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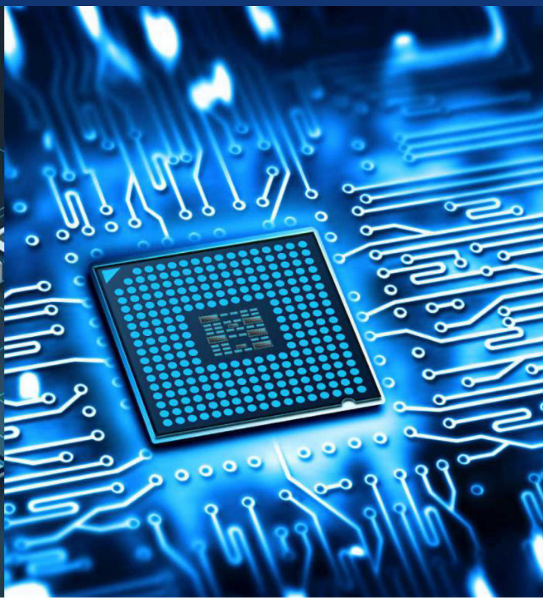

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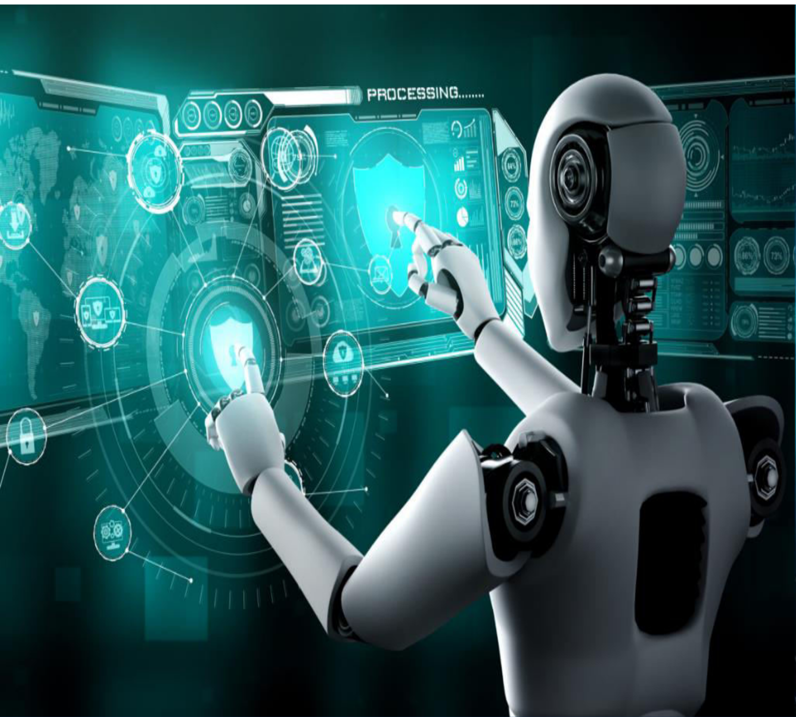

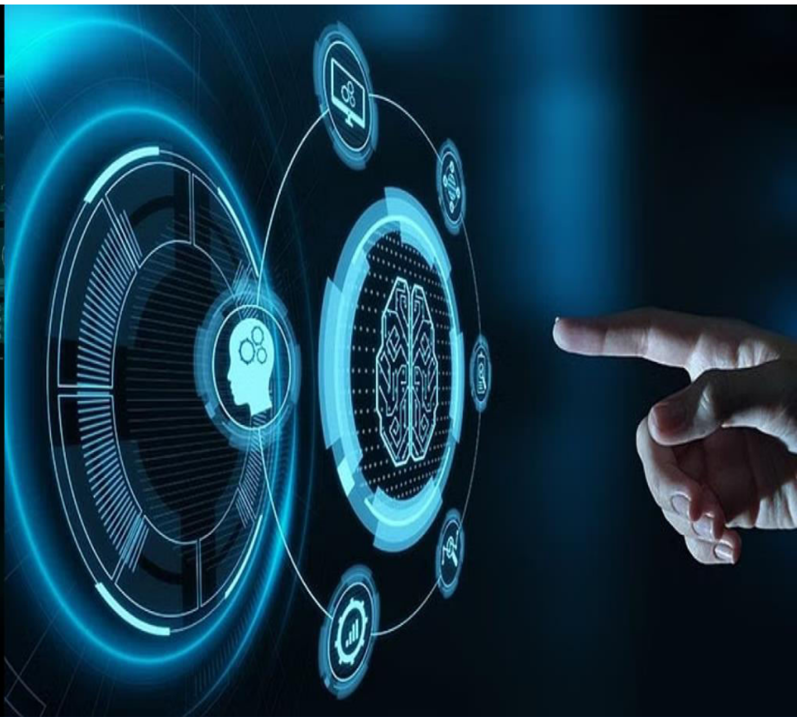

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Medical Image Fusion on Latent Low Rank Representation and Hesitant Fuzzy Granular Energy

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ABSTRACT: Multi-modal medical fused images encapsulate rich pathological tissue information, offering critical support for clinical decision-making and assisted diagnosis. However, prevailing medical image fusion methodologies exhibit deficiencies in concurrently enhancing visual fidelity and preserving intrinsic energy information of tissues. For this purpose, we construct a new fusion framework of MRI and PET joint latent low rank representation with truncated Huber filtering. Under the proposed framework, feature information, low frequency parts and high frequency parts can be obtained. To effectively detect energy information of tissues in medical images, we propose a hesitant fuzzy granular energy which imitates the cognitive ability of human beings with multiple levels and perspectives. And hesitant fuzzy granular energy with fast guide filter is constructed to fuse low frequency parts. Also, we propose the directional pseudo spatial frequency to detect fine size information on oblique directions of tissues. And directional pseudo spatial frequency with dual channel PCNN is employed for fusing high frequency parts and feature information. Experimental results display that the proposed fusion method has a superior performance in visual perception, and also has advantages in a variety of evaluation metrics, by comparing with 10 state-of-the-art methods.

KEYWORDS: Hesitant fuzzy set ·Latent low rank representation · Granular computing · Hesitant fuzzy granular energy · Medical image fusion

I. INTRODUCTION

Medical imaging technologies such as MRI, CT, PET, SPECT, and Ultrasound are widely used in hospitals for diagnosis and treatment planning. Each imaging modality provides different types of information. For example, MRI and CT provide anatomical structure information, while PET and SPECT provide functional and metabolic information. However, a single imaging modality cannot provide complete information about the disease. Therefore, multimodal medical image fusion is used to combine complementary information from different imaging modalities into a single fused image. This helps doctors make better clinical decisions and improves diagnosis accuracy.

Medical image fusion faces several challenges such as noise, resolution differences, and data inconsistency between different imaging modalities. To overcome these problems, different fusion methods such as multi-scale transform methods, deep learning methods, sparse representation methods, and filter-based methods have been developed. However, these methods still have limitations such as noise sensitivity, need for large datasets, and computational complexity. Therefore, this paper proposes a new fusion framework based on latent low rank representation and hesitant fuzzy granular energy to improve fusion performance.

II. RELATED WORK

Medical image fusion methods are generally classified into four main categories. Multi-Scale Transform (MST) methods decompose images into multiple scales and directions in order to extract structural and textural information, providing good fusion performance, but they are sensitive to noise. Deep Learning (DL) methods automatically learn features from medical images and produce high-quality fusion results; however, they require large training datasets and high computational power. Sparse Representation (SR) methods focus on removing redundant information while preserving important features, thereby improving efficiency and reducing memory usage. Filter-based methods preserve edges and structural information while reducing noise, but they may not perform well under complex image conditions. Although many medical image fusion methods have been developed, challenges such as noise, data inconsistency, and lack of interpretability still remain. Therefore, a new fusion framework is proposed in this paper to improve fusion quality and overall performance.

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III. METHODOLOGY

The proposed medical image fusion method is designed to effectively combine information from multiple medical imaging modalities such as MRI and PET to produce a more informative fused image. Initially, the source images are taken as input and processed using latent low rank representation (LatLRR), which decomposes the images into base components and feature components. This decomposition helps in separating important structural and detailed information from the original images. The base components are further processed using truncated Huber filtering, which divides them into low-frequency and high-frequency parts. The low-frequency components mainly contain intensity and brightness information, while the high-frequency components contain edge and texture details.

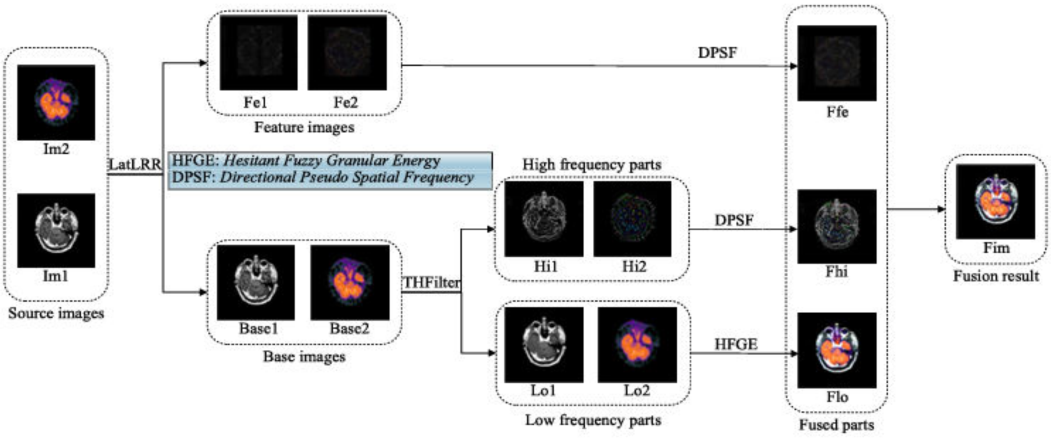

FIG 1:BLOCK DIAGRAM OF DECOMPOSING FRAMEWORK AND FUSION METHODS OF OUR WORK

For the fusion of low-frequency components, hesitant fuzzy granular energy (HFGE) combined with a fast guided filter is used. This approach helps in preserving the energy distribution and improves the clarity of the fused image. For high-frequency and feature components, directional pseudo spatial frequency (DPSF) along with a dual-channel pulse-coupled neural network (PCNN) is applied. This method effectively captures directional details and enhances edges, textures, and fine structures present in the images. The fusion rules are designed in such a way that important information from both input images is retained while reducing redundancy.

After fusing the low-frequency, high-frequency, and feature components separately, all the fused parts are combined to reconstruct the final fused image. The overall framework of this process is illustrated in Fig. 1, which shows the step-by-step flow from input images to the final fusion result. This methodology ensures better preservation of both anatomical and functional information, leading to improved visual quality and diagnostic accuracy. Additionally, the proposed method reduces noise effects and enhances important image features, making it more reliable for medical image analysis and clinical applications.

In addition to the fusion process, image normalization and registration are performed before decomposition to ensure that the input MRI and PET images are properly aligned and scaled. Image registration is an important step in medical image fusion because different imaging modalities may have different resolutions, orientations, and intensity ranges. Therefore, spatial alignment techniques are used so that corresponding pixels in both images represent the same anatomical location. After registration, image normalization is applied to adjust the intensity values, which helps improve the accuracy of the fusion process and ensures consistent brightness and contrast levels in the fused image.

IV. EXPERIMENTAL RESULTS

The experiments were conducted using MRI-PET medical image datasets. The proposed method was compared with ten existing medical image fusion methods. The performance was evaluated using the following metrics:

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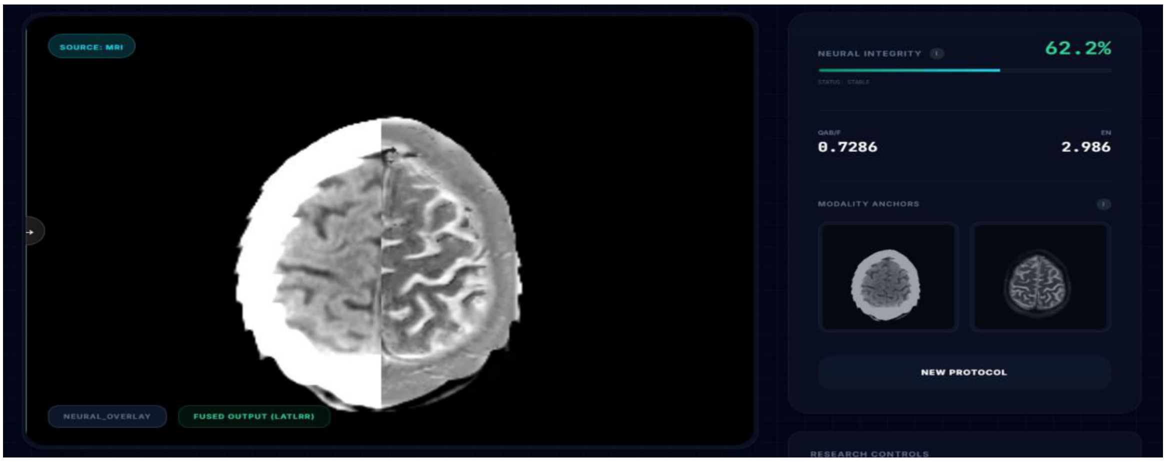

Fig : Entropy

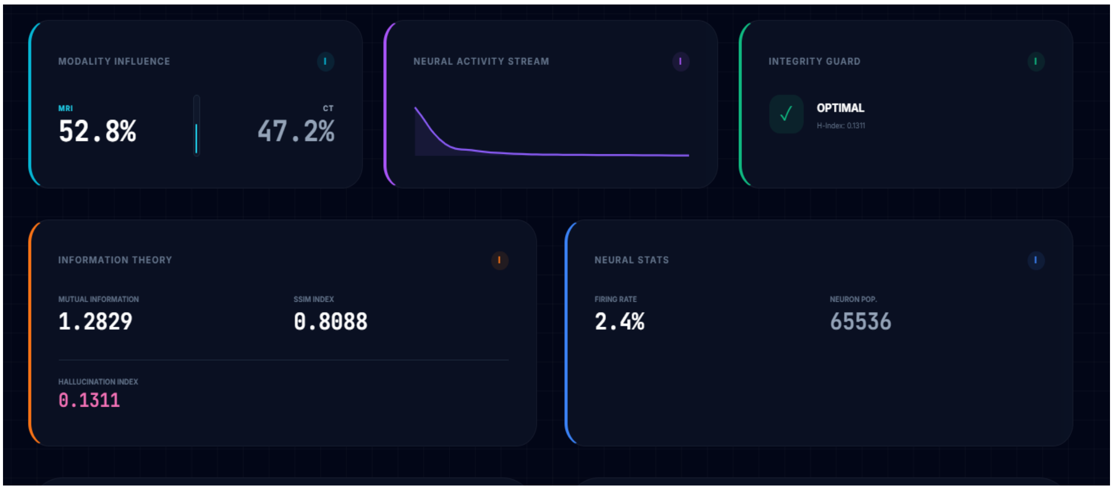

Fig : Analysis

Fig : Neural Integrity

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V. CONCLUSION

Medical image fusion is an important technique for improving clinical diagnosis by combining information from multiple imaging modalities. In this paper, a new medical image fusion method based on latent low rank representation and hesitant fuzzy granular energy was proposed. The method decomposes images into different components and fuses them using advanced fusion techniques such as fast guided filter and dual-channel PCNN. Experimental results show that the proposed method provides better fusion performance compared to existing methods in terms of both visual quality and evaluation metrics. Therefore, this method can be effectively used in medical diagnosis and clinical decision support systems.

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