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Multimodality medical image fusion algorithm based on gradient minimization smoothing filter and pulse coupled neural network

Xingbin Liu, Wenbo Mei, Huiqian Du*

School of Information and Electronics, Beijing Institute of Technology, Beijing 100081, China

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ABSTRACT

We propose a novel multimodality medical image fusion algorithm which involves L_0 gradient minimization smoothing filter (GMSF) and pulse coupled neural network (PCNN). Firstly, an excellent multi-scale edge-preserving decomposition framework based on GMSF is proposed to decompose each source image into one base image and a series of detail images. For extracting and preserving more salient features and detail information, different fusion rules are designed to fuse the separated subimages. The base images are fused using the regional weighted sum of pixel energy and gradient energy, and a biologically inspired feedback neural network is used to fuse the detail images. The final fused image is obtained by synthesizing the fused base image and detail images. Experimental results on several datasets of CT and MRI images show that the proposed algorithm outperforms other compared methods in terms of both subjective and objective assessment.

1. Introduction

Multimodality medical image fusion is an emerging and important technique in the field of medical image processing [1]. The complementary information provided by multimodality medical images is integrated into one composite image, which can reduce the redundancy and uncertainty to improve accuracy and efficiency of clinical diagnosis and analysis.

Thus far, various kinds of image fusion algorithms have been proposed [2–9], among which multi-scale decomposition tools such as pyramid and wavelet transforms are widely applied [10–13]. However, pyramid transforms may introduce halo artifacts in the fused images since they employ linear filters in the decomposition process. Curvelet and contourlet transforms may smooth some details in the fused images as they implement upsampling and downsampling operations in the transform process [14,15]. To overcome these drawbacks, nonsubsampled contourlet transform (NSCT) or nonsubsampled shearlet transform (NSST) are introduced in the multimodality medical image fusion algorithms to improve fusion outcomes, but which suffer from high computation complexity [16–18].

In this paper, we propose a novel multimodality medical image fusion algorithm based on L_0 gradient minimization smoothing filter (GMSF) and pulse coupled neural network (PCNN). Human eyes are generally sensitive to the edge features during visual perception and recognition, therefore edge preserved enhancement is useful and important in the fusion of medical images. Recently, researchers proposed several algorithms to preserve and enhance edges while fusing images. Bai et al. proposed a multiscale toggle contrast operator based image fusion algorithm, which can efficiently preserve edges of source images [19]. Kavitha et al. achieved edge preserved and enhanced fusion results by integrating the swarm intelligence and neural network techniques [20]. Considering the GMSF is an advanced tool used to smooth image while enhancing salient edges [21], a multi-scale edge-preserving decomposition framework (MEDF) is constructed by changing the smoothing factor. Each source image is decomposed into one base image and a series of detail images by using MEDF. Detail information won't be lost in the decomposition process since no upsampling or downsampling operation involved. Moreover, the halo artifacts can be efficiently suppressed due to the nonlinearity of GMSF.

A good multi-scale decomposition based fusion method depends not only on choosing an excellent multi-scale decomposition tool but also on formulating appropriate fusion rules. Here we fuse base and detail images with different rules. The pixels in the fused base image are selected through comparison of the regional weighted sum of energy, which can efficiently avoid contrast reduction and information loss. As PCNN has the characteristics of global couple and pulse synchronization, it is suitable to be applied in the

* Corresponding author.
E-mail address: duhuiqian@bit.edu.cn (H. Du).

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Fig. 1. Demonstration of L_0 gradient minimization smoothing filter with different λ. (a) Original image Barbara, (b) smoothed image with $\lambda = 0.008$, (c) smoothed image with $\lambda = 0.015$.

fusion of detail images. The pixels with more firing times are picked into the fused detail images, and thus the features in source images can be extracted and transferred into the fused image as much as possible. Experimental results show that the proposed algorithm is more effective in preserving edges and outperforms several state-of-the-art image fusion methods both in visual sense and objective assessment.

The rest of this paper is organized as follows. The theories of GMSF and PCNN are briefly introduced in Section 2. In Section 3, the designed image fusion scheme is illustrated in detail. The experimental results and discussions are shown in Section 4. Conclusions are drawn in the final section.

2. Basic theory

2.1. Edge-preserving smoothing filters

In recent decades, several edge-preserving smoothing filters have been proposed, such as anisotropic filter [22], bilateral filter [23] and weighted least squares filter [24]. The GMSF [21] is a recently proposed approach, which can effectively suppress low-amplitude details and sharpen salient edges globally via L_0 gradient minimization.

Suppose the input image is denoted as f and the smoothed output result is denoted as g. For each pixel p, the gradient of g is calculated along the x and y directions, i.e., $\nabla g_p = \left(\partial_x g_p, \partial_y g_p\right)^{\mathrm{T}}$. By counting non-zero gradient pixel number in g,

$$C(g) = \#\left\{p \,|\, |\partial_x g_p| + |\partial_y g_p| \neq 0\right\}, \tag{1}$$

the smoothed image g can be estimated by solving the following optimization problem,

$$\min_g \left\{ \sum_p \left(g_p - f_p\right)^2 + \lambda C(g) \right\}, \tag{2}$$

where λ is the smoothing factor to control the smooth extent. It is hard to solve Eq. (2) as it involves a discrete counting metric. An alternating optimization method by introducing two auxiliary variables h_p and v_p is adopted, and $\left(h_p, v_p\right)$ is correspond to $\left(\partial_x g_p, \partial_y g_p\right)$. The new objective function can be written as:

$$\min_{g,h,v} \left\{ \sum_p (g_p - f_p)^2 + \lambda C(h, v) + \gamma\left(\left(\partial_x g_p - h_p\right) + \left(\partial_y g_p - v_p\right)\right) \right\}, \tag{3}$$

where $C(h, v) = \#\left\{p \,|\, |h_p| + |v_p| \neq 0\right\}$. The Eq. (3) can be solved by alternatively minimizing g and (h, v). When γ is large enough, Eq. (3) approximates Eq. (2). In the experiments, the parameter γ is updated in each iteration,

$$\gamma_i = \kappa\gamma_{i-1}, \gamma_{\max} = 10^5, \tag{4}$$

the initial value γ_0 is fixed as 2λ and κ is set to 2.

In order to distinctly show the edge-preserving property of GMSF, the Barbara image obtained from Marco Schmidt's standard test images database [25] is used as test image because it contains more texture and details than CT or MRI images. The smoothed images with different λ are shown in Fig. 1. It can be seen that the larger the value of parameter λ, the more smooth the output image is.

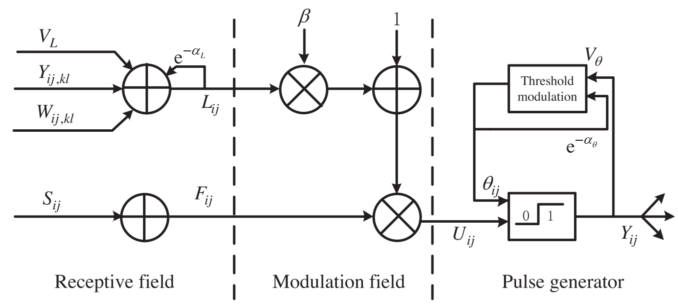

Fig. 2. The basic structure of PCNN model.

2.2. Pulse coupled neural network (PCNN)

The PCNN simulates the synchronous oscillation phenomenon in the visual cortex neurons of mammals, which is a two dimensional artificial neural network model [26–28]. The basic structure of a single pulse-coupled neuron includes the receptive field, the modulation field and the pulse generator, which is shown in Fig. 2. The mathematical model can be expressed as follows,

$$\left\{\begin{aligned} &F_{ij}(n) = S_{ij} \\ &L_{ij}(n) = e^{-\alpha_L} L_{ij}(n-1) + V_L \sum_{kl} W_{ij,kl} Y_{ij,kl}(n-1) \\ &U_{ij}(n) = F_{ij}(n)(1 + \beta L_{ij}(n)) \\ &\theta_{ij}(n) = e^{-\alpha_\theta}\theta_{ij}(n-1) + V_\theta Y_{ij}(n-1) \\ &Y_{ij}(n) = \begin{cases} 1, \text{if} U_{ij}(n) > \theta_{ij}(n) \\ 0, \text{otherwise} \end{cases} \end{aligned}\right. \tag{5}$$

In the receptive field, S_{ij} denotes the pixel value of the input image at (i, j), which serves as the feeding input F_{ij}. The linking input L_{ij} is calculated through surrounding neurons with the synaptic