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Research Article

Adaptive neural network framework for improved image filtering using Hebbian learning

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ABSTRACT

A processed function is used to transform an original image into a processed one in traditional image processing. This paper introduce a approach that processes images without any required for transformation functions, utilizing artificial neural networks based on the Hebbian learning rule. The main contribution of this method is its ability to learn from the visual features of images rather than algorithmic approach. The proposed framework features an adaptive Artificial Neural Networks topology that adjusts in response to variations in the local characteristics of the input image. Moreover, this paper presents an adaptive Hebbian learning algorithm designed to for image filtering processes by the application of neural network . Traditional image filtering methods often struggle with noise and detail preservation, leading to sub optimal results in various applications. This approach based the principles of Hebbian learning, which focuses on the correlation of neural activations, to dynamically adjust the filtering parameters based on the input data characteristics. The proposed method(Adaptive Hebbian Neural Network) demonstrates increase the performance compared to traditional algorithms with 0.0019 and 0.9309 for the Least Mean Squares and Delta rule algorithms, respectively. It usful for advanced image processing applications, offering a powerful tool for researchers and practitioners in the field.

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INTRODUCTION

In the realm of image processing, filtering plays a crucial role in enhancing image quality, removing noise, and preserving important features. Traditional filtering techniques, such as Gaussian and median filters, rely heavily on fixed mathematical transformations to process images. While effective in certain scenarios, these methods often fall short in dynamically adapting to varying image

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conditions, leading to either loss of detail or inadequate noise reduction. An ANNs is a network of interconnected artificial neurons that processes data using a mathematical or computational model based on a connection approach. An ANN is, in most situations, an adaptive system that changes its structure in response to external or internal data flowing through the network [1,2]. In the context of ANNs, a learning process can be thought of as the challenge of changing network connection weights so that a network can efficiently accomplish a task. The connection weights are usually learned by the network using accessible training patterns.

Digital images are frequently degraded by noise during the acquisition, digitization, and transmission operations. As a result, image filtering is the most fundamental and perhaps most essential operation in image processing. It is used in many image processing applications to improve the look of images for human viewers and to increase the performance of image processing systems. ANNS is a useful tool for image processing [3-6]. Rather than constructing an algorithm, one may build an example data set and an error criterion, and then train ANNs to execute the necessary input-output mapping. Pixels or image measurements can be used as network input. The output, on the other hand, can include pixels, decisions, labels, and other items as long as they can be numerically coded (no assumptions are made). This means adaptive approaches can handle several phases in the image processing chain at the same time. In this paper, an adaptive trained ANNs was proposed based on the generalized Hebbian learning rule, with no learning examples was required, to filter the images degraded by Gaussian noise. This is formed for effectively reducing Gaussian noise while preserving image details for gray scale and color images [7-10].

A neural networks, have used novel methods for improving image filtering techniques. Hebbian learning worked by the way biological neural networks adapt and learn. It introduces a promising framework for developing more flexible and responsive filtering algorithms. This learning rule based on the importance of correlation between neuron activation and networks to adjust the parameters based on the features present in the input data. This paper introduces an Adaptive Hebbian Learning Algorithm (AHNN) to enhance image filtering performance. The AHNN framework does not require a predefined algorithms but used learning visual features directly from the images [11-13]. By using an adaptive neural network topology that adjusts in response to local variations in the input image, This approach offers a significant improvement over conventional filtering techniques. The paper demonstrates the effectiveness of the AHNN by comparing its performance against other methods, such as Least Mean Squares (LMS) and Delta rule methods, through various metrics, including Mean Squared Error (MSE) and Contrast Measurements (CM). The results gives the proposed adaptive learning approach improves image quality with preserves information that is useful for more advanced applications in image processing.

The main contribution of this study is:

- Introduces a novel architecture tailored for image filtering, allowing dynamic adjustments based on image characteristics.
- Leverages Hebbian learning principles to enhance connection strengths based on input feature correlations, improving feature extraction.
- Addresses a significant limitation of existing image filtering techniques that often struggle to balance noise removal with the preservation of fine details.
- Achieves significant enhancements in image quality metrics such as MES and CM, leading to better noise reduction and detail preservation.
- Process images quickly and adaptively, making it suitable for applications requiring fast and accurate filtering, such as video processing and medical imaging.
- Offers a significant advancement in the field of image filtering by combining the adaptability of neural networks with the efficiency of Hebbian learning, ultimately providing a more effective solution for improving image quality in a variety of practical applications.

In the following sections, related work will present in Section 2. Section 3 will delve into the methodology of the AHNN. Section 4 will present experimental results, and discuss. The implications of our findings for the future of adaptive image filtering techniques will be in Section 5.

RELATED WORK

Recent studies have recommended Hopfield and back propagation networks for use in various image processing and computer vision applications such as stereo matching, edge detection, and image segmentation [14-19]. Pinho, 1996 [20] showed some results on ANNs to reduce noise in digital images. The method based on the supervised neural networks' ability to learn from examples, which eliminates the requirement for explicit knowledge of the image distortion function. The filter was created using current back-propagation feed-forward neural networks, and it focused on calculating the first differences between neighbor pixels. Kumar and Zhang, 2017 [21,22] proposed a neural network-based nonlinear filter that could eliminate noise and sharpen edges in images based a nonlinear filter is utilized. The noise reduction and edge sharpening was achieved by combining the smoothed image with the output of an edge detector using a synthesizer. Layered neural networks were used to create the smoother and synthesizer.

Main area of research involves the use of convolutional neural networks (CNNs) for image filtering. CNNs have been used in tasks such as denoising and deblurring by learning hierarchical features directly from images [23]. Zhang et al.,2017 [24] introduced a DnCNN model that uses residual learning to effectively remove Gaussian noise from images, achieving state of the art performance. Moreover, other methods have used deep learning architectures to handle various filtering challenges, but these approaches often require additional computational resources and large datasets for training. Hebbian learning that emphasizes the correlation of neural activation, has also been explored within the image processing. Early works, such as those by Aguilar,2020 [25] demonstrated the utility of Hebbian learning for feature extraction. More recently, researchers integrate Hebbian learning into neural networks to develop unsupervised learning algorithms that adaptively respond to input data. For example, experiments with Hebbian based learning rules have shown promise in image processing tasks

Ushikoshi et al. 2024 [26] considers a recently proposed method based on Hebbian learning with kernel-based embedding of input data, which performs a likelihood-based projection where linear separability and generalization capacity are enhanced in an autonomous fashion. Moreover, Kuderov et al. 2024 [27] proposes a general online unsupervised algorithm for spatial data encoding using fast Hebbian learning. Inspired by the Hierarchical Temporal Memory (HTM) framework, we introduce the SpatialEncoder algorithm, which learns the spatial specialization of neurons' receptive fields through Hebbian plasticity and k-WTA (k winners take all) inhibition Although the AHNN adapts to local image features, its performance may vary significantly across different types of images or noise conditions. The algorithm might require retraining or fine-tuning for specific image characteristics, which could limit its versatility. Further research is needed to establish robust theoretical foundations for the algorithm's performance as well as additional qualitative assessments may be necessary to evaluate the practical effectiveness of the approach.

Previous works have the ability lack to adapt to changing image characteristics or noise patterns in real time. While some neural network approaches use predefined filters that fails to dynamically adjust to new or unseen data without extensive retraining, which limits their practical application in environments where input images vary significantly.Therefore, a hybrid approach that combines adaptive Hebbian learning with neural network architectures is relatively unexplored but holds promise for dynamic filtering tasks. The proposed method builds on concepts like Sanger's generalized Hebbian algorithm, which enables networks to adapt and optimize weights over time, enhancing performance in variable filtering conditions. Furthermore, it aims to develop filtering method that leverages Hebbian learning principles within a neural network framework, potentially filling gaps in existing literature on combining biologically inspired learning with advanced image processing techniques.

MATERIALS AND METHODS

Hebbian Learning

The ability to learn is a basic feature of intelligence, despite the difficulty of defining it precisely. Hebbian learning is a key paradigm for unsupervised learning in ANNs. Hebbian learning ANNs are distinguished by the fact that the activation of a unit is determined by the sum of the weights. This rule has some intriguing features, such as locality and the ability to be applied to neuron models with a basic weight-and-sum structure [28-31]. The weights adjustment in Hebbian rule is calculated by eq. (1)

$$\Delta \mathrm{w_{ij}} = \mathrm{c.\,o_i.\,x_j}\ ,\mathrm{j} = 1{,}2 \ldots \mathrm{n} \tag{1}$$

c is a positive learning constant; o_i is the actual output of neuron i and x_j is the j_{th} element in the input vector. In the training process, many steps were done: (a) The weights of the neural network are initialized randomly. Initially, the network's weights are not optimized and need to adapt over time using Hebbian learning, (b) The noisy image (or image patch) is passed through the network, layer by layer, to produce filtered image. The network processes each pixel value and its neighboring values, adjusting the weights according to Hebbian learning, (c) Using the Hebbian learning rule, the weights are updated based on the correlations between the input and output neurons during each pass through the network. This update is done continuously as the image passes through the network, allowing it to learn how to remove noise while preserving key image features, (d) The process is repeated for multiple iterations, with the network adapting its weights to improve filtering performance. After each pass, the output image is compared to the expected output to evaluate the network's performance, (e) The training continues until the network's output stabilizes and converges to a satisfactory filtered image. The convergence criterion can be defined by monitoring the mean squared error (MSE) between the network's output and the target image.

ADAPTIVE HEBBIAN NEURAL NETWORK (AHNN)

An image denoising approach based on ANNs and a generalized Hebbian learning rule is proposed. To generate noise-free pixels, trained ANNs are used as a nonlinear filter. Through the learning of a training image, the architecture of ANNs may adapt to variance noise environments. The AHNN approach selects a threshold that achieves a compromise between noise reduction and signal distortion (blurring). If the threshold is less than the local variance, then the topology is considered as a feed-forward full connected ANNs as input layer with four nodes (because of less blurring), two hidden layers, the first one with three nodes but the second one with two nodes), and output layer with one node i.e. (4-3-2-1) as shown in Figure 1. Otherwise, if the threshold is greater than the local variance, then the topology is considered as full connected ANNs as input layer with five nodes, three hidden layers, (the first one with four nodes, the second one with three nodes, and the last one with two nodes, and output layer with one node i.e. (5-4-3-2-1) as shown in Figure 2. In summary, randomly initialize weights between the input layer and the first hidden layer, then calculate weighted sum for each of the 3 neurons in the first hidden layer using the input values and the initialized weights and apply activation function (e.g., sigmoid, ReLU) to obtain output values, Finally, Use the outputs of the first hidden layer as inputs for the second hidden layer and calculate the weighted sum and apply the activation function.

The threshold is compared with the local variance because the variance measurement gives impression for the characteristic of a specific region in the image. Large variance means high frequencies (fine edges and details), but low variance means low frequencies (background area).

The number of neurons in the hidden layers of ANNs is extremely important. Underfitting can be caused by few of neurons. Overfitting can be caused by having too many neurons. There is no reliable way for determining how many buried neurons are appropriate. Inadequate hidden

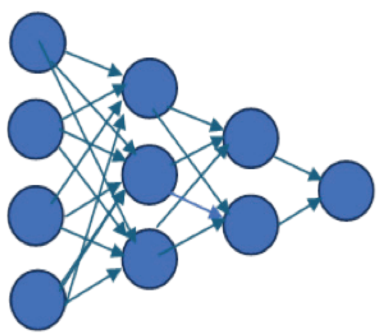

Figure 1. Full connected ANN (4-3-2-1).

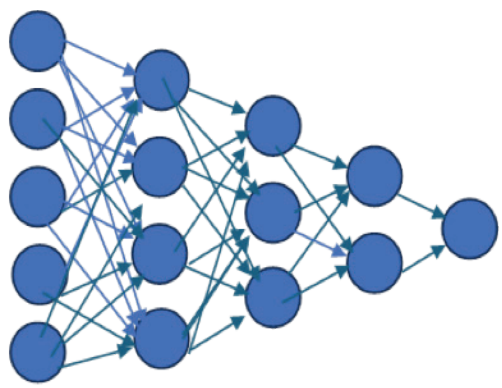

Figure 2. Full connected ANN (5-4-3-2-1).

neurons may result in poor error tolerance. In another approach, having too many buried neurons can increase the time it takes to learn. There is currently no effective technique for choosing the number of concealed neurons. The number of hidden neurons may be thought of as an input, which will be calculated throughout the training phase. Image filtering implementation on neural networks based on generalized Hebbian learning rule for (4-3-2-1) network is described by the following steps:

Step-1 Initialize the synaptic weights of network, w_{ji}, v_{ji}, and u_{ji} to small random values w_{ji} is a weight that connects the j'th neuron in first hidden layer with the i'th input in input layer; v_{ji} is a weight that connects the j'th neuron in second hidden layer with the i'th neuron in the first hidden layer; u_{ji} is a weight that connects the j'th neuron in a second hidden layer with the i'th neuron in output layer)

Step-2 Assign a small positive value to the learning-rate parameter η.

Step-3 Assign $e_i = 4$ & $e_j = 3$. (where the e_i is the number of nodes in the input layer and e_j is the number of nodes in the first hidden layer).

Step-4 For n = 1; n is the iteration number.

Step-5 For each four neighboring pixels in a specific window that runs over the entire image pixel-by-pixel, generating new (filtered) values of the pixels do the following steps

Step-6 Assign the four pixels to input data vector X , X=[x1,x2 ,x3 ,x4].

Step-7 For j = 1,..., e_j; Compute in eq.(2):

$$y_j = \sum_{i=1}^{e_i} w_{ji} x_i \tag{2}$$

Step-8 For j = 1,…, e_j and For i = 1,…, e_i; Compute eq.(3):

$$\Delta w_{ji} = \eta(y_j x_i - y_j \sum_{k=1}^{j} w_{ki} y_k)\ w_{ji} = w_{ji} + \Delta w_{ji} \tag{3}$$

Step-9 For j = 1,… , e_j - 1 ; Compute:

$$r_j = \sum_{i=1}^{e_i - 1} v_{ji} y_i$$

Step-10 For j = 1,…, e_j - 1 and For i = 1,…, e_i - 1; Compute in eq. (4):

$$\Delta v_{ji} = \eta(r_j y_i - v_{ji} = v_{ji} + \Delta v_{ji}) \tag{4}$$

Step-11 For j = 1,…, e_j - 2 ; Compute in eq.(5):

$$s_j = \sum_{i=1}^{e_i - 2} u_{ji} r_i \tag{5}$$

Step-12 For j = 1,…, e_j - 2 and For i = 1,…, e_i - 2 ; Compute in eq. (6):

$$\Delta u_{ji} = \eta(s_j r_i - s_j \sum_{k\ 1}^{j} u_{ki} s_k)\ u_{ji} = u_{ji} + \Delta u_{ji} \quad (6)$$

Step-13 Increase n by 1 and continue until the synaptic weights reach their steady-state values.

Image filtering implementation on neural networks based on generalized Hebbian learning rule for (5-4-3-2-1) network is described as follows:

In step 3; $e_i = 5$ and $e_j = 4$, in step 6 the input data vector X becomes X=[x1,x2 ,x3 ,x4 ,x5]. The synaptic weight Z_{ij} (Z_{ij} is a weight that connects the i'th neuron in third hidden layer with the j'th neuron in output layer) is adjusted according to eq. (7)

For j = 1,…, e_j - 3; Compute in eq. (7):

$$c_j = \sum_{i=1}^{e_i - 2} z_{ij} s_i \quad (7)$$

and For j = 1,…, e_j - 3 and For i = 1,…, e_i - 3 ; Compute in eq. (8):

$$\Delta z_{ji} = \eta(c_j s_i - c_j \sum_{k=1}^{j} z_{ki} c_k)\ z_{ji} = z_{ji} + \Delta z_{ji} \quad (8)$$

The proposed methodology combines the adaptive capabilities of a multi-layer neural network with the efficiency Hebbian learning to create an advanced image filtering framework. By continuously adjusting its weights based on image data, the network is able to filter noise while preserving important image features. The approach is flexible, scalable, and effective across a range of noise types and image characteristics, making it a promising solution for real-world image filtering tasks.

RESULT AND DISCUSSION

Evaluation Results

The suggested approach AHNN is used to filter grayscale and color images that have been damaged by Gaussian noise. In addition, the results of adaptive filters using least mean square (LMS) [32,33] and Delta learning rule algorithms [34,35] are compared. The LMS algorithm is a stochastic gradient algorithm that iterates each tap weight in the filter in the direction of the gradient of the squared amplitude of an error signal with respect to that tap weight. It is an approximation of the steepest descent algorithm which uses an instantaneous estimate of the gradient vector. The estimate of the gradient is based on sample values of the tap input vector and an error signal. The algorithm iterates over each tap weight in the filter, moving it in the direction of the approximated gradient. The LMS is described as follows:

where W(n) is the weight vector at step n; μ is the step size; X(n) is the input vector; e(n) is the error signal and can be computed as

$$W(n+1) = W(n) + \mu X(n) e(n) \quad (9)$$

$$e(n) = d(n) - y(n) \quad (10)$$

such that d(n) is the desired output and y(n) is the filter output. The change in the weight vector of the delta rule algorithm is described as

$$\Delta w_{ij} = c(d_i - o_i)\emptyset'(v_i)x_j \quad j = 1,2,3,\ldots\ldots.. n \quad (11)$$

Ø'is the first derivative of the activation function Ø and o_i is the actual output of neuron *i*. The proposed approach for noise removal and fine detail preservation has been shown to be successful both visually and numerically. Figure 3 and Figure 4 present the visual comparison results between the LMS, Delta Rule, and AHNN filtering methods for grayscale and color images, respectively. As shown in these figures, the AHNN filtering framework outperforms both the LMS and Delta Rule filters. This is evident when examining the performance metrics, particularly the Mean Square Error (MSE) and Contrast Measurement (CM) [36,37], which are provided in Table 1 and Figure 5. The AHNN framework consistently shows lower MSE and higher CM values, indicating better image quality and superior filtering performance compared to the other two methods.

$$MSE = \frac{1}{m.n} \sum_{i=1}^{m} \sum_{j=1}^{n} (f(i,j) - y(i,j))^2 \quad (12)$$

where *m* and *n* represent the number of rows and column in the image respectively. *f* and *y* represent the original and processed images, respectively. The contrast measurement is given by [38-47]:

$$C = \frac{r-s}{r+s} \quad (13)$$

where *r* is mean gray level value of a particular object in the image called foreground, and *s* is the mean gray level value of a surrounding region called the background. For the human eye then, we need to increase *C* above 2%.

The proposed AHNNs algorithm presents an approach to image filtering, based on Hebbian learning to enhance neural network performance for noise reduction. This indicates that this method effectively improves image quality respect to various metrics. The main idea of this algorithm is its adaptive way. By adjusting the weights based on local image characteristics, the algorithm can high performance to varying images. The adaptability allows the network to increase the performance by reducing noise and enhancing details. The learning process is based on previous filtering outcomes, further enhancing the efficacy of the image processing. The performance of the proposed algorithm was evaluated using standard metrics, including Mean Square Error (MSE) and Contrast Measurement (CM). Results demonstrate an improvement in image quality rather to traditional filtering methods and other neural network. The adaptive Hebbian learning algorithm consistently

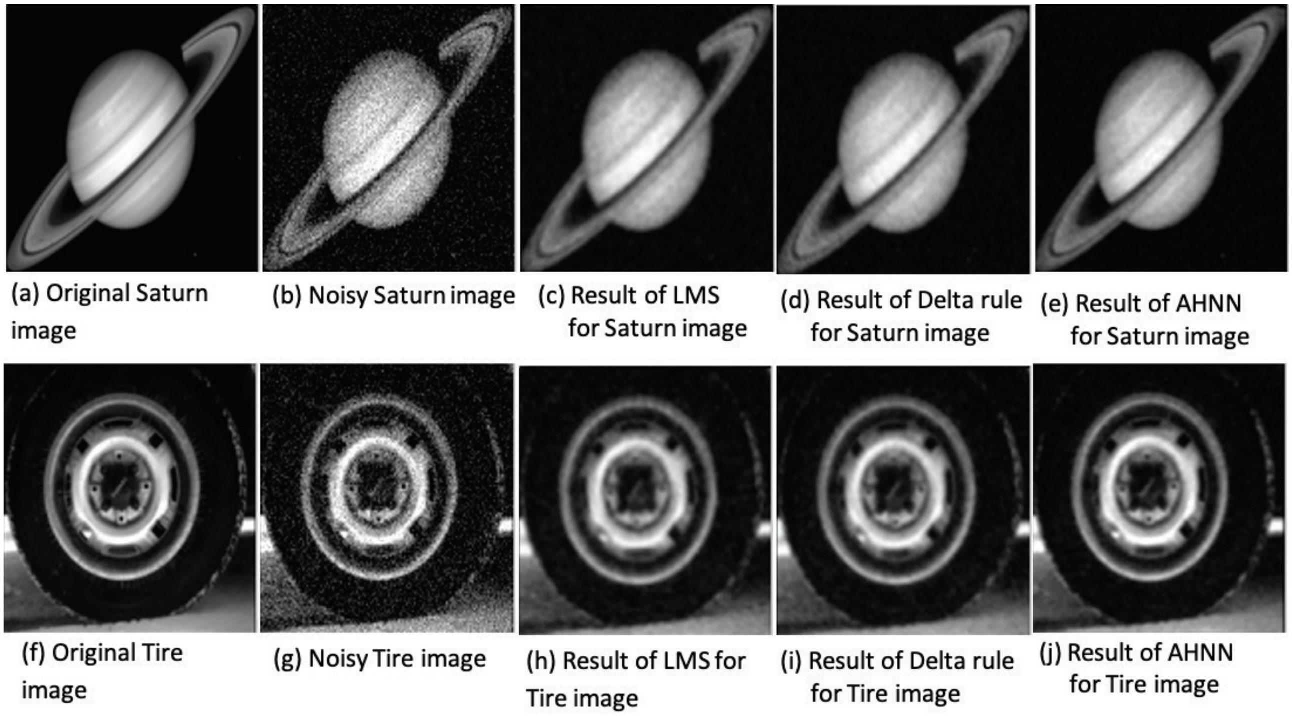

Figure 3. The performance of LMS, Delta rule, and AHNN for color images.

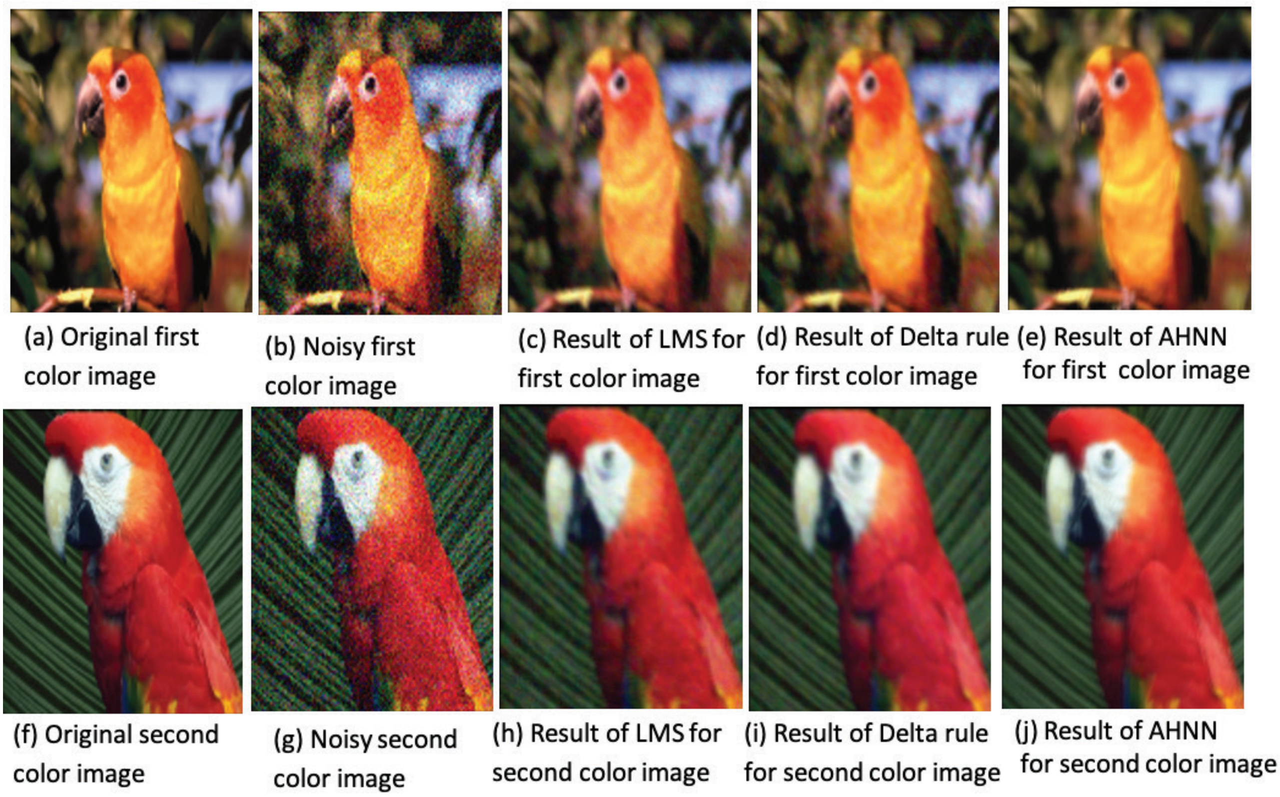

Figure 4. The performance of LMS, Delta rule, and AHNN for color images.

Table 1. Numerical comparison between LMS, Delta rule, and AHNN

Images	Measurement	Method: LMS	Method: Delta Rule	Method: Proposed AHNN
Saturn	MSE	0.0029	0.0023	**0.0019**
	CM	0.8326	0.8592	**0.9309**
Tire	MSE	0.0053	0.0050	**0.0043**
	CM	0.7028	0.7037	**0.7874**
First color	MSE	0.0030	0.0027	**0.0025**
	CM	0.2198	0.2322	**0.2420**
Second color	MSE	0.0051	0.0049	**0.0041**
	CM	0.1395	0.1407	

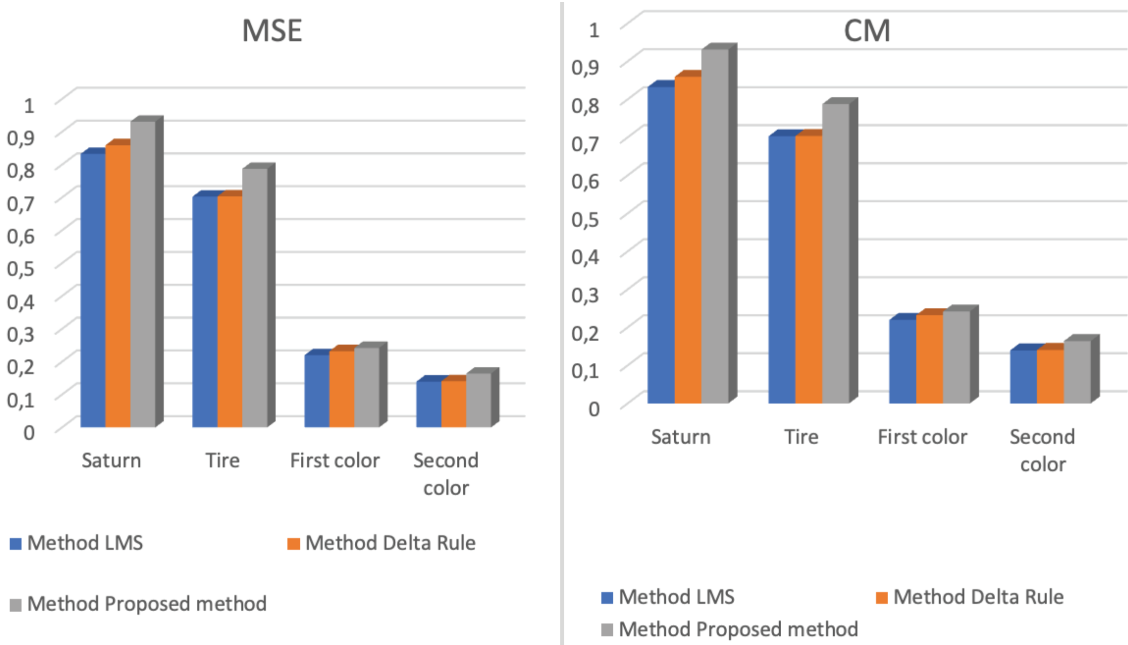

Figure 5. Comparison between LMS, Delta rule and AHNN.

outperformed static models, showcasing its flexibility with noise and image artifacts.

CONCLUSION

An adaptive method is presented for removing Gaussian noise while preserving image details. This paper have introduced the Adaptive Hebbian Learning Algorithm (AHNN) as a novel approach to image filtering that based on Hebbian learning . It demonstrates that the AHNN effectively adapts to improve filtering performance without based on predefined algorithms. This adaptability enables the network to learn and optimize filtering processes based on the image features. Future work will focus on further optimizing the algorithm and exploring its applicability in real time image processing scenarios. Our research lays the groundwork for more intelligent and responsive image processing systems, contributing to advancements in fields such as computer vision, medical imaging, and multimedia technology.

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