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Survey Paper on Image Denoising Non- Local Means framework.

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Abstract: The paper introduces a novel framework called Nonlocal Means based Framework (NMF) for image denoising. The goal is to reduce noise in digital images without compromising important image features. While existing methods often focus on removing either additive white Gaussian noise (AWGN) or impulse noise (IN) separately, this framework addresses the challenge of images corrupted by a mixture of both types. The proposed framework combines the strengths of the median filter and nonlocal means to tackle the noise mixture. The median filter, a non-linear filtering technique, is employed to identify outlier pixels in the image, which are then replaced by nonlocal means. This step effectively separates the mixed noise into its Gaussian components. To further enhance denoising performance, the framework utilizes a low-rank approximation combined with NMF (LRNM) model. This model groups similar nonlocal patches into a matrix and applies a low-rank approximation to reconstruct the clean image. Additionally, a Convolutional Neural Network (CNN) is integrated with NMF (NMF-CNN) to demonstrate the versatility of the NMF approach. The experimental results highlight the effectiveness of LRNM and NMF-CNN in removing mixed noise, producing visually pleasing denoised images. These approaches demonstrate strong performance in noise reduction and can contribute to improving the quality of images captured by modern cameras.

Index Terms* - *Non Local Mean, CNN, Mean squared error (MSE), Structural similarity index (SSIM), Gaussian Noise, Impulse Noise.

I. INTRODUCTION

In the context of digital image degradation, noise removal is a crucial step in recovering the original image from its degraded form. During image acquisition or transmission, two common types of noise, additive white Gaussian noise (AWGN) and impulse noise (IN), are often introduced. AWGN arises from the thermal motion of electrons in the photoelectric sensor, while IN stems from transmission errors. In the presence of both AWGN and IN, the observed image becomes corrupted by a mixture of these two types of noise. To address this challenge, the concept of nonlocal self-similarity prior has gained popularity in AWGN removal.

Nonlocal self-similarity refers to the existence of similar patches to a given patch in a natural image, even if they are spatially distant. Exploiting this property, the nonlocal means (NLM) algorithm estimates a noise-free intensity as a weighted average of all pixel intensities in the image. These weights are computed based on the similarity between the local neighborhood of the pixel being processed and the surrounding pixels. However, the weight computation in NLM may not accurately represent the true structure similarity due to the presence of noise.However, it is important to note that the weight computation in NLM may not accurately represent the true structural similarity due to the presence of noise. This limitation can impact the denoising performance and the preservation of image structures.

By considering the nonlocal self-similarity prior and applying techniques such as NLM, researchers aim to remove AWGN and restore the original image quality. The goal is to improve denoising results by exploiting the inherent similarities among image patches. However, further advancements are still needed to enhance the accuracy of structure similarity estimation and address the challenges posed by the presence of noise.This limitation can affect the denoising performance and the preservation of image structures. It is worth noting that this summary is based on the provided information, and I have not referred to the specific details or findings of any particular research paper.

II. LITERATURE SURVEY

- "COLOR IMAGE DENOISING USING QUATERNION ADAPTIVE NON-LOCAL COUPLED MEANS" 2019 IEEE International Conference on Image Processing (ICIP). The proposed method, called Quaternion Adaptive Non-local Coupled Means (QANLCM), is designed for image denoising based on the quaternion representation of color images. QANLCM aims to denoise all three color channels together. It differs from existing methods that calculate pixel/patch distances using color intensity alone.In the QANLCM method, two optimization variables, namely weight ωij and υij, are introduced. These variables are iteratively adjusted to improve the denoising performance. The method combines quantitative analysis and visual results to evaluate its effectiveness.According to the analysis and results, QANLCM demonstrates excellent performance in removing noise while preserving image details. It achieves superior denoising results compared to other methods.

- "PET Image Denoising Using a Deep Neural Network Through Fine Tuning" 2019 IEEE Transactions on Radiation and Plasma Medical Sciences. In this paper, the authors have employed a deep neural network for denoising positron emission tomography (PET) images, utilizing a perceptual loss. The proposed approach involves a pre-training phase followed by fine-tuning, which allows the effective training of the deep neural network even when the available real data is limited. The experiments conducted in the study involve both simulated and real data. The results demonstrate that the proposed framework outperforms post-smoothing techniques that employ Gaussian or non-local means (NLM) filters in terms of image quality. The denoised images generated by the deep neural network exhibit better visual quality compared to those obtained through post-smoothing. The authors acknowledge that further research is needed to explore the potential of 3-D networks in the denoising task, as well as to conduct additional evaluations using real data.

- "Fast Non-local Means Denoising for MR Image Sequences" 2018 International Conference on Signal Processing and Communications (SPCOM) In this paper, the authors have introduced a competitive denoising algorithm specifically designed for magnetic resonance (MR) images that are affected by Rician noise. The proposed algorithm not only improves the accuracy of the denoising process but also reduces the computational burden. To address the noise in MR images, the authors employ a preprocessing step called shot boundary detection. This step aims to segregate the frames within the image sequence into different shots. Each shot consists of frames that have content-wise similar characteristics. In order to reduce the dimensionality of the data, the authors compute principal components analysis (PCA) globally for each shot

- "GMSD-based Perceptually Motivated Non-local Means Filter for Image Denoising" 2019 IEEE International Symposium on Haptic, Audio and Visual Environments and Games (HAVE).In this work, the authors have proposed an image denoising algorithm based on the gradient magnitude similarity deviation (GMSD) metric. GMSD is a visual quality assessment metric that measures local structural variations between corresponding image patches, making it suitable for effective denoising.The authors argue that each local patch in an image exhibits diverse structural features. By capturing this diversity, it becomes easier to identify patches with similar characteristics, which is crucial for denoising. Therefore, the GMSD metric is incorporated into the conventional mean squared error (MSE)-based non-local means (NLM) filter.The conventional MSE-based approach focuses solely on visible errors and does not align well with human visual perception. As a result, images processed with MSE-based mechanisms often exhibit poor visual quality, especially when the noise levels (variance) are high.

- "Image Denoising Based on A CNN Model" 2018 4th International Conference on Control, Automation and Robotics (ICCAR). In this paper, the authors have introduced image denoising approaches based on a linear CNN model. The experiments conducted in the study indicate that the filtering method utilizing the linear CNN model demonstrates the best performance in removing Gaussian noise. Furthermore, for salt-and-pepper noise, the linear CNN model outperforms two traditional filters and performs on par with median filtering. The linear CNN model shows an improvement in performance compared to traditional image filters, as observed from the experimental results. The authors measure the results using mean squared error (MSE), and these results are presented in Table IV of the paper.

- "Gradient Histogram Edge Preservation with Non-Local Mean Filtering For Image Denoising" 2016 Online International Conference on Green Engineering and Technologies (IC-GET).Image denoising is a fundamental problem in the field of image processing, and wavelets have proven to be effective due to their properties of sparsity and multiresolution structure. In this paper, the authors propose a method for image denoising using the combination of the Generalized Hermite Polynomials (GHP) and Non-Local Mean (NLM) filtering. The GHP is utilized to enhance the texture structures in the denoising process. By leveraging the properties of wavelets and the GHP, the proposed method aims to improve the preservation and reconstruction of texture details in the denoised images. Additionally, the NLM filtering technique is employed in conjunction with the GHP for further enhancement. Non-Local Means filtering is a popular approach in image denoising that exploits the similarity between image patches to reduce noise while preserving edges and structures.

- "Fast Denoising for Fluorescence Image Sequences in a Nonlocal Means Framework" 2014 International Conference on Signal Processing and Communications (SPCOM).In this paper, the authors have introduced a novel denoising scheme specifically designed for fluorescence image sequences. The denoising process is performed within a nonlocal means framework, which is a popular approach for image denoising. To reduce the computational cost of the original nonlocal means with variance (NLMV) method, the authors propose a technique that involves projecting higher dimensional neighborhoods onto a lower dimensional subspace. By carrying out the denoising process in this reduced subspace, the computational burden is alleviated.

Studying a literature survey is important because it helps researchers understand the current state of knowledge in a particular field. By reviewing existing research, researchers can identify gaps, build a foundation for their own work, and avoid duplicating previous studies. Literature surveys provide insights into methodologies, results, and limitations of prior research, helping researchers design their own studies and contribute something new to the field.

III. METHODS USED

Convolutional Neural Networks (CNNs):

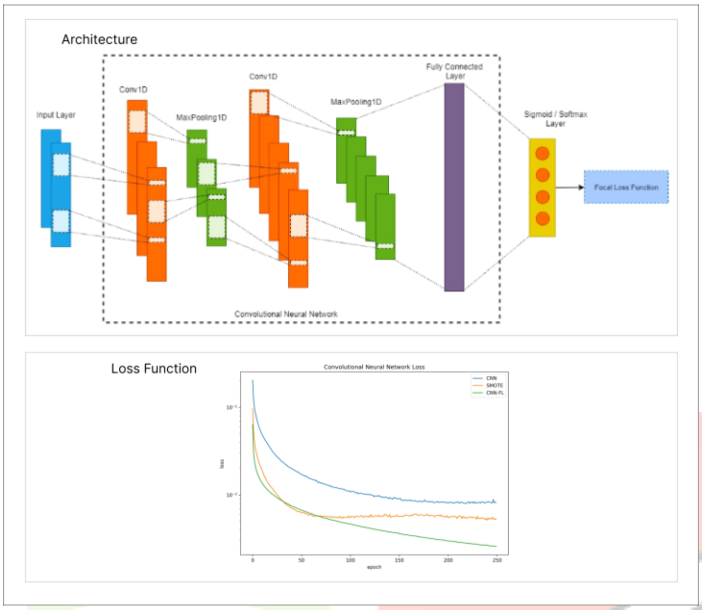
- Architecture Design: CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The architecture is designed to capture hierarchical features and learn complex mappings between noisy and clean images.

- Training: CNNs are trained using a large dataset of noisy and clean image pairs. The network parameters (weights and biases) are learned through an optimization process, typically using backpropagation and stochastic gradient descent. Training involves minimizing a loss function that measures the difference between the denoised output and the ground truth clean image.

- Loss Functions: Various loss functions can be used, such as mean squared error (MSE), perceptual loss, or adversarial loss. MSE focuses on pixel-wise differences, while perceptual loss considers high-level image features. Adversarial loss introduces a discriminator network to distinguish denoised images from clean images, promoting more realistic results.

- Data Augmentation: Data augmentation techniques, such as random cropping, rotation, or flipping, are often employed to increase the diversity and generalization ability of the training data.

- Transfer Learning: Pre-training CNN models on large-scale datasets, such as ImageNet, can be beneficial. Transfer learning involves initializing the CNN with pre-trained weights and then fine-tuning the network on the denoising task using the specific dataset.



Non-Local Means (NLM):

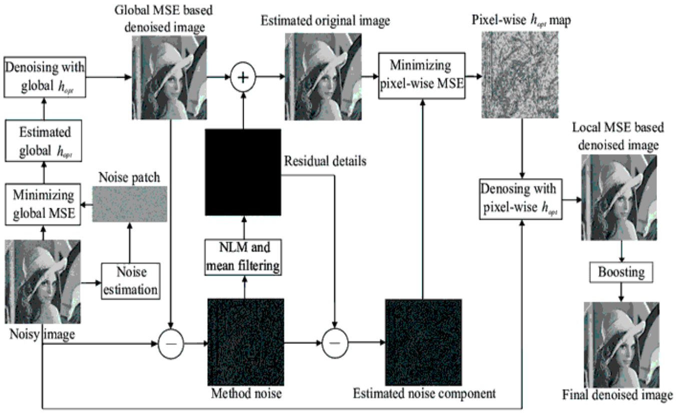
- Patch Similarity Calculation: NLM computes the similarity between patches in an image. It compares the pixel intensities of local patches and evaluates their similarity using measures like Euclidean distance or Gaussian weighted differences.

- Weighted Averaging: The NLM algorithm estimates a denoised pixel value as a weighted average of neighboring pixels. The weights are determined based on the patch similarity, where more similar patches have higher weights.

- Gaussian Filtering: NLM often employs Gaussian filtering to smooth the noisy image and reduce the influence of noisy pixels on the denoising process.

- Search Window and Patch Sizes: The sizes of the search window and patch are important parameters in NLM. The search window defines the region within which similar patches are searched, and the patch size determines the size of the local neighborhoods for similarity calculation.

- Denoising Parameters: NLM involves several parameters that need to be carefully tuned, such as the strength of filtering, the degree of patch similarity, and the decay of weights with increasing dissimilarity.



IV. CONCLUSION

In this survey, a novel nonlocal means based framework (NMF) was proposed for the removal of mixed noise in digital images. The framework employed a combination of techniques to effectively address the challenge of mixed noise. Outliers in the image were detected using a median filter and then replaced by nonlocal means, resulting in a mixture of noise that approximately followed a Gaussian distribution. Furthermore, the framework incorporated a low-rank approximation (LRNM) and a Convolutional Neural Network (CNN) to enhance the denoising performance.

In LRNM, similar nonlocal patches were grouped together in a matrix, and a low-rank approximation was applied to reconstruct the clean image. To preserve texture details, gradient regularization was introduced. The experimental results demonstrated that LRNM achieved comparable or superior denoising performance compared to traditional methods specifically designed for mixed noise removal. Additionally, NMF-CNN exhibited excellent denoising performance when compared to state-of-the-art CNN-based algorithms for mixed noise removal. Overall, the proposed NMF framework, along with its LRNM and NMF-CNN variations, showed promising results in effectively reducing mixed noise and preserving image details, showcasing their potential for practical image denoising applications.

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