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Medical Image Enhancement using PCA-based NSCT Fusion Methodology

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Abstract

Combining the information from two or more images into a solitary image is known as image combination that can keep down all the essential features of the first images. The principal target of image combination is to generate an image which depicts a scene preferred or considerably higher over any single image concerning some important properties giving a useful image. These combination techniques are most vital in diagnosing and treating growth in therapeutic fields. This article focuses on the development and analysis of medical image enhancement using principal component-based nonsubsampled contourlet transform (PCA-NSCT) fusion methodology with comparison to various enhancement techniques using discrete wavelet transform (DWT), stationary wavelet transform (SWT), fast discrete curvelet transform (F-DCT), NSCT-based fusion algorithms. Further, the quality of the fused image also evaluated using a set of quality metrics which is known as image quality assessment (IQA) such as peak signal-to-noise ratio (PSNR), correlation coefficient (CC), entropy (E), and root mean square error (RMSE).

Keywords: *medical image fusion, PCA, wavelet transform, nonsubsampled contourlet transform, curvelet transform and quality metrics.*

1. INTRODUCTION

The fundamental point of combination is to integrate two or more images into a solitary image to get more applicable information than individual information of any image [1]. Image combination concept can be utilized to distinguish the items obviously better than the first info images. Indeed, even it has been demonstrated for all intents and purposes in old days. Because of its reliability and magnificence, this innovation has been pulled in by numerous scientists, for example, image analysis and understanding, video analysis, PC vision, satellite imaging, therapeutic determination and machine adapting even in the field of optical remote detecting, route help. The principle thought process of image combination is to build up an upgraded scene by incorporating the caught information from various sensors without presenting the artifacts. Because of sensor constraints, satellite images exhibit high ghastly with low spatial resolution or the other way around. A few remote detecting applications require a solitary image that exhibit high spatial and ghastly resolution, which cannot be acquired straightforwardly by the camera. Doctors discover hard to concentrate features that may not be ordinarily noticeable in images by various modalities. In this way the arrangement is Image Fusion. Structure the previous decades there are such a variety of algorithms have been produced for image combination applications by utilizing spatial and transformation areas [2, 3]. All the condition of workmanship algorithms is based on previously mentioned classes. In any case, they were experiencing couple of constraints, for example, higher multifaceted nature, less solid, more calculations and less precision. An identified and powerful tool that is very practicable for the application of fusion and many other image processing is referred as multi scale (MS) transform [4, 5]. The procedure of image fusion that utilizes MS transform is as follows: Initially, MS-based novel methods are applied to improve the diagnostic details in medical images through registration and fusion techniques and representations of source image are retrieved by employing the MS transform, where the characteristics of an image are represented using a frequency transform. Next, a rule for fusing these MS representations is utilized to get a fused outcome where the specified rule assumes the coefficients activity level, and the correlations of neighbouring pixels and distinctive scale's coefficients. In the recent days, various efforts are made to resolve these couple of issues, which are explained as follows:

In earlier works, transforms such as pyramids and wavelets are the largely employed multi-scale decomposition approaches for fusing the images, where the pyramid and wavelets include Laplacian pyramid (LP) [6], DWT [7], and SWT. An approach for image fusion using MATLAB is presented in [8] where LP decomposition and reconstruction is utilized for fusing the images. However, the LP is believed as being unable to represent outline and contrast of the images well. To undertake these jobs, in [9] authors proposed an approach based on union LP with numerous characteristics for exactly channelizing the prominent characteristics from the source medical images into a solitary fused outcome. Initially, source medical image is mapped into their theatrics of MS by employing LP. Afterwards, the feature maps of contrast and outline are evoked from the source images at every scale, and then an efficacious scheme of fusion was implemented to unify coefficients of pyramid. At last, the inverse pyramid reconstruction procedure is utilized to get a fused image. However, the image fusion metrics utilized in this, only assess the fused image quality from a restricted view, and it is quite complicate to differentiate which non-subjective metric is importantly amended. The DWT is most popular MS fusion approach. It provides much better fusion results as compared to the pyramid transforms due to its better simultaneous representation of spatial and spectral information. In [10] authors proposed a fusion strategy of medical images with global energy method based on the DWT, in which the match measures are calculated to select the wavelet coefficients coming from different sub images of the same scale. However, the DWT based fusion algorithms suffers from shift variance, aliasing, and lack of directionality. In [11] authors presented a multimodal medical image fusion method based on nonlinear anisotropic filtering (NLAF) and PCA, which unify both the NLAF and PCA advantages and obtained better fusion performance. First, NLAF is utilized to decompose the input medical images to be fused, and then the PCA is utilized for the coefficient selection. Finally, inverse NLAF is applied to obtain the fused medical image. In [12] authors presented a novel approach for MR and CT image enhancement and fusion using integrated guided NLAF with image statistics. First, the source medical images which are degraded and nonreadable due to several factors are pre-processed to enhance the quality of the input images using guided filter. These enhanced images are then fused by utilizing NLAF for brain regions with different activity levels. It showed around 80-90% more accurate outcomes with mitigated color distortion and without losing any anatomical information in comparison with the existing medical fusion techniques. In [13] authors presented the on weighted parameter adaptive dual channel PCNN (WPAD-PCNN) and sparse representation based medical image fusion approach to overcome the shift variance restriction. Recently, parameter adaptive PCNN (PA-PCNN) techniques are developed for medical image fusion is presented in [14], which extracts more spectral features in different orientations other than normal neural networks.

However, it also suffers from the lack of directionality. To avoid these limitations, productive fusion of images is employed by ant colony optimization-based ensemble empirical mode decomposition (ACO-EEMD) presented in [15]. Shift invariance and directional selectivity are the central benefits of ACO-EEMD over other wavelet transform variants like DWT and SWT, which mitigates the artifacts innovated by these two variants. In [16] authors are focused on feature level image fusion based on MSD with local energy maxima, which is utilized to produce region maps by segmenting the features of registered source images with watershed, transform either jointly or separately. To solve the constraints related problems, new sum of modified anisotropic Laplacian (NSMAL) was introduced in [17] to evaluate the characteristics. Then the calculated region characteristics are utilized to fuse the images. a fusion approach in which first the input images were decomposed by employing NSMAL and afterwards, the max and local energy fusion laws were employed to integrate the obtained coefficients at low and high frequencies severally. However, existing fusion methodologies failed to enhance the fused image with respect to texture, visual quality, and quantitative analysis. Therefore, this article focuses on the development and analysis of medical image enhancement using PCA-based NSCT fusion methodology with comparison to various enhancement techniques using DWT, SWT, F-DCT, and NSCT-based fusion algorithms. Further, the quality of the fused image also evaluated using a set of quality metrics such as PSNR, CC, E, and RMSE. Rest of the article is as follows: section describes the existing fusion techniques. Rest of the article is as follows: section 2 describes the proposed PCA-based NSCT fusion methodology. Section 3 demonstrate the results and discussion of existing and proposed fusion approaches. Section 4 explains the conclusions followed by bibliography.

2. PROPOSED METHODOLOGY

2.1. Background: NSCT

Authors in [19] addressed the concept of Contourlet transform (CT), which is good enough for building the expansions of multiresolution with numerous directions and potential to identify the edge element discontinuity and the fluency across the contours. CT employ Laplacian pyramidal filter banks (LPFBs) [8] and directional filter banks (DFBs) in the first and latter stages at angular decomposition. But shift invariancy and structural info was not rendered by CT, Therefore, fusion performance might get degraded. Recently, several methodologies have been addressed to innovate the fusion approaches with image transforms. In [20], authors introduced octave band DFBs which produce the decompositions in eight bands rather than four. Another approach is named as critically sampled CT, that utilized a single level filter bank with on-separable function [21]. Another issue with the CT is the artifacts occurrence introduced by fixing several transform coefficients to zero for the approximations in nonlinear while processing the fusion, where this results in an occurrence of undesired artifacts at useful locations. Thus, the substantial data might be lost after completion of the fusion procedure [22]. Hence, NSCT innovated in this article to improve the fusion performance.

The NSCT consist a structure of filter bank as shown in figure 1, which decomposes a 2-D image into couple of shift invariant sections as follows:

- A nonsubsampled structure of pyramid which ensures the properties of multi scaling.
- A nonsubsampled structure of DFB which allows the multiscale directionality.

Following are the attributes of NSCT:

- Multi-resolution.
- Multi-directionality.
- Shift invariancy.
- Regularity.
- J+1 redundancy, where J is number of decomposition levels.

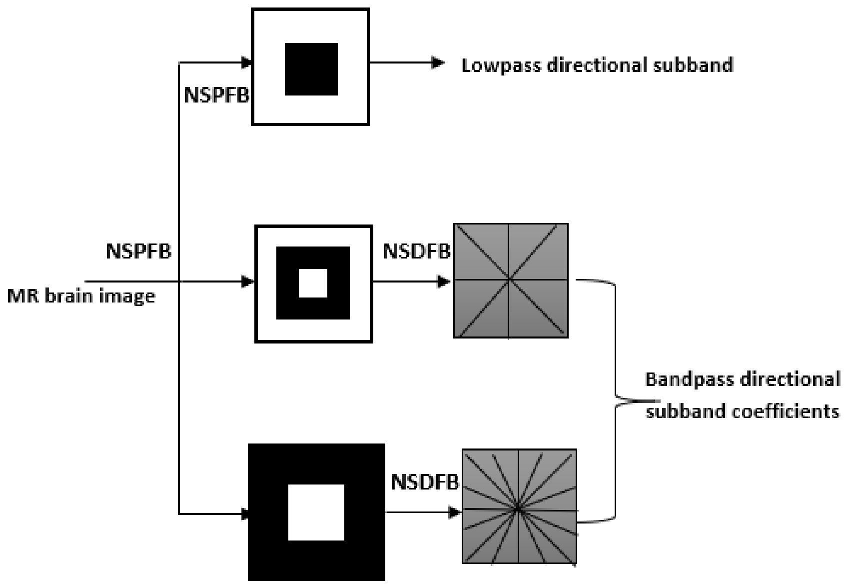

Fig. 1: Structure of NSCT.

PCA-based NSCT fusion system shown in figure 2 is implemented as follows.

Step-I: Usually, couple of images which are already registered from various sensors are separately corresponded to NSCT and results in attainment of band pass coefficients.

Step-II: Next, by employing another decomposition level, directional coefficients will be gained. After, decomposing the image into 3 level, there will be total of 9 components i.e., one approximated and eight detailed components.

Step-III: Now, fusion rule is employed using PCA on to the obtained outcome of Step II.

A. Fusion rule

After obtaining the approximate and detail layers from the source MR and CT images PCA is applied to find out principal components for getting better analysis over conventional fusion algorithms presented in the literature. Now, to get a fused output image a rule must be utilized to obtain optimum output from the proposed fusion process. We first combine the approximate layers of MR and CT images. Then sum the detail layers by multiplying with the principal components denoted as $\mathfrak{p}$ obtained by PCA algorithm. Finally, integrate these two process outputs to obtain fused image.

$$\mathcal{F}(x,y) = A(x,y) + D(x,y) \quad (1)$$

Where

$$A(x,y) = A_{In}(x,y) + A_{Jn}(x,y) \quad (2)$$

$$D(x,y) = \mathfrak{p}(1) * D_{In}(x,y) + \mathfrak{p}(2) * D_{Jn}(x,y) \quad (3)$$

Step-IV: Finally, obtain the fused outcome with better enhanced perception vision by employing inverse NSCT.

2.1. Image quality metrics

Here, we used image quality metrics to measure the output fused image quality which is obtained by using existing and proposed algorithms. Those are:

- Mean Square Error (MSE)

$$MSE = \frac{1}{m \times n} \sum_{i=0}^{m} \sum_{j=0}^{n} \left(A_{i,j} - B_{i,j}\right)^2 \tag{4}$$

Where, A= first input image

B = Second input image

i, j= number of rows and columns

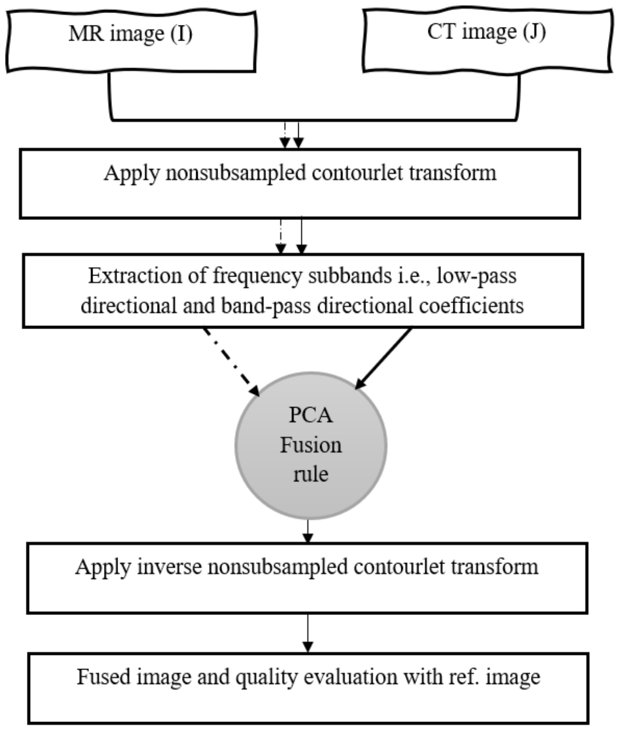

Fig. 2: PCA-based NSCT image fusion system.

- Peak Signal to Noise Ratio (PSNR)

$$PSNR = 10 \times \log_{10} \frac{255^2}{MSE} \text{ (For grayscale)} \tag{5}$$

$$PSNR = 10 \times \log_{10} \frac{1}{MSE} \text{ (For binary)} \tag{6}$$

$$CC = \frac{\sum_i \sum_j (A_{ij} - \bar{A})(B_{ij} - \bar{B})}{\sqrt{\left(\sum_i \sum_j (A_{ij} - \bar{A})^2\right)\left(\sum_i \sum_j (B_{ij} - \bar{B})^2\right)}} \tag{7}$$

Where $\bar{A}$=mean of A and $\bar{B}$= mean of B

$$E = -\sum(p.* \log_2 p) \tag{8}$$

Where p contains the normalized histogram counts.

3. RESULTS AND DISCUSSION

In this section, all the experiments that have been done in MATLAB are presented. Various images have been tested with existing and proposed PCA-based NSCT fusion approaches for image enhancement.

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Figure 3 shows that datasets of MR and CT images to be fused which is denoted as dataset 1 and dataset 2. Figure 4 shows that obtained fused images using DWT, SWT, F-DCT, NSCT and proposed PCA-based NSCT fusion approaches, respectively. Similarly, Figure 5 demonstrates the outcome of dataset 2 with the existing and proposed PCA-based NSCT fusion approaches. From both the figures, it can be observed that fused outcome of proposed PCA-based NSCT consists of higher texture and even good enough visual quality as compared to existing fusion methodologies like DWT, SWT, F-DCT, and even that of NSCT.

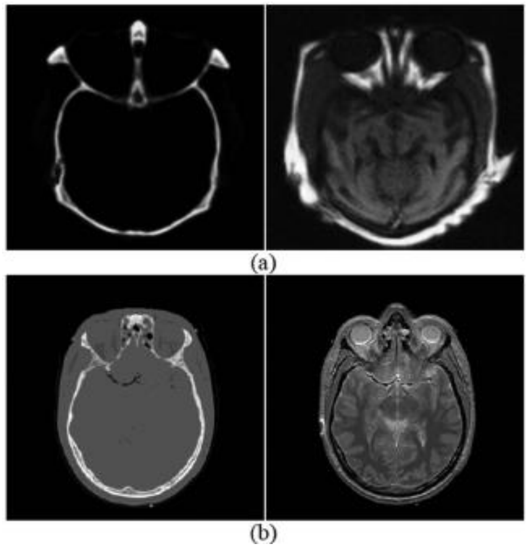
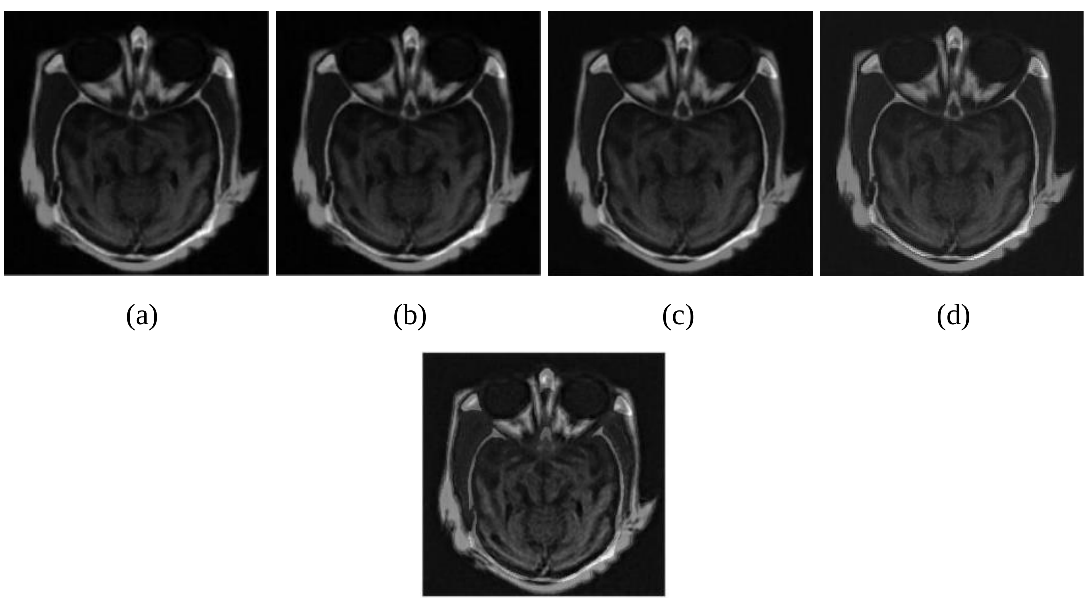


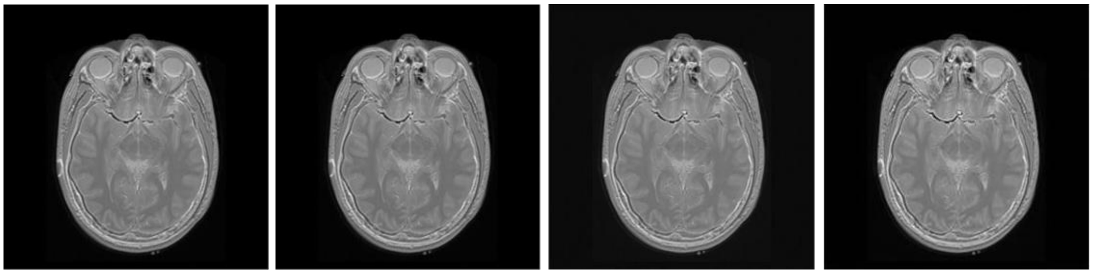
Fig. 3: CT and MR images. (a) dataset 1. (b) dataset 2.



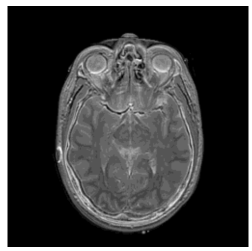
(a) (b) (c) (d)

(e)

Fig. 4: Obtained fused images of dataset 1 using existing fusion approaches. (a) DWT. (b) SWT. (c) F-DCT. (d) NSCT. (e) proposed PCA-based NSCT.



(a) (b) (c) (d)



(e)

Fig. 5: Obtained fused images of dataset 2 using existing and proposed fusion approaches. (a) DWT. (b) SWT. (c) F-DCT. (d) NSCT. (e) PCA-based NSCT.

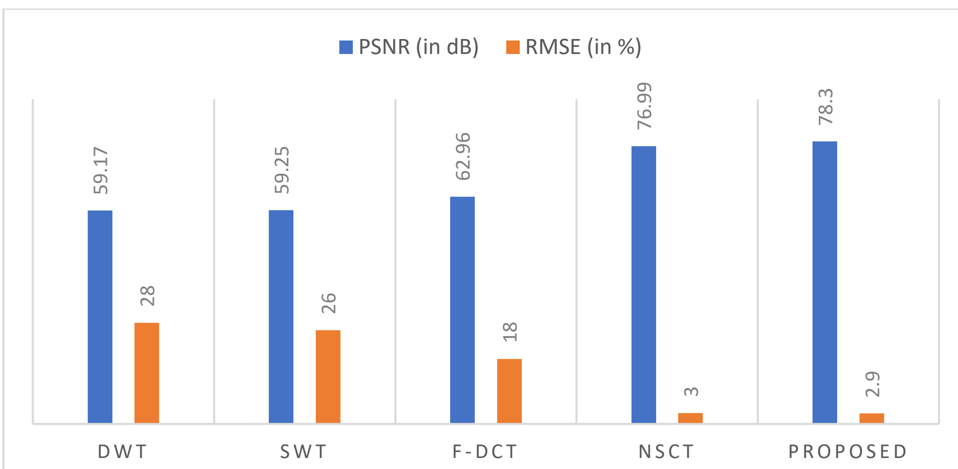


Fig. 6: Performance analysis of PSNR and RMSE with existing and proposed fusion methodologies for dataset 1.

Comparison performance of PSNR and RMSE values for existing and proposed PCA-based NSCT fusion methodologies for dataset 1 is given in figure 6, where the proposed PCA-based NSCT fusion algorithm got 78.3dB with enhanced quality in the fused image as compared to existing fusion algorithms. Similarly, CC, and E values comparison is demonstrated in figure 7.

Performance evaluation of existing and proposed PCA-based NSCT fusion methodologies in terms of PSNR and RMSE values for dataset 2 is given in figure 8, where the proposed PCA-based NSCT fusion algorithm obtained 68.3dB of PSNR, which is quite higher and even visual quality of fused image also enhanced as disclosed in Figure 5 as compared to existing fusion algorithms. Similarly, CC, and E values comparison is demonstrated in figure 9.

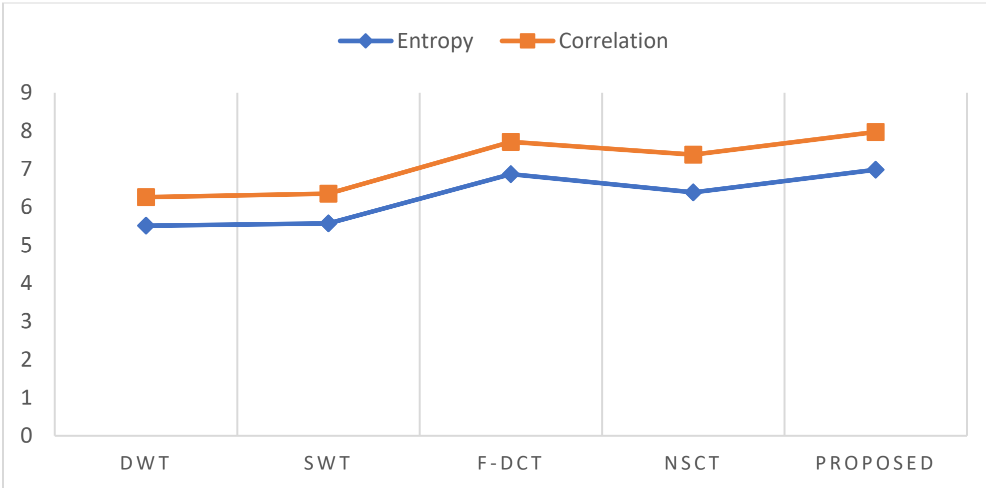


Fig. 7: Performance evaluation using E and CC with dataset 1.

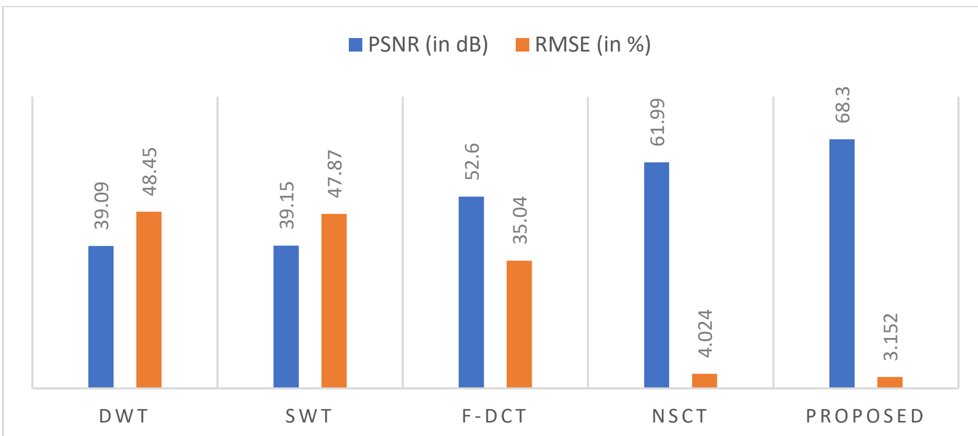


Fig. 8: Performance analysis of PSNR and RMSE with existing and proposed fusion methodologies for dataset 2.

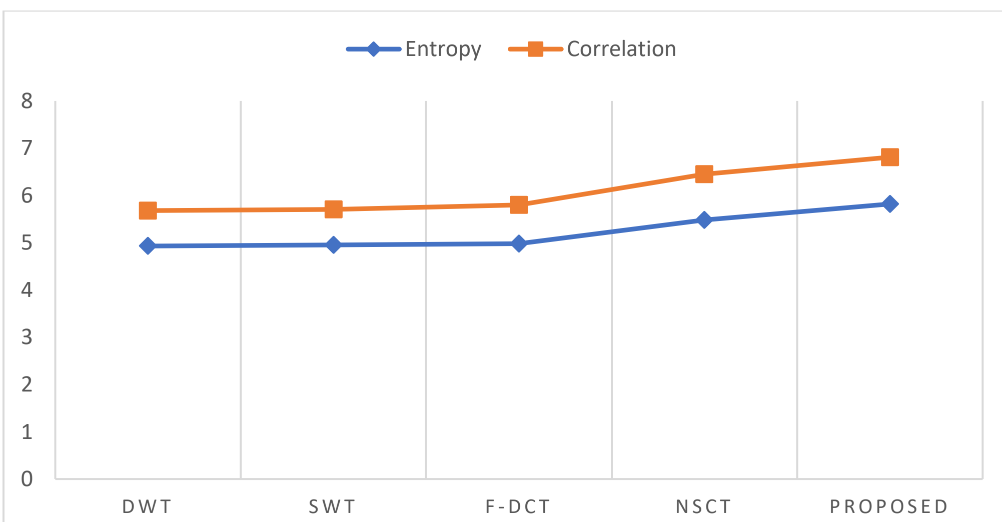


Fig. 9: Performance evaluation using E and CC with dataset 2.

5. CONCLUSION

This article presented a medical image enhancement approach using PCA-based NSCT fusion methodology, which utilized the advantages of both NSCT and PCA to fuse the MR and CT images with good quantitative and qualitative performance. In addition, different datasets are considered to show the effectiveness and robustness of proposed PCA-based NSCT fusion algorithm. Simulation results disclosed the superiority of proposed approach in terms of PSNR, RMSE, E, and CC values as compared to existing fusion approaches like DWT, SWT, F-DCT and even that of NSCT. In future, we will continue to focus on the application of recent progress of multi-resolution analysis theory in 3D medical image fusion.

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