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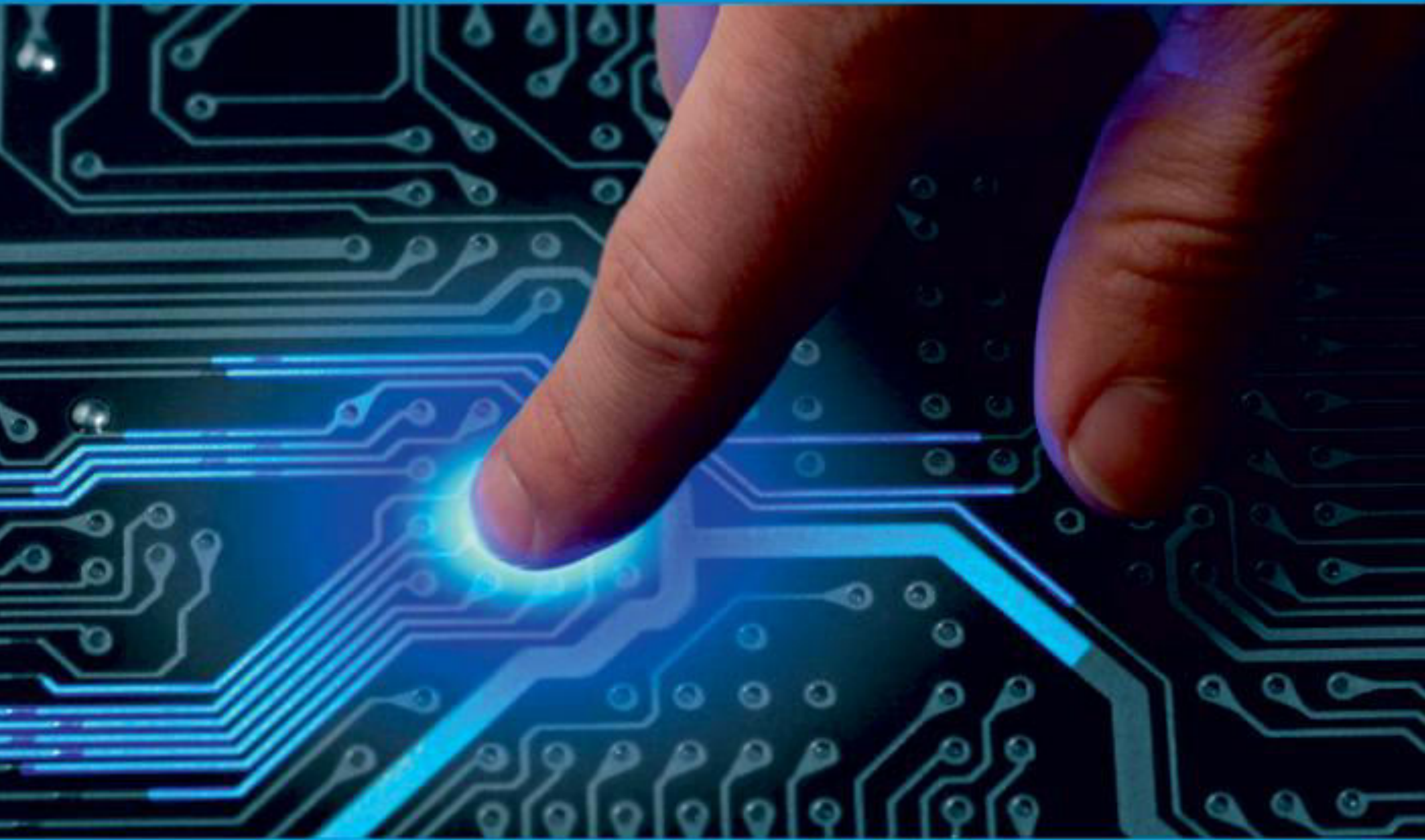

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A Deep Overview on Image Denoising Approaches

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ABSTRACT: The need for more accurate and visually beautiful photos is growing in tandem with the growth in the amount of digital images created daily. However, noise inevitably degrades the images produced by modern cameras, resulting in poor visual image quality. As a result, work must be done to minimize noise without sacrificing image quality (edges, corners, and other sharp structures). Various strategies for reducing noise have already been proposed by researchers. Each method has its own set of benefits and drawbacks. We outline some notable research in the field of picture DENOISING in this publication. We describe different picture DENOISING techniques after first presenting the concept of the image DENOISING problem.

KEYWORDS: Image Denoising; Manets; transform techniques; CNN-based Denoising methods; Deep learning Denoising Methods

I. INTRODUCTION

Images are inherently corrupted by noise during capturing, compressing, and communication due to the impact of the surroundings, the transmission medium, and other factors, resulting in distortion and loss of picture information. Possible following image processing activities, like video processing, image processing, and navigation, are harmed by the existence of noise.

Image DENOISING is the procedure of eliminating noise from a noisy picture and restoring the original image. Because noise, edge, and texture are all elements with a high frequency, it's impossible to tell them apart during the DENOISING operation and the DENOISED photos will definitely miss certain information. Consequently, retrieving relevant information from noisy photos throughout the noise elimination process to generate high resolution pictures is a major challenge currently.

In fact, picture DENOISING is a well-known issue that has been researched extensively. Nonetheless, it continues to be a big and unfinished process. The major reasoning for this is that picture DENOISING is an inverse issue with no unique solution from a mathematical standpoint. Great advances have been made in the field of picture DENOISING in latest generations [1-5], and they are discussed in the subsequent sections. Image Denoising is a type of Image processing techniques[6-7].

II. RELATED WORK

In [8] authors presented a survey on image Denoising techniques. Authors analyzed that Image noise reduction, or denoising, is an active area of research, although many of the techniques cited in the literature mainly target additive white noise. Thorough the review and evaluation of state-of-the-art denoising methods, it was found that the representation of images is substantially important for the denoising technique. At the same time, an improvement on one of the nonlocal denoising method was proposed, which improves the representation of images by the integration of Gaussian blur, clustering and Rotationally Invariant Block Matching. In this review work the successful application of sparse coding in compressive sensing, the image self-similarity by using a sparse representation based on wavelet coefficients in a nonlocal and hierarchical way, which generates competitive results compared to the state-of-the-art denoising algorithms. In [9], authors have represented a comparitive study of image denoising. Authors stated that Removing noise from any refined image is very important noise should be removed in such a way that important information of image should be preserved. Noise reducing from the original signal is still a difficult problem for researchers. Image noise is random change of brightness or colour information in images, and is usually an aspect of

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electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and irrelevant information. There have been multiple published algorithms and each approach has its assumptions, advantages, and boundaries. This paper provides a review of some significant work in the area of image Denoising.

III. CLASSICAL DENOISING METHOD

A. *Spatial Domain Filtering:*

As filtering is a common method of image processing, picture DENOISING has been subjected to a wide variety of spatial filters [10,11], which may be divided into two categories: linear and non-linear filters. Formerly, to eliminate noise in the spatial domain, linear filters were used, however they failed to maintain image textures. Mean filtering [12] has been used to reduce Gaussian noise, although it could over-smooth pictures with a lot of noise [13]. Wiener filtering [14] has been used to alleviate this problem, however it can quickly muddy sharp edges. Noise can be subdued without any characterization via non-linear filters like median filtering [15] and weighted median filtering [16]. Bilateral filtering [10] is commonly employed for picture DENOISING as a non-linear, edge conserving, and noise-eliminating smoothing filter. Every pixel's intensity value is modified with a weighted average of surrounding pixels' intensity values. The efficacy of the bilateral filter is one issue. When the kernel radius r is big, the brute-force computation consumes O (Nr2) time, which is unacceptably long.Low pass filtering is used on pixel groups in spatial filters, with the assumption that noise inhabits a greater range spectrum region. Commonly, spatial filters reduce noise to a respectable level; however at the expense of image distorting that causes sharp edges to be lost.

B. *Variational DENOISING Approaches:*

To determine the DENOISED image xˆ, prevailing DENOISING algorithms usage image priors and lessen an energy function E. Initially, from a noisy picture y, we construct a function E, and then utilise a mapping procedure to match a low figure to a noise-free picture. Next, By decreasing E, we may get a DENOISED picture xˆ.

C. *Total Variation Regularization*:

The benefits of non-quadratic regularizations have been studied for a lengthy duration, starting with Tikhonov regularization [17]. The Tikohonov technique, which minimizes R(x) using the L2 norm, is the simplest, but it over-smooths, picture specifications [18]. Although anisotropic diffusion-based [19] approaches have been employed to tackle this obstacle and maintain picture details, the borders are still distorted [20].In the realm of picture DENOISING, this is the biggest prominent study. The factual statement that actual images are spatially even and pixel concentration progressively fluctuates in most locations underpins TV regularization.It has had a lot of achievement in image DENOISING since it is able to determine the best solution and also keeps the sharpness of the edges. Furthermore, it has three fundamental flaws: textures are overly smoothed, flat portions are estimated by a piecewise continuous texture, producing a stair-casing impression and the picture loses contrast.Extensive investigations in picture smoothing using partial differential equations have been undertaken to increase the efficiency of the TV-based regularization prototype. Authors in [16], for example, developed a quick gradient-cantered technique for restricted TV, that serves as a basic structure for dealing with different forms of non-smooth regularizes. Even though it enhances PSNR figures, it only takes into consideration the image's local features. Fig. 1 shows an instance of Total variation regularization.

D. *Non-local regularization*:

Despite the fact that local DENOISING technologies have a low time complexity, their efficiency is restricted when the noise level is excessive the explanation for this is that high-level noise substantially disrupts the correlations of nearby pixels. Up till now, some approaches have smeared the NSS prior [21]. This is due to the fact that photos contain a lot of comparable patches in different places. The main aim of weighted filtering[22] is to create a pointwise prediction of the image, with all pixels generated as a weighted average of pixels concentrated at zones that are identical to the anticipated pixel's domain. NLM(xi) specifies the non-local means filtered value for a particular pixel xi in a picture x. Fig 2 shows an instance of local method vs Non-local method for image processing

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E. *Sparse Representation:*

Each picture patch must be described as a linear amalgamation of many patches from a comprehensive dictionary in order to be sparsely represented [23]. Many contemporary picture DENOISING algorithms take advantage of natural image sparsity priors. Methodologies based on sparse representations encode a picture across a vocabulary. With the K-SVD approach, the dimensionality reduction model can be studied from a dataset and also from the picture itself as a dictionary learning strategy [24].Sparse representation models with learnt dictionaries outperform planned dictionaries because learned dictionaries can more adaptably signify picture formations.When there is a lot of noise, local information is severely disrupted, and DENOISING is ineffective.

F. *Low-rank minimization:*

This low-rank-based model, unlike the sparse representation model, formats related patches as a matrix. A stretched patch vector is in each column of this matrix. This prototypical may efficiently reduce noise in a picture by utilising the low-rank of the matrix [25]. The low-rank approach originally originated in the area of matrix filling, and it has progressed rapidly. In latest days, the low-rank prototype has produced worthy DENOISING outcomes, leading to a greater interest in low-rank DENOISING techniques. For the regeneration of noisy data, there are two low rank matrix method: factorization [26] and nuclear norm minimization [27].The first group of procedures estimates a given data matrix by combining two matrices of static low rank. On the basis of low-rank matrix recovery, a video DENOISING methodology was presented. To reduce noise from videos, these algorithms use low-rank decomposition to breakdown related patches. Authors in [28] suggested and achieved good results with an image DENOISING system founded on low-rank matrix retrieval. A low-rank matrix recovery-based hybrid noise removal technique was described in [29]. To describe the sparse depiction of non-locally comparable image patches, Authors in [30] suggested a low-rank technique founded on SVD. To eliminate noise, this approach used singular value iteration compression in the Bayes-Shrink structure. The fundamental drawback of these procedures is that they require the rank as an input, and values that are too big or too small would cause into detailed loss or noise conservation, correspondingly. Fig. 3 shows a classification of spatial and transform image Denoising techniques.

IV. TRANSFORM TECHNIQUES IN IMAGE DENOISING

From the first spatial domain approaches to the current transform domain approaches, image DENOISING approaches have evolved over time. The Fourier transform was first used to produce transform domain methodologies, but ever since, a variability of transform domain approaches have appeared [31], and 3D filtering (BM3D) [32]. The following observation is used in transform domain approaches: In the transform domain, picture information and noise have different properties.Convert domain filtering methods, contrary to spatial domain filtering approaches, modify the given noisy picture to the next realm before smearing a DENOISING approach to the modified image based on the image's and noise's various features (The high frequency segment of the picture i.e. the features or edges, is represented by larger coefficients. Noise is represented by lesser coefficients). The primary transform functions employed in the transform domain filtering procedures may be classified into two classes: data adaptive and non-data adaptive [33].

A. *Data adaptive transform*:

The transform tools used on the specific noisy pictures are (ICA) [34] and PCA [35]. Among them, the ICA approach for DENOISING non-Gaussian data has been effectively implemented. These two approaches are data adaptive, and the criteria about the image-noise discrepancy remain the same. Nonetheless, they utilize sliding windows and need a section of noiseless data or at least 2 image frames from the similar scenario, they have a significant computational cost. Nonetheless, noise-free training data may be tough to obtain by in some applications.

B. *Non-data adaptive transform*:

The spatial-frequency domain and the wavelet domain are two domains of non-data adaptive transform algorithms. Low pass filtering is employed in spatial-frequency domain filtering strategies which involve building a frequency domain filter that passes all frequencies below and suppresses all frequencies beyond a threshold wavelength. Generally, picture information ranges in the low frequency domain after being converted by low-pass filters, like the Fourier transform, but noise ranges in the high frequency domains. By picking appropriate transform domain features and translating them back to the image domain, we may eliminate noise. These solutions, however, take time and are

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depending on behavior of the cut-off frequency and filter function.The wavelet transform, which is the most studied alter in DENOISING, split the input data into a scale-space depiction. Wavelets have been shown to excellently decrease noise whereas keeping visual features, irrespective of the frequency content. Filtering processes in the wavelet domain can be classified into linear and non-linear approaches, just like in the spatial domain. Because the wavelet transform has many desirable properties, like sparseness and multi-scale, it is still a hot topic in picture DENOISING studies. The wavelet transform, on the other hand, issignificantly reliant on the wavelet bases used. If the assortment is incorrect, the image displayed in the wavelet domain will not be accurately reproduced, resulting in a poor DENOISING effect. As a result, this strategy is not adaptable.

C. *BM3D (Block-matching and 3D filtering):*

The most prominent DENOISING process is BM3D, which was introduced by Dabov et al. [36] as an extremely powerful extension of the NLM methodology. In the transform domain, BM3D is a two separate collaborative screening algorithm. Analogous patches are stacked into 3D clusters using block matching, and the 3D clusters are then translated into the wavelet domain using this method. The wavelet domain is then used for hard thresholding or Wiener screening with constants. Subsequently, all approximated patches are combined to reconstitute the entire image following an inverse transform of coefficients. When noise levels rise progressively, though, BM3D's DENOISING efficacy plummets and artefacts appear, particularly in flat regions.The BM3D (fig. 4 [37]) is considered to be one of the most advanced algorithms available today. In summary, the BM3D algorithm comprises two fundamental steps: fundamental estimation and conclusion estimation

V. CNN-BASED DENOISING METHODS

Generally, objective function solving procedures are based on the image deterioration phase and image priors, and they are split into two subgroups: (CNN)-based approaches and model-based optimization techniques. The above-mentioned variational DENOISING methods are model-based optimization schemes that seek out the best solutions for reconstructing the DENOISED image. Such methods, on the other hand, frequently entail complex repetitive derivation. The CNN-based DENOISING approaches, on the other hand, seek to optimize a loss function on a training set of diminished pairs of images to acquire a mapping function [38].

Freshly, CNN-centered approaches have been rapidly developed and have shown to be effective in a variety of low-level image processing. The usage of a CNN for picture DENOISING can be traced back to the development of a five-layer network. Various CNN-based DENOISING methodologies have been established in recent times. The efficiency of these procedures has vastly enhanced when compared to other models. Additionally, there are two types of CNN-based DENOISING methods: Models of multi-layer perception (MLP) and deep learning techniques.

A. *MLP models:*

This approach category has a number of benefits. First, because there are fewer ratiocination stages in these approaches, they are more efficient. Furthermore, because optimization algorithms may derive the discriminative design, these approaches are simpler to comprehend. Alternatively, the comprehensibility can raise the rate of efficiency; for instance, the MAP prototype [39] limits the learnt priors and implication technique.

B. *Deep learning-based DENOISING methods:*

CNNs are commonly used in advanced deep learning DENOISING approaches. DnCNNs have two primary features: To develop a mapping function, the model uses a residual learning formulation and merges it with batch standardization to speed up the training process whereas enhancing the DENOISING outcomes. It becomes out that residual learning and batch standardization can aid each other, and that combining the two can help speed up training and improve DENOISING efficiency. Even though trained DnCNN can manage compaction and interposition faults, the trained paradigm for other noise variances is not adequate. The DENOISING approach should permit the user to create an adaptive swaps between noise suppression and texture protection when the noise level is uncertain

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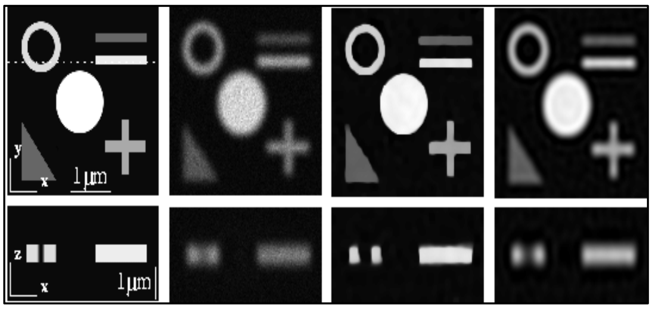

Fig.1.An instance of Total variation regularization for image processing

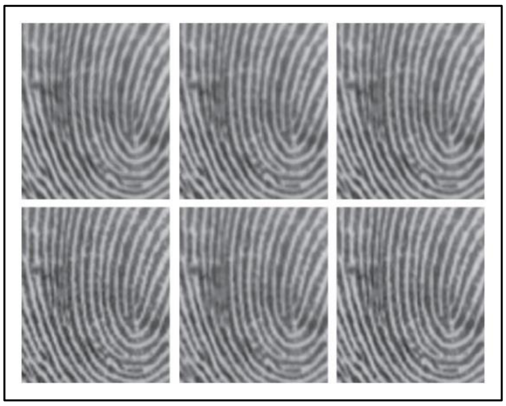

Fig. 2. An instance of local method vs Non-local method

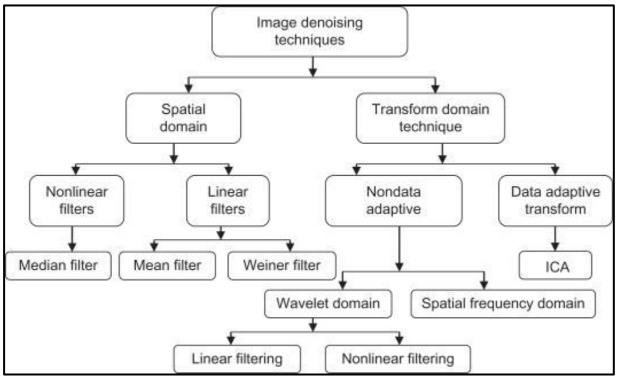

Fig. 3. Classification of Denoising techniques

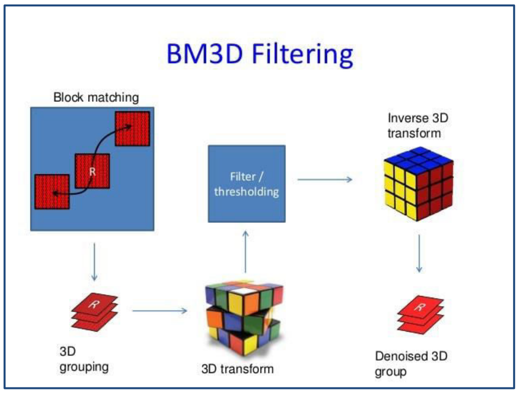

Fig 4. BM3D Filtering

VI. CONCLUSION AND FUTURE WORK

Most image processing algorithms are only as good as the parameters they're given. DENOISING procedures, for example, frequently need the setting of a DENOISING power or a patch size. These settings can be tweaked per image, although ignoring local image properties leads to less-than-ideal outcomes.Adjusting the filtering parameters adaptively offers clear advantages: the DENOISING strength can be higher in smooth sections with a minimal risk of blurring out features, and lower in highly textured parts with less visible noise. Adaptivity may also be simply produced by combining the outcome of various procedures, each of which performs well in a specific portion of an image.In this study, we have addressed the advantages and disadvantages of many picture DENOISING algorithms that have recently been developed. The advent of NLM has recently supplanted the old local DENOISING model, resulting in substantial breakthroughs in image DENOISING techniques such as sparse depiction, low-rank, and CNN (precisely deep learning) approaches. Despite the widespread usage of picture sparsity and low-rank priors recently, CNN-based approaches, which have been proven to be operative, have seen tremendous evolution in this period.

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