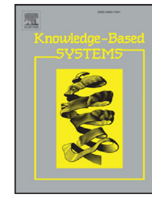
Knowledge-Based Systems 000 (2016) 1–9

Contents lists available at ScienceDirect

Knowledge-Based Systems

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



Medical image fusion by combining parallel features on multi-scale local extrema scheme

Jiao Du, Weisheng Li*, Bin Xiao, Qamar Nawaz

Chongqing Key Laboratory of Computational Intelligence, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

A R T I C L E I N F O

Article history:
Received 5 April 2016
Revised 7 September 2016
Accepted 12 September 2016
Available online xxx

Keywords:
Local extrema scheme
Parallel features
Edge saliency weighted map
Color saliency weighted map
MRI-CT fusion
MRI-PET fusion

A B S T R A C T

Two efficient image fusion algorithms are proposed for constructing a fused image through combining parallel features on multi-scale local extrema scheme. Firstly, the source image is decomposed into a series of smoothed and detailed images at different scales by local extrema scheme. Secondly, the parallel features of edge and color are extracted to get the saliency maps. The edge saliency weighted map aims to preserve the structural information using Canny edge detection operator; Meanwhile, the color saliency weighted map works for extracting the color and luminance information by context-aware operator. Thirdly, the average and weighted average schemes are used as the fusion rules for grouping the coefficients of weighted maps obtained from smoothed and detailed images. Finally, the fused image is reconstructed by the fused smoothed and the fused detailed images. Experimental results demonstrate that the proposed algorithms show the best performances among the other fusion methods in the domain of MRI-CT and MRI-PET fusion.

1. Introduction

Medical image fusion is a task to obtain a single fused image in terms of human visual perception in order to increase the clinical applicability of medical images for diagnosis and assessment of medical problems [1]. Different breakdown frameworks can be found in the literature based on morphology operator [2], knowledge [3–4], artificial neural networks [5–6], and multi-scale analysis (MSA) [7–22].

Instead of working with a single scale [2–6], the fusion methods based on MSA [7–22] are widely used for fusing multi-modal medical image on account of its properties of extracting and combining saliency feature at different scales. Pyramid transform based methods are well-known MSA schemes in medical image fusion [7–10]. They are formed as a difference between successive levels of Gaussian pyramid with filters, such as Laplacian and gradient filters. However, pyramid transform based fusion methods, such as gradient pyramid (GRP) [7], lack of the direction information. Later, wavelet transforms, such as discrete wavelet transform (DWT) [11], contourlet transform (COT) [12] and shearlet transform (ST) [13–15], provide a framework that the source image is decomposed into a series of low-pass and high-pass sub-images at different scales and directions. The limitations and problems of wavelet transforms are: (1) Wavelet-based methods are with the higher computational complexity; (2) The fused images are blurred with low-contrast; And (3) the saliency features are sensitive to shift and noise. Since human beings are the ultimate receivers, it is very necessary for researchers to investigate the human visual system (HVS) in the field of medical image fusion. HVS which simulates the perceptual process a human performs is applied to medical image fusion and then achieved excellent performance [16–19]. In contrast to wavelet transform based fusion methods, HVS based methods aim to decompose the input image into its multi-scale representation to perform exactly the way the optical cells of human being does in spatial domain. The problem of HVS based fusion methods is the requirement of appropriate parameter values for the psychological model. In order to overcome the computational complexity and plenty of parameterization in wavelet transform and HVS based methods, edge-preserving filtering such as bilateral filter [20], guided filer [21], and local extrema [22–23] can separate the input image into smoothed layers and detailed layers efficiently. The input image after edge-preserving smoothing operation is smoothed layers. Then, detailed layers are constructed by the difference between the input image and smoothed layer. However, these methods have only been used to fuse gray scale images rather than color images.

Although many advanced image fusion methods have been proposed in application of multi-modal medical image fusion, there still exists large room for improvement. In this study, we introduce new MSA image fusion methods with parallel features: edge saliency feature (ESF) [24] and color saliency feature (CSF)

* Corresponding author.
E-mail address: liws@cqupt.edu.cn (W. Li).

http://dx.doi.org/10.1016/j.knosys.2016.09.008
0950-7051/© 2016 Published by Elsevier B.V.

[25] based on local extrema scheme (LES) [23]. There are many different interpretations of the scale in MSA framework [26]. In this study, we assume that the scale of LES is related to the window size of local regions, the scale of ESF is related to the window size of edge detection filter, and the scale of CSF is related to the ratio of color information to position information. In the proposed methods, the first problem to be solved is to determine the MSA decomposition tool. In this study, we chose LES since it defines smoothed layer as mean values of local minima and maxima envelopes rather than to solve a complex optimization problem. The second problem to be solved in the proposed methods is the image fusion rule. Image fusion rule process [27] guarantees that the salient feature information from images is combined into a single image. Each image modal owns its specific properties. For example, structural 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. To preserve salient feature information from different medical images, the proposed methods is to generate parallel features [24-25] to explore the properties. The motivation of parallel features is to combine the structural information using edge saliency features (ESF) method [24] and the functional information using color saliency feature (CSF) method [25]. Experimental results show that the proposed methods give an improved performance compared with state-of-the-art multi-modal medical image fusion approaches. The main contributions of the proposed image fusion methods are highlighted in the following.

1) Edge saliency features (ESF) method [24] is proposed as the fusion rule to combine the Canny edge information from the smoothed layer of structural medical images (such as MRI, CT modal).
2) For the detailed layer of functional medical images (such as PET modal), color saliency feature (CSF) [25] method is used as the fusion rule to combine prominent color information.

The rest of this paper is organized as follows. Firstly, it introduces the related work about the multi-scale decomposition analysis tool and the fusion rules with the parallel features of edge and color. Secondly, in Section 3, two algorithms are presented for MRI-CT and MRI-PET image fusions. Then, Section 4 illustrates experimental evaluation. Finally, Section 5 gives the conclusion.

2. Related work

2.1. Local extrema scheme

Compared to the single-scale based methods, MSA has the advantage of extracting and combining image features at different scales. LES is one of the edge-preserving smoothing operators. The input image I can be transformed into two components: smoothed image S and detailed image D. Smoothed image S contains the coarse part of the source image. And detailed image D refers to the texture, luminance and edge information. S and D can be calculated using LES which consists of three steps: (1) To discover the local minima and local maxima in the given image I within a sliding window $w\times w$; (2) To compute minimal extremal envelope and maxima extremal envelope; And (3) to obtain smoothed image S as the medial plane of the local maximal and minimal envelops. In addition, detailed image D can be obtained by subtracting smoothed image from the source image defined as $D=I-S$.

We use LES to construct a multi-scale image representation scheme of the input image I in this study. After getting L recursive smoothing operations using LES, a single input image I is transferred into a series of smoothed images S_l and a series of detailed images D_l at increasing scales of the window size $w=2l-1(l=1,\cdots,L)$,

$$\mathrm{LES}(I)=\sum_{l=1}^{L}(S_l+D_l) \tag{1}$$

where L is the maximum level. In our experiments we choose $l=2$, $l=3$, and $l=4$ as the sizes of the local window for the multi-scale decomposition scheme.

2.2. Image fusion rules

Fusion rules refer to algorithms that seek to highlight the interested features in images and restrain the features of insignificance. The main contributions of the rules are the combination with multiple original images into a single image. An effective fusion rule plays a significant role in affecting the objective quality assessments of the fused image. A fusion rule normally includes three components: activity-level measurement, coefficient grouping and coefficient combination.

(1) Activity-level measurement: The activity-level scheme measures the saliency of each coefficient at different scales. ESF [24] and CSF [25] are selected as the activity-level measurements in this study.
The ESF uses the Canny edge detector to extract the edge and margin information from the two-dimension (2D) images by scale multiplication [24]. The scale multiplication function is used as the responses of the edge detection filter at different scales. Firstly, two filters for detecting edges in vertical and horizontal directions are constructed:

$$f_s^x(x,y)=-xe^{-x^2/(2s^2)}/s^2,\; f_s^y(x,y)=-ye^{-y^2/(2s^2)}/s^2 \tag{2}$$

where s is the scale of the input image $I(x, y)$. Secondly, the responses to the edge detection filters $f_s^x(x,y), f_s^y(x,y)$ at two scales s_1, s_2 are $H_{s_1}^x(x,y), H_{s_2}^x(x,y), H_{s_1}^y(x,y), H_{s_2}^y(x,y)$. Thirdly, the scale multiplication of the responses is:

$$P_I^x(x,y)=H_{s_1}^x(x,y)\cdot H_{s_2}^x(x,y);\; P_I^y(x,y)=H_{s_1}^y(x,y)\cdot H_{s_2}^y(x,y) \tag{3}$$

where s_1 is a constant, $s_2=2s_1$. Fourthly, edge points are obtained by computation of the local maximal of $M_I(x, y)$ in the direction of $A_I(x, y)$:

$$M_I(x,y)=\sqrt{P_I^x(x,y)+P_I^y(x,y)} \tag{4}$$

$$A_I(x,y)=\arctan\left(\frac{\mathrm{sgn}(H_y^{s_1}(x,y))\cdot\sqrt{P_I^y(x,y)}}{\mathrm{sgn}(H_x^{s_1}(x,y))\cdot\sqrt{P_I^x(x,y)}}\right) \tag{5}$$

Finally, the multi-scale product is denosing through a threshold T

$$\mathrm{ESF}(I)=M_I(x,y)-T \tag{6}$$

The CSF aims at detecting the saliency feature which contains both the prominent object and some of background that convey the context [25]. The CSF measurement is driven by low-level saliency features, such as color, orientation and intensity. The CSF follows four principles: (1) Local low-level feature is of the considerations. (2) Global feature maintains the feature deviated from the norm. (3) The approach should consist with human visual organization rules. And (4) the saliency regions are apt to center. The CSF algorithm contains local-global single-scale saliency, multi-scale saliency and center prior. Firstly, the single-scale saliency F_i^l of pixel i at scale r is obtained as:

$$s_i^r=1-\exp\left\{-\frac{1}{K}\sum_{k=1}^{K}d\left(q_i^r,q_k^r\right)\right\} \tag{7}$$

Please cite this article as: J. Du et al., Medical image fusion by combining parallel features on multi-scale local extrema scheme, Knowledge-Based Systems (2016), http://dx.doi.org/10.1016/j.knosys.2016.09.008