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IMAGE DENOISING USING MODIFIED SINGULAR VALUE DECOMPOSITION METHOD

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ABSTRACT

Noises in the image leads to pixels degradation and the quality of the image will be reduced. Removal of noises (Gaussian, Poisson and Speckle) from the image leads to develop the better image. Lowering of radiation dose leads to deterioration of quality of the image. Hence, we proposed the new modified Singular Value Decomposition Method for image denoising. In addition to that Inverse Discrete Wavelet Transform and Singular Value Decomposition is applied at the post processing step to remove the noise in the filtered image. Parameters are carefully formulated and evaluated. Experimental results show the better improvement in image demising.

KEYWORDS: *Modified Singular Value Decomposition, Peak Signal to Noise Ratio (PSNR), Root Means Square Error (RMSE), Structural Similarity Index (SSIM)*

I INTRODUCTION

Computer Tomography (CT) is widely used in diagnostic, industrial and other applications. One of the challenging tasks in image processing is noise removal. Noises are affecting the visual appearance of the images. Poor generation of transmission in electronic circuits leads to generation of gaussian noise. Poisson noise originates due to movement of packets (Photons). Speckle noise is generated by backscattered signals which affect the image interpretation. Noises will be introduced in the image during transmission or acquisition or hardware issues. General methods of reducing the radiation dose are reducing tube voltage, tube current and scanning time. Quantification of the noise will be determined by the corrupted pixel in the image. If the pixel range becomes high then the quality of image increases and it reduces the noise. The image quality has been represented by distance between the pixels. Over the past decades, many algorithms and techniques were proposed: Fractional Integral filtering [1] - [3], KSVD[4], BM3D[5][6], Convolutional Neural Network (CNN)[7], etc. Various noise detectors are also introduced for the removal of noise ie., DWM[8], RILD-EPR[9], ROR-NLM[10]. Existing algorithms are having less PSNR value, high RMSE and during filtering process additional pixels will be neglected i.e., loss of original information. To overcome these problems, a modified algorithm is proposed. This proposed algorithm shows improved Peak Signal to Noise Ratio(PSNR) and reduced Root Means Square Error (RMSE).

II ALGORITHM PROPOSED

The proposed algorithm for image denoising is given in the following steps.

I. After the preprocessing and histogram equalization,

II. Addition of artificial noise with the original image

III. Application of Discrete Wavelet Transform to get LL Image.

IV. Calculation of ε and ∑

V. Calculation of SSIM, RMSE and PSNR.

VI. Calculation of SVD & DWT.

Histogram plots provide useful information about the fluctuation in image contrast. This variation suffers from a low contrast problem in medical photographs, which is frequently caused by the concentration of grey levels in pixels.

As a result, SVD can solve this issue by adjusting image intensities to enhance such low contrast images. As a result, we consider low contrast T1-w brain MR images as input images (A1), on which we apply the GHE approach to produce equalised images (A2) (with zero as mean and one as variance). We obtain four frequency sub-bands marked (LL1), (LH1), (HL1), (HH1) and (LL2), (LH2), (HL2), (HH2) by utilising the DWT [20] for the original and processed equalised pictures; (A1) and (A2).SVD would be applied to the (LL1) and (LL2) subbands of the original and equalised pictures, respectively. The reason for employing the (LL) sub-band was to protect the edge information presented in high frequencies while modifying the intensity information concentrated in low frequencies.

SVD approach can lead to a matrix factorization in the form of

$$A = U.\Sigma.V^{\top}$$

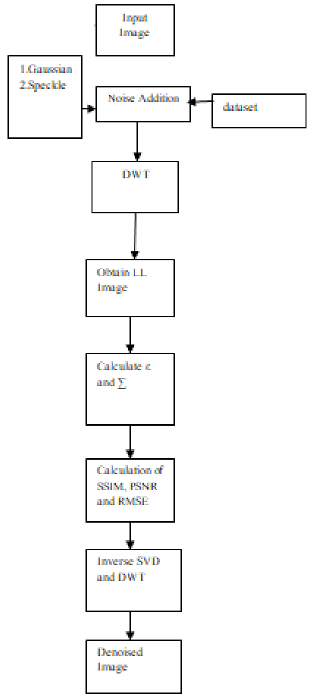

Figure 1: Flowchart of the Proposed Algorithm.

To equalize intensity information of the image, we apply SVD method which uses the ratio of the largest singular value of the generated equalized matrix, over a normalized input image to generate a correction coefficient (ξ) formulated as

$$\xi = \frac{\max(\Sigma_{2\ (\mu=0, var=1)})}{\max(\Sigma_1)}$$

Bhandri, et.al derived an equation as follows

$$\xi = \frac{\max(U_{LL_2})}{\max(U_{LL_1})}$$

The above equation is modified as

$$\xi = \frac{\max\left(U_{LL_2}\right) + \max(V_{LL_2})}{\max\left(U_{LL_1}\right) + \max(V_{LL_1})}$$

We have derived new ε and it is given

$$New\ \Sigma = 0.5(\xi . \Sigma_{LL_1} + \frac{1}{\xi} . \Sigma_{LL_2})$$

However, this method cannot be applicable for all images because multiplying the singular matrix of both input and equalized images by a constant and fixed factor (0.5) is not applicable for all types of input image. To overcome this limitation, in our present development, we propose a new adjustable method to calculate the new singular matrix (New ε). This new Equation uses an empirically adjustable parameter (μ) and the modified singular matrix (New ε) is computed accordingly.

$$New\ \Sigma = (\mu.\xi.\Sigma_{LL_1}) + ((1-\mu).\frac{1}{\xi}.\Sigma_{LL_2})$$

In this work our goal is to design a network that reproduces the K-SVD denoising algorithm, while having the capacity to better learn its parameters. By reposing each of the operations within the K-SVD algorithm in a differentiable manner, we aim to be able to back-propagate through its parameters and obtain a version of the algorithm that outperforms its earlier variants. Note that in this supervised mode of work, we adopt the weaker version of the K-SVD denoising algorithm that relies on a universal dictionary for all images, as opposed to the image-adapted option that was shown to be superior.

An EPLL version of the K-SVD can be envisioned, in which the process of cleaning the patches is repeated several times. This implies that once the above architecture obtains its output Xˆ , the whole scheme could be applied again (and again). This diffusion process of repeated denoising has been shown into improve the K-SVD denoising performance. However, the difficulty is in setting the noise level to target in each patch after the first denoising, as it is no longer pσ2 . In our case, we adopt a crude version of the EPLL scheme, in which we disregard the noise level problem altogether, and simply assume that the λ evaluation stage takes care of this challenge, adjusting the MLP in each round to best predict the λ values to be used. Thus, our iterated scheme shares the dictionary across all denoising stages, while allowing a different λ evaluation network for each stage.

Training Settings: During training we randomly sample cropped images of size 128 × 128 from the training set. We add i.i.d. Gaussian noise with zero mean and a specified level of noise σ to each cropped image as the noisy input during training. We train a different model for each noise level, considering σ = 15, 25, 50

We use SGD optimizer to minimize the loss function. We set the learning rate as 1e−4 and consider one cropped image as the minibatch size during training. We use the same initialization as in the K-SVD algorithm to initialize the dictionary D, i.e the over complete DCT matrix. We also initialize the normalization paramater c of the sparse coding stage using the squared spectral norm of the DCT matrix. The other parameters of the network are randomly initialized using Kaiming Uniform method.

Root Means Square Error (RMSE) is calculated by the following equation

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(u_n - u_{original}\right)^2}$$

Measure of Peak Signal-to-Noise Ratio (PSNR) measures the ratio between the maximum possible value of a signal and the power of distorting noise that affects the quality of its representation. PSNR value of proposed method is the highest as compared to the other methods. This involves better quality of the image as well as best noise reduction.

Peak Signal to Noise Ratio is calculated by the following equation

$$\mathrm{PSNR} = 10\log \frac{\max\left(u_n, u_{original}\right)^2}{\frac{1}{N}\sum_{n=1}^{N}\left(u_n - u_{original}\right)^2}$$

Structural Similarity Index (SSIM) can be calculated by

$$\mathrm{SSIM} = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}$$

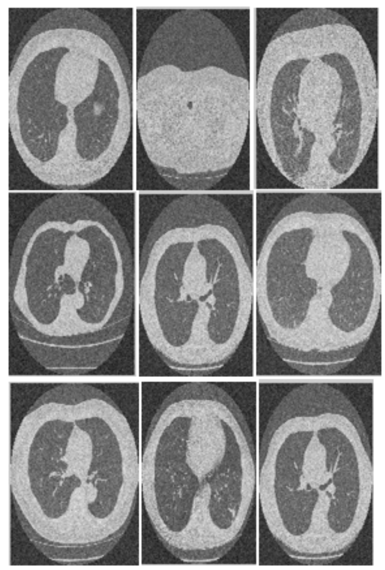

Figure 1: (a-h) Noisy Images.

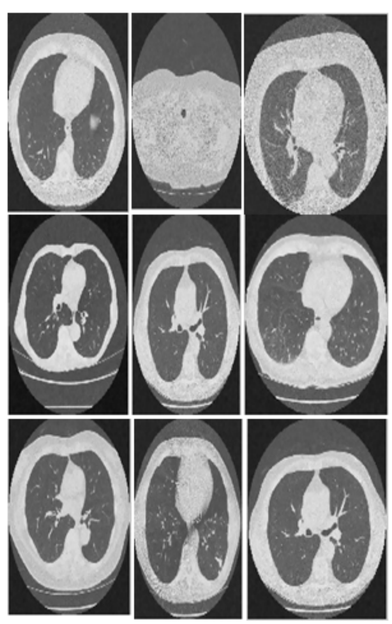

Figure 1: (a-h) Denoised images.

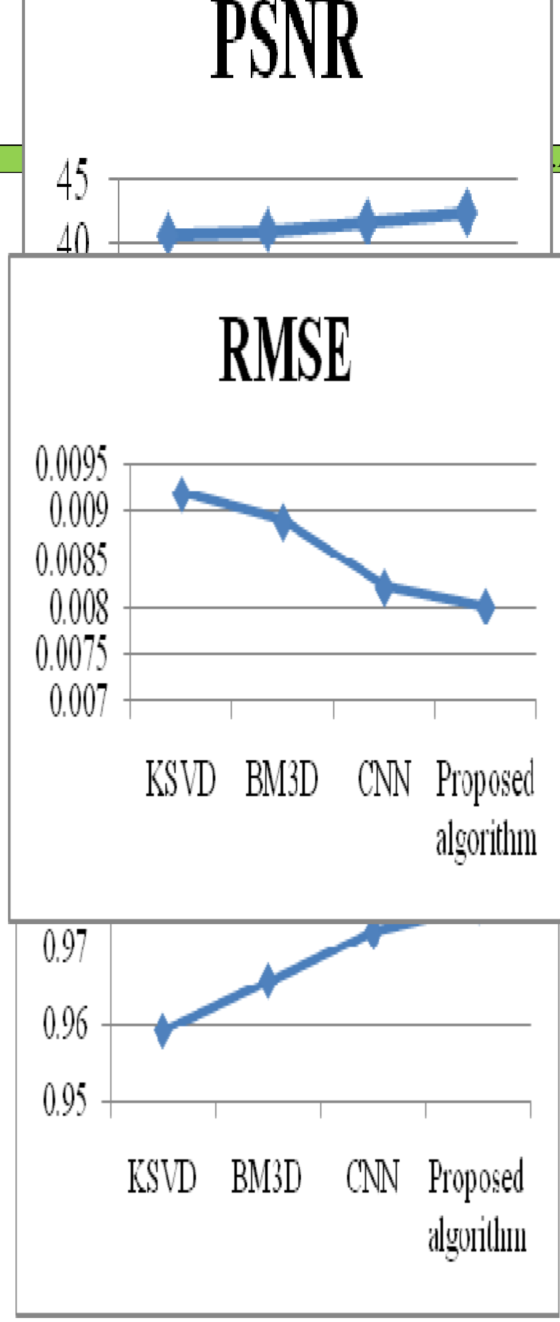

Figure 1: Graph for Comparing SSIM Values.

III CONCLUSIONS

In this paper, we have implemented modified Singular Value Decomposition Method. A set of 50 images is considered for evaluation of the algorithm. This proposed algorithm shows the improvement in Peak Signal to Noise Ratio (PSNR), Root Means Square Error (RMSE) and Structural Similarity Index (SSIM). This algorithm is implemented in MATLAB 2021.

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