Neurocomputing 194 (2016) 326–339

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Union Laplacian pyramid with multiple features for medical image fusion

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A R T I C L E I N F O

Article history:
Received 15 July 2015
Received in revised form
18 February 2016
Accepted 20 February 2016
Available online 4 March 2016

Keywords:
Image fusion
Pyramid
Multiple features
Contrast enhancement
Outline enhancement
Objective image quality metrics

A B S T R A C T

The Laplacian pyramid has been widely used for decomposing images into multiple scales. However, the Laplacian pyramid is believed as being unable to represent outline and contrast of the images well. To tackle these tasks, an approach union Laplacian pyramid with multiple features is presented for accurately transferring salient features from the input medical images into a single fused image. Firstly, the input images are transformed into their multi-scale representations by Laplacian pyramid. Secondly, the contrast feature map and outline feature map are extracted from the images at each scale, respectively. Thirdly, after extracting the multiple features, an efficient fusion scheme is developed to combine the pyramid coefficients. Lastly, the fused image is obtained by a reconstruction process of the inversed pyramid. Visual and statistical analyses show that the quality of fused image can be significantly improved over that of typical image quality assessment metrics in terms of structural similarity, peak-signal-to-noise ratio, standard deviation, and tone mapped image quality index metrics. The contrast is also well preserved by histogram analysis of images.

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1. Introduction

The multi-modal medical image fusion is the process of merging multiple images from a single or multiple imaging modalities. The research of medical image fusion is focused on algorithms with aim to improve the imaging quality with preserving the specific features for increasing the clinical applicability of medical images for diagnosis and assessment of medical problems. Medical image fusion methods involve the fields of image processing, computer vision, pattern recognition, machine learning and artificial intelligence [1,2]. Thus far, medical image fusion methods can be implemented at three levels: pixel-level, feature-level and decision-level [3–5]. At the pixel-level of medical image fusion methods, most of the salient information is preserved in the fused image [3]. Feature-level image fusion methods [4] are performed on a feature-by-feature basis, such as edges, textures. And medical image fusion methods at the decision-level refer to make a final fused decision [5]. In this paper, we aim to generate a fused image combining the important information from multi-modal medical images at the pixel-level. Traditionally, the existing fusion methods can be summarized to implement by the following steps: image decomposition, image fusion rules, image reconstruction and image quality assessment [1,2]. Especially, the decomposition-based fusion methods decompose the input image into single-scale, two-scale or multi-scale sub-images.

At the pixel-level of medical image fusion methods, single-scale tools have been adopted for image fusion, e.g., fuzzy logic [6], knowledge [7], artificial neutral network (ANN) [8], principle component analysis (PCA) [9] and intensity hue luminance (IHS) [10] methods. Under the single-scale framework, the efficient image fusion rules are directly used to combine the input images with strategies to get the fused image. The fuzzy logic rule for each pixel in input images is utilized to uncertain reason for obtaining the final fused image [6]. In knowledge based method [7], both input medical images and medical reports are necessary to construct an image representation. In addition, ANN based method [8] applies the clustering method to divide the pixels into feature pixels and secondary pixels. PCA based method [9] is related to data-driven technique as well as higher order statistics to reveal hidden saliency structure. The fused image is constituted by new irrelevant principle components given by the convariance matrix of two decomposed coefficients. Then, IHS based method [10] is exposed to be a well quality images with a visually beautiful color medical images. The fused image is obtained by the substituted higher spatial resolution intensity component, original hue and saturation components.

The second category is the two-scale fusion methods, such as image fusion with guided filtering (GFF) [11]. Each input medical image is firstly decomposed into a base layer and a detail layer by average filter. Guided filtering is then performed on both base

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http://dx.doi.org/10.1016/j.neucom.2016.02.047
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layers and detail layers to get the fused layers which mean that the activity-level measurement of base layers is as same as detail layers. However, the guided filtering is good at blurring the image details while preserving the edges of the image. Since base layers represent the most information from the input images, maybe it is not fair to implement the guided filtering on the based layers to preserve the edge information but not the other significant information, such as texture information. Lastly, the fused image is obtained by combining the fused base layers and fused detail layers.

The last category is the multi-scale fusion methods. In the past few decades, many multi-scale geometric analysis (MGA) tools are adopted in the multi-modal image fusion and a large number of image fusion methods [12–25] with MGA have been proposed in literatures. MGA scheme can transfer the most important information of input multi-scale coefficients into the fused coefficients, such as pyramid transform (PT) [12–15], wavelet transform (WT) [16–25]. Specially, these PT MGA fusion methods include morphology pyramid [12], ratio pyramid (ROP) [13], Laplacian pyramid (LAP) [14], etc. And WT MRA fusion methods include discrete wavelet (DWT) [16,17], non-subsampled contourlet transform (NSCT) [22–24], and shearlet transform (ST) [25], etc. In MGA fusion methods, the multi-scale tool, transform is applied firstly to separate the input medical images into high resolution images and low resolution images. Image fusion rules are used to combine multiple high resolution images and low resolution images from different original input images, respectively. The fused high resolution images and fused low resolution images are then converted back into the fused image using the inverted transform. LAP [14] is formed as a difference between corresponding levels of the Gaussian and their expanded low-pass approximation images. NSCT [22–24] produces various directional decompositions due to non-subsampled directional filter bank. ST based decomposition methods [25] can capture more directional layers, compared with LAP, DWT, and NSCT. The average rule scheme for each pixel in input images is usually utilized in the low resolution images. Besides, a single feature is used to combine the high resolution images, such as max rule and local energy scheme. The computations of PT fusion [12–15] are relatively simple, however the WT fusion [16–25] provides result images at the express of considerably greater computation.

Although many advanced image fusion methods have been proposed in multi-modal medical image fusion applications, there still exists large room for improvement. In this study, we introduce a multiple features in LAP domain fusion method for multi-modal medical image fusion. The shortcoming of image fusion rules based on a single feature is to implement the same strategy in processing the residual-images from input images with different modalities. However, each image modality owns its properties. For example, anatomical image provides structural information, and functional image provides more activity of the tissues at the molecular level Maybe it is unfair to use a single feature extracted from input images. The proposed algorithm is to generate a multiple features of outline-enhanced and contrast-enhanced on the high resolution images to explore the properties from different medical images. The motivation of this fusion method is to combine the significant information of the high resolution images modeled as the outline and contrast enhancement by affine transformation [26,27], Kirsch scheme [28,29] and PCA [9]. The outline-enhance high resolution images is achieved using affine transformation [25,26] to enhance the edge information in horizontal and vertical orientations. And the contrast-enhance high resolution images is achieved using Kirsch scheme [28,29] and PCA [9]. The proposed fusion method in this paper is able to simultaneously combine the significant information of contrast-enhance, outline-enhanced. Therefore, multiple features are taken into consideration of fusing image in this paper. LAP is chosen as the decomposition and reconstruction scheme with the advantage that it can be implemented using simple image resizing routines in spatial domain. Outline weight map and contrast weight map are used to combine the decomposed high resolution images. Experimental results proved that our method is superior to the existing fusion approaches without loss of outline and color contrast. The study of this paper is:

1) The standard PT fusion method is directly transformed into several levels which are not capable to incorporate the detailed information. In this paper, the affine transformation is proposed to augment orientation information at each level.
2) Unlike the traditional PT method, the image fusion rule is inspired by the contrast and outline feature of the input images.
3) Designing multiple features for enhancing contrast and outline of images. The contrast information is attributed to Kirsch operator and PCA. And the outline information is extracted by affine transformation.

The rest of this paper is structured as follows: Section II gives a brief introduction of the pyramid transform based medical image fusion methods. Section III contains the details of the image fusion algorithm, and outline and contrast enhancement is provided. And Section IV discusses the image quality obtained with the proposed method by three groups of experiments of MRI-CT, MRI-PET, and MRI-SPECT fusion measurements. Finally, the conclusion is given in Section V.

2. A brief introduction of the pyramid transform fusion

The PT fusion methods include morphology pyramid (MOP) [12], ratio pyramid (ROP) [13], gradient pyramid (GRP) [12], and LAP [14]. The morphology filtered image is used to construct the high-pass frequency images in MOP based fusion methods. In ROP scheme, the ratio of adjacent image is applied to obtain the high-pass information. Moreover, GRP represents the high-pass frequency images by gradient of the corresponding images at different levels. Recently, LAP images are obtained as the difference between successive Gaussian filtered images using simple image resizing routines and smooth Gaussian kernels.

The PT fusion [12–15] mainly consists of three stages: image decomposition, image fusion and image reconstruction (shown in Fig. 1). PT is utilized to get the multi-scale representation of input images at the beginning. Secondly, the image at different scales is fused by efficient image rules. Finally, the fused image is obtained by the inversed PT. Please refer to Table 1 for important definitions used throughout the rest of this paper.

In Fig. 2, it is for the framework of a MRI image decomposition with three-level PT. A sequential order of images $\{L_1, L_2 \ldots L_i\}(i=3)$ is obtained by PT and the order is a couple of base-images B_i and residual images R_i. The base-images of the MRI image with three-levels are shown in Figs. 2 (b1), (c1), (d1). And the residual-images are shown in Figs. 2 (b2), (c2), (d2).

$$L_i = \begin{cases} \check{F} \times I, & i=1 \\ \check{F} \times L_{i-1}, & 2 \le i \le n \end{cases} \tag{1}$$

where L_i is the i-th level, n is the maximum number of levels, $\check{F}$ is a filter with down-sampling and I is the input image.

The base-images B_i and residual-images R_i of L_i are obtained.

$$B_i = L_i \times F_L, \quad R_i = L_i \times F_H \tag{2}$$

where F_L is a low-pass filter, F_H is a high-pass filter.

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