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# Ripplet domain fusion approach for CT and MR medical image information

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ABSTRACT

Multimodal medical image fusion (MIF) plays an important role as an assistant for medical professionals by providing a better visualization of diagnostic information using different imaging modalities. The process of image fusion helps the radiologists in the precise diagnosis of several critical diseases and its treatment. In this paper, the proposed framework presents a fusion approach for multimodal medical images that utilize both the features extracted by the discrete ripplet transform (DRT) and pulse coupled neural network. The DRT having different features and a competent depiction of the image coefficients provides several directional high-frequency subband coefficients. The DRT decomposition can preserve more detailed information present in the reference images and further enhance the visualization of the fused images. Firstly, the DRT is applied to decompose the reference images into several low and high-frequency subimage coefficients that are fused by computing the novel sum modified Laplacian and novel modified spatial frequency motivated pulse coupled neural model. This model is used to preserve the redundant information also. Finally, fused images are reconstructed by applying the inverse DRT. The performance of the proposed fusion approach is validated by extensive simulation on the different CT-MR image datasets. Experimental results demonstrate that the proposed method provides the better fused images in terms of visual quality along with the quantitative measures as compared to several existing fusion approaches.



## 1. Introduction

In the recent years, multimodal MIF technology has emerged as a potential research area because most of the screening programs are focused on the analyzing of digital images and detection based these programs is a major asset in the struggle against the critical diseases like Cancer, Hemorrhage and Alzheimer and so many others. This is only the main reason for attracting towards the fusion of multimodal images because there are several modalities of medical imaging, giving a different insight of the human body. However, because of the several sources of medical images used by the radiologist, the problem of information overloading occurs. None of the imaging modality is able to produce comprehensive and accurate information, especially in critical diseases that is very rigorous, costly, time consuming, the chance of human errors and most importantly requires lots of years of experience. This is the main motivation by capturing the most relevant diagnostic information from the source CT and MR images into a single image that plays an important role in the medical diagnosis. Moreover, the advanced imaging modalities are too much costlier that also puts an extra burden on the individuals. Another reason for this attraction is the possibility to fuse all complementary and contrasting information acquired from the multiple images of the same organs into a single fused image. Therefore, there is a need to develop some effective fusion approaches to merge all of the features into a single image that has a significant clinical interpretation and suitable for the effective diagnostic analysis.

Previously, lots of researchers have concentrated on the fusion of medical images (MIF) [1–5]. Image fusion (IF) approach can be developed at the different pixel, feature or decision level. The fusion, at the pixel level is again categorized as spatial and transform domain. The spatial domain approach is based on averaging and weighted averaging the source images [6]. This method leads to reduce the contrast of the fused images and there would be a loss of the few structures in the fused image. Partitioning of the image based method has been presented [1] in which the selection of the block is based on its saliency or activity. In this approach, the selection of a block, their size, and saliency criteria decide the quality of fused images. It suffers from the loss of information at each location that also affects the diagnosis. Different authors [2–4]

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have employed neural network for pixel selection or region selection. The dimensionality reduction techniques based on the PCA were studied in [5]. Joshita and Selin [7] proposed a PCA based fusion approach of several input images as a weighted superposition of all input images to improve the resolution of an image. In [8], Liu et al. quoted a fusion approach based on average gradient and mutual information to fuse high-frequency information. This approach retains more detail information; however, it still suffered from blocking artifacts. To boost the performance of the IF/MIF approaches, the authors have also moved towards the transform domain.

In 1989, Toet et al. [9] introduced different pyramid schemes for data fusion. In [10], the authors proposed a wavelet transform (WT) based fusion approach using maximum selection rule. However, this approach suffers from the blocking effects/artifacts. Pajares et al. also presented a fusion approach with the similar or different resolution level of multiple images [11]. In [12], the authors presented another WT based fusion approach for multispectral and panchromatic images. In [13], Yang et al. presented a WT based approach in which visibility and variance based fusion rules are selected to fuse the low and high frequency subband coefficients, respectively. The MIF methods based on the WT is capable only to capture of 1-dimensional singularity. It means that it has only limited directional information, thus it causes artifacts along the edges and loose the important diagnostic information also. To overcome the limitations of the WT, ridgelet transform has been introduced to extract the edges [14], but it did not do well for capturing the curve singularities. So, Donoho et al. have introduced the curvelet transform (CVT) to capture 2-D singularities of any arbitrary curve [15]. However, the CVT cannot be built directly in the discrete domain [16]. Furthermore, the performance of the IF/MIF methods [17] has been analyzed with other multi-scale transformation techniques like curvelet [18–20] and contourlet transform [21–23]. In [24], the authors proposed a contourlet transform based fusion approach in which weighted average and max selection rules are utilized to evaluate the performance of the fusion approach. In [25], NSCT decomposition is utilized to enhance the quality of the fused images based on the pulse coupled neural network motivated by the spatial frequency for highpass subband coefficients. In [26,27], the NSCT based decomposition is further utilized with max selection rule for fusing the low frequency and modified spatial frequency for high frequency coefficients. In [28], NSCT decomposition alongwith the novel sum modified Laplacian (NSML) is utilized for fusing the image components and getting the local features presented in the reference images. However, the NSCT based image decomposition suffers from the lack of shift invariance [29] and the limited number of directional components. To overcome the limitation of the NSCT based approaches, authors presented shearlet based fusion approach along with pulse coupled neural network in [30]. In [31], the author proposed multimodal medical image fusion approach based on the shift-invariant shearlet transform in which averaging and maximum fusion rules were utilized for fusing the decomposed coefficients. In another fusion approach [32], the authors utilized the nonsubsampled shearlet transform and the NSML for fusing the subband image coefficients. To overcome the limitations of the real-valued WT problems, an improved WT i.e. Daubechies complex wavelet transform has been proposed in [33] in which maximum selection fusion rule is utilized. In [34], the authors proposed a fusion approach to enhance the correlation between the subband image based on the discrete fractional wavelet transform. In this approach, all subband coefficients are fused using the weighted regional variance fusion rule. In another approach [35], local extrema is used to decompose the reference images. In this approach, energy and contrast guided fusion rules are applied to evaluate the performance. Jun et al. [36] introduced discrete ripplet transform (DRT) type I which generalizes the CVT by adding two new parameters that assured to present the singularities along arbitrary shaped curves. The DRT is also able to overcome the limitations of other transformation approaches by providing the sparse representation of an image object. In [37], authors proposed a hybrid approach using the WT and DRT in which the approximation component obtained after the WT decomposition, is further decomposed using the DRT, however the results still suffered from shift invariance effect. In last few years, a biologically inspired feedback neural network (BIFNN) [38] i.e. the PCNN, is efficiently introduced in several applications of image processing [27,39–41]. Based on the outcomes of these methods [27,38,40,41], it is observed that they produce good visual results, but they have some problems related to contrast reduction and loss of diagnostic information [2,42]. In [43], another fusion approach was proposed using an improved neural model that also enhances the quality of the fused images. The PCNN and its modified versions with these aforementioned transform techniques have been presented in the IF/MIF domains by various authors in [44–46].

In this paper, the proposed fusion approach is framed based on the concept of DRT and pulse coupled neural model, in which the feeding input is not provided as a conventional PCNN for fusing the low and high-frequency image coefficients. In addition to that, firstly novel sum modified spatial frequency (NMSF) and novel sum modified Laplacian (NSML) are utilized as feeding inputs to the neural model in the DRT domain. The DRT decomposition can preserve more details present in the reference images and further enhance the visualization of the fused images. The NMSF is utilized to express the clarity and activity level of the input images within a specified window. It is also able to reflect the directional informative content present in the reference images. The NSML is utilized as an external input to the neural model for improving the performance of the proposed fusion approach. Furthermore, the performance of the fusion approach is analyzed visually and quantitatively by performing the extensive experiments on source CT and MR image pairs. In addition to this, the salient contribution of the proposed fusion framework in the DRT domain over several other fusion methods developed previously is summarized as follows,

- This paper presents a fusion approach for fusing the CT and MR medical images that rely on the combination of the DRT and PCNN by improving the feeding inputs that provides more details present in the reference images and further enhance the visualization of the fused images.
- Different fusion rules are proposed for combining the low and high-frequency subimage coefficients.
- The biologically inspired feedback neural model is utilized for high and low-frequency DRT subimage coefficients based on the firing times and improved feeding inputs that is also able to capture the suitable differences and provide the resultant images with high contrast and clarity.
- For fusing the low and high-frequency DRT coefficients, the computation of the NSML and NMSF is proposed and used as the inputs to motivate the PCNN model and also able to capture the fine details present in the reference images.

## 2. Methodology

### 2.1. Ripplet Transform

A higher dimensional framework called discrete ripplet transform (DRT) [36] is able to characterized to an image at various scales and directions. The DRT is quite different as compared to curvelet transform that uses a parabolic scaling and captures 2D singularities along $C^2$ curves, but on the other side, the DRT provides a new