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Fusion of Multimodal Medical Images with PA-PCNN in Non-Subsampled Shearlet Transform Domain

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Abstract — *As a successful method to incorporate the data contained in numerous clinical pictures with various modalities, clinical picture combination has developed as an incredible strategy in different clinical applications, for example, illness finding and treatment arranging. In this paper, another multimodal clinical picture combination technique in non subsampled shearlet change (NSST) area is proposed. In the proposed strategy, the NSST deterioration is first performed on the source pictures to acquire their multiscale and multidirection portrayals. The high-recurrence groups are intertwined by a Parameter Adaptive-Pulse Couple Neural Network (PA-PCNN) model, in which all the PCNN boundaries can be adaptively assessed by the information band. The low-recurrence groups are converged by a novel procedure that at the same time tends to two critical issues in clinical picture combination, to be specific, vitality protection and detail extraction. At last, the combined picture is remade by performing opposite NSST on the melded high-recurrence and low-recurrence groups. Exploratory outcomes show that the proposed strategy can get progressively serious execution in contrast with nine agent clinical picture combination techniques, prompting cutting edge results on both visual quality and target appraisal.*

Key Words: Activity level measure, image fusion, medical imaging, nonsubsampled shearlet transform (NSST), pulse coupled neural network (PCNN).

1. INTRODUCTION

As is notable, clinical imaging is going about as an inexorably basic job in different clinical applications, for example, analysis, treatment arranging, and careful route. Because of the decent variety in imaging components, clinical pictures with various modalities center around various classifications of organ/tissue data. The Computed tomography (CT) imaging can definitely recognize thick structures, for example, bones and embeds. The Magnetic Resonance(MR) imaging gives high-goal anatomical data to delicate tissues, however is less touchy to the determination of cracks than CT. Notwithstanding these anatomical imaging strategies, the useful imaging procedures, for example, positron emanation tomography (PET) and single-photon emisson CT (SPECT) are frequently applied to mirror the digestion data of creature, which is of incredible hugeness to numerous situations, for example, vascular ailment determination and tumor recognition. By the by, the spatial goal of practical pictures is typically low. To acquire adequate data for exact analysis, doctors regularly need to successively examine clinical pictures that are caught with various modalities, yet this isolating way may at present get burden numerous cases. A successful method to take care of this issue is known as clinical picture combination procedure [1], [2], which targets producing a composite picture to incorporate the correlative data contained in numerous clinical pictures with various modalities.

A variety of medical image fusion methods have been proposed over the past decades [3]–[10]. Since there is strong evidence that the human visual system (HVS) processes information in a multiresolution fashion, most medical image fusion methods are introduced under a multiscale transform (MST)-based framework to pursue perceptually good results. In general, the MST-based fusion methods consist of three basic steps. First, the source images are converted into an MST domain. Then, the transformed coefficients are merged using some predesigned fusion strategies. Finally, the fused image is reconstructed from the merged coefficients by performing the inverse transform. MST approaches that are commonly used in image fusion include pyramid based ones (e.g., Laplacian pyramid (LP) and morphological pyramid), wavelet-based ones (e.g., discrete wavelet transform and dual-tree complex wavelet transform), and multiscale geometric analysis (MGA)-based ones (e.g., nonsubsampled contourlet transform (NSCT) and nonsubsampled shearlet transform (NSST)). Among them, the MGA-based methods, especially for the NSCT- and NSST-based methods, have exhibited significant advantages over other methods on account of their higher effectiveness in image representation. In addition to the selection of image transform, the design of fusion strategies for both the highfrequency and low-frequency coefficients is another crucial issue in MST-based fusion methods. Traditionally, the activity level of high-frequency coefficients is usually calculated based on their absolute values using a pixel-based or window based manner, and then a simple fusion rule such as choose max or weighted average is applied to obtain the fused coefficients. The most popular low-frequency fusion strategy in the early days is just averaging the coefficients from different source images. Plenty of studies in the literature indicate that the performances of the MST-based methods could be significantly improved by designing more effective fusion strategies.

With the astonishing development happening in computing and imaging techniques, there has been enormous research happening in visual information processing, image analysis and image understanding. This needs integration of images or image details or extracted features or decisions. This laborious integration task is accomplished by the concept called image fusion and hence finds wide applications in remote sensing, surveillance and navigation, change detection-target tracking, robotics and medical image analysis.

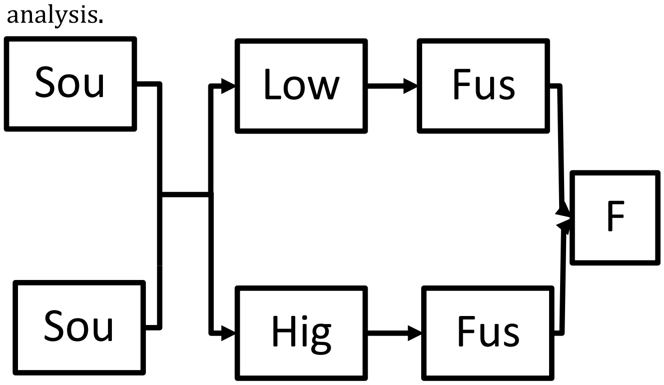

Fig-1 BLOCK DIAGRAM OF PROPOSED METHOD

2.METHODOLOGIES

The proposed fusion method can be straightforwardly extended to fuse more than two source images. The PA-PCNN model presented in Section III is applied to fuse the high-frequency bands. The PA-PCNN model is adopted to fuse high-frequency coefficients with all the PCNN parameters adaptively calculated based on the input bands, which can overcome the difficulty of setting free parameters in the conventional PCNN models. We present a novel low-frequency fusion strategy that simultaneously addresses two crucial factors in medical image fusion, namely, energy preservation and detail extraction. Shearlet is a relatively new member in the family of MGA. In comparison to some earlier multiscale approaches for image representation such as pyramid, wavelet, and curvelet, shearlet can capture the details/features of an image at diverse directions more effectively and is able to obtain a more optimal representation (often measured by the sparsity) for the targeting image. The implementation process of shearlet transform (ST) is similar to that of contourlet transform, but the directional filters in contourlet are replaced by the shearing filters. This paper introduce a parameter-adaptive PCNN (PA-PCNN) model into the field of image fusion. The PA-PCNN model is adopted to fuse high-frequency coefficients with all the PCNN parameters adaptively calculated based on the input bands, which can overcome the difficulty of setting free parameters in the conventional PCNN models. In addition, the PA-PCNN is experimentally verified to have a fast convergence speed with fewer iterations than some commonly used PCNN models in image fusion. To the best of our knowledge, this is the first time that the PA-PCNN model is applied to image fusion.

They present a novel low-frequency fusion strategy that simultaneously addresses two crucial factors in medical image fusion, namely, energy preservation and detail extraction. To this end, two new activity level measures named weighted local energy (WLE) and weighted sum of eight-neighborhood-based modified Laplacian (WSEML) are defined in this paper, respectively. Then propose a new medical image fusion method in the NSST domain by applying the fusion strategies mentioned earlier. Extensive experiments are conducted to verify the effectiveness of our method on four different types of medical image fusion problems (CT and MR, MR-T1 and MR-T2, MR and PET, and MR and SPECT) with more than 80 pairs of source images. Nine representative medical image fusion methods are used for comparison and several of them were proposed very recently. Experimental results demonstrate that the proposed method can achieve stateof- the-art performances on both the visual quality and objective assessment.

2.1 Nonsubsampled shearlet Transform

It is a relatively new member in the family of MGA. In comparison to some earlier multiscale approaches for image representation such as pyramid, wavelet, and curvelet, shearlet can capture the details/features of an image at diverse directions more effectively and is able to obtain a more optimal representation (often measured by the sparsity) for the targeting image. The implementation process of shearlet transform (ST) is similar to that of contourlet transform, but the directional filters in contourlet are replaced by the shearing filters. An important advantage of shearlet over contourlet is that there are no restrictions on the number of directions in shearlet.

2.2. Fusion of high frequency bands

The PA-PCNN model is applied to fuse the high-frequency bands. Unlike the most existing artificial neural networks, PCNN is based on iterative calculation and does not require any training process. The PCNN model applied in image processing tasks is generally a single-layer network with a 2-D array input. There is a one-to-one correspondence between input image pixels and PCNN neurons, so the number of neurons is equal to that of pixels. Each neuron is linked with its neighboring neurons for information transmission and coupling.

2.2.1 Parameter adaptive PCNN

As an effective way to integrate the information contained in multiple medical images with different modalities, medical image fusion has emerged as a powerful technique in various clinical applications such as disease diagnosis and treatment planning. In this paper, a new multimodal medical image fusion method in nonsubsampled shearlet transform (NSST) domain is proposed. In the proposed method, the NSST decomposition is first performed on the source images to obtain their multiscale and multidirection representations.

The high-frequency bands are fused by a parameter-adaptive pulse-coupled neural network (PA-PCNN) model, in which all the PCNN parameters can be adaptively estimated by the input band. The low-frequency bands are merged by a novel strategy that simultaneously addresses two crucial issues in medical image fusion, namely, energy preservation and detail extraction. Finally, the fused image is reconstructed by performing inverse NSST on the fused high-frequency and low-frequency bands.

The effectiveness of the proposed method is verified by four different categories of medical image fusion problems [computed tomography (CT) and magnetic resonance (MR), MR-T1 and MR-T2, MR and positron emission tomography, and MR and single-photon emission CT] with more than 80 pairs of source images in total. Experimental results demonstrate that the proposed method can obtain more competitive performance in comparison to nine representative medical image fusion methods, leading to state-of-the-art results on both visual quality and objective assessment.

2.3. Fusion of low frequency bands

The fusion strategy for low-frequency bands also has significant impact on the final fusion quality. In proposed method, a strategy that simultaneously addresses two crucial factors (energy preservation and detail extraction) in medical image fusion is designed. Since an image can be generally viewed as a 2-D piecewise smooth signal, its energy is mostly contained in its low frequency component. In medical image fusion, the intensities of different source images at the same location may vary significantly, because the source images are captured with different imaging mechanisms. Therefore, the conventional averaging-based low-frequency fusion rule tends to cause the loss of energy in the fused image. As a result, the brightness of some regions may have a sharp decrease, leading to inferior visual perception.

2.3.1 Weighted local energy

In which the local information, the nonlocal information, and the class information are all used sufficiently. For WLE, we make use of the local information and the nonlocal information distinctively according to their different effects. We highlight some advantages of WLE algorithm as follows:

1. WLE is a supervised learning method, which leads to its better classification ability than unsupervised learning method like PCA and LPP.

2. By manifold learning theory, we know that the local information is more important than the nonlocal information in discovering the underlying manifold structure of the dataset. WLE treats the local information and the nonlocal information differently, so it has better performance than LDA that treats these two kinds of information equally.

3. WLE considers the nonlocal information and the local information simultaneously. So it has better discriminative power than the methods which only use the local information like LDE.

2.3.2 Weighted sum of eight-neighborhood-based modified laplacian (WSEML)

Medical image fusion encompasses a broad range of general image fusion techniques to integrate complementary information from different modalities of medical images. It offers a great diversity of image features for medical analysis, and often leads to the robust medical diagnosis. The additional information acquired from the integrated images can be well utilized to precisely discover the position of lesion.

Due to the high requirements of multi-modality medical image fusion, a number of fusion techniques has been developed in the last few years. Generally, image fusion techniques can be categorized into two classes, such as spatial and transform domain methods.

2.4 NSST Reconstruction

we have implemented the more flexible decomposition with 2n directional sub bands at each scale using NSST to obtain the prominent sparser representation for MR images. In addition, the mixed L1-L2 norm of the coefficients from the prior component and residual component is used to enforce joint sparsity. Numerical experiments demonstrate that the proposed method can significantly increase signal sparsity and improve the ill-conditioning of MR imaging system using NSST sparsity regularization. The evaluations on a T2-weighted brain image and a MR phantom experiment demonstrate superior performance of the proposed method in terms of reconstruction error reduction, detail preservation and aliasing, Gibbs ringing artifacts suppression compared to state-of-the-art technique. Its performance in objective evaluation indices outperforms conventional CS-MRI methods prominently.

RESULT AND DISCUSSION

To verify the effectiveness of the proposed method, pairs of multimodal medical images is used. To quantitatively assess the performances of different methods, five widely recognized objective fusion metrics are applied in our experiments.

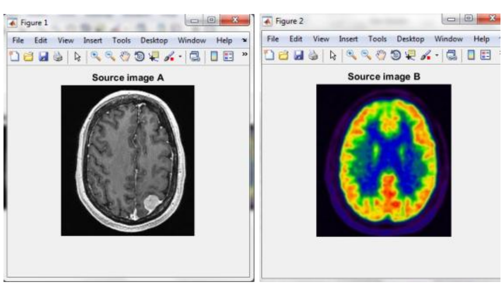

Fig-1 Source images

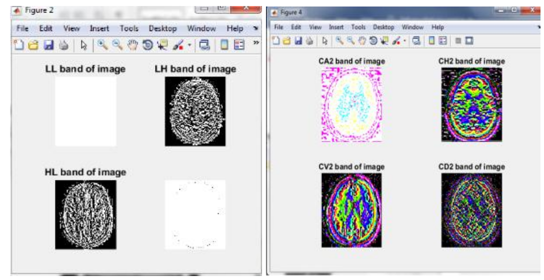

Fig-2 NSST images

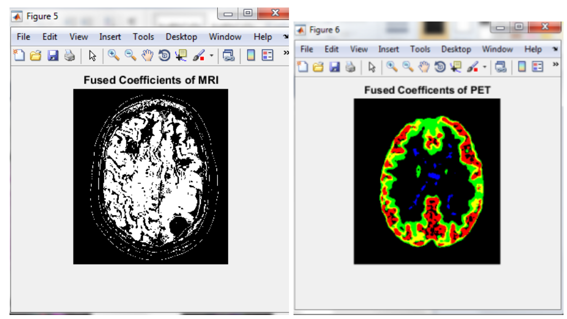

Fig-3 Fused coefficients

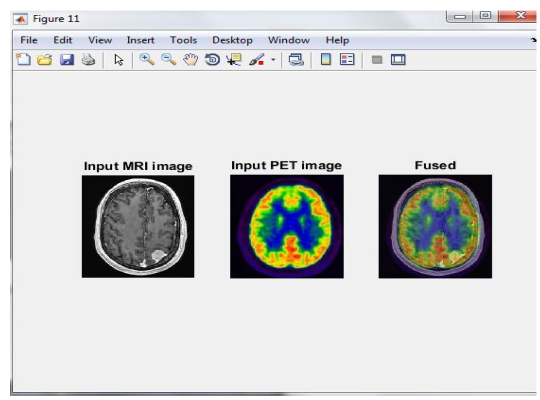

Fig-4 Output image

CONCLUSION

In this paper, another clinical picture combination strategy in the NSST space is introduced. The primary curiosity of the proposed strategy is twofold. For a certain something, we bring a PA-PCNN model into the combination of high-recurrence coefficients. All the free boundaries in the PCNN model can be adaptively determined by the information band and the model has a quick assembly speed. For another, we propose a lowfrequency combination technique that all the while addresses two vital issues in clinical picture combination, specifically, vitality safeguarding and detail extraction. Two new action level estimates dependent on nearby vitality and ML are intended to accomplish this objective. Broad examinations are directed utilizing sets of source pictures more than four classifications of clinical picture combination issues to check the viability of the proposed technique. Nine agent combination strategies are utilized for examination and the outcomes exhibit that the proposed technique can accomplish best in class execution as far as both the visual discernment and target evaluation.

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