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Medical images fusion by using weighted least squares filter and sparse representation☆

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ABSTRACT

Multi-modal medical image fusion can obtain more comprehensive and high quality image by integrating the complementary information of medical images, which can provide more accurate data for clinical diagnosis and treatment. To preserve the detailed information and structure information of the source image, in this paper, a novel medical image fusion method exploiting multi-scale edge-preserving decomposition and sparse representation is proposed. In our method, medical source images are decomposed into low-frequency (LF) layers and high-frequency (HF) layers by the weighted least squares filter. The rule which combined by Laplacian pyramid and sparse representation is employed to fuse LF layers. The HF layers are merged using max-absolute fusion rule. Finally, the fused LF and HF layers are combined to obtain the fused image. Experimental results prove that our method outperforms many other methods in terms of both visual and quantitative evaluations.

1. Introduction

With the development of medical diagnostic techniques, medical images are becoming more and more important in clinical diagnosis. Many kinds of medical images can be obtained for diagnosis, such as ultrasound, X-ray, single photon emission computed tomography (SPECT), computed tomography (CT), magnetic resonance imaging (MRI), PET etc. These images are derived from different sensors, and have their own advantages. Sometimes, only one kind of medical image cannot provide sufficient information for doctor to diagnose. Combining the multiple kinds of medical images is necessary. Medical image fusion combines the information of multiple kinds of medical images [1], helping doctors to make an accurate diagnosis.

Currently, there are two categories of medical image fusion methods, they are spatial domain based methods, and transform domain based methods. Spatial domain based methods are directly operating the pixel point of an image in the spatial domain [2,3]. These methods are fast in calculating. However they always bring spatial distortions in fusion result and cannot provide more spectral information. Recently, Bhatnagar et al. [4] proposed a novel spatial domain fusion method which based on the local activity features, this method could obtain a preferable fusion result, but it was lack of robustness to image misregistration. The transform domain methods are performed by decomposing source images into transform coefficients, then apply fusion rules to obtain the fused image.

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Traditional transform domain based fusion methods include Laplacian pyramid (LP) [5], steerable pyramid [6], discrete wavelet transform (DWT) [7], dual-tree complex wavelet transform (DTCWT) [8], stationary wavelet transform (SWT) [9] and non-sub-sampled contourlet transform (NSCT) [10] etc. The traditional transform domain-based methods can robustly extract the salient information of the image. But most of them employ linear filter producing halos near edges. In recent years, many non-linear edge-preserving filters have been applied in image fusion processing. In [11], the authors proposed a method introducing the multi-scale bilateral filter to fuse images improving the quality of fusion result. Li et al. [12] adopted the Guided filter (GF) to fuse images exhibiting favourable performance. Gan et al. [13] proposed a novel scheme with weighted least squares filter (WLS) and phase congruency (PC), which could obtain superior result than GF based method, but it was difficult to accelerate the fusion process. In our propose method, we perform the weighted least squares (WLS) filter to decompose the source images and we adopt different fusion rules to obtain the fused image. Although WLS-based fusion methods can preserve the spatial information, they suffer from fusion rule problem. Conventionally, the image fusion rules such as average, weighted average or maximum are simple to implement in a short time. However, it brings the fusion result with redundant information or obscure edge. In recent years, many improved HF layer fusion rules are being used. Compared with the great concentration on developed effective rules for high-frequency layer, these methods pay less attention in fusing the LF layers, the LF layers are merged by using the simplest rule such as "averaging rule".

Sparse representation (SR) theory has recently drawn significant interest in image processing due to its good enhanced performance. SR theory assumes that the signal $x \in R^n$ can be sparsely represented by using an over-complete dictionary. The mathematical model of sparse representation is

$$x = D\alpha \tag{1}$$

where $D \in R^{n \times m}(n < m)$ is an over-complete dictionary, $\alpha \in R^m$ is the sparse coefficient. The purpose of SR is to find a solution vector α which contains the most zero value in all solution vectors. Particularly, the maximal l_1-norm rule is selected to fuse the sparse vectors. Recently, the SR-based fusion methods have gradually matured and many improved methods have been proposed [14–16].

Inspired by the spirit of transform domain based method and SR-based method, we combine them together to overcome the problems current methods suffered. In our method, to keep clear edge information in the process of decomposition, WLS filter is applied to decompose the source image into LF layers and HF layers. To avoid loss of spectral information, Laplacian pyramid is adopted to decompose the LF layers again. Then we merge the LF layers by using the Laplacian pyramid and sparse resolution rule (LP-SR-based) method and merge the HF layers with max-absolute rule. In our experiment, we give a number of contrasting experiments to validate the effectiveness of the proposed method. The proposed method in this paper has the following contributions to improve the medical fusion process:

1. To effectively extract the medical image features, WLS filter is applied to decompose the source images in multi-scales. This method can achieve the unique property of preserving the information of specific and improve the quality of the fused image.

2. To preserve structure and detailed information, the SR-based fusion rule for LF layers is applied to preserve the detailed information of source images, while area max-absolute fusion rule for HF layers is implemented to reduce redundant information.

3. To preserve the energy of the source images, a novel combination fusion rule is proposed. LF layers are secondary decomposed by Laplacian pyramid, and subsequently the SR fusion rule is used to merge the transform coefficients. As a result, the fused image would appear more naturally and more suitable for medical diagnosis.

The rest of this paper is structured as follows: Section 2 introduces the related works; Section 3 presents the proposed framework; Section 4 provides experimental results and discussions; and Section 5 concludes this paper.

2. Related work

2.1. Dictionary learning

An over-complete dictionary plays a decisive role in sparse representation. K-SVD is a widely used adaptive dictionary learning technique in recent years. Compared with the traditional transform techniques, the dictionary which is learned by using K-SVD can better represent various image structures. Suppose $\{patch_i\}_{i=1}^N$ are the sampled patches which are obtained by using a fixed size window $\sqrt{n} \times \sqrt{n}$ to randomly sample from a set of high-quality images, N denotes the total number of sampled patches. Then each patch is rearranged to column vector and subtracted its own mean value so that each patch's intensity is around zero. In order to ensure that patches have enough edge information, we set a threshold of intensity variance to remove the smooth patches. Denote $\{p_i\}_{i=1}^M$ as the training patches, the dictionary can be formulated by

$$\min_{D,\alpha_i} \sum_{i=0}^{M} \|\alpha_i\|_0 \quad \text{s.t. } \|p_i - D\alpha_i\|_2 < \varepsilon,\ i \in \{1, \ldots, M\} \tag{2}$$

where $\varepsilon > 0$ is the tolerance factor, $\{\alpha_i\}_{i=1}^M$ are the sparse coefficients and D is the dictionary to be learned.

2.2. Weighted least squares filter

The weighted least squares (WLS) filter is a non-linear, edge-preserving, smoothing filter, which is first proposed in [17]. WLS filter can effectively capture details at multiple scales via multi-scale edge-preserving decomposition. It has been applied to various image processing applications, such as image enhancement, image fusion etc. Compared with other edge-preserving filters, such as bilateral filter, the WLS filter can effectively balance between blurring and sharpening. Specifically, given an input image I, WLS filter