IOP Conference Series: Materials Science and Engineering

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To cite this article: Huibin Yan and Zhongmin Li 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **563** 042023

IOP Conf. Series: Materials Science and Engineering **563** (2019) 042023 doi:10.1088/1757-899X/563/4/042023

Anatomical and functional image fusion with guided filtering

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Abstract. Multi-modal medical image fusion (MMIF) technology is playing an increasingly important role in many clinical applications. In this paper, a novel anatomical and functional image fusion method based on guided filtering (GF) is proposed. In our proposed method, GF is firstly used to decompose the anatomical image into a base image and a detail image. Then the base image and the Y channel of the functional image are combined according to the local energy maximum fusion rule, and the detail image is used to enhance the details of the anatomical image. The proposed method has potential practical value for clinical applications due to its high computational efficiency. Experimental results demonstrate that the proposed method can achieve better results in term of subjective observation and objective metrics.

1. Introduction

Medical images with different modalities can only reflect certain information due to different imaging mechanisms. Anatomical images (computed tomography (CT) and magnetic resonance (MR) imaging) have higher resolution and can reflect the structural information of tissues or organs more clearly. Functional images (positron emission tomography (PET) and single-photon emission CT (SPECT)) can reflect information about the body's metabolism, but have a lower resolution [1]. In order to judge the patient's condition more accurately, doctors have to see the information of images with different modalities in the same image at the same time. Therefore, multi-mode medical image fusion (MMIF) technology comes into being. This paper focuses on MR-PET and MR-SPECT image fusion.

In recent years, a large number of MMIF methods have been proposed [2,3]. In this paper, these methods are classified to two groups, i.e. transform domain (TD) based methods and spatial domain (SD) based methods. Multi-scale transform (MST) based methods are typical TD based methods. MMIF methods based on MST can generally achieve perceptually good results because they process information in a way consistent with the human visual system (HVS)[4]. Generally speaking, the MST-based fusion method consists of three parts. First, the corresponding coefficients are obtained by a certain MST. The obtained coefficients are then combined using a specific fusion strategy. Finally, the corresponding inverse MST is used to reconstruct the fusion result. In the MST-based fusion methods, the design and selection of image transform and fusion rules are two key issues. Du et al. proposed a method for MR-PET and MR-SPECT image fusion using local laplacian filtering (LLF) as the image transform; they also designed a novel fusion rule based on information of interest (IOI) [2]. Although their method can enhance the details of the source images, two obvious problems exist in it. The first one is that their method is time consuming due to LLF used for image transform. Color distortion is the second problem of their method due to the designed fusion rule IOI. The current fusion rules based on pulse coupled neural network (PCNN) have a greater correlation with the information processing mechanism of HVS, which is obviously superior to the traditional fusion rules directly based on the decomposed coefficients. Since the free parameters of PCNN have a greater impact on the fusion results and they are always fixed to constants, Liu et al. introduce parameter adaptive PCNN (PAPCNN) into MMIF; their method can achieve satisfactory fusion results for multi-modal medical images [3]. Although the PAPCNN based fusion rule has higher computational efficiency than the traditional PCNN based fusion rules, their method still do not has a high computational efficiency in general.

The SD based methods are different from the TD based methods. In those methods, the pixels of the source images are directly used to fuse these images, and they always have low computational complexity. A typical example in this area is the image fusion method based on guided filtering (GF), which was proposed by Li et al. [5]. Their method can achieve general fusion results. However, as for MR-PET and MR-SPECT image fusion, it tends to introduce color distortion into the fused images.

In summary, current methods for MR-PET and MR-SPECT image fusion cannot simultaneously cope with the following three problems. First, as many fusion methods focus on preserving the details of the source images as much as possible, few of them concentrate on enhancing the details of the source images, which can help doctors make more accurate decisions. Second, the color information of the functional (PET and SPECT) images can be used to trace tumors or study blood flow. However, some current methods introduce less color information into the fused images. Third, some fusion methods have high computational complexity, which limits its clinical applications.

In this paper, we propose a novel anatomical and functional image fusion method based on GF. The main contributions and novelties of this paper are outlined as follows.

1) Our proposed method can simultaneously perform image fusion and enhancement.

2) Our proposed method can be easily implemented, and has high computational efficiency, which means it has potential practical value for clinical applications.

3) We propose a novel anatomical and functional image fusion method based on GF. Experimental results demonstrate that the proposed method is effective in both subjective observation and objective metrics.

The remaining parts of this paper are outlined as follows: Section 2 briefly explains GF used in the proposed method. Section 3 elaborates on the fusion method. Experimental results and discussions are provided in Section 4. Finally, Section 5 concludes the paper.

2. Guided filtering

Guided filters, weighted least squares filters and local extrema filters are edge-preserving filters widely used in the field of image processing recently, which can avoid ringing artifacts because they have strong capabilities of edge preservation. Among them, the size of the target has no effect on the calculation time of the guided filter.

In guided filter theories[6], there is a linear relationship between the filtering output O and the guidance image I in a local window w_k centered at pixel k .

$$O_i = \bar{a}_i I_i + \bar{b}_i \tag{1}$$

Where, $\bar{a}_i = \frac{1}{|w|}\sum_{k\in w_i} a_k$, $\bar{b}_i = \frac{1}{|w|}\sum_{k\in w_i} b_k$. The parameters a_k and b_k are defined as follows:

$$a_k = \frac{\frac{1}{|w|}\sum_{i\in w_k} I_i P_i - \mu_k \bar{P}_k}{\delta_k + \varepsilon} \tag{2}$$

$$b_k = \bar{P}_k - a_k \mu_k \tag{3}$$

Where, μ_k , δ_k , $|w|$ and $\bar{P}_k$ are related to the local window w_k . Specifically, μ_k and δ_k represent the average value and variance of I in w_k , respectively, $|w|$ is the total number of pixels of w_k , and $\bar{P}_k$ is the average value of the input image P in w_k . The resulted image can be obtained with the two coefficients a_k and b_k using the formula (1). For convenience, the guided filtering operation is defined as $\mathrm{GF}_{r,\varepsilon}(P,I)$, and the two subfigures r and ε are the size and blur degree of the guided filter, respectively.

3. The proposed fusion method

3.1 Overview

The schematic of the proposed MMIF method is shown in Figure 1. The detailed fusion process can be summarized as the following four steps: image decomposition and conversion, fusion of base image and Y channel, fusion based on details added, and image reconstruction.

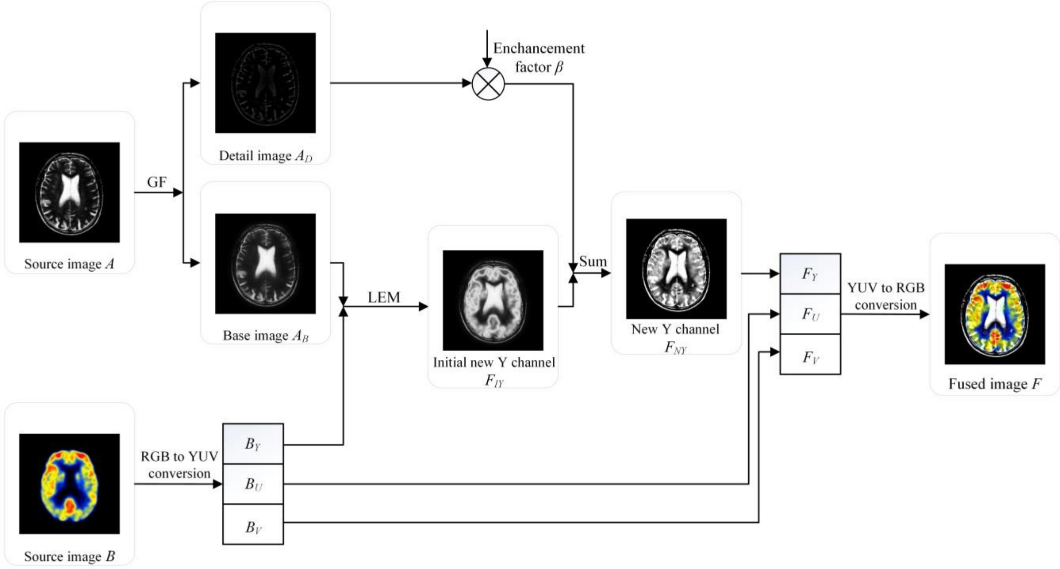

Figure 1. Schematic of the proposed anatomical and functional image fusion method

3.2 Detailed fusion scheme

1) Image decomposition and conversion: First, we use GF to decompose source image A (anatomical image) into detail image A_D and base image A_B with the source image A as the input image and the guidance image. Second, we convert the source image B (functional image) from the RGB color space to the YUV color space to get its Y channel B_Y, U channel B_U, and V channel B_V.

2) Fusion of Base Image and Y Channel: We use the local energy maximum (LEM) rule to fuse the base image A_B of source image A and the Y channel B_Y of source image B to get the initial new Y channel F_{IY}. In this paper, notation $*$ represents the convolution operation. Notations $\times$ and $.\times$ represent the multiplication and point multiplication operation, respectively.

First, we calculate the energy maps of the base image A_B and the Y channel B_Y according to the following the formula.

$$E_X = X * W \tag{4}$$

Where, $X \in \{A_B, B_Y\}$, E_X represents the energy map of X, and W is set as follows.

$$W = \frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \tag{5}$$

Second, we achieve the decision map as follows.

$$M = E_{A_B} > E_{B_Y} \tag{6}$$

Finally, the initial new Y channel is obtained as follows.

$$F_{IY} = M. \times A_B + \sim M. \times B_Y \tag{7}$$

3) Fusion Based on Details Added: The new Y channel F_{NY} is obtained by the following formula.

$$F_{NY} = \beta \times A_D + F_{IY} \tag{8}$$

Where, β is the enhancement factor, and we set it 3 in our experiments.

4) Image Reconstruction: The fused image F is reconstructed by performing the color space conversion (YUV to RGB) on the obtained channels F_{NY} , $F_U(B_U)$ and $F_V(B_V)$.

4. Experiments and discussions

4.1 Experimental setup

In our experiments, we test 60 pairs of anatomical and functional images including 30 pairs of MR and PET images and 30 pairs of MR and SPECT images. These source images are downloaded from the website: http://www.med.harvard.edu/AANLIB/. Among them, we show four pairs of MR and PET images in Figure 2 and four pairs of MR and SPECT images in Figure 3. Meanwhile, three image quality evaluation metrics are selected to make objective assessment, which are contrast (SD), edge intensity (EI) and the visual information fidelity fusion ($VIFF$) metric [7]. For all the three metrics, a higher value means a better fusion performance.

Three representative methods, which are the GF method [5], the LLF-IOI based method [2] and the NSST-PAPCNN based method [3], are used to compare with the proposed fusion method in this paper. The parameters of the compared methods remain unchanged.

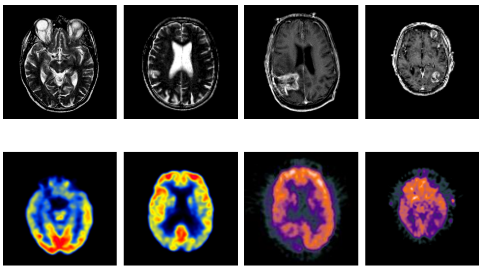

Figure 2. Four pairs of source images used in the experiments (MR and PET).

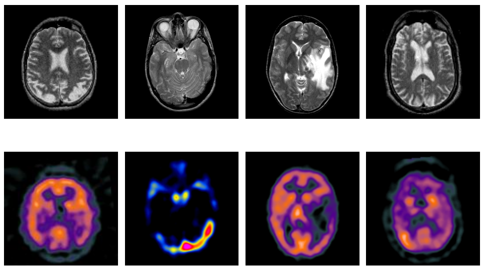

Figure 3. Four pairs of source images used in the experiments (MR and SPECT).

4.2 Experimental results and discussions

The fusion results on two pairs of MR and PET images are shown in Figures 4-5. The GF based method has severe color distortion in the fused images. Compared with the proposed method, color distortion more or less exists in the fusion results obtained by the LLF-IOI based method, and the details of the MR images are less obvious in the fused images obtained by the NSST-PAPCNN based method.

The fusion results on two pairs of MR and SPECT images are shown in Figures 6-7. Compared with the proposed method, the details of the MR images are less obvious in the fused images obtained by other three methods, and the fused images obtained by the LLF-IOI based method are noisy.

Table 1 shows the average value of each metric of different methods on each fusion problem. The largest value among the four methods is shown as bold for each metric. From Table 1, we can see that the proposed method has clear advantages over other three methods on all the three metrics for two categories of MMIF problems.

Finally, computational efficiency of different fusion methods is compared. All the experiments are tested on a computer with a 3.20 GHz CPU and 4.00 GB RAM. The average running time of different methods for fusing sixty pairs of source images is listed in Table 2. It can be seen that the proposed method has the highest computational efficiency.

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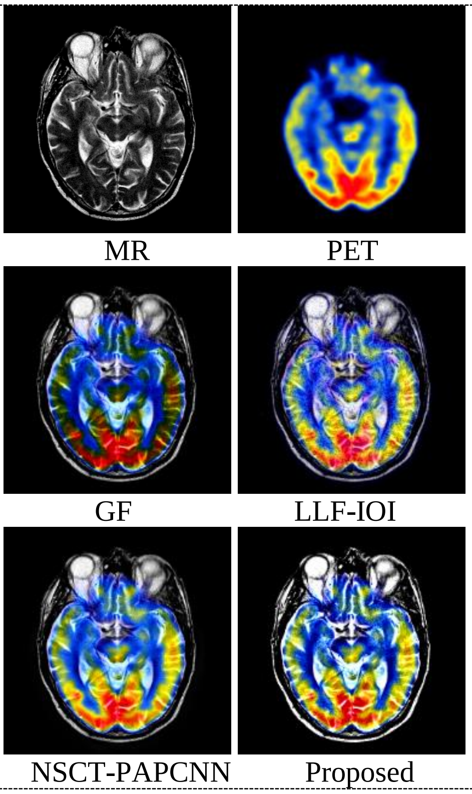

Figure 4. Fusion results on a pair of MR and PET images.

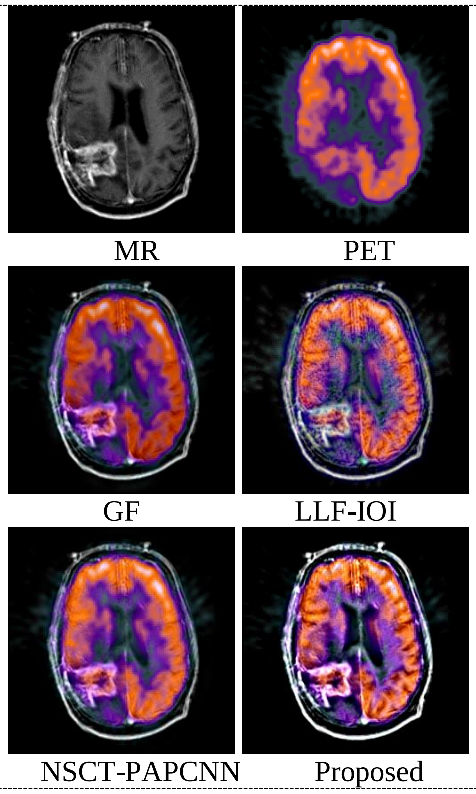

Figure 5. Fusion results on a pair of MR and PET images.

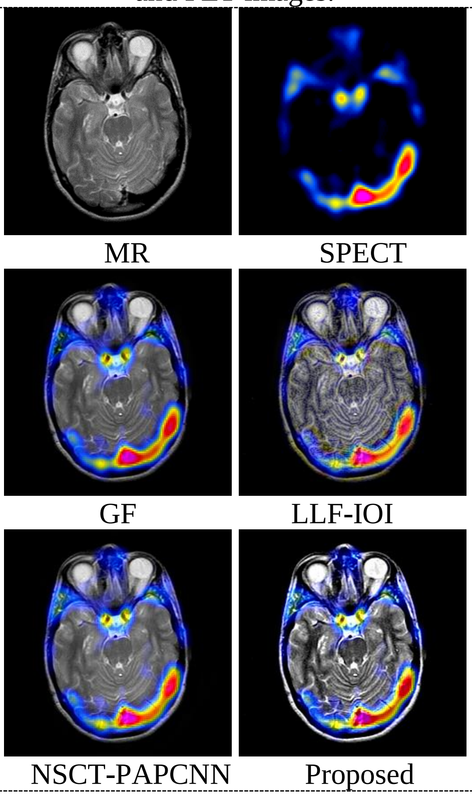

Figure 6. Fusion results on a pair of MR and SPECT images.

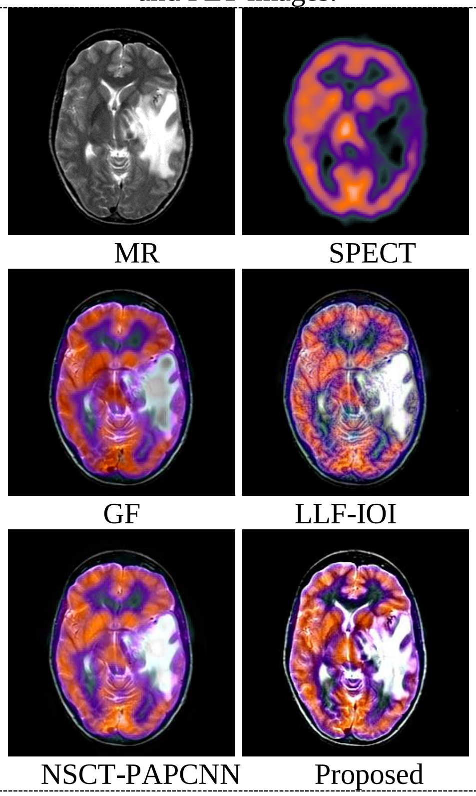

Figure 7. Fusion results on a pair of MR and SPECT images.

Table 1. The average value of each metric of different methods.

	Method	GF	LLF-IOI	NSST-PAPCNN	Proposed
MR-PET	*SD*	54.1869	65.8515	66.1639	**76.0510**
	EI	68.7029	82.0860	71.2147	**105.5116**
	VIFF	0.3583	0.4962	0.5317	**0.5675**
MR-SPECT	*SD*	55.7218	63.0498	61.5014	**74.2520**
	EI	58.0702	81.6658	60.2775	**108.4333**
	VIFF	0.4316	0.4998	0.5076	**0.6576**

Table 2. Average running time of different methods for fusion sixty pairs of source images of size 256×256 pixels (unit: second).

Method	GF	LLF-IOI	NSST-PAPCNN	Proposed
Time	0.1705	182.9213	23.6975	0.0683

5. Conclusions

In this paper, we propose a novel anatomical and functional image fusion method based on guided filtering (GF). Our proposed method can simultaneously perform image fusion and enhancement. In addition, the proposed method can be easily implemented, and has high computational efficiency, which means it has potential practical value for clinical applications. Experimental results demonstrate that the proposed method can achieve better results in term of subjective observation and objective metrics. To be more precise, our fusion results can retain not only the structural information of anatomical MR images, but also the color information of functional images such as PET or SPECT. Furthermore, compared with three state of the art fusion methods, the proposed method has great advantages in terms of three image fusion quality evaluation metrics.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant No. 61263040), the Science and Technology Research Project of Education Department of Jiangxi Province(Grant No. GJJ170602), and the Foundation of Nanchang Hangkong University (Grant No.YC2018019).

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