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An Extensive Study on the Multimodal Medical Image Fusion Techniques

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ABSTRACT
Medical image fusion is the method of registering and combining multiple images from single or multiple imaging modalities. Multimodal medical image fusion has become a powerful tool for medical diagnoses. In order to obtain a more absolute and more consistent medical image, this paper presents a novel approach for multimodal medical image fusion using an improved pulse-coupled neural network (IPCNN) in non sub sampled contour let transform (NSCT) domain. First, the image is stale into sub-bands with different scales and different directions by NSP and NSDFB. Next, local area singular value is introduced to determine the structural information factor which will be the linking strength parameter of PCNN. Finally, inverse NSCT is build for fused images. Using the ‘max selection’ rule low frequency sub bands (LFSs) are fused. A PCNN model is utilized for the fusion of high-frequency sub bands (HFSs). Modified Spatial Frequency (MSF) in DRT domain is input to motivate the PCNN and coefficients in DRT domain with large firing times are selected as coefficients of the fused image. Then inverse DRT (IDRT) is applied to the fused coefficients to get the fused image. On study of Multi-modal medical image fusion algorithms and devices, it improves clinical accuracy of decisions based on medical images. We characterize the medical image fusion research based on (1) the widely used image fusion methods, (2) imaging modalities and (3) imaging of organs that are under study. Our proposed algorithm in multimodal medical image fusion is proved to perform better in robustness and reliability over the existing methods, meeting the requirement of human vision.

Keywords:- Medical Image Fusion, Multimodal Image fusion, Principle Component analysis, MRI Images, PET Images, CT Images, PCNN, NSCT

I. INTRODUCTION

Medical image fusion is an important task to retrieve an image which provides as much as information of the same organ at the same times it also helps to reduce the storage capacity to a single image. For instance, X-ray and Computed Tomography (CT) are able to display the bones and other hard tissues structures according to the differences in density and thickness whereas MRI can display soft tissues like blood vessels. And Positron Emission Computed Tomography (PET) is able to show physiological and pathological contents of human organs [1]. In practical clinical applications, a single modality of image is often unable to provide sufficient information. Multimodal medical image fusion technique can combine several source images to provide more comprehensive and more reliable information aiming to assist clinicians to diagnose and treat diseases accurately [1]. It is also used to obtain a more complete and accurate description of the same object, which provides an easy access for image-guided medical diagnostic and treatment [2]. To fuse the image, primary step as image denoising methods has to be applied in order to smooth and obtain the details of the features in the image in detail.

In data integration approaches, data from different modalities are usually analyzed through separate pipelines and the results combined at the interpretation level to yield decision level fusion [3]. Therefore, the quality of image fusion highly depends on the performance of image feature extraction. The multivariate model using structure and sparse component on image fusion techniques to the multimodal medical image has been defined as proposed model. Through imposed sparsity, parsimonious multivariate methods increase the interpretability of the output and potentially improve the generalizability of the produced model.

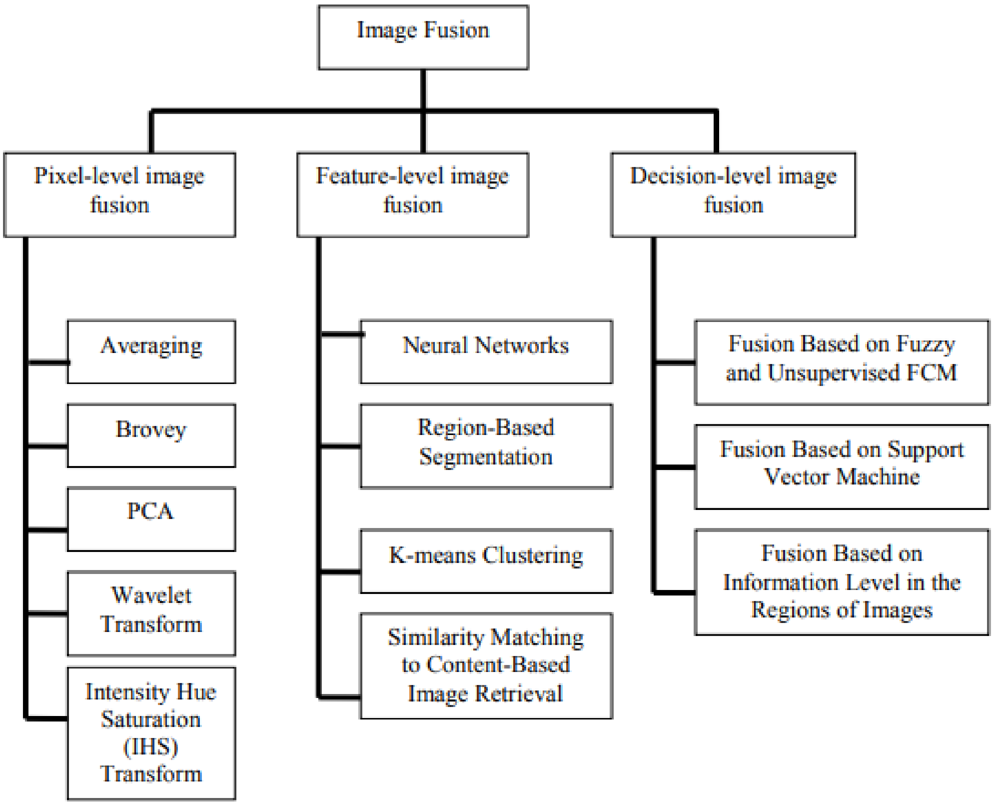
II. REVIEW OF LITERATURES

In this section, the Multimodal image fusion techniques under multimodality were examined in detail, the literatures as follows

We propose a novel feature space transform fusion method for multi-focus images with dense scale invariant feature transform (DSIFT). In our method, via the sliding window technique, the dense SIFT descriptor is first used to measure the activity level of source image patches to obtain an initial decision map, and then the decision map is refined with feature matching and local focus measure comparison. Thus, the proposed algorithm also has some distinct characteristics of spatial domain fusion methods. To the best of our knowledge, image local feature descriptors have not been directly applied to image fusion so far. The most significant contribution of this paper is it indicates that some image local features such as the dense SIFT can construct an effective feature space for image fusion. In particular, the local feature descriptors can not only be employed as the activity level measurement, but also be used to match the mis-registered pixels between multiple source images to improve the fused quality of both object motion regions and object edges. Experimental results on twelve pairs of multi-focus images demonstrate that the proposed fusion method can be competitive with or even outperform some state-of-the-art fusion methods in terms of both subjective visual perception and six objective assessment metrics.

Image fusion algorithms can be categorized into different levels: low, middle, and high; or pixel, feature, and symbolic levels. The pixel-level method works either in the spatial domain or in the transform domain. The prerequisite for such an operation is that the images have been acquired by homogeneous sensors, such that the images reproduce similar or comparable physical properties of the scene. The fusion methods, such as averaging, the Brovey method, principle component analysis (PCA), and IHS based methods fall under the spatial domain approaches. The feature-level algorithms typically segment the image into contiguous regions and fuse the regions together using their properties. The features used may be calculated separately from each image or they may be obtained by the simultaneous processing of all the images. Paellas proposed several activity level measures including the absolute value, the median, or the contrast to neighbors measures (Piella, 2003). Finally, she proposed a region-based scheme using a local correlation measurement to perform the fusion of each region (Piella, 2003). Decision-level fusion algorithms combine image descriptions to the fused image, such as in the form of a relational graph (Shapiro, 1982) and (Williams et al., 1999). This is a description of fusion by decision, such as when the classification results are obtained from single images. In this fusion method, inhomogeneous sensors may be used, which allows the generation of decisions that are compatible on a decision level (Beyerer, 2008).

A portion of the image fusion research from recent years. The theory of image fusion has advanced quickly in the past few years. Currently, image fusion approaches with considerable complexity have been proposed. As previously stated, the fused image usually contains more information about the target or scene than any of the individual images used in the fusion process. The images used for fusion can be taken from multi-modal imaging sensors or from the same imaging sensor at different times. The target or scene in the images can be exactly the same or partially the same, for example, some objects and labels may have disappeared or new objects may be added to the images. Our topic, image fusion, has been investigated by many research groups and a number of algorithms have previously been developed (Scheunders et al., 2001), (Chan et al., 2003), (Rajan et al., 2002), and (Zhang et al., 1999). Although each algorithm has shown promising aspects, there seems to be a lack of universal criteria to measure the quality of the fusion algorithms. In many cases, qualitative criteria, such as visual analysis, are used to assess the resulting fused images.



Fusion using Principle Component Analysis (PCA):

The PCA image fusion method simply uses the pixel values of all source images at each pixel location, adds a weight factor to each pixel value, and takes an average of the weighted pixel values to produce the result for the fused image at the same pixel location. The optimal weighted factors are determined by the PCA technique. The PCA technique is useful for image encoding, image data compression, image enhancement, pattern recognition (especially for object detection), and image fusion. It is a statistical technique that transforms a multivariate data set of inter-correlated variable into a data set of new uncorrelated linear combinations of the original variables. It generates a new set of axes which is orthogonal. By using this method, the redundancy of the image data can be decreased. (Pohl et al., 1998)

Fusion using Laplacian pyramid method: The IHS fusion converts a color MS image from the RGB space into the IHS color space. Because the intensity (I) band resembles a panchromatic (PAN) image, it is replaced by a high-resolution PAN image in the fusion. A reverse IHS transform is then performed on the PAN, together with the hue (H) and saturation (S) bands, resulting in an IHS fused image. (Aiazzi et al., 2003)

Fusion using Laplacian pyramid method: The Laplacian pyramid fusion consists of an iterative process of calculating the Gaussian and Laplacian pyramids of each source image, fusing the Laplacian images at each pyramid level by selecting the pixel with the larger absolute value, combining the fused Laplacian pyramid with the combined pyramid expanded from the lower level, and then expanding the combined pyramids to the upper level. The fusing step above can also be done using a PCA-based weighted averaging technique. (Zeng et al., 2006)

Fusion using gradient pyramid method: A gradient pyramid is obtained by applying a set of 4 directional gradient filters (horizontal, vertical, and 2 diagonal) to the Gaussian pyramid at each level. At each level, these 4 directional gradient pyramids are combined together to obtain a combined gradient pyramid that is similar to a Laplacian pyramid. The gradient pyramid fusion is therefore the same as the fusion using the Laplacian pyramid method except replacing the Laplacian pyramid with the combined gradient pyramid. (Zeng et al., 2006) and (Smith et al., 2005)

Fusion using filter-subtract-decimate (FSD) pyramid method: The FSD pyramid fusion method is conceptually identical to the Laplacian pyramid fusion method. The only difference is in the step of obtaining the difference images in creating the pyramid. In a Laplacian pyramid, the difference image Lk at level k is obtained by subtracting an image up-sampled and then low-pass filtered from level k+1 from the Gaussian image Gk at level k, while in the FSD pyramid, this difference image is obtained directly from the Gaussian image Gk at level k subtracted by the low pass filtered image of Gk. It is therefore obvious that the FSD pyramid fusion method is computationally more efficient than the Laplacian pyramid method by skipping an up-sampling step. (Zeng et al., 2006).

1.1. Multimodal Sensor Medical Image Fusion Based on type-2 fuzzy logic in NSCT Domain

In this literature, Noises and artifacts are introduced to medical images due to acquisition techniques and systems. This interference leads to low contrast and distortion in images, which not only impacts the effectiveness of the medical image but also seriously affects the clinical diagnoses. This defined algorithm in this model used for medical image enhancement based on the non-subsampled contoured transform (NSCT), which combines adaptive threshold and an improved fuzzy set. First, the original image is decomposed into the NSCT domain with a low-frequency sub-band and several high-frequency sub bands. Then, a linear transformation is adopted for the coefficients of the low-frequency component. An adaptive threshold method is used for the removal of high-frequency image noise. Finally, the improved fuzzy set is used to enhance the global contrast and the Laplace operator is used to enhance the details of the medical images. Experiments and simulation results show that the defined method is superior to other methods of image noise removal, improves the contrast of the image significantly, and obtains a better visual effect [4].

1.2. Local Energy Based Multi-modal Medical image fusion in curveletdomain

In this literature , various multimodal medical images like computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography, single photon emission CT and structural MRI have different characteristics and carry different types of complementary anatomical and functional information. Therefore, fusion of multimodal images is required, in order to achieve good spatial resolution images carrying both anatomical and functional information. In this work, the authors have proposed a fusion technique based on curvelet transform. Curvelet transform is a multi-scale, multidirectional transform having anisotropic property and is very efficient in capturing edge points in images. Edges in an image are the important information carrying points used to show better visual structure of the image. They use local energy-based fusion rule which is more effective than single pixel-based fusion rules. Comparison of the proposed method with other existing spatial and wavelet transform based methods, in terms of visual and quantitative measures show the effectiveness of the proposed method. For quantitative analysis of the method, they used five fusion metrics as entropy, standard deviation, edge-strength, sharpness and average gradient [5].

1.3. A Novel Method of multimodal medical image fusion using fuzzy transform

In this literature, combined analysis of medical images obtained from multiple imaging modalities is extensively used by clinical professionals for quick diagnosis and treatment of critical diseases. Therefore, multimodal medical image fusion, that fuses information from different medical images into a single fused image, has gained potential interest of researchers in recent years. A multimodal medical image fusion method using fuzzy transform is proposed. FTR based fusion helps in preservation as well as effective transfer of detailed information present in input images into a fused image. Combination of entropy and select maxima based rule is used to perform fusion. To evaluate and prove better performance of the proposed fusion method, a number of experiments and comparisons with other existing methods of fusion have been carried out in this literature. Experimental results and comparative analysis prove that the proposed fusion algorithm is effective and generates better results. Fused image obtained using proposed method facilitates quick diagnosis and better treatment of diseases [6].

1.4. Union Laplacian pyramid with multiple features for medical image fusion

In this literature, 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 [7].

1.5. Medical image fusion using discrete fractional wavelet transform

In this literature, a multimodal medical image fusion method based on discrete fractional wavelet (DFRWT) is presented. With a change in *p* order in domain (0, 1] source medical images are decomposed by DFRWT in different *p* order. The sparsity character of the mode coefficients in sub-band images changes. According to the method, to enhance the correlation between sub-band coefficients, the nonsparsity character of the mode coefficients in low *p* order should be utilized. The coefficients of the all sub-bands are fused using the weighted regional variance rule. Finally, inverse DFRWT is applied to obtain a fused image. Subjective and objective analyses of the results and comparisons with other multi-resolution domain techniques show the effectiveness of the proposed scheme in fusing multimodal medical images [8].

1.6. Fusion of multimodal medical images using Daubechies complex wavelet transform

In this literature, Multimodal medical image fusion is an important task for the retrieval of complementary information from medical images. Shift sensitivity, lack of phase information and poor directionality of real valued wavelet transforms motivated us to use complex wavelet transform for fusion. Author has used Daubechies complex wavelet transform (DCxWT) for image fusion which is approximately shifting invariant and provides phase information. In the current work, multimodal medical image fusion using DCxWT at multiple levels which is based on multi-resolution principle has been considered. The method fuses the complex wavelet coefficients of source images using maximum selection rule. Experiments have been performed over three different sets of multimodal medical images. The proposed fusion method is visually and quantitatively compared with wavelet domain (Dual tree complex wavelet transform (DTCWT), Lifting wavelet transform (LWT), Multi-wavelet transform (MWT), Stationary wavelet transform (SWT)) and spatial domain (Principal component analysis (PCA), linear and sharp) image fusion methods. The method is further compared with Contour let transform (CT) and Non-subsampled contour let transform (NSCT) based image fusion methods. For comparison of the current method, five fusion metrics used namely entropy, edge strength, standard deviation, and fusion factor and fusion symmetry. Comparison results prove that performance of the proposed fusion method is better than any of the above existing fusion methods. Robustness of the proposed method is tested against Gaussian, salt & pepper and speckle noise and the plots of fusion metrics for different noise cases established the superiority of the proposed fusion method [9].

1.7. Multimodality medical image fusion algorithm based on gradient minimization smoothing filter and pulse coupled neural network

In this literature, multimodality medical image fusion algorithm which involves L_0 gradient minimization smoothing filter (GMSF) and pulse coupled neural network (PCNN) has been analyzed in depth. Firstly, an excellent multi-scale edge-preserving decomposition framework based on GMSF is proposed to decompose each source image into one base image and a series of detail images. For extracting and preserving more salient features and detail information, different fusion rules are designed to fuse the separated sub images. The base images are fused using the regional weighted sum of pixel energy and gradient energy, and a biologically inspired feedback neural network is used to fuse the detail images. The final fused image is obtained by synthesizing the fused base image and detail images. Experimental results on several datasets of CT and MRI images show that the current algorithm outperforms other compared methods in terms of both subjective and objective assessment [10].

1.8. A new contrast based multimodal medical image fusion framework

In this literature, Medical image fusion plays an important role in clinical applications such as image-guided surgery, image-guided radiotherapy, noninvasive diagnosis, and treatment planning has been considered. The main motivation is to fuse different multimodal information into a single output. In this instance, framework for spatially registered multimodal medical image fusion has been considered, which is primarily based on the non-subsampled contourlet transform (NSCT). The proposed method enables the decomposition of source medical images into low- and high-frequency bands in NSCT domain. Different fusion rules are then applied to the varied frequency bands of the transformed images. Fusion coefficients are achieved by the following fusion rule: low-frequency components are fused using an activity measure based on the normalized Shannon entropy, which essentially selects low-frequency components from the focused regions with high degree of clearness. In contrast, high-frequency components are fused using the directive contrast, which essentially collects all the informative textures from the source. Integrating these fusion rules, more spatial feature and functional information can be preserved and transferred into the fused images. The performance of the framework is illustrated using four groups of human brain and two clinical bone images from different sources as our experimental subjects. The experimental results and comparison with other methods show the superior performance of the framework in both subjective and objective assessment criteria [11].

1.9. Group-sparse representation with dictionary learning for medical image denoising and fusion

In this literature, recently, sparse representation has attracted a lot of interest in various areas. However, the standard sparse representation does not consider the intrinsic structure, i.e., the nonzero elements occur in clusters, called group sparsity. Furthermore, there is no dictionary learning method for group sparse representation considering the geometrical structure of space spanned by atoms. In this paper, l dictionary learning method, called Dictionary Learning with Group Sparsity and Graph Regularization (DL-GSGR) has been considered. First, the geometrical structure of atoms is modeled as the graph regularization. Then, combining group sparsity and graph regularization, the DL-GSGR is presented, which is solved by alternating the group sparse coding and dictionary updating. In this way, the group coherence of learned dictionary can be enforced small enough such that any signal can be group sparse coded effectively. Finally, group sparse representation with DL-GSGR is applied to 3-D medical image denoising and image fusion. Specifically, in 3-D medical image denoising, a 3-D processing mechanism (using the similarity among nearby slices) and temporal regularization (to perverse the correlations across nearby slices) are exploited. The experimental results on 3-D image denoising and image fusion demonstrate the superiority of our denoising and fusion approaches [12].

1.10. Image fusion with guided filtering

In this literature, a fast and effective image fusion method is analyzed for creating a highly informative fused image through merging multiple images. The current method is based on a two-scale decomposition of an image into a base layer containing large scale variations in intensity, and a detail layer capturing small scale details. A guided filtering-based weighted average technique is proposed to make full use of spatial consistency for fusion of the base and detail layers. Experimental results demonstrate that the current method can obtain state-of-the-art performance for fusion of multispectral, multifocal, multimodal and multiexposure images [13].

III. CONCLUSION AND FUTURE WORK

In this Study, we propose a multimodal medical image fusion algorithm using IPCNN based on local singular value decomposition in NSCT domain. NSCT is a kind of multidirectional and multi-scale analysis method, which is composed of NSP and NSDFB. Based on the classical PCNN model, the local structure information factor is constructed by using the local area singular value, which is used as the linking strength Parameter of PCNN. In the experimental part, we use two groups of MRI-CT, one group of MRI-SPECT, one group of MRI-PET to generate the image results. We have carried out extensive study and explained the Multimodal image Fusion Technique on the CT and MRI image to provide different characteristic of image to medical diagnosis and treatment. In this work, Noise elimination technique is discussed in detail using various filters and feature extraction methods also considered in large extent. Additionally image transformation principles have been discussed to generate the optimal resolution image. The Experimental analysis of techniques discussed provides a strong discrimination on the each technique in terms of performance and accuracy. In the general transformation methods how to extract the most significant features (wavelet coefficients in our case) in order to improve the spatial resolution becomes very difficult task. The future work fuses the detailed wavelet coefficients of input images using features selection algorithm.

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