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A NOVEL FUSION RULE FOR THE FUSION OF CT ANDMRI IMAGES WITH A SCRUTINY OF DIFFERENT FUSION RULES FOR IMAGE FUSION

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Abstract
The multimodal medical image that is generated by the image fusion technique aids in increasing the efficiency of diagnosis and information gathering. The significant factor that plays major role in the efficiency of this technique is fusion rule. Pan sharpening in the Non-subsampled shearlet Transform domain is proposed as futuristic fusion rule for image fusion. The efficiency of the image generated by the fusion technique is validated based on the four various parameters. Proposed method preserves more edges and keeps the quality of the image visually intact;therefore, it provides better efficiency in NSST domain than in other domains.
Keywords: Fusion Rule, Pan Sharpening, Spiking Cortical Model.

抽象的
通过图像融合技术生成的多模态医学图像有助于提高诊断和信息收集的效率。 **在**该技术的效率中起主要作用的重要因素是融合规则。 **非下采**样剪切波变换**域中的全色**锐化被提议作为图像融合的未来融合规则。 **融合技**术生成的图像的效率基于四个不同的参数进行验证。 **所提出的方法保留了更多的**边缘，并在视觉上保持了图像质量的完整性；因此，它在 **NSST 域中比在其他域中提供了更好的效率。**
关键词：融合规则，泛锐化，尖峰皮质模型。

1. Introduction

With ever-increasing technological advancement in noval clinical imaging, various number of imaging models are aided in diagnosis and analysis of medical conditions. Attribution of variance in imaging mechanism and the high unpredictability of human histology, medical images of numerous model give an assortment of complementary information about the human body. For example, CT imaging is suitable for imaging dense structures like non-metallic implants and bones with moderately less distortion. Likewise, MRI can scan the pathological tissues that are soft in better way

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while PET quantifies the measure of metabolic action in the body.

Aid of imaging technology and its advancements have increased in the field of medical diagnosis and investigations.Be that as it may, because of the constrains in the technology, the nature of medical image obtained is inadmissible, and thus it leads to the incorrect decisions and cause trouble. Hence, it is difficult for the doctors to diagnose and treat the patients with the single image with the low resolution and insufficient data. Using fusion algorithm to fuse these single images is significant to overcome the above said problem.

In current era, image fusioning is the significant method to increse efficiency of the images using varoius number of images. It's a kind of enhancement process that involves fusing images from different types of sensors to develope an informative image that can help with subsequent handling or answerable. The keys to an excellent fusion method are successful image information extraction and proper fusion principles, which permit valuable data to be extracted from initial images and integrating them into the merged image without adding objects. To put it another way, the aim of image fusion points is to create an informative image by merging the latent data of multiple images captured by electron multi-sensors in the same scene into a single image. Image fusion is often referred to as image enhancement in some cases, implying that more accurate and correlative data is derived from multi-source files. It is notable that image fusion is an significant subject of exploration and plays an even most important role in image examination, target detection and medical diagnosis [1].

In general, medical imaging technology, by investigating and fusing multimodal clinical image content, is more likely to reflect its pattern properties and thus increasing the information provoided to increase diagnose accuracy . By and large, clinical imaging innovation by exploring and combining multimodal clinical picture information is to all the more likely mirror its property of examples and further incresing the precision of malady finding. For example, using the CT and MRI imaging method to produce the distinctive medical images; the CT images can provide the skeletal system details, where the MRI images provoides data regarding the tissue that are soft in nature. As a result, image fusion techniques combine the MRI images and CT images to create an enlightening merged image that preserves the insights into bone structure and soft tissue while still providing better system perception or fidelity than the source images. Clinical image fusion increases the accuracy of clinical images, making them more scientifically relevant. Physicians may make an informed assessment in a limited period of time when images are digitally assessed using computer-aided imaging techniques. Also, information that are not visible to naked human eye. For this, fusion images containing information from beyond what one image can give a more exact localization of the infection or abnormality [2]. There are a few image fusion models available, but the Spiking cortical model is specifically designed for image processing applications.

This reserch performs an analyais on the existing fusion rules utilized for the fusion of images and proposes an fusion rule based on pan sharpening using spiking cortical model.

This paper is organized as follows: Section 2 discusses in detail about the recent image fusion techniques with a study on the different fusion rules applied. In Section 3, we proposed a new fusion rule. In Section 4, we perform the performance analysis of the proposed scheme in terms of four different measures. Section 5 concludes this paper.

2. Related Work

Wang R et al (2013) proposed a novel strategy for medical image fusion using the spiking cortical model (SCM) to overcome the absence of all inclusiveness in managing various types of medical images. The mathematical model of SCM is firstly depicted and afterward image fusion algorithm with SCM is introduced. The

suggested approach was related to the Comparison pyramid, Laplacian pyramid, Ratio pyramid, and Morphological pyramid using diagnostic photos from around three pairs of different modalities. The different techniques were investigated under various performance metrics. The outcomes reveal that this proposed methodology beats different strategies in both visual effect and objective assessment. It demonstrates that the SCM-based approach is a highly efficient multi-modal medical image fusion strategy due to its reliability and usability. Liu Shuaiqi et al. (2015) demonstrated a non-sub sampled shearlet transform (NSST) and SCM-based medical image fusion process. For the initial disintegration of images, NSST is used. Aside from low and high frequency NSST coefficients, a fired map of efficiency improved SCM (ISCM) is used to integrate them both, which is influenced by a larger Sum Modified-Laplacian (SML). Finally, inverse NSST picked up the fusion image. Both the data of the source images and pixel distortion are well protected by the algorithm. According to the validation results, the aforementioned approach outperforms the best in class fusion processes.
Clinical image fusion was suggested by Shuaiqi L et al, (2015) to address the limitations of image distortion and information leakage due to image exposure to noise. It is developed by fusing the rolling guidance filter (RGF) and SCM. Initially, saliency of medical images can be caught by RGF. Besides, a self-adaptive threshold of SCM is picked up by using the mean and source images variances.Finally, SCM influenced by RGF coefficients is used to create the fused image. In terms of visual output and quantitative metrics, research findings suggest that the illustrated approach outperforms other persisting methods.

Wang N. et al. (2015) established a algorithm for fusion illustrated by non sampled contourlet transform (NSCT) and spiking cortical model, in addition to the difficulties associated with medical multi-focus photographs (SCM). In contrast to standard MSR, that is formed by following the fusion rules of sub-band coefficients of NSCT, lower frequencies coefficients are glued together by MSR. The spatial frequency (SF) for and high frequency sub-band is utilized as a gradient function to encourage SCM networks and produce neural pulses, and the time matrix of SCM was further utilized as a metric to aid coefficients of low - frequency sub to merge the high frequency coefficients. The visual inspection and verification findings indicate that this fusion technique has a lot of potential. The robustness and durability of this approach was demonstrated by testing and validating noise images under different conditions.

Zhang X et al. (2016) developed a dynamic SCM solution to solve the problem of image data loss or to generate low-contrast fused images in terms of the inclusion of features. A weighting approach that relies on SCM firing cycles is being used to create a high-quality image. In the arrangement of weighting fusion, the weight is done by adding the entropy data of the SCM's pulse outputs with the Weber local predictor operating on the firing tracking images produced from generated output pulse. In comparison to other state-of-the-art MIF methods, the proposed approach effectively protects image specifics and avoids the inclusion of objects, and It increases the precision of fused images in relation to human vision and practical measuring criteria including shared awareness and edge preservation index, structural similarity standard deviation, fusion stability index, fusion similarity metric, and contingent metric.

Kong,W et al. (2017) , prposed a new algorithm for multi-focused image fusion that relies on enhanced SCM. A new algorithm for integration of algorithm for multi-focus image was generated using enhanced SCM. As an improved estimation of the third era of ANN, the spiking cortical model (SCM) has been used as a viable tool for addressing image processing

challenges.The standard SCM is first upgraded to become a modified version. After that, the parameters are given and presented. Finally, numerous documented groups of source images are used to test the proposed algorithm's appropriateness and functionality. Experiments demonstrate that this algorithm outperforms the original algorithm in terms of both visual presentation and analytical evaluations, in comparison to existing conventional ANN models.

Huang, Z et al., (2017) proposed a novel strategy fusion of medical image that integrate the NSST with the SCM. The NSST is used to disintegrate the recorded source images into multi-scale and multidirectional sub-bands, which are then processed with the SCM to produce the relevant firing mapping images. Following that, fused sub-bands can be obtained in any scale and direction by selecting coefficients from the sub-bands in relation to local energy (LE) of the coincide images of firing mapping. Finally, using the inverse NSST, the combined image is formed by fusing sub-bands. The modelling studies contrasted the results of technique with a number of fusion techniques. Human vision and quantitative assessment measures both respect this strategy's success. It is observed from the results that this strategy performs better in information preservation and avoidance of artefact.

Hou, R et al., (2019) structured a novel method for fusion of medical images dependent on CNNs and a DCSCM. The source image is first disintegrated into a high and low frequency coefficient using the non-sub sampled shearlet transform (NSST). Furthermore, the CNN framework is being used to fuse low-frequency coefficients, in which the weight map is generated using a progression of function maps and an adaptive selection rule, and DCSCM is used to fuse high-frequency coefficients, using the revised logistic regression of the high-frequency coefficients as input stimulus. Through inverse NSST, the fused image is obtained. Test results demonstrate that this scheme executed well in both visual performance and also objective assessment and better in retention of image detail and enhanced visualization over other current typical ones.

Liu, S et al., (2019) proposed an image algorithm joined with versatile dual-channel SCM (dual SCM) in NSST.Initially, the focus areas of the input image are based primarily on the discrepancy image between the basic fused image and the original images in the NSST domain; later, the focus areas of the input image are defined based on the discrepancy image between some of the basic fused image and the original images; and eventually, the fused image is created by joining the focal regions. This algorithm will preserve the details of the original image well and display a transparent image more in line with human visual visualisations because of the dual-global SCM's fusing, the signal's synchronisation features, and the NSST's direction. The suggested fusion algorithm outperforms several complex algorithms.

Liu, Y et al., (2020) introduced a modified image decomposition algorithm to get a decent compromise among speed and performance. In particular, it uses the total-variational transform into moving least squares method (TVMLS), which can make the outcome more vigorous to noise and completely hold the dominant structure. Initially, total-variational decomposition was performed on the source images and yields a progression of detail and base layers. The layers, as well as CNNs and the perfectly alright fusion law, are fused by RA-DCSCM. The image fusion scheme was subjected to a broad qualitative investigation of both subjective visual inspection and consistency measurements to ensure that it is more successful than other current approaches.

2.1 Analysis on Fusion Rule

The fusion rules used in the different studied fusion techniques are compared in table 1.
Table 1. Comparison of different fusion rules

	Paper	Fusion rule		Advantage of proposed algorithm	Parameters used and value
		For low frequency components	For high frequency components		
1	Zhang, X et al., (2016)	Weighting Fusion	Weighting Fusion	It can create more clear, more enlightening, higher contrast fused images as far as human vision and outperforms the compared methods in terms of mutual information, edge preservations metric, structural similarity and standard deviation	f= 0.9, g=0.3, h=20;Lp=1;V_{Θ}=0.5, α_L=0.5
2	Wang, R et al., (2013)	SCM	SCM	The effective clinical image fusion by means of the firing times of the neurons in the SCM. In terms of visual effect and objective criteria such as shared knowledge and edge protection principles, it outperforms	g= 0.7; f=0.8; h=20; n=40; a=0.5; T_{th}=1,W= [0.1091, 0.1409, 0.1091; 0.1409, 0, 0.1409; 0.1091, 0.1409, 0.1091]

				state-of-the-art fusion algorithms, local structural compatibility and an image value index that is universal.	
3	Wang, N et al., (2015)	Maximum Selection Rule (MSR)	Spatial Frequency (SF)	This method can be used in noisy image processing field.	T_{th}=1; f=0.2; g=0.9, h=20; γ=1, W=[0.1091, 0.1409,10.1091; 0.1409,0,0.1409; 0.1091,0.1409,0.1091]
4	Liu Shuaiqi et al., (2015)	fired map of improved SCM (ISCM), which motivated by larger sum-modified-Laplacian (SML)	fired map of improved SCM (ISCM), which motivated by larger sum-modified-Laplacian (SML)	ISCM preserves more texture information of source images and robust than PCNN ISCM can effectively suppress the MGA fusion method's image distortion.	T_{th}=0.5
5	Hou, R et al., (2019)	simple weighted averaging or maximum value-based	Dual-Channel Spiking Cortical Model (DCSCM)	This fusion scheme has better application prospect in the field of medical image fusion	f=0:2; g=0:6; V_{θ}=20
6	Huang, Z et al., (2017)	Sum-Modified-Laplacian (SML)	Sum-Modified-Laplacian (SML)	The algorithm can both preserve the information of the source images well and suppress	f=0.7; g=0.8; h=20

				pixel distortion	
7	Shuaiqi, L et al., (2015)	RGF	SCM	It has a higher contrast in all the fused methods and pre-serves the texture information of source images, smothering pointless image information for example, square impact and artifacts.	g = 0.7; f = 0.8, ;n=40; T_{th}=1
8	Liu, Y et a., (2020)	CNN	RA-DCSCM	This method is good in performance in medical image fusion	γ =4;p=0.6
9	Liu, S et al., (2019)	Sum-Modified-Laplacian	Sum-Modified-Laplacian	Proposed algorithm can produce clearer images, better visual effects and extract the detailed features of images more effectively.	f=0.7; g=0.8; h=20
10	Kong, et al., (2017)	ISCM	ISCM	Better subjective visual effects and objective evaluation results.	T_{th}=1; f=0.2; g=0.9; h=20; γ=1;W=[0.1035,0.1465, 0.1035;0.1465,0,0.1465; 0.1035,0.1465,0.1035]

Algorithm for clinical image have devoleped in many numbers. For instance the types include comparison pyramids, Laplacian pyramids, Morphological pyramids, Ratio pyramids, as well as others. In the fusion process, these techniques would either lose a lot of information from the source images or generate a lot of fake data that isn't present in the source images. The

SCM is obtained from Eckhorn's model and it adjusts to the physiological trait of human visual neural system. Image processing techniques such as smoothing, segmentation, edge detection, enhancement have also been shown to be benefited from SCM. There are approximately 30 unique types of medical image fusion evaluation metrics available. Various quantitative assessment criteria are used to measure the fusion method's success. MI measures the amount of information transmitted from the source images to the fused file. The AB/FQ uses the Sobel edge detector to measure how much edge information is transmitted from the source images to the fused image. The higher MI and QAB/F and the better fusion performance will be. LAB/F is introduced to evaluate the information lost during the fusion process. Fusion objects added into the fused image during the fusion process are represented by N AB/F . It is clear that the L AB/F and N AB/F are smaller, the better the result is. As a human visual neural network, the SCM can facilitate extracting more detail information from source images (Wang, R et al., 2013). The low and high frequency coefficients of NSST are all fused by fired map of improved SCM (ISCM), which motivated by larger Sum-Modified-Laplacian (SML) can give fused image which can both retain source picture information and counteract pixel distortions with greater reciprocal information and minimal data loss (Liu Shuaiqi et al., 2015). Likewise, in the NSST domain, the latest image fusion algorithm based upon on Dual -SCM provides higher shared knowledge, resulting in smoother images, improved visual effects, and more efficiently extracting the precise image features (Liu, S et al., 2019). The combination of WLD and entropy data can help determine the fusion weight more efficiently because they can accurately explain the local image structure and gray-level information of source images, resulting in simpler, more detailed, and higher intensity fused images (Zhang, X., et al., 2016).The algorithm designed for medical image fusion will yield more noise-resistant fused image effects, in which the Robust Adaptive Dual-Channel Spiking Cortical Model is used to merge high frequency coefficients and CNN is being used to fuse low coefficient coefficients (Liu, Y et al., 2016). The proposed a new medical image fusion technique that combines the NSST and the SCM worked well in terms of material retention and artefact removal (Huang, Z et al., 2017).

3. Proposed Fusion Rule and its Implementation Steps

Presume that the CT images and MRI images have been rightfully calibrated and handled with the same measurement. The following are the requirements in the image fusion process.

Step-1: Decompose the CT and MRI images using NSST to obtain their low pass coefficients and a series of high pass coefficients at each K-scale and l-direction, where $1 \leq k \leq K$.

Step-2: In the low frequency the fusion rule of pan sharpening is proposed. The edges of the low pass coefficient are effectively fused using this pan sharpening.

The Pan sharpening method increases spatial details while retaining spectral data. It is mostly applied to high resolution PAN and low-resolution MS images in order to obtain the new improved MS image.

Step-3: The high coefficients values are fused in the SCM.

Step-4: The inverse NSST were performed for the fused low pass and the high pass coefficients to obtain the fused image.

4. Performance Analysis

Five sets of images are taken for the implementation of proposed fusion method as shown in figures 1 to 5.

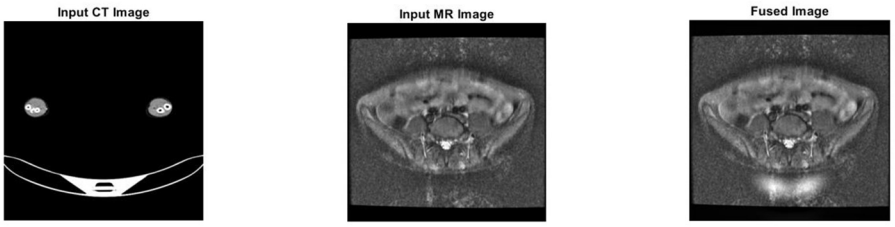

Fig. 1a,1b,1c. Image set 1 with fused image

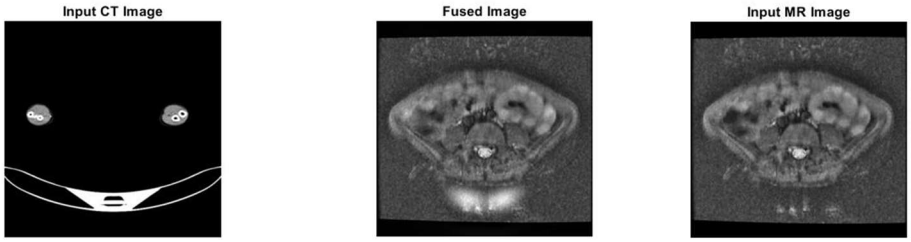

Fig.2a,2b,2c. Image set 2 with fused image

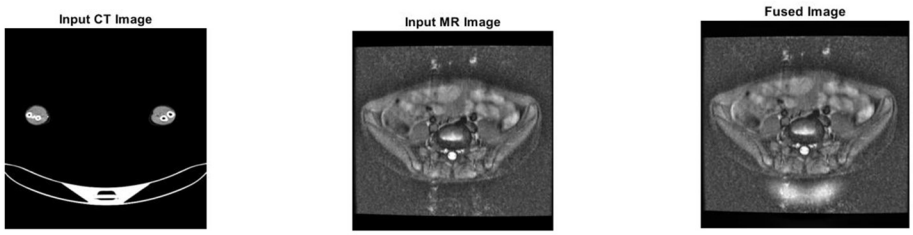

Fig. 3a,3b,3c. Image set 3with fused image

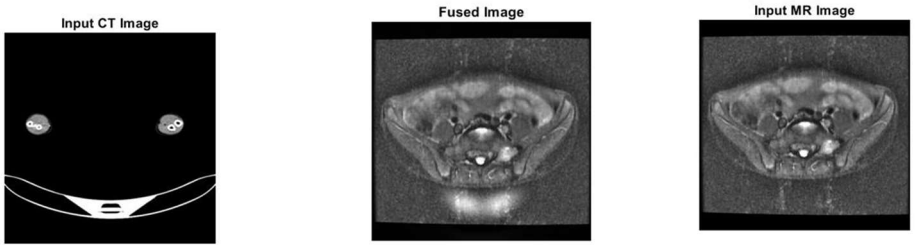

Fig. 4a,4b,4c. Image set 4with fused image

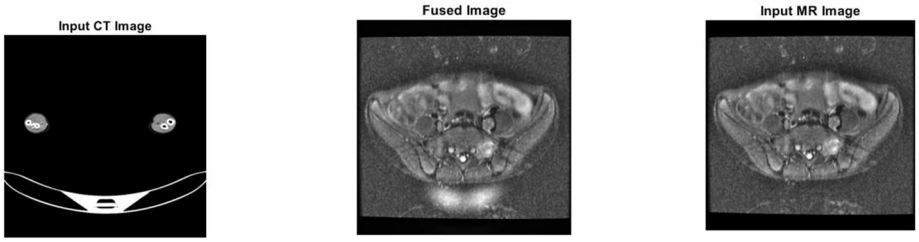

Fig. 5a,5b,5c. Image set 5 with fused image

4.1 Performance Metrics

Table 2 lists the output parameters used for objectively examining the fused image produced by the proposed technique.

1.Mutual Information(MI)

It determines how detailed the fused image produced from the image features was.

2.Structural Content (SC)

It expresses the proportion of the content of the fused image to the content of the input images.

3.Normalized Absolute Error(NAE)

The fused image's performance is opposite to NAE variables.

4.Xydeas and Petrovic Measure(QAB/F)

The sum of data conveyed from the input images to the fused image is represented by this value.

Table 2.Parametric analysis for the fused image

	MI	SC	NAE	QAB/F
Image set 1	2.4927	0.8816	0.0818	0.5550
Image set 2	2.5645	0.9052	0.0711	0.5823
Image set 3	2.5710	0.9091	0.0704	0.5899
Image set 4	2.5199	0.9013	0.0750	0.5800
Image set 5	2.5458	0.9099	0.0730	0.5903

5. Conclusion

Image fusion techniques efficiency can be increased by various meyhods like spatial domain, transform domain and deep learning. Its swift enhancement further reflects the success of computer-assisted clinical research. Different researchers propose different fusion methods, each of which has its own advantages indifferent evaluation indicators. This paper introduced a thesis on a fusion rule for image fusion based on SCM, as well as the fundamental principles behind it. A new pan sharpening fusion rule has significantly enhanced the QAB/F values, meaning that the fusion technique is more successful.

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