional basis for discrete signal in $L^2(\mathbb{Z}^2)$ that is composed of the impulse responses of 2^l directional synthesis filters and their shift. They can be represented as

$$g_k^{(l)}[n - S_k^{(l)}n]_{0 \leq k < 2^l, n \in \mathbb{Z}^2} \quad (2)$$

$$g[n] = \frac{2\pi}{n_1} \left[\psi \left(\frac{n_1(l+1)}{N} + n_2 \right) - \psi \left(\frac{n_1 l}{N} + n_2 \right) \right] \quad (3)$$

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