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ENHANCEMENT TECHNIQUE FOR PET IMAGES USING STATIONARY WAVELET TRANSFORM AND HIGH BOOST FILTERING

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ABSTRACT

Positron Emission Tomography (PET) images generally have a low resolution and are blurred in nature. This necessitates the need for image enhancement in PET. Stationary Wavelet Transform (SWT) helps in reducing noise thereby improving the quality of the images. The detail modulus of SWT decomposed image is deployed in high boost filtering for the proposed enhancement technique. This technique can be used as a pre-processing step before segmentation of the images. The proposed technique shows a PSNR around 39 dB which itself is an indicator to the enhancement achieved. The visual inspection also shows the improvement in quality of the images.

KEYWORDS: Contrast Improvement Index, Detail Modulus, Enhancement Measure, Image Contrast, Image Enhancement, Positron Emission Tomography, Stationary Wavelet Transform

INTRODUCTION

Positron Emission Tomography (PET) is a nuclear medicine medical imaging technique that produces a three dimensional image of functional processes in the body [1]. The main principle of PET is based on the detection of photons emitted from the patient after the injection of a short-lived radio- pharmaceutical like fluoro-deoxy-glucose (FDG). These photons are detected by the PET scanner which allows the reconstruction of a three dimensional image [2]. In PET imaging, the patient is injected with radioactive isotopes that emit particles called positrons. When a positron meets an electron, the collision produces a pair of gamma ray photons having the same energy but moving in opposite directions. From the position and delay between the photon pair receptor, the origin of the photons can be determined. PET is a functional modality that can be used to visualize pathologies at much finer molecular level. This is achieved by employing radioisotopes that have different rates of intake for different tissues. The patient is surrounded by multiple rings of gamma photon detectors, so no detector rotation is required. PET images have spatial resolution of about 2mm [3]. PET can be used to quantitatively measure physiological parameters, such as blood flow, or glucose metabolic rate [4].

The advantages of PET are clear localization of regions of metabolism in brain and heart, identification and sizing of heart infarcts and quantitative permeability for brain tissue. PET imaging allows the evaluation of a drug by identifying and measuring regional metabolic changes as a result of drug therapy. PET is also highly sensitive to early signs of any disease. In PET images, exact location and extent of the lesion are measured by detecting early biochemical changes and checking whether the targeted tissue is metabolically active. The doctor can assess the biochemical process underlying the abnormality of an organ accurately with interpretation of good quality PET images [2].

The downside of PET is its relatively low spatial resolution, as a result of which its role in detecting direct invasion to adjacent structures such as stomach or duodenum or encasement of blood vessels become limited. Another short coming of PET imaging is the blurry nature of PET images and the high noise-to-signal ratio. The blurriness and the low spatial resolution in PET images, leads to a need for an enhancement technique that is capable on enhancing the quality of PET images without altering its dominant features[5].

Davis and Abidi modeled and filtered the noise in PET images utilizing the spectral characteristics and mapped to polar coordinates so as to enhance the images [2]. Another method developed for edge enhancement in PET images is implemented by higher order derivative systems that emphasis the details in PET images [5]. A 3-Dimensional (3D) wavelet based image processing tool, a wavelet filter, is suggested for denoising and enhancement of dynamic PET image data. The filter is based on multi-scale thresholding and cross-scale regularization [6]. The enhancement by reconstruction of PET data by using Expectation Maximization (EM) is also a newly discussed method [7]. The RGB image is changed to XYZ and YUV color space to ensure a better quality PET image with minimal data loss [8]. Another proposed technique is based on the interpolation of sub-band images derived using Discrete Wavelet Transform (DWT) which works well with 2-Dimensional (2D) and 3D images, enhancing the image details and preserving the edges [9]. PET images are enhanced by de-noising using a 3D wavelet expansion and thresholding with cross-scale regularization [10]. In this paper we propose a method to enhance PET images using Stationary wavelet transform (SWT), detail modulus of the transform and unsharp masking.

THEORY

The necessary basic knowledge in the areas of SWT, modulus maxima and high boost filtering are given in the following sections, since the proposed work is footed on the above areas.

Stationary Wavelet Transform

The basic idea of stationary wavelet transform is to fill the gap caused by decimation in the standard wavelet transform. This results in over determined representation of the original data, having much statistical potential [11]. The SWT is an inherently redundant scheme, as the output of each level of SWT contains the same number of samples as the input. SWT is similar to the DWT except that the filters are up-sampled instead of sub-sampling the signal at each level of decomposition. Each level's filters are up-sampled versions of the previous ones. The decomposition and filters are shown in Figure 1a. In Figure 1b, the 2D SWT decomposition along with filters is shown. H_j and L_j represent high-pass and low-pass filters at scale j, resulting from interleaved zero padding of filters H_{j-1} and L_{j-1} (j>1). LL_0 is the original image and the output of scale j, LL_j, would be the input of scale $j+1$. LL_{j+1} denotes the low-frequency (LF) estimation after the stationary wavelet decomposition, while LH_{j+1}, HL_{j+1} and HH_{j+1} denote the high frequency (HF) detailed information along the horizontal, vertical and diagonal directions, respectively.

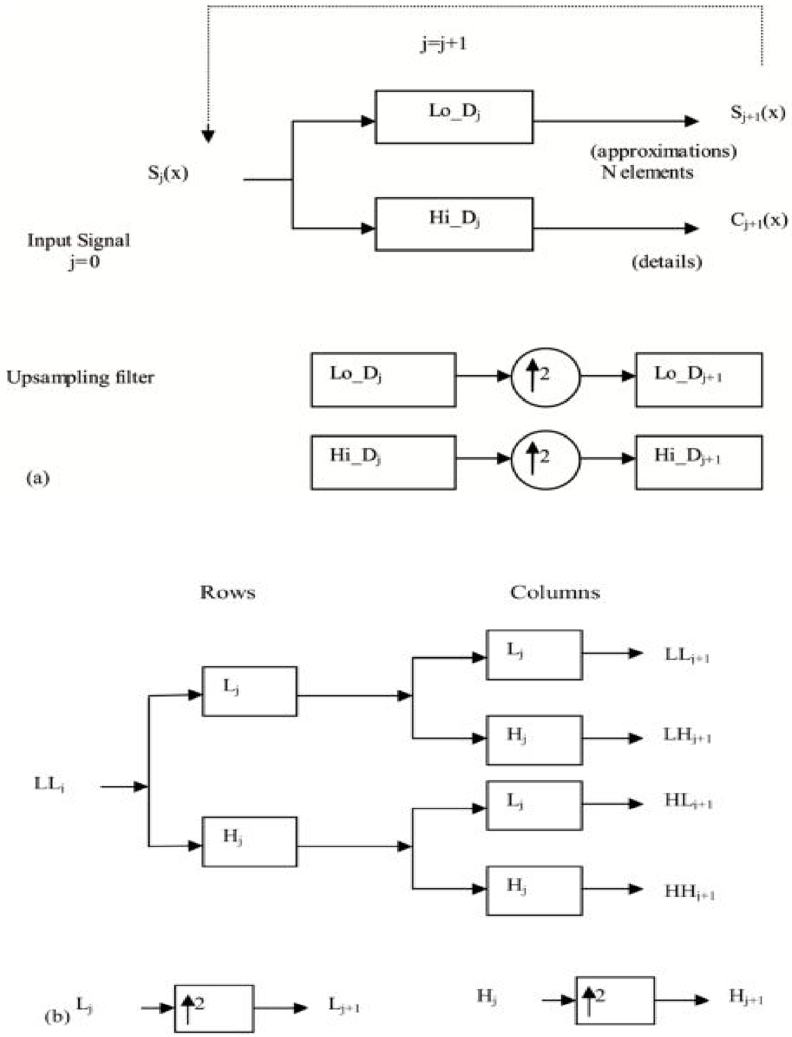


Figure 1: SWT Decomposition (a) 1D (b) 2D [12]

The single level decomposition and reconstruction using SWT of standard image '*rice*' is shown in Figure 2.

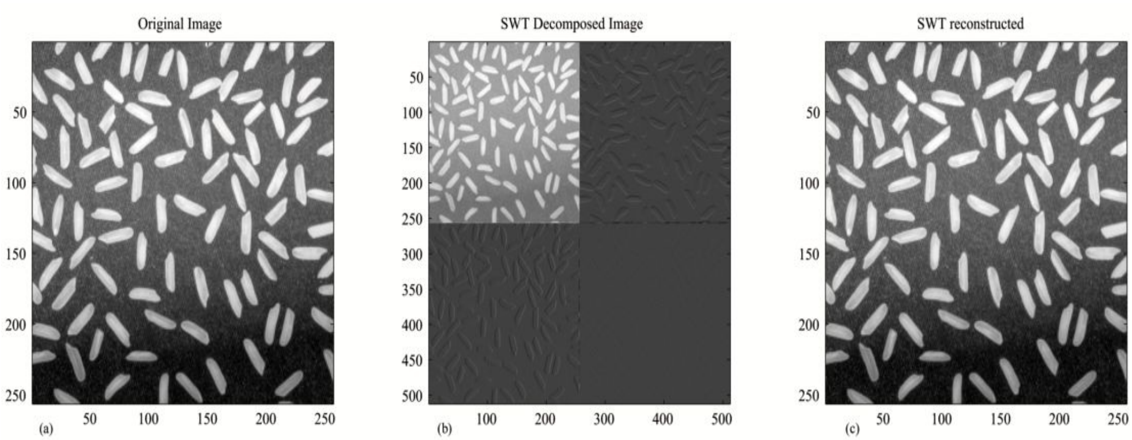


Figure 2: Decomposition and Reconstruction Using SWT (a) Original Image (b) Result of Single Level Decomposition and (c) Reconstructed Image

Detail Modulus

The modulus maxima of the wavelet transform provide a nearly complete characterization of an image. A definition of local maxima of the wavelet transform modulus is: Let $Wf(s, x)$ be the wavelet transform of a function $f(x)$.The modulus maximum is any point(s_0, x_0), such that $|Wf(s_0, x)| < |Wf(s_0, x_0)|$when x belongs to either a right or the left neighborhood of x_0, and $|Wf(s_0, x)| \leq |Wf(s_0, x_0)|$ when x belongs to the other side of the neighborhood of x_0. The local maxima of the wavelet transform modulus provide enough information to detect and analyze all discontinuities inside images and local Lips chits exponents can often be measured from the evolution across scales of the wavelet transform [13]. Consider wavelet decomposition of an image $f(x, y)$ at scale j, we get an approximation and three detail images represented as $W_j^h f$, $W_j^v f$, $W_j^d f$ where the superscripts h, v and d denote the horizontal, vertical and diagonal details. The image edges are characterized at scale j by the local modulus maxima denoted as $M_j f$ [14].

$$M_j f(x,y) = \sqrt{\left|W_j^h f(x,y)\right|^2 + \left|W_j^v f(x,y)\right|^2} \tag{1}$$

Considering the fair treatment of edges at different orientations, detail modulus can be defined as

$$D_j f(x,y) = \sqrt{\left|W_j^h f(x,y)\right|^2 + \left|W_j^v f(x,y)\right|^2 + \left|W_j^d f(x,y)\right|^2} \tag{2}$$

The detail modulus gives a better characterization of edges making it useful for image enhancement [15].

High Boost Filtering

A high boost filter can be defined as a weighted combination of original image ($I_{Original}$) and the high pass filtered version of the image ($I_{Highpass}$). It is also called as high frequency emphasis filter. The high boost filter I_{HBF} is defined as

$$I_{HBF} = K \times I_{Original} + I_{Highpass} \tag{3}$$

The weight is decided by K and weighted version of original image is added to the high pass filtered image to get high boost filtered image [16]. The high boost filter not only preserves the low frequency information but also enhances the high frequency detail information. This enhances the similarity feature value within similar regions and dissimilarity feature value among the dissimilar regions. The high boost filter is simple and the implementation cost is less.

PROPOSED METHOD

The proposed method starts with 2DSWT decomposition of the image and finding the detail modulus of each level. SWT is performed on the image up to three levels. For each level, the absolute maximum wavelet coefficient, called detail modulus maximum, is computed. T_n is set up to include all wavelet coefficients whose absolute value is within the range of the threshold of the wavelet detail modulus maximum. A high pass filtered image is obtained by discarding all the remaining co-efficient, which is used for high boost filtering.

Let $D_i f(x, y)$ be detail modulus of the image at the level i who has highest absolute value M_i among all the coefficients of each scale. Any wavelet coefficients $Wf(2^i, x, y)$ at each scale satisfying either of the following:

$$Wf(2^i, x, y) \leq -M_i + T_n \quad \text{If} \quad Wf(2^i, x, y) < 0$$

$$Wf(2^i, x, y) \geq M_i - T_n \text{ If } Wf(2^i, x, y) \geq 0 \tag{4}$$

are kept unchanged, whereas all the other wavelet coefficients are set to zero before the reconstruction of the image. The approximation is also put to zero and the inverse SWT is calculated. The original image is enhanced by adding reconstructed image to the original. Figure 3 shows the enhanced image using the proposed method.

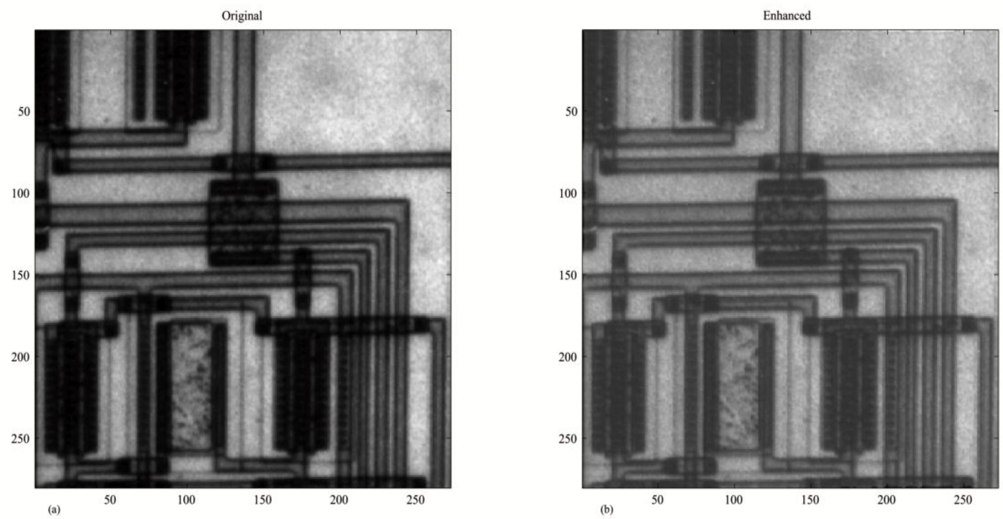


Figure 3: Result of Proposed Method (a) Original and (b) Enhanced Image

PERFORMANCE MEASURES

Enhancement of an image is verified by subjective as well as objective measures. The objective measures used here for measuring enhancement are contrast, measure of enhancement, entropy, contrast improvement ratio and PSNR. The contrast of an image is evaluated by employing the metric function given below:

$$C_C = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} f'^2(i,j) - \left|\sum_{i=1}^{M}\sum_{j=1}^{N} f'(i,j)\right|^2 \tag{5}$$

Where M and N are height and width of the image, respectively, and $f'(i, j)$ is the enhanced image. The larger the value of C_C, the better the contrast of the image

A quantization measure of contrast enhancement is defined by a contrast improvement index (*CII*), which is expressed as

$$CII = \frac{C_{processed}}{C_{original}} \tag{6}$$

Where $C_{processed}$ and $C_{original}$ are the contrasts of the processed and original images, respectively C is the average value of the local region contrast in the processed or original image. Thus, the CII value of original image is equal to one. The local contrast at each pixel is measured as $(X_{max} - X_{min})/(X_{max} + X_{min})$ in its local window size [17].

The measure of enhancement or measure of improvement (EME) is another performance measure used to quantify image enhancement. For defining EME, the image $x(n, m)$ is split into k_1k_2 blocks $w_{kl}(i, j)$ of sizes l_1xl_2. Then the quantity, enhancement measure by entropy (EMEE) is given as

$$EMEE = \max_{\phi \in \{\Phi\}} \chi(EME(\phi)) \tag{7}$$

Where $\chi(EME(\phi))$ is defined as

$$\chi(EME(\phi)) = \frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} \frac{I^w_{max;k,l}}{I^w_{min;k,l}} log \frac{I^w_{max;k,l}}{I^w_{min;k,l}} \tag{8}$$

Is measure of enhancement by entropy? Higher the value of EMEE, better the enhancement [18].

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as

$$H = -\sum p \, log_2 \, p \tag{9}$$

Where p contains the histogram counts In other words, it is defined as

$$H = -\sum_{i=1}^{L} P(i) log_2 P(i) \tag{10}$$

Where $P(i)$ is the probability of occurrence of i^{th} gray level and L is the no. of gray levels. A higher value in entropy indicates better quality of the image. Peak Signal to Noise Ratio (PSNR) can also be used as a measure to quantify enhancement. It is defined as

$$PSNR = 10 \, log_{10} \frac{(L-1)^2}{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [f'(i,j) - f(i,j)]^2} \tag{11}$$

Where $f(i, j)$ is the original image of size MxN, $f'(i, j)$ is the enhanced image and$L-1$ is the maximum possible value in $f(i, j)$. Small values of PSNR indicate that image is of poor quality [19].

RESULTS AND DISCUSSIONS

The database used for this study is on coped DB, a freely available realistic simulated database of whole body 18F-FDG PET images for oncology. This database contains 100 images, including 50 normal cases coming from different realizations of noise of the healthy model and 50 pathological cases including lesions of calibrated uptakes and various diameters. A model of lesion extent based on the clinical description of lymphoma patients is used. Lymphoma affects the lymphatic system through the lymph nodes and other organs implied in the immune system. It mostly affects young adults and is particularly reactive to conventional treatments, such as chemotherapy or radiotherapy. PET is used for the crucial part of staging and treatment follow-up of lymphoma, due to a higher sensitivity and specificity than anatomical medical imaging modalities. Lymphoma is characterized by small lesions that are mainly localized in the lymph nodes and can also extend in other organs such as the liver, the spleen, and the lungs [20].

Each image in this database is of size 128 x 128 x 375. Standardized uptake values (SUV) are widely used to measure FDG uptake. The more reliable SUV normalization of FDG uptake for the body surface area is used here [21]. To reduce the complexity of computation each of the axial slices is taken one by one and processed. The wavelet chosen here is *symlet5*. The original and enhanced slice from the PET image having no lesion is shown in Figure 4 while Figure 5 shows that of an image having two lesions.

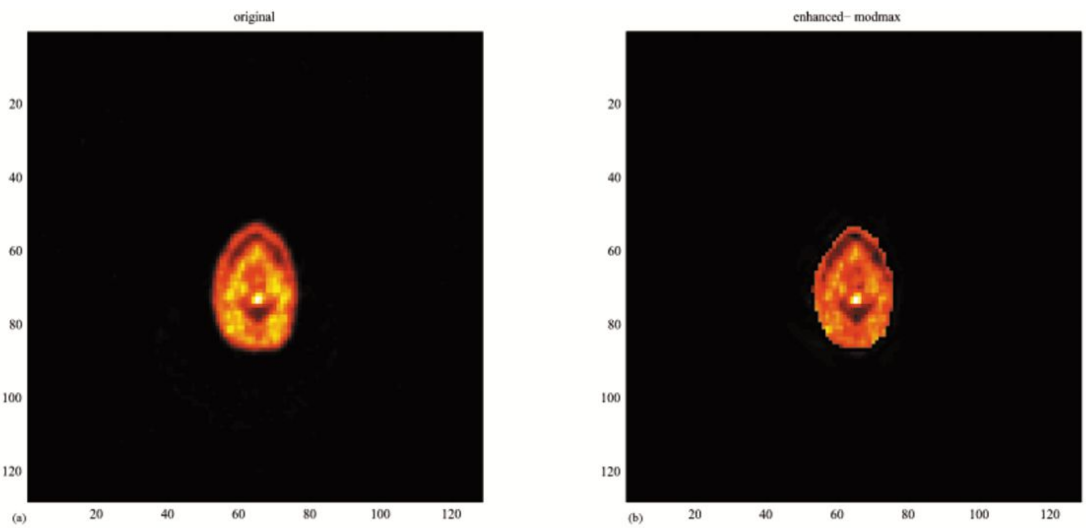


Figure 4: Result of Enhancement on a Slice of Normal Image
(a)Original Image (b) Enhanced Image

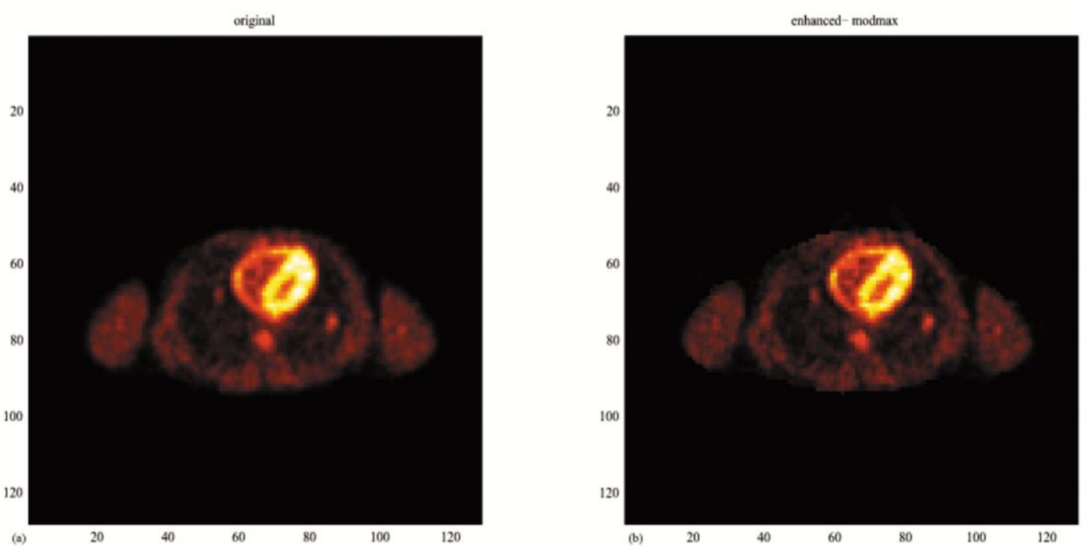


Figure 5: Result of Enhancement on an Image Slice with Two Lesions
(a) Original Image (b) Enhanced Image

The contrast, CII, EMEE, entropy and PSNR of the corresponding slices in the original and enhanced images are calculated and compared. The plot of average contrast of images with lesions and without lesions and that of enhanced images are shown in Figure 6. A clear improvement in contrast is observed in the images enhanced using the proposed method. The average value of contrast for normal images increased by 40after enhancement, while for images having lesions it is increased by about 22

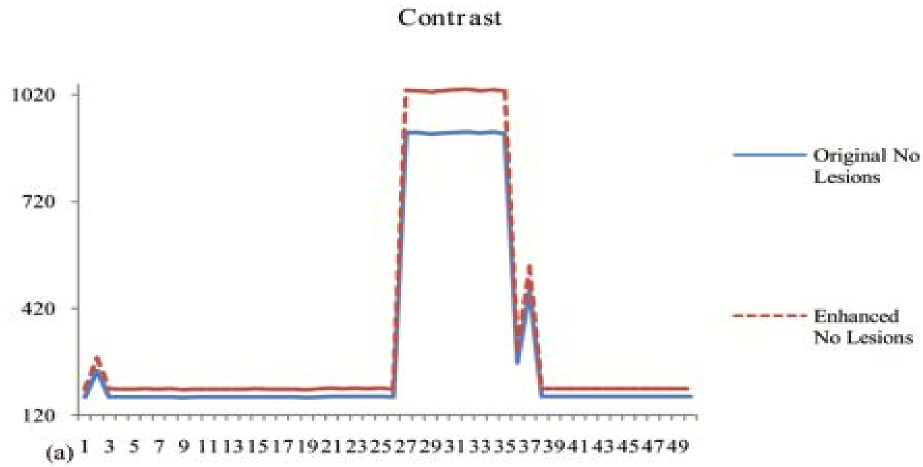


Figure 6(a): Contrast of Original and Enhanced Normal Images

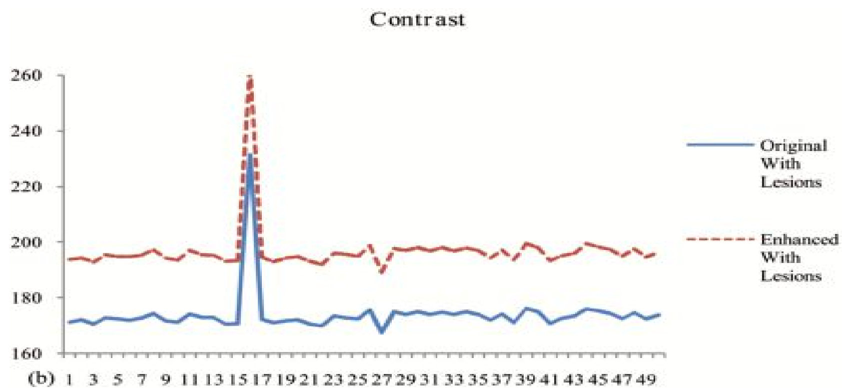
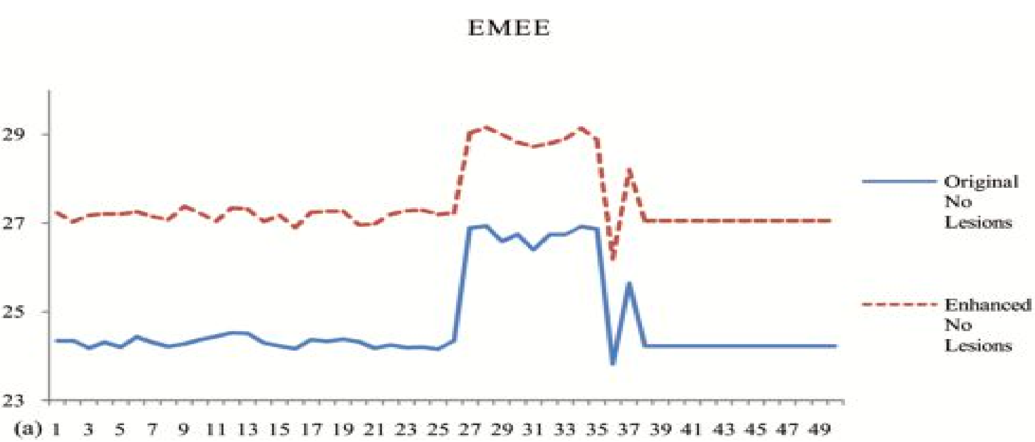


Figure 6(b): Contrast of Original and Enhanced -Images with Lesion

The mean CII for images with lesions and without lesions are measured as 11 and16 respectively using the proposed method. The local contrast is obtained by dividing the image into blocks of size 7x7 pixels. This window size gives optimum value for CII.

The average value of EMEE for normal images as well as those having lesions is increased by an amount of 3 the average EMEE for normal and abnormal images in original and enhanced versions are plotted in Figure 7.



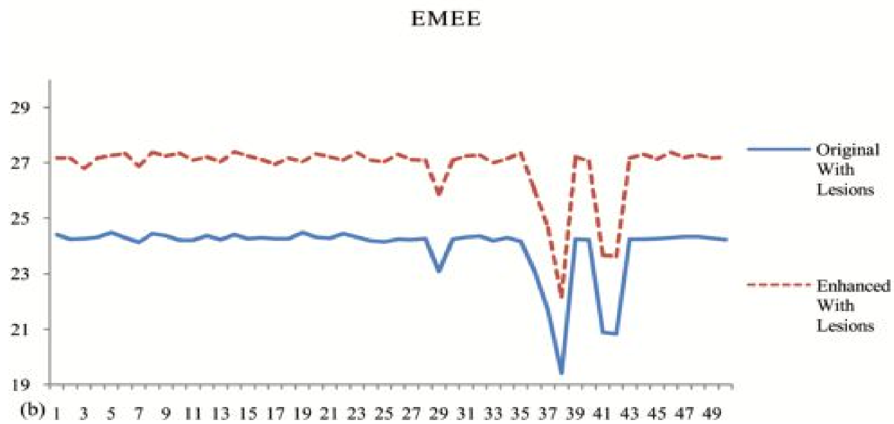


Figure 7: EMEE of Original and Enhanced (a) Normal Images (b) Images with Lesions

A boost of about 2 in average entropy value is obtained for normal images as well as images with lesion. The PSNR value in decibels is calculated between the corresponding slices in the original and enhanced images. The plot of average PSNR value of images with and without lesions is given in Figure 8 and it clearly shows the occurrence of enhancement. The average value of PSNR in dB for images with lesions is 39.97 while for normal images it is 39.87.

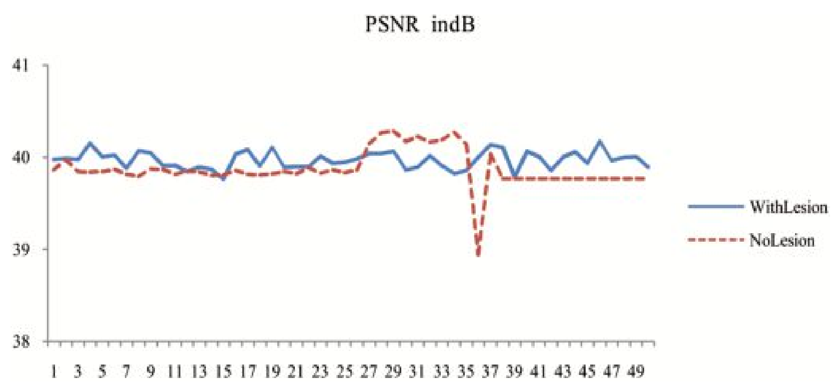


Figure 8: PSNR of Images with and Without Lesions

CONCLUSIONS

The proposed method used detail modulus of SWT coefficients and high boost filtering to achieve enhancement of PET images. The performance measures viz., contrast, CII, EME, entropy and PSNR are evaluated and they clearly show the enhancement. The proposed method is suitable in improving diagnostic information from PET images.

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