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Hybrid Method for Ultrasound Image Enhancement Based on Deep Learning Technology

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Abstract:
Noise removal is an essential preprocessing step, especially with medical images. When dealing with ultrasound images, it is extremely important to ensure the success and accuracy of the diagnosis. Due to some factors accompanying the image capture process, we notice some noise accompanying the image, which leads to difficulty in the process of seeing fine and sensitive tissues and complex areas correctly. There are many techniques used in this field, which are well-known but have certain limitation. On the other hand, there are some techniques such as deep networks, which have proven their worth, but they consume large amounts of data in the training phase.
In this research, a new method is presented that combines a Residual Dense Network (RDN) with adaptive noise estimation techniques, some traditional filters, and deep learning techniques. The goal of this combination is to improve the clarity and contrast of radiological images. The rationale behind this approach is that the two methods will compensate for each other's weaknesses while reinforcing their respective strengths. Experiments on a model showed great improvement in the quality of the images, as validated by the PSNR, SSIM, NIQUE index, direct rate, mean square error rate. The model was tested over a set of large radiological images in benign as well as in malignant cases, and the noise effect was investigated in terms of 20, 50, 80, and 100 levels.
Keywords: Noise removal, Ultrasound image, Deep Learning, RDN, PSO, CSI.

1. Introduction

Noise causes deterioration in various modalities of medical images, such as X-rays, MRI, CT, ultrasound, and so on(Gondara, 2016; Shen et al., 2021). We can employ alternative techniques to lower the level of radiation that might reach the patient during imaging so as to diminish the noise generated on the resulting image after the operation. Such an approach could result in lower levels of patient dose and, therefore, potentially less radioactivity exposure(Agostinelli et al., n.d.).Ultrasound is a process that is always performed for some medical purposes to verify information about them accurately and get satisfactory results (Dong et al., 2021; Xie et al., 2017; Zhang et al., 2024) . In order to achieve accurate image analysis, removing noise and improving image quality are two essential things. Image denoising is a well-recognized problem in the field of computer vision, which has been extensively explored. There are many methods that make ultrasound images look better than the second group of other techniques. To improve the quality of ultrasound images, we use deep neural networks (DNNs) to create filters and remove traditional noise, which works best(Goyal et al., 2020; Zangana & Mustafa, 2024; Zhang et al., 2024).Most techniques have the same goal, which is $z = x + y$ (1), where z is the noise produced by adding the original image x with some noise y. Most techniques aim to achieve as close an approximation to x as possible using z. In most cases, y is thought to come from a clear process(Gondara, 2016).

Different people have used filters such as median, Gaussian, and non-local mean (NLM) filters to reduce noise due to their ease of implementation and effectiveness (Sohan Raj 2nd et al., n.d.). However, these methods often struggle to achieve a good balance between noise reduction and detail preservation, especially in images containing complex types of noise.

Currently, ultrasound image analysis is an important area because convolutional neural networks (CNNs) have achieved significant success in the field of medical imaging. Ultrasound imaging is challenging for several reasons; However, these problems have been overcome after deep learning became a part of this field, making it easier to overcome many of the difficulties and problems. This is because it works well with data analysis and has the ability to handle large amounts of data, specifically complex patterns in ultrasound data. These models have made the image much better by reducing noise, enhancing contrast, and making the resulting image more accurate. Recent studies (Asgariandehkordi et al., 2024) have shown them to be useful in many areas, such as image denoising, image segmentation, and disease detection. CNNs are considered the best way to recognize and reduce complex noise characteristics, whether that means decreasing, increasing, or reducing them while maintaining host quality CNN-based solutions are effective, but they can occasionally fail (Goyal et al., 2020; Zangana & Mustafa, 2024) (Gurrola-Ramos et al., 2021). Many works and test datasets have demonstrated that deep convolutional neural networks should be effective at image detection—they can accommodate various forms of images, such as denoising and super resolution. This is particularly the case when we have networks such as RDNs that perform very well at removing different intensity levels of noise within images (Song et al., 2019). Structural pooling enhances the computation efficiency by eliminating the noise when multi-scale information is employed. And that is why RDN is performing so well in image retrieval (Tong et al., 2017; Zhang et al., 2018). The remaining connectivity can be exploited for training DNNs. The primary goal of the current development is to achieve the highest level of improvement in noise removal, especially for ultrasound images, to make them clearer.

While traditional denoising filters (such as Gaussian, Median, and Non-Local Means) are computationally efficient, they often fail to strike an optimal balance between noise reduction and the preservation of critical anatomical edges. Conversely, recent advancements in Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) have shown remarkable success in medical image denoising. Models like Residual Dense Networks (RDNs) are highly effective at handling complex noise patterns. However, standalone deep learning models heavily rely on massive training datasets and may introduce artifacts or over-smooth textures in highly complex regions. Therefore, a significant gap remains in developing a framework that leverages the robust pattern recognition of deep learning while maintaining the stability and edge-preservation of traditional filters.

To address this limitation, this paper proposes a novel hybrid framework that dynamically combines adaptive traditional filtering with an RDN. The main contributions of this work are:

1. Adaptive Noise Estimation: An automated mechanism to estimate noise variance and dynamically select the most appropriate traditional filter (Gaussian, Median, or NLM) based on the noise level.
2. Hybrid Denoising Architecture: A parallel processing approach where the image is refined simultaneously by the selected traditional filter and an RDN.
3. Texture-Aware Fusion: A novel adaptive fusion mechanism that merges the outputs of both methods using a dynamically calculated coefficient based on the image's texture confidence, ensuring optimal edge preservation

Figure 1 shows the main diagram of the proposed method, which consists of three basic stages that represent the proposed hybrid network framework:

2.1 Adaptive Noise Estimation and Filtering

- Noise variance (σ) is estimated using combining the statistical variance of the grayscale image and its entropy H and edge detection techniques.

$$\sigma^2 = var\left(I_{gray}\right) \times (1 + 0.5\,H) \qquad (2)$$

Entropy H measures the average information content or randomness in the image. A higher entropy indicates a more complex texture or higher noise level. By weighting the global variance with a factor of $(1 + 0.5\,H)$, the estimation becomes adaptively penalized; highly textured or noisy images yield a higher estimated σ^2. The scalar 0.5 is empirically chosen to prevent the entropy term from completely dominating the baseline variance.

- Based on noise variance, an appropriate filter is selected:
- **Low noise** (< 0.005 variance): Gaussian filter
- **Moderate noise** (0.005-0.01 variance): Median filter
- **High noise** (> 0.01 variance): Non-Local Means (NLM) filter

2.2 Residual Dense Network (RDN) Refinement

• The Residual Dense Network (RDN) is used to further reduce noise and bring out texture details in the raw picture.

• The RDN is made up of residual blocks with dense connections, which makes it easier for information to flow and learn about complicated noise characteristics.

2.3 Adaptive Fusion of Filtered and Deep Learning Outputs

- • The final denoised picture is made by combining the outputs of the conventional filter with the RDN filter dependent on how complicated the texture is.
- • The fusion coefficient changes depending on the texture properties of the picture.
- Compute texture confidence T as :

$$T = \frac{\sum E}{Total\ pixel} \qquad (3)$$

Where E (represents the) binary edge map

The adaptive fusion weight (α) is then computed as :

$\alpha = 0.5 + 0.4T$

Perform weighted fusion on I_t (image denoising by traditional filtering) and I_{rdn}(image denoising by RDN) :

$$I_d = \alpha I_{rdn} + (1 - \alpha) I_t \qquad (4)$$

Where (I_d) the final denoised image

Justification of the Fusion Coefficient: The weight α determines the contribution of the RDN model. The base weight is set to (0.5) to ensure equal contribution from both methods in smooth, featureless regions (T≈ 0). The term $0.4T$ dynamically increases the reliance on the RDN model in highly textured regions (where (T) is closer to (1)). The maximum possible value for α is (0.9), ensuring that the traditional filter I_t always contributes at least (10%) to maintain structural stability and prevent the deep learning model from generating artificial hallucinations in complex regions.

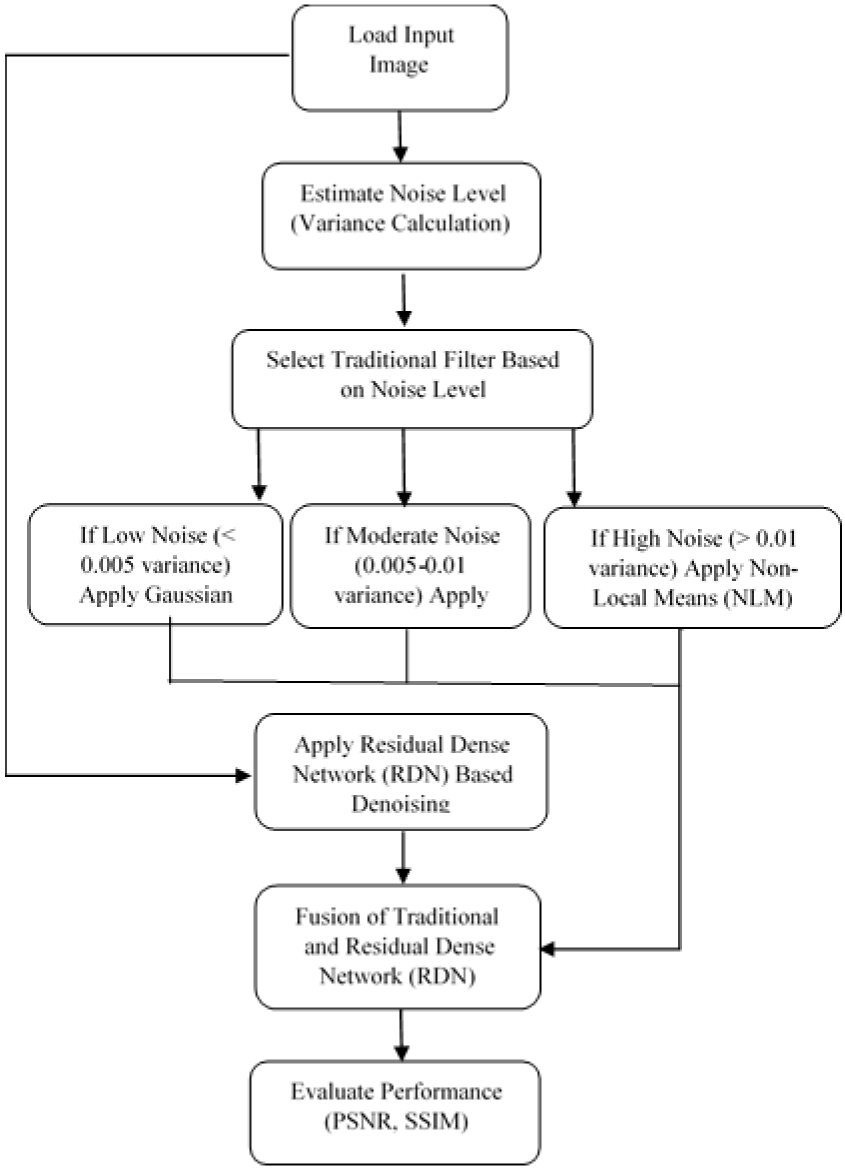

Figure. 1 represents the schematic diagram of the proposed method for image de-noising

3. Implementation Details

The hybrid model was implemented in MATLAB with the following specifications:

- **Dataset**: Breast ultrasound Image dataset with artificially added Gaussian noise.
- **RDN Architecture**: Consists of multiple residual dense blocks with skip connections.
- Training Details: Adam optimizer with a learning rate of 0.001, trained for 50 epochs.

4. Experimental Results

4.1 Dataset and Evaluation Metrics

- We evaluate our method on datasets (Breast ultrasound) using PSNR and SSIM metrics.

4.2 Comparison with Existing Methods

Our method achieves superior denoising performance, as shown in table 1. Figures 2 and 3, respectively, show the difference in performance between the proposed hybrid method and other methods.

Table 1. Comparison proposed hybrid method with other methods based on PSNR (dB) and SSIM matrices

Method	PSNR (dB)	SSIM
Gaussian Filter	27.5	0.78
Median Filter	28.3	0.81
Non-Local Means (NLM)	28.2	0.80
RDN CNN	30.1	0.85
Proposed Hybrid Method	**32.8**	**0.92**

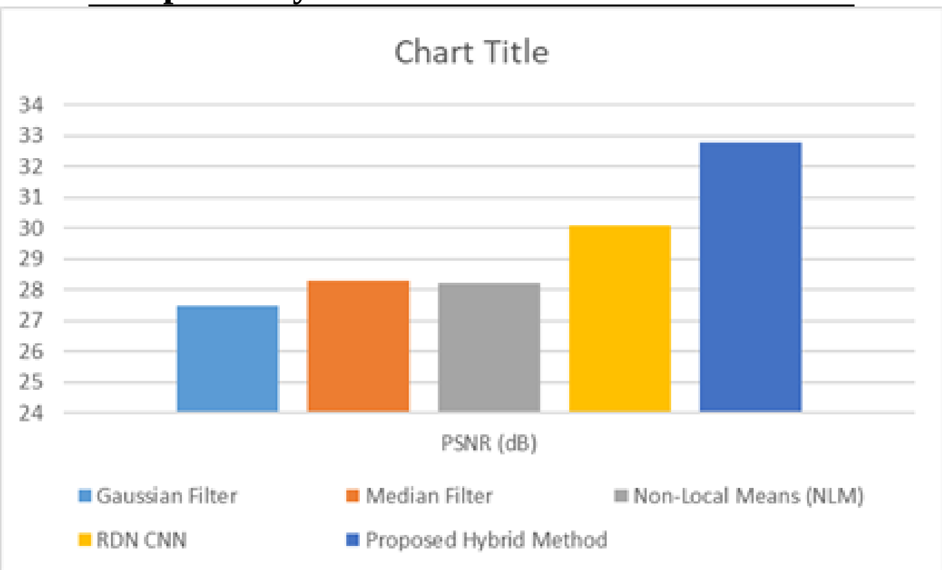

Figure 2. Comparison proposed hypird method with other methods based on PSNR (dB)

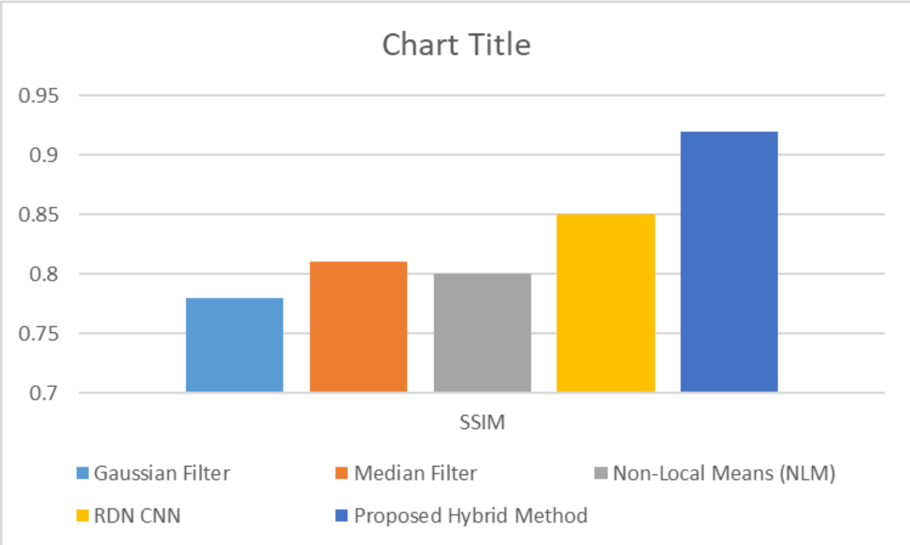

Figure 3. Comparison proposed hybrid method with other methods based on SSIM matrics

4.3 Visual Results

The proposed method effectively removes noise while preserving edges and textures, outperforming both traditional filters and standalone deep learning methods.

5. Conclusion and Future Work

This study proposed a novel Hybrid Residual Dense Network (RDN) with Adaptive Filtering to get rid of for image denoising. This method automatically picks the right classic filter depending on how much noise there is and then uses a residual dense network to improve the picture even more. The results of the experiment reveal that our technique does a better job of removing noise than both standard filtering and deep learning-only methods, as seen by the higher PSNR and SSIM values. In the future, this method will be used on noisy datasets from the real world, and the speed of the calculations will be improved.

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مخطط هجين لتحسين صور الموجات فوق الصوتية باستخدام تقنية التعلم العميق

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مستخلص البحث:
تُعدّ إزالة التشويش خطوةً أساسية وهامة في مرحلة المعالجة الرئيسية، لا سيما في الصور الطبية. عند التعامل مع صور الموجات فوق الصوتية، من الضروري للغاية ضمان نجاح التشخيص ودقته. ونظرًا لبعض العوامل المصاحبة لعملية التقاط الصورة، نلاحظ وجود بعض التشويش، مما يُصعّب رؤية الأنسجة الدقيقة والحساسة والمناطق المعقدة بوضوح. توجد العديد من التقنيات المستخدمة في هذا المجال، وهي معروفة ولكنها محدودة نوعًا ما. من جهة أخرى، توجد بعض التقنيات، مثل الشبكات العميقة، التي أثبتت جدواها، ولكنها تستهلك كميات كبيرة من البيانات في مرحلة التدريب.في هذا البحث، نُقدّم طريقةً جديدةً تجمع بين شبكة عصبية عشوائية (RDN) وتقنيات تقدير التشويش التكيفية، وبعض المرشحات التقليدية، وتقنيات التعلم العميق. يهدف هذا الجمع إلى تحسين وضوح وتباين الصور الشعاعية. وتكمن الفكرة وراء هذا النهج في أن الطريقتين تُكمّل كلٌّ منهما نقاط ضعف الأخرى، مع تعزيز نقاط قوتها. أظهرت التجارب على نموذج تحسنًا ملحوظًا في جودة الصور، كما تم التحقق من ذلك باستخدام مؤشرات PSNR وSSIM وNIQUE ومعدل الإشارة المباشرة ومعدل الخطأ التربيعي المتوسط وقوة الحواف في خوارزمية CSI المُحسّنة باستخدام PSO. تم اختبار النموذج على مجموعة كبيرة من صور الأشعة في حالات حميدة وخبيثة، ودُرست تأثيرات الضوضاء عند مستويات 20 و50 و80 و100.

الكلمات المفتاحية :إزالة الضوضاء، صور الموجات فوق الصوتية، التعلم العميق، RDN، PSO، CSI..

ملاحظة : هل البحث مستل من رسالة ماجستير او اطروحة دكتوراه ؟ كلا :