# Medical Images Fusion Based on Different Frequency band Selection Schemes

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**Abstract.** A novel curvelet-based sub-band selection approach for medical image fusion is presented in this paper using the Parameterized Logarithmic Image Processing (PLIP) model. Both MRA and MRI image have different features, in this paper we use the different frequency band selection fusion rules yield novel fusion schemes for combining the coefficients, and fused MRA and MRI images to form a single image with as much information as possible. The experiments show that the proposed method is effective and can get satisfactory fusion results.

## Introduction

In the recent years, the study of medical image fusion attracts much attention including diagnosis, research, and treatment, with the rapid development in high-technology and modern instrumentations. Image fusion is the combination of multimodality source images which vary in resolution, instrument modality, or image capture technique into a single composite representation [1]. Multimodality medical images mainly include the following images, such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiography(MRA) and so on [2]. With more available multimodality medical images in clinical applications, the idea of combining images from different modalities becomes very important and medical image fusion has merged as a new and promising research field. The main objective of medical imaging is to obtain a high resolution image with as much details as possible for the sake of diagnosis. MR and the CT techniques are medical imaging techniques. Both techniques give special sophisticated characteristics of the organ to be imaged. So, it is expected that the fusion of the MR and the CT images of the same organ would result in an integrated image of much more details. Due to this question, the application of the curvelet transform use the different frequency band selection fusion rules for image fusion is introduced in this paper.

## Curvelet Transform

The curvelet transform has evolved as a tool for the representation of curved shapes in graphical applications. Then, it was extended to the fields of edge detection and image denoising.The first generation curvelet transform is more complex involves a series of steps. Due to its complexity, the second generation curvelet is much preferred. The detailed fusion steps based on curvelet transform can be summarized below.

**Wrapping Algorithm**

① Perform FFT on the original image.

② Divide FFT into collection of tiles .

③ For each tile apply

a. Translate tile to the origin.

b. Wrap parallelogram shaped support of tile around the rectangle with center .

c. Take inverse FFT of wrapped one

d. Add curvelet array to collection of curvelet coefficients.

**Inverse Wrapping Algorithm**

① For each curvelet coefficient array

a. Take FFT of the array.
b. Unwrap rectangular support to original orientation shape.
c. Translate it back to the original position
d. Store the translated array

② Add all the translated curvelet arrays
③ Take inverse FFT to reconstruct the image.

**Image fusion using curvelet transform of PLIP Model**

Since the main objective of image fusion is to fuse the multimodal medical images, the characteristics of the images should also be considered. For the fusion example of MRA and MRI images.

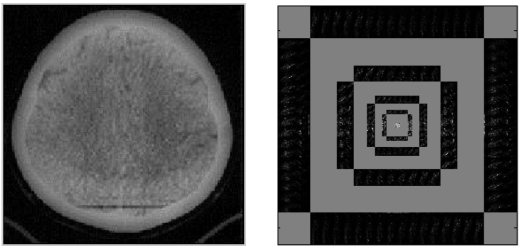


Fig.1 Curvelet transform of MRI Image

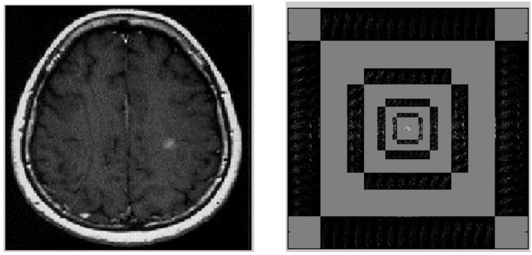


Fig.2 Curvelet transform of MRA Image

**Weighted Average method in low frequency sub-band**

The approximation coefficients at the highest level of decomposition are most commonly fused via uniform averaging because of its mean intensity value of the source images and minimal loss of salient features [6]. While the weighted average method proposed in [12] remains one of the most effective after more than ten years since its inception. The method is based on a local-Gaussian assumption for wavelet sub-bands. In this section, the weighted average method can be reformulated and modified in order to cope with more appropriate statistical assumptions like the generalized Gaussian based on [12] and [13]. We also consider only two original images, *A* and *B*, and their fused image *Y*. And the multi scale decompositions of the original and fused images are denoted by $C_A$, $C_B$ and $C_Y$ .

$$\mu(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N} C(m+i,n+j,k,l) \quad (1)$$

$$\Upsilon(\mu(p))=\left(\frac{1}{\mu(p)}\right)^{\alpha} \quad (2)$$

$$\varpi(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N}\Upsilon(\mu(p))\cdot\frac{|C(m+i,n+j,k,l)-\mu(p)|}{\mu(p)} \quad (3)$$

where $W_N$ is a $N\times N$ block, $\varpi(p)$ is the weighting factor, $\alpha$ is a constant by perceptual experiment, and it has a peak, when around peak values can achieve very good effect, too big or too small can't achieve the ideal effect. After calculating the visibility of all the coefficients in the low-frequency band, the approximation coefficients for the fused image $Y$ at the highest level of decomposition use weighted averaging by

$$C_Y(p)=\frac{\varpi_A(p)\cdot C_A(p)+\varpi_B(p)\cdot C_B(p)}{\varpi_A(p)+\varpi_B(p)} \quad (4)$$

**Fusion Scheme in high frequency sub-bands**

For the high-frequency bands, it is generally believed that the details of an image are mainly included in the high-frequency of the image. Therefore, it is important to select a suitable image fusion algorithm that produces maximizing amount of information in fused image. As we know a pixel in an image must have some relations with its neighboring pixels, which means that a decomposed wavelet coefficient will also have relations with its neighboring coefficients. So we propose a scheme by calculating the neighborhood variance of high frequency sub-bands to select the high-frequency coefficients using PLIP-curvelet model. The procedure can be formulated as follows.

For each pixel of the $l$ high frequency sub-band at $k$ level of decomposition, the neighborhood variance of the two input image detail coefficients $C_A(p), C_B(p)$ and their covariance are determined by

$$\sigma_A(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N}(C_A(m+i,n+j,k,l)-\mu_A(p))^2 \qquad (4)$$

$$\sigma_B(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N}(C_B(m+i,n+j,k,l)-\mu_B(p))^2 \qquad (5)$$

$$\mu_A(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N}C_A(m+i,n+j,k,l) \qquad (6)$$

$$\mu_B(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N}C_B(m+i,n+j,k,l) \qquad (7)$$

$$\sigma_{AB}(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N}(C_A(m+i,n+j,k,l)\cdot C_B(m+i,n+j,k,l)-\mu_{AB}(p))^2 \qquad (8)$$

$$\mu_{AB}(p)=\frac{1}{N^2}\sum_{(i,j)\in W_N}C_A(m+i,n+j,k,l)\cdot C_B(m+i,n+j,k,l) \qquad (9)$$

The local matching coefficient measure of each sub-band between source images is given as

$$M_{AB}(p)=\frac{2\sigma_{AB}(p)}{\sigma_A^2(p)+\sigma_B^2(p)} \qquad (10)$$

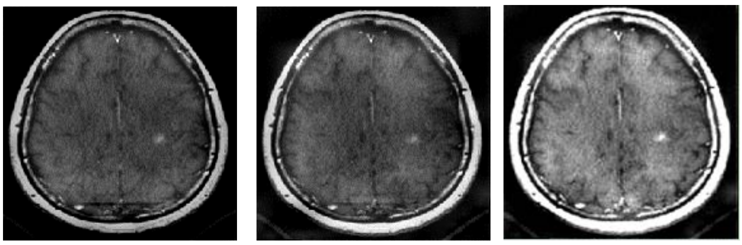
Comparing the matching measure to a threshold $T$ determines if detail coefficients are to be combined by simple selection or by weighted averaging.

$$\delta(p)=\begin{cases} 1-\dfrac{M_{AB}(p)-T}{2(1-T)}, & \sigma_A(p)>\sigma_B(p),\ M_{AB}(p)>T \\ \dfrac{M_{AB}(p)-T}{2(1-T)}, & \sigma_A(p)<\sigma_B(p),\ M_{AB}(p)>T \\ 1 & \sigma_A(p)>\sigma_B(p),\ M_{AB}(p)>T \\ 0 & \sigma_A(p)<\sigma_B(p),\ M_{AB}(p)>T \end{cases} \qquad (11)$$

where $\delta(p)$ indicts the factor of multiplicative weight averaging. The fused coefficients are calculated using the following formula.

$$C_Y(p)=\delta(p)\cdot C_A(p)+(1-\delta(p))\cdot C_B(p) \qquad (12)$$

This method cannot guarantee the homogeneity in the resultant fused image, especially for the high frequency sub-bands. In this paper we apply a window-based verification to the fused high frequency coefficients.



(a) (b) (c)

Fig.3 Different fusion results of the different weighting factor.(a) when $\alpha$ =0.2;(b) when $\alpha$ =-3.0;(c) when $\alpha$ =-1.3.

## Conclusions

In this paper, we present a novel curvelet-based sub-band selection approach for medical image fusion is presented in this paper using the Parameterized Logarithmic Image Processing (PLIP) model. Firstly, from the comparison of experimental results, it is seen that the curvelet decomposition using the PLIP model provides the best balance between extracting the soft tissues information, scarf, pathological edges, and their features in the image. Secondly, the fused image is reconstructed by all using composite coefficients and inverse isomorphic transform. The experimental results showed that the proposed fusion method out perform some existing fusion methods by both qualitative and quantitative means and it can get satisfactory fusion results.

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