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Multi-Modal Medical Image Fusion using Laplacian Re-Decomposition Framework

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ABSTRACT:

In clinical applications multi-modal medical image fusion has proven to be a great tool. The essential goal is to mix several multimodal medical images received from various imaging modalitiesinto one fused image that can utilize to diagnose and treat disorders. Within the last ten years,the sector of multimodal medical image fusion has advanced dramatically. Previous approaches were constantly suff-ering from colour distortion, blurring and noise. In this paper, a singular LRD framework applied to multimodal medical image fusion is used. The suggested algorithm's main goal is to extend the performanceof multimodal medical image fusion system by cooperating two technical advances.Firsta Laplacian decision graphdecomposition scheme with image enhancement is employed to get complementary information, redun-dant information and low frequency sub-band complementary information. The concept of overlapping domain and non-overlapping domain are introduced. Additionally, using the decision graph to reconstruct high frequency sub-band images an inverse re-decomposition approach presented.

1.INTRODUCTION

Medical images play an inextricably important role in medical treatment and diagnosis as a fundamental and capable tool. IMAGE fusion is a strategy for enhancing human perception as well as machine vision processing by combining salient or complementary information from several source images gathered by multimodal imaging equipment in the same scene. Multimodal medical image fusion is a significant sub-field of image fusion that has advanced significantly over the years. Anatomic functional image fusion, in particular, has recently been a research focus. Anatomic-functional images come in a variety of shapes and sizes, each with its own set of features. Computed Tom, as an example. For example, Computed Tomography (CT) is good at providing information about bone structure but not so excellent at providing information about soft tissues, metabolism, and other factors. The anatomical image magnetic resonance imaging (MRI) provides better soft tissue information and higher resolution; the positron emission tomography (PET) image contains rich information about tumour cell function and metabolism; and the single

photon emission computed tomography (SPECT) image can reflect tissue and organ blood flow.

Unfortunately, both the PET and SPECT images have low resolution. To assist pathologists in making decisions, the information in multimodal medical images should be utilized to the fullest extent possible. Image fusion is a common strategy for accomplishing this aim, in which the fused result maintains both the location information from the MRI image, such as the skull profile, and the molecular activity information from PET and SPECT images, such as tumors and organ. The task of MRI-PET and MRI-SPECT multimodal medical image fusion is the subject of this research.

In general, the work's key contributions can be described as follows: In the domain of multimodal medical image fusion, we introduce the LRD scheme. LRD was able to simultaneously gather LSI and decompose complimentary and redundant information from HSI, boosting the Laplacian's detail information extraction capacity and resulting in a higher quality fusion outcome. To construct two fusion rules, we introduce the overlapping domain (OD) and nonoverlapping domain (NOD) notions. The first is in charge of detecting image details and pixel energy, while the second is in charge of preserving domain information. By re-planning pixels around the OD and building two global decision graphs, we introduce the inverse LRD fusion rule to reconstruct high frequency images. Extensive trials are carried out to validate the efficiency of the suggested LRD. The results show that LRD can preserve more information quantity in the fused output and exceeds other common approaches in both subjective and quantitative visual perception.

2.LITERATURE REVIEW

Medical specialists can benefit from the fusion of multimodal imaging data since it provides them with a wealth of information for better illness diagnosis and clinical research. The focus of this research is to provide a list of recent scientific papers on medical image fusion to summarise the field's current progress and future development. The following sections make up the majority of this paper:

1. An overview of current fusion techniques
2. Multimodal fusion mode
3. Using the same evaluation index to compare data from multiple medical image fusion algorithms in the same database.
4. Examining the difficulties of medical image fusion algorithms as well as potential research directions.

The spatial domain and transform domain are separated in traditional medical picture fusion algorithms. The early study focused on medical picture fusion approaches based on spatial domain. Principal analysis and HIS are two common methodologies. Spatial domain technology, on the other hand, causes spectral and spatial distortion in fused images [2]. Researchers are concentrating their efforts on the transform domain in order to improve fusion effects. It then executes reconstruction procedures after transforming the source image into the frequency domain or other domains to fuse them.

The four layers of the fusion process are signal, feature, symbol, and pixel level. Contour transformation, discrete wavelet transform, and pyramid transform are examples of pixel-level transformations that are commonly employed nowadays. The transform domain-based technique offers

the benefits of good structure and little distortion, but it also generates noise during fusion processing. As a result, image fusion faces a de-noising issue.

3.EXISTING SYSTEM

In the field of medical image fusion, the multi-scale trans form (MST)-based approach may be a popular modelling paradigm. The MST-based approaches contains three steps: decomposition, fusion rule selection, and reconstruction. The source images are first decomposed into high frequency sub-band images (HSI) and low-frequency sub-band images (LFSI) using MST techniques. The HSI primarily contains texture features from the source images, while the LSI contains background information; second, various fusion rules are wont to fuse the HSI and LSI, respectively; and eventually, the decomposition process is employed to reconstruct the fused result using the inverse decomposition operation. Laplacian pyramid transform (LP), gradient pyramid transform, discrete wavelet transforms (DWT), dual-tree complex wavelet transform (DTCWT), and shearlet transform are some notable instances. The resolution of the current level is reduced because each level of sub-band image is obtained by subsampling from the preceding level. As a result, the fused outcome is always warped. The non-subsampling approach is presented as a solution to this problem. Non-subsampling contour transformation (NSCT) and nonsubsampled shearlet transform (NSST) are two approaches based on this concept.

Designing more effective fusion strategies to fuse HSI and LSI is just as important as selecting MST tools. Image energy level calculation and fusion decision design are two aspects of HSI fusion. The first factor is always met at the pixel or window level, and the fusion decision is made using either the weighted average or maximum strategy for the second. These decisions, on the other hand, do not take into account other potential fusion influencing elements, which limits their efficacy to some extent. More complex and efficient fusion decision schemes were later proposed. Principal component analysis (PCA), sparse representation (SR), and pulse coupled neural network (PCNN) are some of the most popular. Fusion results are created from the PCA of the source pictures in the PCA-based approach; SR and PCNN require a training phase, which is always time-consuming. Furthermore, the SR-based technique is vulnerable to misregistration.

MST-based decomposition techniques and fusion algorithms have gotten a lot of attention in recent years. Liu et al. proposed the curvelet transform and sparse representation, for example (CVT-SR). For medical image fusion, Liu et al. suggested a deep convolutional neural network (CNN). Du et al. introduced a local Laplacian filtering approach for decomposing the source picture, as well as an information-based technique for fusing the HSI (LLF-IOI). Yin et al. proposed a nonsubsampled shearlet transform decomposition methodology and a parameter-adaptive pulse coupled neural network model for medical picture fusion (NSST-PAPCNN). The decomposition scheme and the fusion rule are two crucial aspects that affect the fusion result, as shown in the preceding discussion. Also, the standard Laplacian decomposition approach is well known for failing to adequately explain the structural information of source image. As a result, Du et al. developed the improved Laplacian decomposition technique for local Laplacian filtering. The fundamental idea behind local

Laplacian filtering is to brighten source images using edge-preserving filters. Two fusion rules are introduced on this basis: information of interest and local energy maximum (LEM). To achieve HSI and LSI fusion, the authors use two different fusion rules. However, there are three issues with this approach:

1) Since the edge-preserving filter fails to discriminate noise in sub-band images, the fused output always has some noise.
2) In the local area of fused image, there are always colour distortion due to the local Laplacian filtering could not fully analyse the complementary and redundant information between various sub-band images.
3) Because the maximum local energy of the aberrant area in the functional image may be smaller than that of the non-interested area in the anatomical image, the interest-based information fusion rule always makes a mistake.

To address these problems, we present the novel Laplacian re-decomposition (LRD) scheme to fulfil the image decomposition.

4.PROPOSED SYSTEM

In this paper, we proposed the novel Laplacian re-decomposition (LRD) framework to model the medical image fusion task. The improved image high-frequency information lifting coefficient and the simplified mapping function are implemented to enhance the image gradient information to highlight the image details and reduce the noise, This effectively improves LRD's capacity to represent visual information. Then, when HSI complementary information is fused, redundant information might cause decision mistakes, resulting in detail blur and colour distortion. As a result, we propose classifying redundant and complementary information to limit mutual interference, and then using decomposition to get images of overlapping and non-overlapping areas. Furthermore, while fusing overlapping domain images, we build a fusion decision technique based on two deliberate characteristics of image detail intensity and pixel energy to avoid making incorrect decisions. which means that this scheme has the ability to make accurate decisions on anatomical image structural information and functional image abnormal areas.

Non-overlapping domain images, on the other hand, do not contain duplicate information, hence we suggest a simple addition fusion rule that significantly decreases colour distortion. Therefore, we design an inverse re-decomposition scheme (IRS) fusion rule with the functions of image reconstruction and artifact elimination. In general, the work's key contributions can be described as follows: In the domain of multimodal medical image fusion, we introduce the LRD scheme. LRD was able to simultaneously gather LSI and decompose complimentary and redundant information from HSI, boosting the Laplacian's detail information extraction capacity and resulting in a higher quality fusion outcome. To construct two fusion rules, we introduce the overlapping domain (OD) and nonoverlapping domain (NOD) notions. The first is in charge of detecting image details and pixel energy, while the second is in charge of preserving domain information. By re-planning pixels around the OD and building two global decision graphs, we introduce the inverse LRD fusion rule to reconstruct high frequency

images. Extensive trials are carried out to validate the efficiency of the suggested LRD. The results show that LRD can preserve more information quantity in the fused output and exceeds other common approaches in both subjective and quantitative visual perception.

4.1 BLOCK DIAGRAM

The block diagram of multimodal medical image fusion is shown in below

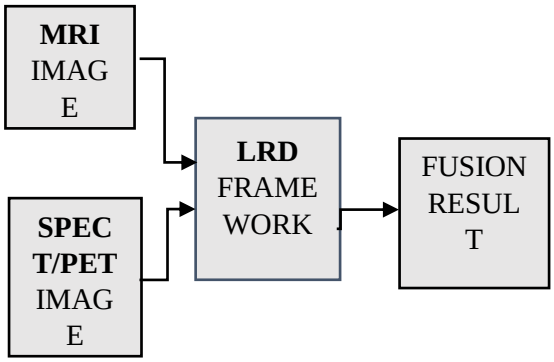

Figure 1: multimodal medical image fusion

The image has a high-frequency information lifting coefficient, and the simplified mapping function is used to enhance the image gradient information in order to highlight the image details and reduce noise, effectively increasing LRD'S ability to represent the image details.

The LRD framework, consisting of three components: gradient domain image enhancement (GDIE), LP, and decision graph re-decomposition (DGR). GDIE is in charge of improving the LRD's ability to extract detail by adaptively mapping gradient information. LP contributes to the multi-scale decomposition of picture features. Global decision graphs are produced by DGR to generate overlapping and non-overlapping domain images for improved fusion results due to the varied properties of redundant and complementary information. The proposed DGR is capable of accurately classifying HSI's redundant and complementary data. Furthermore, DGR could decompose HSI into overlapping and non-overlapping domain images, allowing for more targeted design fusion rules with less interphase interference. DGR creates two classifiers based on the pixel position connection of redundant and complementary information using the global decision graphs of multi-source HSI. The first classifier was successful in separating redundant data from overlapping domain images. In the image of the non-overlapping domain, the second classifier stores complementary information.

4.2. PROPOSED ALGORITHM

The schematic characteristics of the current work shows in Figure 2. The source images are decomposed into LSI, overlapping, and non-overlapping HSI pictures via LRD. The LSI provides estimated information, while the HSI provides detailed information. The LSI contains the most of the information. The HF sub - bands contain edge and boundary information. The LEM fusion rule is used to fuse LSI images. The OD and NOD fusion rules are used to fuse overlapping and non-overlapping pictures.

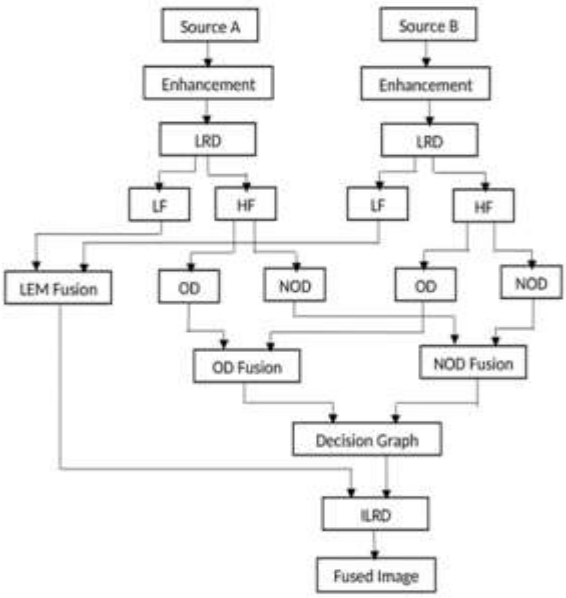

Figure2. Schematic diagram of LRD algorithm

There's a risk that after OD and NOD fusion, there will be artefacts in the output that weren't present in the source photos. IRS fusion rule is proposed to recreate HSI fusion image. Finally, the inverse Laplacian procedure is employed to create the fused image.

4.2.1 LEM Fusion Rule

The most key aspects of anatomical images are Texture and details So much low-frequency information can be found in different, useful images. LEM is defined as the square of the sum of local window pixels in the reference. The square operation tends to lead to unstable energy acquisition due to the difference in interest information between anatomical and functional images. For example, when the sum of pixels is less than 1, the square operation within the range of normalizing pixels will produce smaller results, and when the sum of pixels is greater than 1, the square operation will produce larger results.

4.2.2 NOD Fusion Rule

According to DGR's concept of non-overlapping domain, the fusion images could be anatomical and functional images. The non-overlapping domain is in capable of ensuring domain information.

4.2.3 OD Fusion Rule

OD has made three important initiatives to improve the overlapping domain fusion images contain more meaningful information:

1) To highlight the boundaries and details of anatomical images, a local decision maximums (LDM) approach was proposed employing MLD and LEM.

2) Another LDM marker method for functional image abnormal areas is presented employing the MLD decision scheme and LEM.

3) The binary decision graph is formed by comparing the sizes of the two LDMs, and the fusion image of the overlapping domain is obtained.

As a result, OD has a greater advantage in merging anatomical and functional images feature information.

4.2.4. IRS Fusion Rule

The IRS fusion rule is proposed to reconstruct high-frequency sub-band fusion images and reduce image flaws. Image errors in the reconstruction of high-frequency sub-band fusion images are possible since we fuse redundant and complementary information separately in HSI. To solve this problem, we replan the pixels surrounding the overlapping region and establish two global decision graphs. The first decision graph essentially completes the reconstruction process, while the second decision graph is employed to remove artefacts in conjunction with the local mean algorithm IRS.

4.2.5. Reconstructed Fused Image

Medical images could be combined using Laplacian multiscale reconstruction. In this article, the standard inverse Laplacian transform method is used to rebuild the fused images i.e the fusion images are obtained by the inverse operation of the decomposition process.

5.SIMULATION RESULTS

In order to validate the effectiveness of our method, we compared with seven sample algorithms, including DWT, NSCT, CVT-SR, DTCWT-SR, CNN, LLF-IOI, and NSST-PAPCNN. In order to validate its effectiveness,The definition of the image

could not be adequately evaluated due to the limitation of a single subjective observation. As a result, it is vital to employ STD in order to avoid chromatic aberration. However, MI and UQI metrics give an objective framework for assessing meaningful data and fusion performance. A combination of MRI and SPECT is shown in Figure 3. Because structural features are mostly contained in MRI, practically every approach works well in terms of detailed information, with the colour fidelity being the key variation

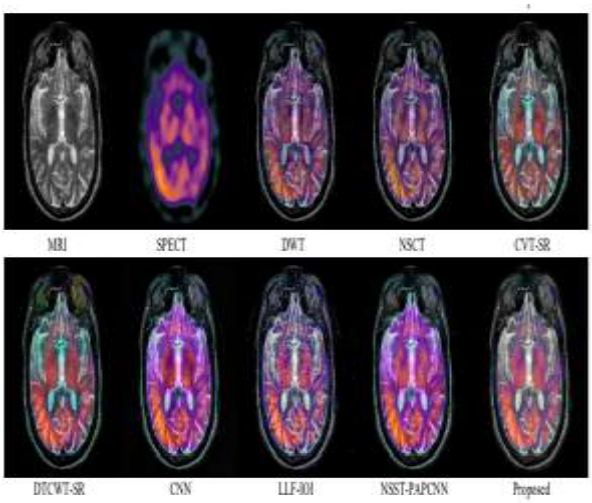

Figure-3: Comparison results of various fusion algorithms based on two groups MRI-SPECT images

The LLF-IOI approach over-improves anatomical details in MRI pictures, while DWT, NSCT, CVT-SR, and DTCWT-SR see on retaining colors fidelity are comparably low substantial visual inconsistencies. Although CNN and NSST-PAPCNN do a good job of preserving the functional information of the SPECT source image, significant structural elements are nevertheless lost. Figure-4 depicts the outcomes of MRI and PET image fusion using various approaches. The fusion result of the DWT, NSCT, CVT-SR, and DTCWT-SR, on the other hand, plainly shows a huge colour distortion. Although CNN and NSST-PAPCNN perform better, both approaches suffer from local detail loss and colour distortion. Despite the fact that the LLF-IOI was able to maintain colour information, the spatial structure information of the MRI source pictures was overly boosted, and the original picture information was lost.

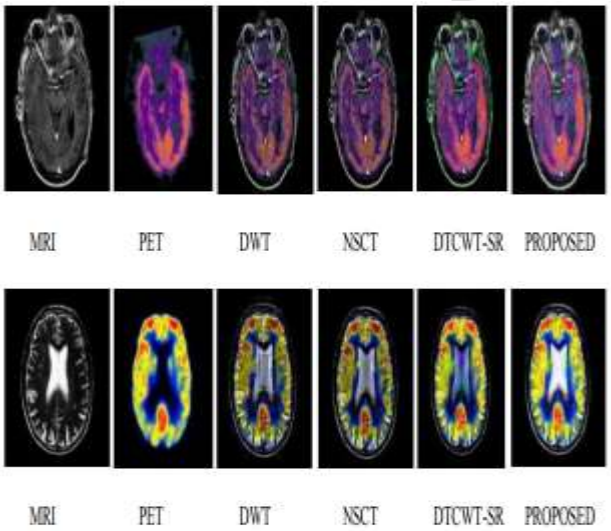

Figure-4: Comparison results of various fusion algorithms based on two groups MRI-PET images

In comparison to existing methods, our suggested method shows evident advantages in faithfulness and visual quality in Fig.3 and Fig.4, as well as higher definition in the local features of the fused image. Table VI shows the objective evaluation of the eight image fusion algorithms. The suggested method outperforms the other seven approaches on all measures, as shown in Table VI. For more information, STD denotes that the fused image has a greater resolution. Our fusion framework has more advantages in getting source image information and fusion performance, according to MI and UQI, indicating that the suggested framework can reduce information loss. Therefore, the maximum TMQI confirms the accuracy of

the above study on two levels: structural integrity and statistical naturalness.

Table 1: objective evaluation of various methods

Metrics	MI	UQI	TMQI	STD
DWT	1.3771	0.6011	0.6990	49.9073
NSCT	1.3700	0.5140	0.7010	49.5526
CVT-SR	1.3750	0.3129	0.6816	53.2626
DTCWT-SR	1.4011	0.5019	0.6899	54.8935
CNN	1.5350	0.4944	0.7014	58.9424
LLF-IOI	1.4724	0.5899	0.7122	62.6011
NSST-PAPCNN	1.6166	0.6120	0.7100	61.2276
proposed	1.6326	0.6384	0.7199	64.0890

CONCLUSION

In this paper, we proposed the LRD for multimodal medical image fusion. We developed the DGR technique to overcome two problems: Laplacian decomposition always fails to retain image structure information well, and previous decomposition techniques do not completely incorporate the redundant and complimentary information between high frequency sub-band images. We suggested the OD fusion rule for detecting redundant data and the NOD fusion rule for integrating complementary data. The two fusion criteria ensure that the fusion choice is made with great precision, resulting in a fusion image with improved structure information and color accuracy. Many researches have been used to prove the usefulness of LRD. Facts demonstrate that the suggested LRD is superior to alternative approaches on a subjective level and the running time must be evaluated objectively. This can still be decreased by proposing quick solutions. In the future, methodologies with efficient transform and effective fusion approaches will be used.

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