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Low rank sparse coefficient based nuchal translucency image de-noising

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Abstract

The process of eliminating distortion or noise from an image is known as image de-noising. Random noise is introduced to ultrasonic imaging, resulting in reduced contrast in the images. For Nuchal translucency (NT) detection, image de-noising is a crucial stage. Although deep-learning methods have been extensively studied for this problem and have shown compelling results, most networks may result in disappearing or inflating gradients

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and need more memory and time to attain a spectacular performance. To achieve better overall framework optimization, Novel Methodology of anisotropic filtering followed by a compressed sensing based on Low Rank Sparse Coefficient(LRSC) for ultrasound image de-noising is proposed to achieve better overall framework optimization, this article proposes anisotropic filtering followed by a compressed sensing based on Low Rank Sparse Coefficient(LRSC) for ultrasound image de-noising. This hybrid technique is quite effective at reducing noise while yet retaining fine image details. Real-time hospital images are utilized to assess the efficiency of the proposed model, taking into account clinical accessibility and imaging features. The peak signal-to-noise ratio (PSNR), mean square error (MSE), and structural similarity index (SSIM) were used to evaluate the proposed method's performance. Average SSIM, PSNR, MSE values are 0.98, 42.28 and 49 for HCNN[12], GAN[16] and Proposed method respectively. Proposed method have average MSE of 2.6, HCNN have 14 and GAN have 371.

Subject Classification: *26-XX, 30-XX.*

Keywords: *Nuchal translucency (NT), Low rank sparse coefficient (LRSC), Anisotropic filtering, De-noising, Compressed sensing.*

1. Introduction

Medical image analysis is used by physicians to diagnose illnesses. Medical images are contaminated by noise owing to a variety of causes in medical imaging. De-noising medical images may assist doctors in diagnosing illnesses. All the medical images are captured by various sensors and are polluted by various noises [1,2] such as additive white Gaussian noise (AWGN) [3], speckle noise [4], salt and pepper noise [5], rician noise [6], Brownian noise, and so on. Speckle noise, unlike additive white Gaussian noise, is a kind of multiplicative noise [8][9]. A low rank constraint and sparse nonlocal regularization weighted coding are used for medical picture de-noising technique and suggested to address situation where the de-noising method relies on it which can causes serious loss of details.

Low-dimensional models such as sparsity, low-rank structures, and manifolds have sparked a surge of interest in data approximation in recent years [10]. The suggested de-noising based on Low Rank Depiction method is depending on low rank modeling of image external resemblances to approximate real noise-free image patches. Rank reductions, in which a nuclear norm is used to approximate the rank of a matrix, is one of the most used ways for the LR constraint. Sparse decomposition as well as sparse representation are two powerful tools for efficiently incorporating multiple signal representations. This paper aims to achieve better overall framework optimization, using anisotropic filtering followed by a

compressed sensing based on Low Rank Sparse Coefficient(LRSC) for ultrasound image de-noising, with enhancement in SSIM, PSNR and MSE.

2. Literature Review

B. Yagoub et al. [11] present a new convolutional neural network based method for X-ray image de-noising, as well as a mathematical model to create random vertical line noise artificially. Singh P.et.al.[12] presented a hybrid convolutional neural network with an anisotropic diffusion method for image de-noising. In the first stage of image de-noising, HCNN is used to make a noisy image noise-free, resulting in a de-noised image. In the second stage of image de-noising, the de-noised image is then transferred to anisotropic diffusion. The anisotropic diffusion is used to preserve the edges and corners of things. For real image de-noising, R. Ma et al. [13] proposed an attention neural network and a proportional-integral derivative controller. To discover and utilize discriminative image features, a PID attention network is first constructed. It allows us to reveal residual learning in a flexible way, making network training easier and de-noising performance better. Deep neural network based image de-noising was suggested by Kaiyan Li et al. [14]. They put the ideal observer as well as the Hoteling observer to the test. M. Wang and colleagues[15] Proposed a new Tensor low-rank constraint and ℓ_0 Total Variation model for analyzing the HSI noise reduction framework in order to retain additional information for classification. J. Gu et al. [16] present a new single-generator adjustable cycle GAN design. In particular, adaptive instance normalization layers are used to build a single generator that can be converted from transforming a high-dose CT scan into a low-dose one, then back to a repeated CT scan by just altering the adaptable instance normalization code. G. Shashi et al. [17] present a new de-noising method that uses a Adaptive Neuro Fuzzy Inference system to reduce noise while keeping essential feature information. A feature masking layer drives a hierarchical de-noising architecture for medical images. For medical images technique for extracting features using Explainable Artificial Intelligence has been developed.

3. Materials and Method

Recovering the image's latent high quality from its deteriorated observation is the aim of image de-noising. Many of these algorithms have incorporated picture sparsity priors, usually explicitly or implicitly, and

they have played a critical role in improving image de-noising performance. Low Rank Sparse Coefficient representation-based approaches, in particular, have seen a lot of success in picture de-noising during the previous decade. Sparse representation models can be divided into two types based on the representation scheme of a signal vector: analysis sparse representation models and synthesis sparse representation models. Image de-noising techniques are designed to restore a noisy source's initial image.

$$v(i) = u(i) + n(i) \tag{1}$$

where $v(i)$ represents the observed value, $u(i)$ represents the "actual" value, and $n(i)$ represents the noise perturbation at pixel i. To eliminate the noise and restore the actual image u, many techniques have been suggested.

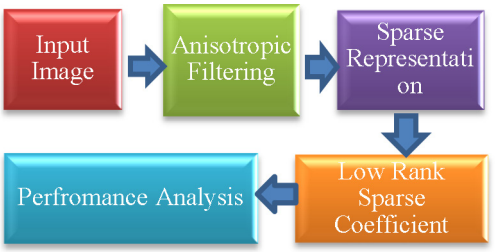


Figure 1

Schematic Block Diagram of the Suggested Approach

3.1 *The Anisotropic Filtering*

Filtering that is anisotropic by convolving the image u at i exclusively in the direction orthogonal to Du, the anisotropic filter tries to prevent the Gaussian's blurring effect (i). Perona and Malik [18] were the first to propose such a filter shown in Figure 1. It is characterized by

$$I_{af} = \int \mathcal{G}_h(t) u\left(i + t\frac{\mathcal{D}u(i)^{\perp}}{|\mathcal{D}u(i)|}\right) dt \tag{2}$$

for x such that $\mathcal{D}u(i) = 0$ and where $(i,j)^{\perp} = (-j,i)$ and $\mathcal{G}_h$ is the one-dimensional Gauss function with variance h^2. Suppose it is considers that the original image u is twice continuously differentiable c^2 at i. On a different point, while sparsity-based approximation of sparse noise has been a hot topic in recent years, only a few studies have looked into the sparsity dictionary-based methodology with huge and dense noise/interference presenting as low-rank. A recursive predicted compressed

sensing method for recovering a sparse representation from large and yet correlated dense noise, based on the assumption that both signal as well as interference components change very slowly over time and heavily relying on projecting the approximate interaction onto the null space of the input signal subspace.

3.2 *Low Rank Sparse Coefficient (LRSC)*

The sparse nonlocal regularization weight coding-based de-noising method remains with several flaws. When medical picture noise is eliminated using the technique with greater information, the noise reduction is insufficient, and the features are severely lost. A low rank constraint term is introduced to enhance the de-noising effectiveness ever since sparse representation with low rank may eliminate picture noise more effectively. The following is the conventional sparse representation de-noising methodology:

$$\alpha^{\wedge} = \arg\min \| y - \phi\alpha \|_2^2 + \lambda R(\alpha) \tag{3}$$

$R(\alpha)$ is a regularization term that relates to α and λ is a regularization parameter with in equation.After weighting the image residuals, a new loss function is applied to improve the uniformity of the input fitting residual distribution. As a result, we have a new mixed noise reduction model:

$$\alpha^{\wedge} = \arg\min \| \mathcal{W}^{1/2} \ (y - \phi\alpha) \|_2^2 + \lambda R(\alpha) \tag{4}$$

$\mathcal{W}$ is a diagonal weight matrix having diagonal elements. The image de-noising process will be enhanced. In the given equation, there is a closed solution, that is,

$$x = (I + \lambda_3 I)^{-1}.(\phi\alpha + \lambda_3 U) \tag{5}$$

The aforementioned issue optimization is performed till the iteration stopping criterion is satisfied. The method ends and stays invariant when none substantial alteration in the ongoing cycle result or the associated optimization problem value, that is, when the discrepancy standard among the two consecutive iterative fixes are smaller than the specified positive norm. The iteration process may also be stopped if the runtime surpasses the upper limit. When the convergence rate exceeds a specified maximum in the experiment, the iteration is terminated.

4. Experiment

In an effort to increase the efficacy of this method, in addition to comparing visual effects, numerical values are subjected to the following criteria displayed in Figure 2: The structural similarity index, the mean square error with the peak signal-to-noise ratio with structural similarity.

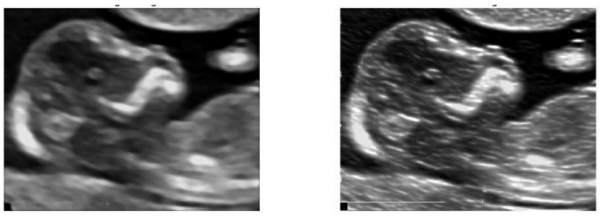


Figure 2

Original and Filtered Image

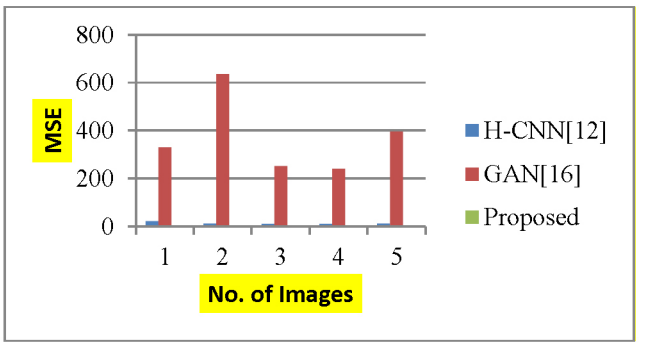


Figure 3

Analogy of MSE

Above Figure 3 shows the mean square error of HCNN [12], GAN [16] and proposed method. Proposed method and HCNN [12] achieved less MSE. Proposed method have average MSE of 2.6, HCNN have 14 and GAN have 371. Figure 4 displays PSNR of HCNN, GAN and proposed method. Proposed method have larger PSNR than rest of the technique. Average PSNR values are 42,28 and 49 for HCNN, GAN and Proposed method respectively. Figure 5 shows SSIM of HCNN, GAN and proposed method. Proposed method and HCNN have larger SSIM than GAN technique. Average SSIM values are 0.98, 0.45 and 0.99 for HCNN, GAN and Proposed method respectively. The comparative performance analysis is presented in Table 1.

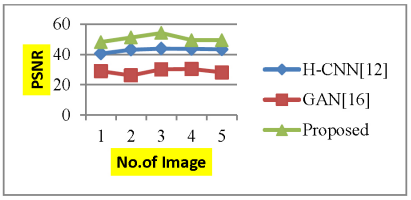


Figure 4
Analogy of PSNR

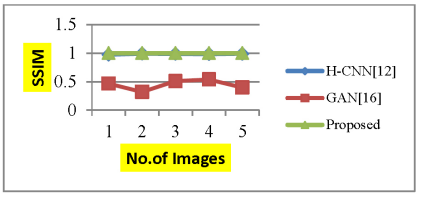


Figure 5
Analogy of SSIM

Table 1
Performance Analysis

Parameter	HCNN [12]	GAN[16]	Proposed
MSE	14.01265	371.5675	2.6
PSNR	42.89501	28.77253	50.47073
SSIM	0.981966	0.445436	0.999996

5. Discussion and Conclusion

In diagnosis and treatment, medical images have now become popular. They may, however, be impacted by different kinds of noise, which reduces image quality and makes obtaining a definitive diagnosis challenging. The primary goal of this study is to efficiently eliminate noise to retain essential image properties. To achieve better overall framework optimization, Novel Methodology of anisotropic filtering followed by a compressed sensing based on Low Rank Sparse Coefficient(LRSC) for ultrasound image de-noising is proposed. Compressed sensing is utilized to de-noise medical images in this research. It outperforms a lot of some of the other methods. This hybrid technique is quite effective at eliminate noise while yet keeping minute details in the image. The peak signal to noise ratio, mean square error, and structural similarity index measure are used to assess the suggested approach. The results of the experiment show that the suggested approach surpasses conventional methods. Average PSNR values are 42,28 and 49 for HCNN, GAN and Proposed method respectively. Proposed method have average MSE of 2.6, HCNN have 14 and GAN have 371.

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