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Medical Image Fusion

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ABSTRACT— 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. Here a new multimodal medical image fusion method in Non subsampled 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 multi-direction 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.

Keywords—MATLAB, PAPCNN, NSST

I. INTRODUCTION

Image fusion is an extensively discussed topic for improving the information content images. The main objective of image fusion algorithm is to combine information from multiple images of a scene.The result of image fusion is a new image which is more feasible for human and machine perception for further image processing operations such as segmentation, feature extraction and object recognition.

One popular approach to medical image fusion is using the Nonsubsampled Shearlet Transform (NSST)and the Pixelwise Adaptive CNN

(PAPCNN) algorithm. NSST is a multi-scale, multi- directional transform that has been proven effective in capturing the geometric and textural information present in medical images. It can represent image features at different scales and orientations, making it suitable for capturing fine details and edges.

The PAPCNN algorithm, on the other hand, is a deep learning-based technique that leverages Convolutional Neural Networks (CNNs) for pixel-level fusion. It learns the fusion weights and fusion rules directly from training data, allowing it to adaptively combine the information from different image sources based on their local characteristics. This enables the algorithm to effectively preserve relevant details and suppress noise or artifacts during the fusion process.

II. LITERATURESURVEY

In this paper[1] The objective of this project is a 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 crucialissuesin 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). 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.

In this paper[2] A new method for combining multimodal medical images using spatial frequency motivated parameter-adaptive PCNN (SF- PAPCNN) is suggested. The multi-modal images are disintegrated into frequency bands by using decomposition NSST. The coefficients of low frequency bands are selected using maximum rule. The coefficients of high frequency bands are combined by SF-PAPCNN. Later the fused medical images is obtained by applying INSST to above coefficients. The quality metrics such as entropy ENT, fusion symmetry FS, deviation STD, mutual information and edge strength are used to validate the efficacy of suggested scheme.

In this paper[3] A novel fusion method based on improved pulse-coupled neural networks (PCNN) model in non- subsampled shearlet transform (NSST) domain for whole body PET/CT images.

Firstly, source images are decomposed using NSST into one low-pass sub-band and several highpass sub-bands. Then, an improved PCNN is used in high pass sub-bands where energy of edge and average gradient are as external input and linking strength respectively. Maximum region energy (MRE) and maximum selection (MS) rules are as fusion rules for high- and low-pass sub-bands respectively. Finally, inverse NSST is adopted to produce fused result. An improved

PCNN model is used in high pass sub-bands where EOE and average gratitude are external input and linking strength. The maximum region energy and maximum selection rules are fusion rules for highand low-pass sub-bands respectively

In this paper[4] Multimodality medical image fusion plays a vital role in diagnosis, treatment planning, and follow-up studies of various diseases. It provides a composite image containing critical information of source images required for better localization and definition of different organs and lesions. In the state-of-the-art image fusion methods based on nonsubsampled shearlet transform(NSST)and pulse coupled neural network (PCNN), authors have used normalized coefficient value to motivate the PCNN-processing both low-frequency (LF) and high-frequency (HF) sub- bands. This makes the fused image blurred and decreases its contrast. The main objective of this work is to design an image fusion method that gives the fused image with better contrast, more detail information, and suitable for clinical use. We propose a novel image fusion method utilizing feature-motivated adaptive PCNN in NSST domain for fusion of anatomical images. The basic PCNN model is simplified, and adaptive-linking streng this used. Different features are used to motivate the PCNN-processing LF and HF sub-bands. The proposed method is extended for fusion of functional image with an anatomical image in improved nonlinear intensity hue and saturation (INIHS) color model. Extensive fusion experiments have been performed on CT-MRI and SPECT-MRI datasets. Visual and quantitative analysis of experimental results proved that the proposed method provides satisfactory fusion outcome compared to other image fusion methods.

III. PROBLEM STATEMENT

- The fusion speed and quality of visual enhancement are still not satisfactory and variation in complexity and robustness from the visual image information.
- To define the anatomical and physiological differences from one dataset to another.

IV. OBJECTIVE AND METHODOLOGY

A. OBJECTIVE

- To implement image fusion technique to analyze medical images to diagnose various diseases.

- To improve the imaging quality and redundancy in order to increase the clinical applicability of medical images for assessment of medical problems.

- Make images clearer and more detailed by merging data from imaging techniques.

B. METHODOLOGY

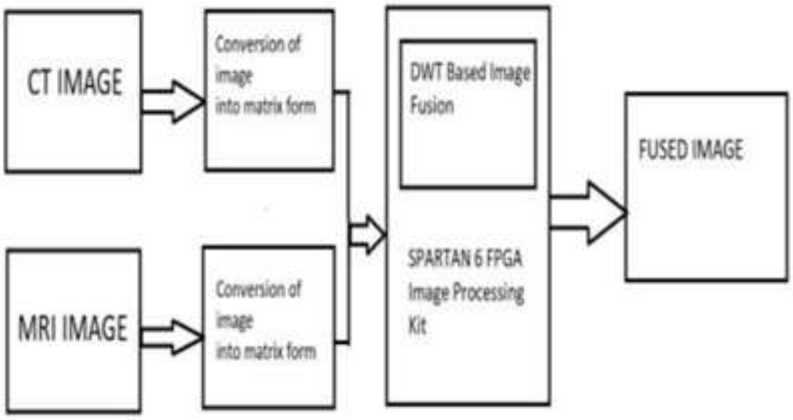

Fig4.2.1:Block diagram of Image Fusion Technique

STEP-1: Selection of CT and MRI images from the image datasets.
STEP-2: Conversion of input medical images into header files in MATLAB. In the process of image fusion technique, a MATLABGUI is built for conversion of images into header files. First the input image 1 i.e., CT scan image is pre-processed by MATLAB and converted into .h file. Then the input image 2i.e., MRI scan image is pre-processed by MATLAB and converted into .h file.
STEP-3: Classification of these images based on the High Frequency bands and low Frequency bands using NSST algorithm.
STEP-4: These classified images are then fused into Low Frequency and High frequency.
STEP5: Final Fused image is Obtained and compared in terms of Accuracy.
STEP-6: Calculation of parameters to see the improvement in content of fused image. The image contains several features which serve as characteristics that capture properties of the image.

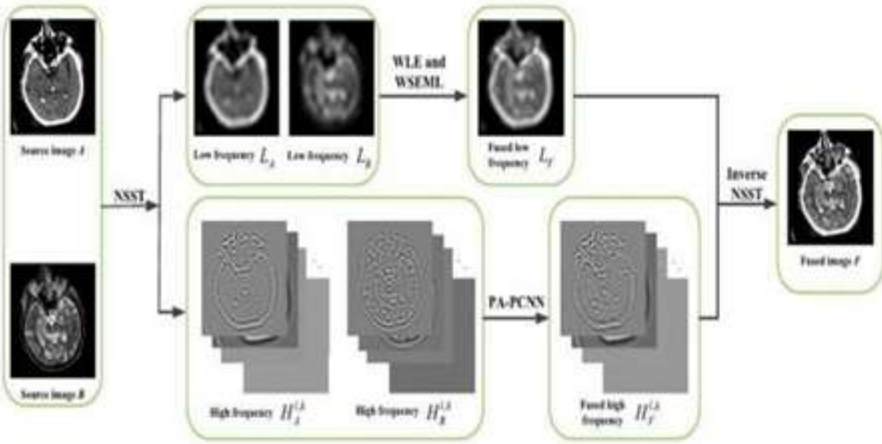

Fig 4.2.2: Schematic of the Medical Image Fusion Method

C. FLOWCHART

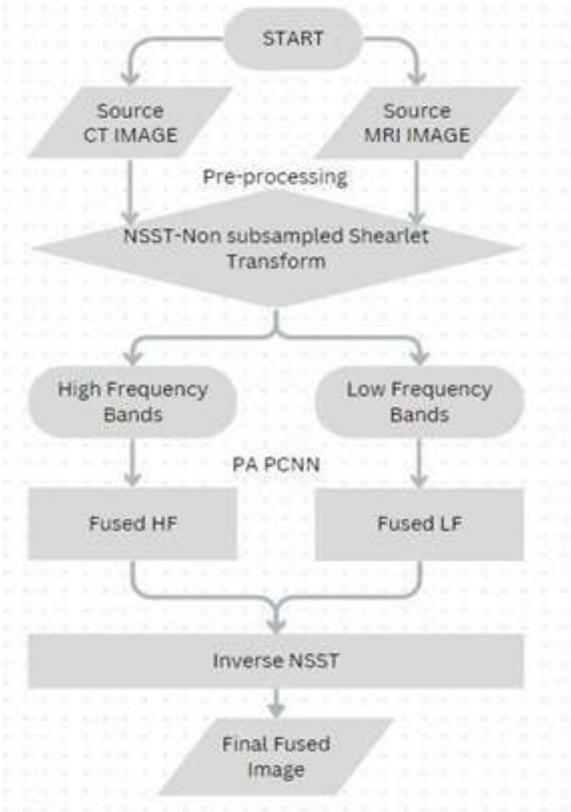

Fig 4.3: Flowchart of the NSST_PAPCNN Algorithm

D. ALGORITHM

NSST-PAPCNN Algorithm

The NSST-PAPCNN algorithm is a complex image denoising method that involves several steps. Here is a brief overview of how the program works:

Pre-processing: The input image is first pre-processed to remove any artifacts or noise that may interfere with the denoising process. This step involves applying a noise-reduction filter to the image.

Non-subsampled shearlet transform (NSST): The NSST is applied to the pre-processed image to extract multi-scale and multi-directional features. The NSST decomposes the image into different sub-bands, each containing features of different scales and orientations.

Patch-based adaptive principal component neural network (PAPCNN): The PAPCNN is a deep learning network that is used to denoise the image. The PAPCNN takes as input a set ofimage patches extracted from the NSST sub-bands and uses a principal component analysis (PCA) method to reduce their dimensionality. The resulting low-dimensional representations are then fed into a neural network for denoising.

Inverse NSST: The denoised patches are combined and then transformed back into the image domain using the inverse NSST.

Post-processing: Finally, the denoised image is post-processed to remove any remaining artifacts or noise.

V. SOFTWARE DESCRIPTION

MATLAB

Fig5.1:MATLAB

MATLAB is a programming platform used for numerical computing, data analysis, and visualization. It offers a high-level programming language, extensive mathematical functions, tools for data analysis and visualization, algorithm development, simulations, application development, and integration with other languages. It is widely used in engineering, science, and finance.

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MATLAB IN IMAGE PROCESSING

MATLAB is a widely used platform for image processing and analysis. It provides numerous functions and tool boxes specifically designed for working with images.

- Image Processing Toolbox: MATLAB's Image Processing Toolbox offers a comprehensive set of functions for image manipulation, enhancement, filtering, segmentation, and feature extraction. It allows for operations like image resizing, noise reduction, edge detection, morphological operations, and more.
- Image Visualization: MATLAB provides various functions for displaying and visualizing images. It supports image display, interactive exploration, and customization of visualizations, including the ability to create 2D and 3D plots, histograms, and color maps.
- Image Analysis: MATLAB enables advanced image analysis techniques such as image registration, image segmentation, and object detection. These functionalities assist in tasks like aligning images, extracting regions of interest, and identifying objects within an image.
- Machine Learning and Deep Learning: MATLAB offers machine learning and deep learning frameworks that can be applied to image analysis tasks. It includes pre-trained models, feature extraction techniques, and algorithms for tasks like image classification, object recognition, and semantic segmentation.
- Medical Imaging: MATLAB provides specialized toolboxes for medical image analysis, allowing for tasks such as image registration, image fusion, image reconstruction, and visualization of medical images like CT scans, MRI, and PET scans.

VI. RESULT

OUTPUT1

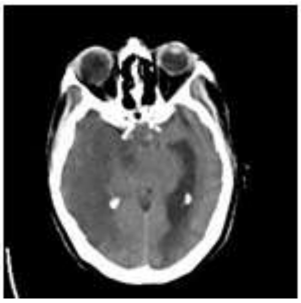

Fig 6.1:CT Image

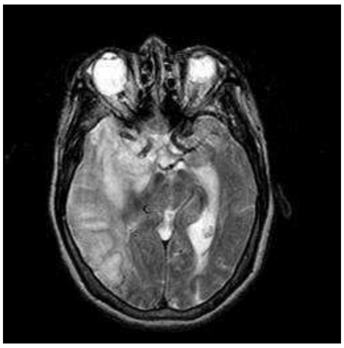

Fig 6.2:MRI Image

Fig 6.3:Fused Image

Clinical Diagnosis: The above fused image gives clinical information of a patient who suffered from acute stroke.