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Fusion of anatomical and functional images using parallel saliency features

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ABSTRACT

An efficient method is proposed for fusion of anatomical and functional images by constructing the fused image through the combination of parallel saliency features in a multi-scale domain. First, the anatomical and functional images are decomposed into a series of smooth layers and detail layers at different scales by the average filter. Second, the parallel saliency features of both sharp edge and color detail are extracted to obtain the saliency maps. The edge saliency weighted map aims to preserve the high-spatial-resolution structural information using the Canny edge detection operator, while the color saliency weighted map extracts the high-intensity color detail using the context-aware operator. Finally, the fused image is reconstructed by the fused smooth layers and the fused detail layers using saliency maps. We demonstrate the application of the proposed method to a medical problem: Alzheimer's disease. Experimental results show that the proposed method for fusion of MRI-CBV and SPECT-Tc images and fusion of MRI-T1 and PET-FDG images successfully presents the pleasing fused medical images with high-spatial-resolution anatomical structural boundaries and high-intensity color detail.

1. Introduction

In the past several decades, a broad range of medical imaging techniques have become available in medical institutions. Tomographic techniques, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT), play an important role in determining the extent of human diseases, evaluating the effectiveness of treatments and guiding surgical procedures. Roughly, tomographic techniques are divided into two categories: anatomical imaging data and functional imaging data. Both CT and MRI images provide high-spatial-resolution anatomical structural information. In contrast to anatomical images, both PET and SPECT images display the high-intensity blood flow to tissues and organs [27]. The fusion of anatomical and functional images, such as fusion of CT and PET images, fusion of CT and PET images, fusion of MRI and PET images, and fusion of MRI and SPECT images [12,31,40], could provide additional advantages, including high-spatial-resolution of soft tissue, lower radiation dose and shorter examination time. For example, fusion of MRI and PET images is helpful in detecting hepatic metastasis [8] and fusion of MRI and SPECT images is useful in locating lesions in patients with tinnitus [9].

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Medical image fusion is the process of merging multiple images from a single or multiple imaging modalities. The purpose of image fusion is to obtain a single final image that preserves specific features to increase the clinical applicability of medical images for diagnosis and assessment of medical problems [12]. Two directions can be explored in terms of the available methods for medical image fusion, to improve the quality of the fused images: advanced image decomposition schemes and effective image fusion rules. In this study, we focus on the latter. Image fusion rules refer to algorithms that seek to highlight the features of interest in images and suppress the insignificant features. The main aim of image fusion rules is the combination of multiple images into a single image. The effectiveness of the image fusion rules is closely related to the quality of the fused image. Prospective effective image fusion rules are generally classified into four categories: substitution, pulse coupled neural network (PCNN), sparse representation (SR), and local feature descriptor methods.

Substitution methods are easily to perform, such as principal component analysis (PCA) [26,32,45] and intensity-hue-saturation (IHS) [6,7,37]. A PCA-based fusion rule is related to a data-driven technique as well as higher-order statistics to reveal hidden saliency structures. PCA depends on the linear combination of vectors forming new irrelevant principle components. The advantage of PCA methods is their ability to preserve spatial information, e.g., adaptive PCA, spectral PCA, spatial PCA, and independent component analysis (ICA). The IHS fusion method, which is a popular technique in the remote sensing community, has been used in fusing panchromatic (Pan) and multispectral (MS) images. The intensity of an MS image is replaced by a Pan image with higher resolution. Based on the framework for fusion of high-spatial-resolution Pan and high-spectral-resolution MS images, IHS is introduced into the fusion of MRI and PET images. Both IHS and PCA can maintain the same spatial resolution as the anatomical image. However, the methods that are based on PCA introduce artificial effects, such as block effects, ringing effects and pseudo Gibbs effects, and the methods that are based on IHS cause the loss of an important saliency feature from one of the source images.

PCNN methods [22,35,41,47] are developed from the biological experimental observations of synchronous pulses in the visual cortex of the cat. Each neural cell is composed of an acceptance domain, a modulation domain and a pulse generator. The intensity of each pixel in the image corresponds to a neural cell in the PCNN framework. The main advantage of PCNN methods is that the information is processed in accordance with the human visual system. However, PCNN methods require a training stage for achieving the optimal image pixel values for fusing images [35]. For medical image fusion, methods that are based on PCNN apply a feedback neural network to fuse the input images that were obtained with different modalities. PCNN-based image fusion rules can be used in the wavelet domain, such as Discrete Wavelet Transform (DWT)-PCNN or the spatial domain, such as Internal Generative Mechanism (IGM)-PCNN and m-PCNN [22,41,47].

SR, which is an effective way to describe medical image signals by a linear combination of atoms using an over-complete dictionary [14,18,24], is widely used for fusion of medical images. The sparse coefficients are treated as the saliency features of the input medical images. The over-complete dictionary affects the performance of the SR-based fusion methods, whose aim is better representation of the input image signal. Unfortunately, it is argued that SR-based fusion methods are good at isolating common and innovative features, but are unsatisfactory for processing edge and texture information.

The local feature descriptor [5,20,43], such as smallest univalve segment assimilating nucleus (SUSAN), dense scale-invariant feature transform (DSIFT), and local extrema scheme (LES), are widely used in the field of medical image fusion. The SUSAN feature is proposed for fusing high-frequency bands that are obtained from the framelet transform. SUSAN is used as a tool for fusing multi-modal medical images, which is a feature descriptor of the image that is inspired by the human visual system. In the SUSAN feature [5], each image pixel corresponds to its local area of similar intensity. DSIFT [20] is adopted to measure the activity level of the original images in the feature space transform. The DSIFT local feature is constructed based on the histogram of gradient orientations in a cell. The experimental results show that the fusion method that uses DSIFT can not only measure the activity level but also match the mis-registered pixels between different original images. The mean of the local minima and maxima envelopes in LES [43] is used to measure the edge detail information of grayscale medical images. The main limitation of the local feature descriptor is that the detection is restricted to image features within local regions.

Although many effective image fusion rules have been proposed in fusion methods, there is still large room for improvement. In the existing fusion methods, a single feature is used to extract the same information from medical imaging data that were obtained with different modalities. In this paper, we propose a new image fusion rule that uses parallel saliency features and considers extracting specific features from different medical images [44]. Parallel saliency features can be divided into two types: edge and color saliency features. Edge saliency feature (ESF) [4] obtained by the Canny edge detection descriptor is useful for preserving high-spatial-resolution soft tissue structural information of the human brain from anatomical images. Color saliency feature (CSF) [10] is used to obtain high-intensity color information from functional images by the context-aware color saliency descriptor. The motivation of the proposed image fusion rules is to extract not only the sharp edge information but also color detail information. Experimental results show the excellent high-intensity and high-spatial-resolution fused image using the proposed method in comparison with state-of-the-art multi-modal medical image fusion approaches.

The rest of this paper is organized as follows. In Section 2, the related work on saliency features is introduced. In Section 3, one method is presented for fusion of anatomical and functional images. Then, the experimental evaluation is presented in Section 4. Finally, Section 5 presents the study's conclusions.