An Efficient Fusion Approach for Multispectral and Panchromatic Medical Imaging

Changtao He[*1], Guiqun Cao[2], Fangnian Lang[1]

[1]School of Electronic Engineering, University of Electronic Science and Technology of China, China
[2]West China Hospital, Sichuan University, China
[*1]hect2009@qq.com; [2]caoguiqun@126.com

Abstract- **Multimodal medical image fusion, as a puissant tool for numerous clinical diagnoses, has developed with the advent of various imaging modalities in the field of medicine. This paper proposes a novel image fusion approach to effectively solve a concurrent problem of spatial characteristics and spectral information in the fused image. As we all know, the intensity-hue-saturation (IHS) transform and retina-inspired model (RIM) fusion technique can preserve more spatial features and more spectral information contents, respectively. However, principal component analysis (PCA) algorithm can extract main feature to minimize redundancy. The proposed algorithm integrates their advantages and powerfully improves fused image quality to avoid color distortions. The experiment demonstrates that the proposed algorithm outperforms state-of-the-art fusion approaches such as PCA, Brovey, RIM, discrete wavelet transform (DWT) in light of visual effect and quantitative evaluation.**

Keywords- Retina-Inspired Model; Intensity-Hue-Saturation Transform; Principal Component Analysis; Image Fusion

I. INTRODUCTION

In last decades, medical imaging has been widely applied into the clinical diagnosis and therapy, an increasing number of image modalities becomes available. Nevertheless, every imaging method has its own limitations, a single image usually cannot meet the needs of the clinical analysis. For example, Structural images for instance magnetic resonance imaging (MRI) and computed tomography (CT) can provide high-resolution images with anatomical information; functional image such as positron emission tomography (PET) and single-photon emission computed tomography (SPECT) provide functional information but with low spatial resolution [1-2]. In view of the present situations of the imaging condition restriction and urgent needs for comprehensive grasp of image contents, An efficient image fusion approach of combining anatomical and functional images to provide far more useful information becomes an indispensable technology.

Image fusion is the process of integrating information from two or more images of the same position into a single image that contains more information and is more appropriate for visual perception. For the purpose of most clinical applications, medical image fusion intends to reduce ambiguity and minimize redundancy in fused image while maximizing the relative information specifics [3]. In the existing fusion approaches, the multiresolution fusion approaches have been widely used in the recent studies because of their efficiency and convenience, yet, their fusion results are usually limited by the number of decomposition layer and the selection of fusion rules [4-5]. IHS transform and PCA technique can keep a better resolution, but, they also distort the spectral characteristics with different degree [6]. Analogously, the Brovey transform can also bring a disastrous fusion result. A detailed study indicated that the color distortion problem arises from the change of the saturation during the fusion process [7]. However, retina-inspired fusion method can just complement this shortcoming of spectral distortion in fusion process. Moreover, many other biomedical fusion methods play a positive role in the aspect of enhance spatial and spectral features from the input data both [4, 8-9].

In this paper, the PET images are shown in pseudo-color, and the MRI images are gray. We integrate their advantages of above-mentioned different approaches, a spatial frequency (SF) motivated PCA, IHS and RIM integrated fusion approach is proposed in this study. Extensive experiments have been made on three groups of multimodality MRI /PET datasets. By comparison, the proposed approach can provide more satisfactory fusion outcomes, compared to conventional image fusion algorithms in the two aspects of visual effect and quantitative analysis.

II. THE IHS, PCA AND RETINA-INSPIRED FUSION MODELS

A. *The RGB-IHS Conversion Model*

The IHS transformation converts a multispectral image or panchromatic image with red, green and blue channels (RGB) to intensity, hue and saturation independent components. The intensity displays the brightness in a spectrum, the hue is the property of the spectral wavelength, and the saturation is the purity of the spectrum. This technique may be used for the fusion of multi-sensor images.

To understand the whole fusion process preferably, we must review the RGB-IHS conversion model. There are two essential RGB-IHS conversion models. In this study, we select a more close to the real visual effect model- triangular spectral model and it can be expressed as follows:

$$I = \frac{R+G+B}{3} \tag{1a}$$

$$H = \frac{G-B}{3I-3B},\ S = \frac{I-B}{I},\ \ if \quad B < R, G \tag{1b}$$

$$H = \frac{B-R}{3I-3R}+1,\ S = \frac{I-R}{I},\ \ if \quad R < B, G \tag{1c}$$

$$H = \frac{R-G}{3I-3G}+2,\ S = \frac{I-G}{I},\ \ if \quad G < R, B \tag{1d}$$

The corresponding inverse IHS transformation is as follows:

$$R = I(1+2S-3SH), \quad G = I(1-S+3SH),$$

$$B = I(1-S),\ \ if \quad B < R, G \tag{2a}$$

$$R = I(1-S), \quad G = I(1+5S-3SH),$$

$$B = I(1-4S+3SH),\ \ if \quad R < B, G \tag{2b}$$

$$R = I(1-7S+3SH), \quad G = I(1-S),$$

$$B = I(1+8S-3SH),\ \ if \quad G < R, B \tag{2c}$$

The IHS triangular model can produce a fused and enhanced spectral image.

B. PCA Transform Fusion Approach

The whole idea of the method is described in detail in References [5-6], and here the fundamentals of PCA fusion are briefly outlined as follows.

Firstly, a multispectral image is transformed with PCA transform and the eigenvalues and corresponding eigenvectors of correlation matrix between images in the multi-spectral image's individual bands are worked out to obtain each matrix's principle components [10].

Next, the panchromatic image is matched by the first principle component using histogram method.

Finally, the first principle component of the multispectral image is replaced with the matched panchromatic image and with other principle components, followed by the transformation with inverse PCA transform to form the fused image.

C. Retina-Inspired Model

The RIM fusion consists of five basic layers, fusion structure diagram of which is depicted in Fig. 1.

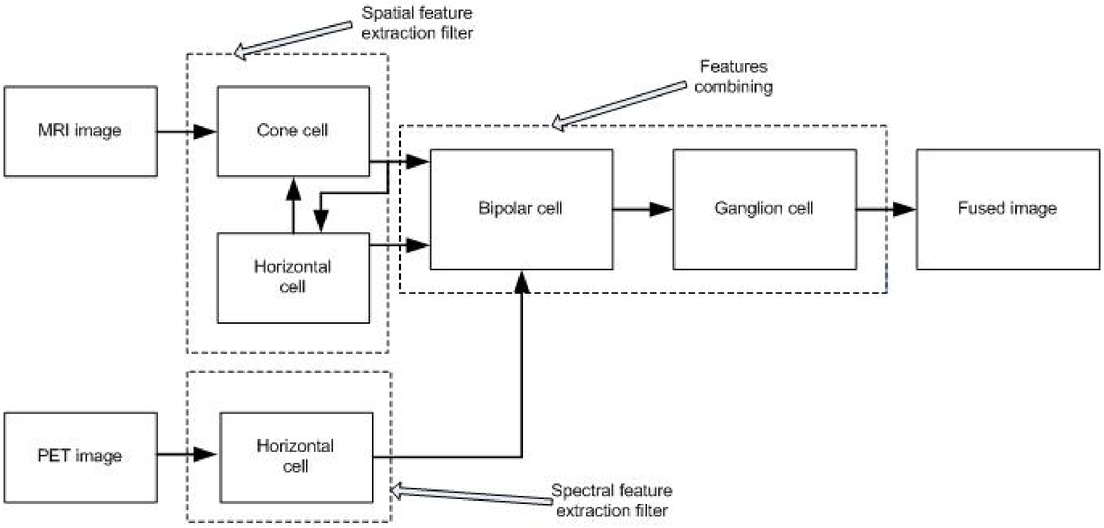


Fig. 1 The structure diagram of image fusion based on RIM

The earliest layer represents an array of high resolution cone photoreceptors, while the second layer is a high scale spatial feature extractor. The third layer is the array of low resolution receptors (horizontal cells), the fourth and the last layers are made of bipolar and ganglion cells. Every layer has its own mathematical model and corresponding expressions. In Papers [11-

12], depict retinal layers and major cell types inspired by the retinal model. Some detailed information and specific mathematical formulas of every cell can be found in Documents [11-13].

In the proposed fusion approach, we use a black box to represent the RIM model, which is just a part in the whole system, its internal structure and some cells detailed information in the fusion process shown the same as Fig. 1.

III. THE PROPOSED FUSION APPROACH

The proposed approach synthesizes the advantages of IHS and PCA transforms, and makes full use of their features of preserving ample spatial structure information. However, due to IHS transform leads to spectral distortions, there is a low correlation between the PET intensity image and fused image. This result is disappointed in the image fusion process. An ideal fusion result is, in general, not only preserving original images' spatial structure information but conserving much spectral information. The retina-inspired image fusion can preserve more spectral information than other conventional approaches. Nevertheless, its fusion result can incur structure information loss and spatial details distortion. In this case, an integrated medical image fusion approach is proposed in order to make up their deficiencies and obtain a satisfied fusion result which is a smooth combination of spectral and spatial features.

Fig. 2 shows the whole fusion process of the proposed approach, which may be divided into the following several steps. Firstly, the PET image is transformed into the IHS triangular model components. Then, histogram matching is applied to match the histogram of the MRI image with the PET intensity component. Next, the PCA transform extracts their own principal components of PET intensity image and new MRI (called New Pan), and selects corresponding components' weight coefficients by calculating their spatial frequency respectively to obtain a new intensity component. Finally, the approach is performed by combining the new intensity component and original PET intensity component, using retina-inspired fusion model. In this stage a final intensity image is obtained, which contains the same spatial detail of the original MRI and has the same intensity distribution to the original PET. In the meantime, it also avoids some superfluous details and artefacts in the previous transformation. Ultimately, we can obtain a satisfied fused image by inverse IHS transform exploiting the new intensity component and original H and S components of PET image. This fusion process generates a new high resolution color image. The new image contains both the spatial details of the MRI source image and the spectral information of the PET source image, simultaneously.

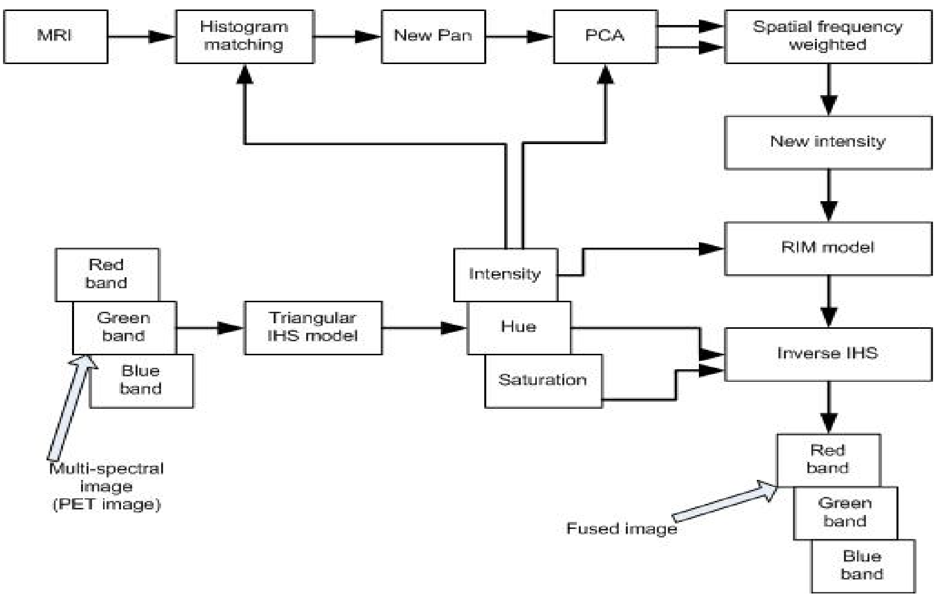


Fig.2 Diagram of the proposed integrated fusion approach

How to select two principal components' weight coefficients after PCA transform is a critical problem. In this paper, we propose an adaptive selection method by calculating spatial frequency (SF) of original PET intensity image and old MRI image. Li et al used SF to measure the clarity of image blocks [14], and it was introduced by Eskicioglu and Fisher [15]. The expression for a $K \times L$ pixels image $f(x, y)$ is defined as:

$$SF = \sqrt{(RF)^2 + (CF)^2} \tag{3}$$

where RF and CF are the row frequency and column frequency respectively.

$$RF = \sqrt{\frac{1}{K \times L} \sum_{x=1}^{K} \sum_{y=2}^{L} [f(x, y) - f(x, y-1)]^2} \tag{4}$$

$$CF = \sqrt{\frac{1}{K \times L} \sum_{y=1}^{L} \sum_{x=2}^{K} [f(x, y) - f(x-1, y)]^2} \tag{5}$$

The selection of two principal components' weight coefficients based on SF can be depicted as:

$$I = \alpha I_1 + \beta I_2 \tag{6}$$

$$\alpha + \beta = 1 \tag{7}$$

where I_1, I_2 represent the principal component of New Pan and original PET intensity component, respectively. α and β are normalized SF values.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

The test data consist of color PET images and high resolution MRI images. The spatial resolution of MRI image and PET image are 256×256 and 128×128 pixels. The color PET images have been registered to the corresponding MRI images. All images were downloaded from the Harvard University site (http: //www.med.harvard. edu/AANLIB/). The test images are divided into three groups including Neoplastic disease image, Alzeimer disease image and Cerebrovascular disease image, the original images and fusion results are displayed in Figs. 3-5.

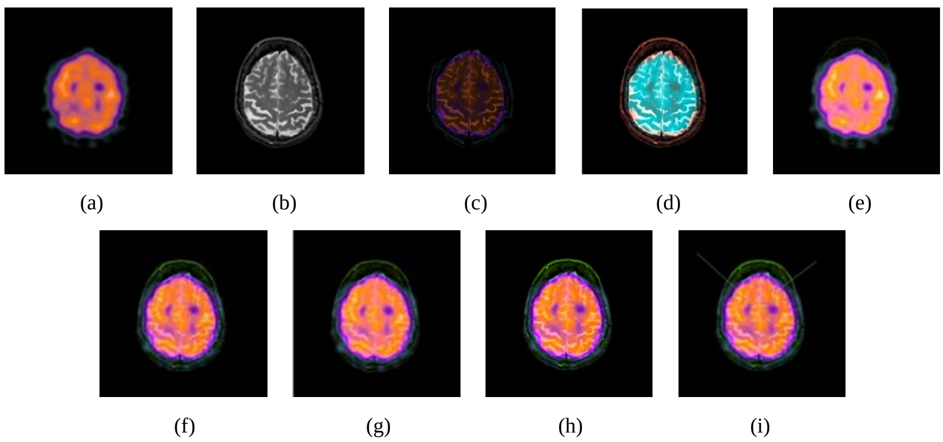


Fig. 3 Neoplastic disease PET and MRI images (a and b), Brovey (c), PCA (d), DWT (e), RIM (f), Reference [1] method (g), the proposed method (h), arrows labeled (i)

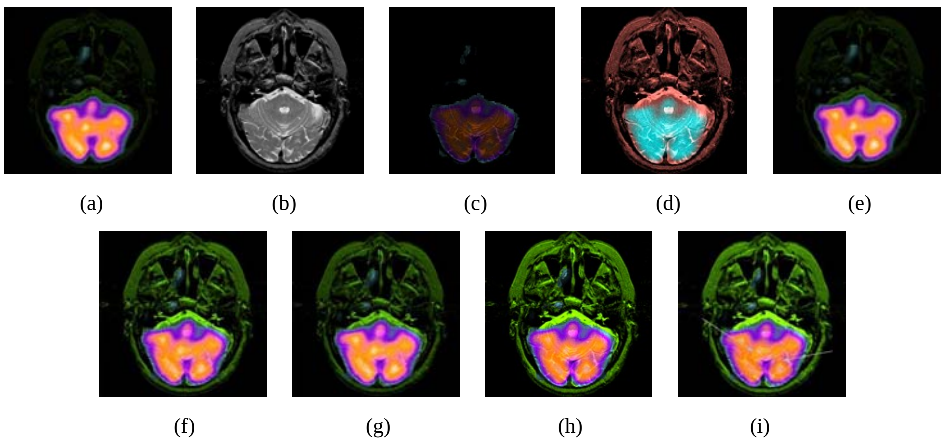
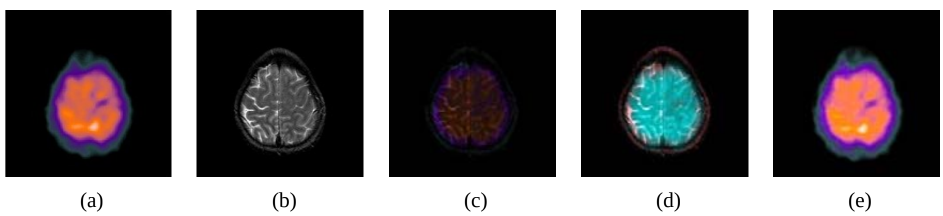
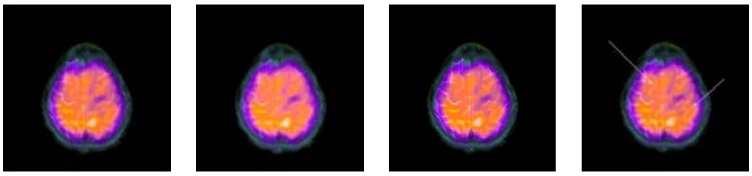


Fig. 4 Alzheimer disease PET and MRI images (a and b), Brovey (c), PCA (d), DWT (e), RIM (f), Reference [1] method (g), the proposed method (h), arrow labeled (i)





(f) (g) (h) (i)

Fig. 5 Cerebrovascular disease PET and MRI images (a and b), Brovey (c), PCA (d), DWT (e), RIM (f), Reference [1] method (g), the proposed method (h), arrow labeled (i)

The IHS transform, PCA, Brovey transform and wavelet transform are the prevailing image fusion methods. However they are often faced with color distortion problems in fused images. As shown in (c-e) of Figs. 3-5. It can be observed that brovey transform and PCA keep the same spatial resolution as the original MRI images but distort the spectral characteristics in different degree, comparatively speaking, wavelet transform is the easiest method to control the trade-off between the spatial and the spectral information. However, wavelet transform method preserves more spectral information but loses more spatial information, illustrated in (e) of Figs. 3-5.

According to Figs. 3-5f, visual analysis demonstrates that RIM based fused results have low spatial resolutions. However, their spectral intensities are strong. This fusion method reflects the nature of retinal-inspired model: the fused results contain smooth spectral information, but discard more texture and spatial detail information. Such fused results cannot satisfy clinical requirements and therefore hamper accurate diagnosis of diseases.

For the Figs. 3-5g, they are the fused results of Reference [1]. Apparently, the results are better than c-f of Figs. 3-5. Although, the results contain both better spectral information and more spatial distribution information, they introduce some artifacts and some major texture distributions are not as clear as the original MRI. These results are also unsatisfying for both subjective visual perception and objective evaluation criterions.

The proposed method demonstrates the best fused results (notice the Figs. 3-5h or the arrows in Figs. 3-5i) among all results visually. The integration method combines the advantages of both IHS transform and PCA. Extracting the principal component minimizes the redundancy and self-adaptive weighted coefficients' selection compensates spectral distortion introduced by IHS transform in a certain extent. In the fused results, the spectral distortion is least, the spatial texture and detailed distributions are as clear as the original MRI, and the integration of spectral and spatial features is natural. The white arrows show the main distributions of white matter and gray matter in fused results with the proposed method. It is clear that their contour and texture details are clear, and they are readily discernible. In general, it obtains the best fused result in both spectral information and spatial structure information. Meanwhile, it also avoids redundancy information and some artifacts in the last fused result.

Except subjective observation of human perception, some objective evaluation criteria are also necessary for the final fused results. Several computational image fusion quality assessment metrics have been proposed in recent years [16-17]. In order to compare different image fusion methods, here we select two acknowledged evaluation criteria to validate superiority of the proposed method.

A. Mutual Information (MI)

Mutual information is a frequently-used metric as a performance measure for image fusion. It is a fundamental concept of the information theory to compute the statistical dependence between two random variables [16]. It uses cross entropy between the joint distribution p_{XY} and the best case distribution of being totally independent random variables as follows:

$$MI(X,Y) = \sum_{x,y} p_{XY}(x,y)\log_2 \frac{p_{XY}(x,y)}{p_X(x)p_Y(y)} \tag{8}$$

where p_{XY} is the joint probability for X and Y, p_X is the probability distribution of X, p_Y is the probability distribution of Y, and x, y are sampling variables.

MI can determine the statistical dependence or information redundancy between two random variables. We use original MRI and PET images as random variables respectively, and the fused image as another random variable. MI can be used to estimate the dependency between them. Two original images X (PET), Y (MRI) and a fused image F are considered, the total information amount that F contains about X and Y can be calculated as:

$$I_{FX}(f,x) = (1/3)\sum_k \sum_{f,x} p_{FX}(f_k, x_k)\log_2 \frac{p_{FX}(f_k, x_k)}{p_F(f_k).p_X(x_k)} \tag{9}$$

$$I_{FY}(f,y) = (1/3)\sum_k \sum_{f,y} p_{FY}(f_k, y)\log_2 \frac{p_{FY}(f_k, y)}{p_F(f_k).p_Y(y)} \tag{10}$$

$$k = R, G, B$$

The MI performance metric can be defined as:

$$M_F^{XY} = \frac{I_{FX}(f,x) + I_{FY}(f,y)}{2} \tag{11}$$

Table 1 tabulates the amount of information of all kinds of different fusion methods.

TABLE I THE FUSION METHODS PERFORMANCE MEASURE BASED ON MI

Fusion methods	MI (Fig.3)	MI (Fig.4)	MI(Fig.5)
Brovey	0.6240	0.5867	0.6319
PCA	0.6133	0.5753	0.6287
DWT	0.6107	0.5702	0.6149
RIM	0.6432	0.6135	0.6245
Document [1]	0.6519	0.6230	0.6271
Proposed method	**0.6557**	**0.6358**	**0.6316**

B. *Structure Similarity Match Measure (SSIM)*

The structural similarity image quality paradigm is based on the assumption that the human visual system is highly adapted for extracting structural information from the scene, and therefore a measure of structural similarity can provide a good approximation to perceived image quality [18]. We denote $s(a_k \mid \omega)$ and $s(b \mid \omega)$ as the local saliencies of the two inputs a (PET) and b (MRI), $\lambda(\omega)$ as a local weight, a typical choice for $\lambda(\omega)$ is:

$$\lambda(\omega) = \frac{s(a_k \mid \omega)}{s(a_k \mid \omega) + s(b \mid \omega)} \tag{12}$$

We define the fusion quality index $Q(a,b,f)$ as

$$Q(a,b,f) = \frac{1}{|W|} \sum_{\omega \in W} (\lambda(\omega) Q_0(a_k, f \mid \omega) + (1-\lambda(\omega)) Q_0(b, f \mid \omega)) \tag{13}$$

$k = R,G,B$

In SSIM computation, ω is a 8×8 window, $Q_0(a_k, f \mid \omega)$ and $Q_0(b, f \mid \omega)$ represent SSIM values between three components of image a, image b and fused image in corresponding window ω respectively. $s(a_k \mid \omega)$ and $s(b \mid \omega)$ represent local variance. Table 2 shows comparing analysis results.

TABLE II SSIM BASED COMPARING RESULTS WITH DIFFERENT FUSION METHODS

Fusion methods	SSIM (Fig.3)	SSIM (Fig.4)	SSIM(Fig.5)
Brovey	0.5763	0.5701	0.5756
PCA	0.5540	0.5598	0.5645
DWT	0.5657	0.5604	0.5703
RIM	0.5789	0.5745	0.5765
Document [1]	0.5832	0.5813	0.5864
Proposed method	**0.5986**	**0.5915**	**0.5994**

Statistical data from Table 1 and Table 2 show that the amount of information and SSIM value of the fused images, with the proposed method, is the highest. These statistical results are consistent with those of the visual analysis.

V. CONCLUSIONS

A novel medical image fusion method was proposed, we assume PET are shown in pseudo-color. The PET produces images with suitable color and low spatial resolution, while MRI provides appropriate spatial resolution with no color information content. In this study, we integrated the merits both preserving spatial information of the IHS transform and minimizing redundancy of PCA transformation, and obtained the satisfying fused results. Compared to the conventional fusion methods including Brovey transform, PCA, DWT, RIM, etc., it is clear that the proposed method is the best in both human visualization and objective evaluation criteria.

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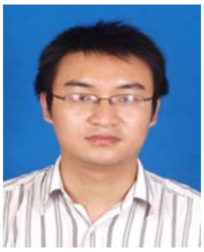

Changtao He received the B.S degree in physics department from the Luoyang normal university in 2004. The M.S degree from the Institute of Electronics information, Sichuan University, Chengdu, China, in 2007. He is currently pursuing the Ph.D. degree in Signal & information processing at University of Electronic Science and Technology of China, Chengdu, China.

His research interests include image processing, computer vision, patter recognition and optical signal processing.