FUSION OF MULTIMODALITY MEDICAL IMAGES BASED ON MULTISCALE DECOMPOSITION USING CONTOURLET TRANSFORM

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ABSTRACT

In this paper, we propose a novel multimodality Medical Image Fusion (MIF) method based on improved Contourlet Transform (CNT) for spatially registered, multi-sensor, multi-resolution medical images. The major drawback of the contourlet construction is that its basis images are not localized in the frequency domain. In this paper we propose a new contourlet construction as a solution. The source medical images are first decomposed by improved CNT. Instead of using the laplacian pyramid in contourlet transform, we employ a new multiscale decomposition defined in the frequency domain. So that the resulting basis images are sharply localized in the frequency domain and exhibit smoothness along their main ridges in the spatial domain. The low-frequency subbands (LFSs) are fused using the novel combined Activity Level Measurement and the high-frequency subbands (HFSs) are fused according to their 'local average energy' of the neighborhood of coefficients. Then inverse contourlet transform (ICNT) is applied to the fused coefficients to get the fused image. The performance, experimental results or comparison of the proposed scheme is evaluated by various quantitative measures like Mutual Information, Spatial Frequency and Entropy etc. The purpose of this paper is to replace the pyramid decomposition with multiscale decomposition to make image much smoother and to increase the efficiency of the fusion method and quality in the Image.

***Keywords**: Image Fusion, Contourlet Transform, Multiscale decomposition, Mutual Information.*

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I. INTRODUCTION

Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. Image fusion is a technique used to integrate a high-resolution panchromatic image with low-resolution multispectral image to produce a high-resolution multispectral image, which contains both the high-resolution spatial information of the panchromatic image and the color information of the multispectral image [1]. Although an increasing number of high-resolution images are available along with sensor technology development, image fusion is still a popular and important method to interpret the image data for obtaining a more suitable image for a variety of applications, such as visual interpretation and digital classification [2]. The main objective of medical imaging is to obtain a high resolution image with as much details as possible for the sake of diagnosis [3].

Image fusion can be broadly defined as the process of combining multiple input images or some of their features into a single image without the introduction of distortion or loss of information. The aim of image fusion is to integrate complementary as well as redundant information from multiple images to create a fused output image. Therefore, the new image generated should contain a more accurate description of the scene than any of the individual source image and is more suitable for human visual and machine perception or further image processing and analysis tasks. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. But the standard image fusion techniques can distort the spectral information of the multispectral data, while merging. The so-called image fusion is that all different sensors at the same time or by the same sensor at different time, is organically synthesized. The image description of the scene is more accuracy, more comprehensive and more reliable than any single image.

Along with the development of the medical image technology, medical image fusion becomes increasingly important in medical analysis and diagnosis. Different medical imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and single photon emission computed tomography (SPET) provide different perspectives and information on the human body ,which are important in the diagnosis of diseases or physical disorders. For example, functional image has relative low spatial resolution, but it provides functional information about visceral metabolism and blood circulation; while anatomical image contains high spatial resolution that provide information about visceral anatomy such as CT, MRI. Multi-modality medical image fusion is to combine complementary medical image information of various modals into one image, so as to provide far more comprehensive information and improves reliability of clinical diagnosis and therapy [4-6].

Image fusion has three levels: pixel-level, feature-level and symbol-level respectively. Image fusion at pixel-level means fusion at the lowest processing level referring to the merging of the measured physical parameters and its application is very wide. Pixel-level fusion is divided into two parts, signal-level and image-point fusion. Signal-level_fusion refers to synthesize a group of signals offered by sensors. The purpose is to obtain high-quality signals, which format is consistent with the original. Image points of every image are directly synthesized in the process of image-point fusion. Pixel-level fusion is operated in the phase of image pre-processing. The purpose is to obtain a further clear image, which is involved in more information. Pixel-level fusion is a low level fusion. Before fusing images, image registration of original images must be done. Because the imaging mechanisms of different from different time, different views of angle and different circumstance, the gray values and features of different images are inconsistent. So the original images must be registered at first. Image registration is the process of matching two or more three images that get from the same scene derived from different time, different sensors or different views of angle. Feature-level fusion is done in the course of image feature extraction. It's the medium level fusion and prepared for decision-level fusion. In the process of feature-level fusion, features of every image are extracted. The typical features are edge, shape, profile, angle, texture, similar lighting area and similar depth of focus area. Decision-level fusion is the highest-level fusion. All decision and control are decided according to the results of decision-level fusion. Medical image fusion is a research focus in the academic circles. With the development of modern medical imaging technology, more and more medical image used in clinical practice [7] [8].

Nowadays, with the rapid development in high-technology and modern instrumentations, medical imaging has become a vital component of a large number of applications, including diagnosis, research, and treatment. In order to support more accurate clinical information for physicians to deal with medical diagnosis and evaluation, multimodality medical images are needed, such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), and positron emission tomography (PET) images. These multimodality medical images usually provide complementary and occasionally conflicting information. For example, the CT image can provide dense structures like bones and implants with less distortion, but it cannot detect physiological changes, while the MRI image can provide normal and pathological soft tissues information, but it cannot support the bones information. In this case, only one kind of image may not be sufficient to provide accurate clinical requirements for the physicians. Therefore, the fusion of the multimodal medical images is necessary and it has become a promising. For medical image fusion, the fusion of images can often lead to additional clinical information not apparent in the separate images. Another advantage is that it can reduce the storage cost by storing just the single fused image instead of multisource images. For instance, structural images like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasonography (USG), Magnetic Resonance Angiography (MRA) etc. provide high-resolution images with anatomical information. On the other hand, functional images such as Position Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) and functional MRI (fMRI) etc. provide low-spatial resolution images with functional information. A single modality of medical image cannot provide comprehensive and accurate information. As a result, combining anatomical and functional medical images to provide much more useful information through image fusion (IF), has become the focus of imaging research [9]. In recent years, Computed tomography (CT) as a medical imaging method is widely used for diagnostic purposes. It is a method of body imaging in which a thin x-ray beam rotates around the patient. Small detectors measure the amount of x-rays that make it through the patient or particular area of interest. A computer analyzes the data to construct a cross-sectional image. These images can be stored, viewed on a monitor, or printed on film. In addition, three-dimensional models of organs can be created by stacking the individual images, or "slices". Due to its ability to provide clear images of bone, muscle, and blood vessels, CT imaging is a valuable tool for the diagnosis and treatment of musculoskeletal disorders and injuries. It is often used to measure bone mineral density and to detect injuries to internal organs. CT imaging is even used for the diagnosis and treatment of certain vascular diseases that, undetected and untreated.

It has been found, that the pixel-level spatial domain IF methods usually leads to contrast reduction. Methods based on Intensity-Hue-Saturation (IHS), Principal Component Analysis (PCA), and the Brovey Transform offers better results, but suffers from spectral degradation.[10] [11].

Methods of image fusion:

Spatial Fusion:

a. Average method: The simplest way of image fusion is to take the average of the two images pixel by pixel. However, this method usually leads to undesirable side effect such as reduced contrast .More robust algorithm for pixel level fusion is the weighted average approach. In this method, the fused pixel is estimated as the weighted average of the corresponding input pixels. However, the weight estimation usually requires a user-specific threshold.

b. Intensity-hue-saturation (IHS), principal component analysis (PCA), and the Brovey transform: These techniques are easy to understand and implement. However, although the fused images obtained by these methods have high spatial quality, they usually suffer from spectral degradation; that is, they can yield high spatial resolution-fused image, but they overlook the high quality of spectral information which is especially crucial for remote sensing image fusion .

c. Artificial neural network (ANN) : The performance of ANN depends on the sample images and this is not an appealing characteristic.

Transform domain fusion:

The multi resolution techniques involve two kinds, one is pyramid transform; another is wavelet transform.

a. Pyramid Method**:** In this, the input images are first transformed into their multi resolution pyramid representations. The fusion process then creates a new fused pyramid from the input image pyramids in a certain fusion rule. The fused image is finally reconstructed by performing an inverse multi resolution transform .However, for the reason of the pyramid method fails to introduce any spatial orientation selectivity in the decomposition process, this method often cause blocking effects in the fusion results.

b. Wavelet based method : which usually used the discrete wavelet transform (DWT) in the fusion. Since the DWT of image signals produces a non redundant image representation, it can provide better spatial and spectral localization of image information as compared to other multi resolution representations. The research results reveal that DWT schemes have some advantages over pyramid schemes such as increased directional information, no blocking artifacts that often occur in pyramid fused images; better signal-to-noise ratios Therefore, the wavelet-based method has been popular widely used for image fusion. Although there are considerable wavelet-based fusion works today, most of them concerned on remote images, multi focus images, and infrared images, while less work has been done for medical images.

II. CONTOURLET TRANSFORM

The major drawback of DWT in two dimensions is their limited ability in capturing directional information. In light of this, Do and Vetterli [12] developed the CNT, based on an efficient two-dimensional multiscale and directional filter bank (DBF). CNT not only possess the main features of DWT, but also offer a high degree of directionality and anisotropy. It allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, CNT uses iterated filter banks, which makes it computationally efficient (O(N) operations for an N-pixels image) [12]. CNT gives a multiresolution, local and directional expansion of image using Pyramidal Directional Filter Bank (PDFB). The PDFB combines Laplacian Pyramid (LP) which captures the point discontinuities, with a DFB which links these discontinuities into linear structures.

A Theory called Multi-scale Geometric Analysis (MGA) for high-dimensional signals has been developed and several MGA tools were proposed like Ridgelet, Curvelet, Contourlet and Ripplet etc. These MGA tools do not suffer from the problems of wavelet that is WT based fusion scheme can preserve spectral information efficiently but can not express the spatial characterstics and salient features of source images efficiently and will probably introduce some artifacts and inconsistency in fused results. Few MIF methods based on these MGA tools were also proposed to improve the fusion result [13] [14]. CNT is based on efficient two dimensional multiscale and directional filter bank (DFB). CNT is capable of resolving two dimensional singularities and representing image edges more efficiently, which makes fused images clearer and more informative. The performance, experimental results or comparison of the proposed scheme is evaluated by various quantitative measures like:

a. Mutual Information: It measures the degree of dependence of the two images. A larger measure implies better quality.
b. Spatial Frequency: It can be used to measure the overall activity and clarity level of an image. Larger SF value denotes better fusion results.
c. Entropy: The entropy of an image is a measure of information content. It is the average number of bits needed to quantize the intensities in the image. An image with high information content would have high entropy. If entropy of fused image is higher than parent images then it indicates that the fused image contains more information.
d. Standard Deviation: It measures the contrast in the fused image. An image with high contrast would have a high standard deviation.

II.1 Algorithm:

The medical images to be fused must be registered to assure that the corresponding pixels are aligned. The following steps take place in the proposed MIF method:

A. Decompose the registered source medical images A and B by CNT to get the LFSs and HFSs.

B. Fused the coefficients of LFSs using the Combined Activity Level Measurement (ALM) by estimating each coefficient contribution to the fused image to get fused LFS.

C. Similarly to get fused HFSs, fused the coefficients of HESs of images A and B according to their 'Local Average Energy' of the neighborhood of the coefficient under consideration.

D. Apply inverse contourlet transform on the fused LFSs and HFSs to get the final fused medical image.

III. IMPROVED CONTOURLET TRANSFORM (CNT BASED ON MULTISCALE DECOMPOSITION)

The major drawback of the contourlet construction is that its basis images are not localized in the frequency domain and there is less regularity in the spatial domain. In the current , we analyze the cause of this problem, and propose a new contourlet construction as a solution. Instead of using the Laplacian pyramid, we employ a new multiscale decomposition defined in the frequency domain. The resulting basis images are sharply localized in the frequency domain and exhibit smoothness along their main ridges in the spatial domain.

III.1 Methodology:

This forms a multiresolution directional tight frame designed to efficiently approximate images made of smooth regions separated by smooth boundaries. The Contourlet transform has a fast implementation based on a Laplacian Pyramid decomposition followed by directional filterbanks applied on each bandpass subband. Medical Image Fusion (MIF) method, based on a novel combined Activity Level Measurement (ALM) and Contourlet Transform (CNT) for spatially registered, multi-sensor, multiresolution medical images. The source medical images are first decomposed by CNT. The low-frequency subbands (LFSs) are fused using the novel combined ALM, and the high-frequency subbands (HFSs) are fused according to their 'local average energy' of the neighborhood of coefficients. Then inverse contourlet transform (ICNT) is applied to the fused coefficients to get the fused image.However Laplacian Pyramid decomposition can be removed with the help of multiscale sharp frequency localization.

III.2 Algorithm:

The medical images to be fused must be registered to assure that the corresponding pixels are aligned. Here we outline the salient steps of the proposed Method which exclude the Laplacian Pyramid decomposition:

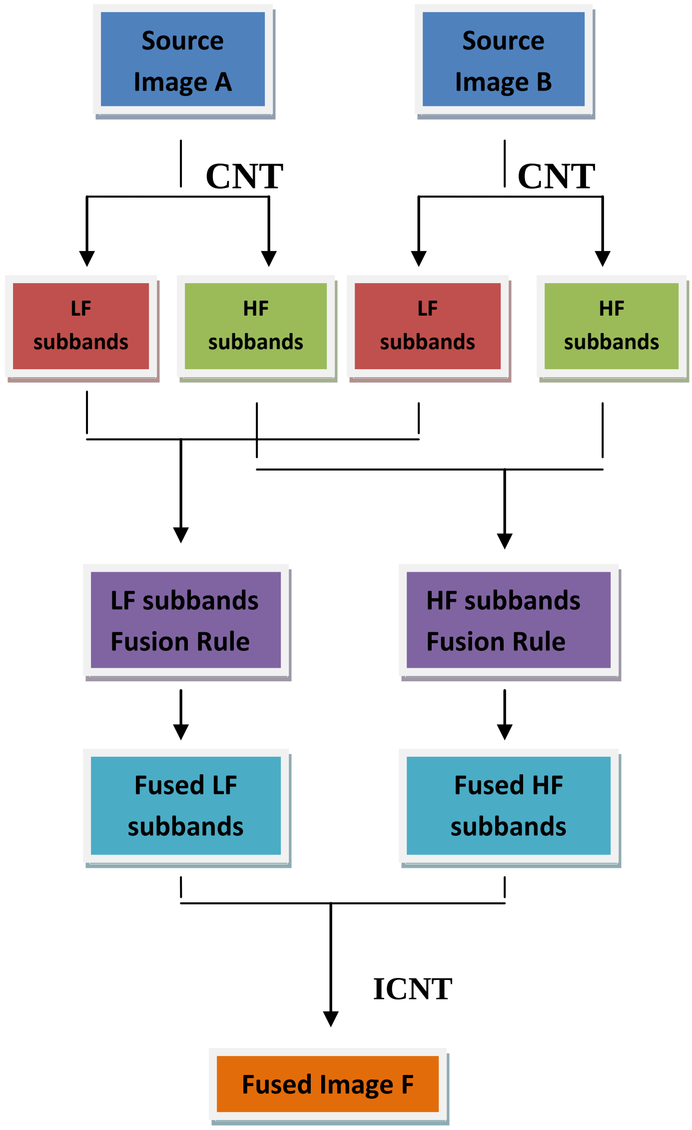
1) Decompose the registered source medical images A and B by multiscale decomposition so that images are sharply localized in the frequency domain and exhibit smoothness along their main ridges in the spatial domain.

2) Fused the coefficients of LFSs using the combined ALM to get the fused LFS.

3) Similarly to get the fused HFSs, fused the HFSs of the images A and B, using fusion rule described in

4) Apply inverse contourlet transform on the fused LFS and HFSs to get the final fused medical image.

The block diagram of the proposed MIF scheme is shown :



IV. CONCLUSION

We propose a novel multimodality MIF method based on improved contourlet transform (multiscale decomposition) using a new combined ALM based fusion rule. The major drawback of the contourlet construction is that its basis images are not localized in the frequency domain and less regularity in the spatial domain. In the current , we analyze the cause of this problem, and propose a new contourlet construction as a solution. Instead of using the Laplacian pyramid, we employ a new multiscale decomposition defined in the frequency domain. The resulting basis images are sharply localized in the frequency domain and exhibit smoothness along their main ridges in the spatial domain. The improved CNT is capable of resolving two dimensional singularities and representing image edges more efficiently, which makes the fused images clearer and more informative.

V. REFERENCES

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