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A Succinct Overview of Image De-Noise Removal Techniques

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Abstract

One of the fundamental and crucial processes in image processing is picture De-noising. Researchers are continually grappling with this difficult and pressing issue. Through the use of electronic or print media, images are crucial representations in every industry, including education, agriculture, geosciences, aerospace, security and entertainment. Noise can taint images, although a lot of research has gone into finding remedies to this issue. Several techniques have been put forth. Each method has its own advantages and disadvantages. In this paper, we summarize some important research in the field of image de-noising. Hereafter, a quick introduction is followed by a summary of several approaches. Based on the methodologies employed, these methods have been grouped.

Keywords: Image de-noising, Derivative Based De-noising, Fuzzy Based De-noising, Mathematical Morphology Based De-noising, Median Based De-noising, Nonlinear De-noising methods, Statistical Modeling Based De-noising, Convolutional neural network

Introduction

Images are invariably contaminated by noise during acquisition, compression, and transmission due to the influence of the environment, transmission channel, and other variables. This results in distortion and loss of picture information. Noise has a negative impact on potential post-image processing tasks like video processing, image analysis, and tracking. As a result, image denoising is crucial in contemporary image processing systems.

Image denoising is the process of taking away noise from an image so that the original image can be seen. Denoised photos may necessarily lose some detail since noise, edge, and texture are high-frequency components that are difficult to differentiate throughout the de-noising process. A significant issue today is the recovery of significant information from noisy photos during the noise removal process in order to produce high-quality photographs.

In actuality, image de-noising [1,2,3,4] is a well-known issue that has been researched for a very long time. It is still a difficult and open task, though. This is mostly due to the fact that image de-noising is an inverse problem with several solutions from a mathematical point of view.

Poor contrast and noise are introduced into digital photos for a variety of reasons, including image transmission, acquisition, compression [5,6,7], quantization, lighting conditions, broken instruments, improper positioning, etc. When an image is processed, these sources immediately lower the visual quality of the image [8]. The goal of image restoration or de-noising is to distinguish the original image from the corrupted image. It is still the most fundamental, extensively researched and unsolved issue. Given that visual communication is an essential component of modern life, an image often contains significant information and specifics. Everywhere there is visual communication, images and videos are used. Edges, thin lines, and loss of image details are just a few examples of how noise negatively impacts image characteristics and degrade spatial resolutions. Therefore, before doing additional processing on damaged pictures such as segmentation, feature matching, edge detection, feature extraction, feature detection of image details utilized for face recognition, etc., noise removal from those images is crucial and required. These de-noised images can be employed for a variety of tasks, including face recognition, content-based image retrieval, medical image reconstruction, a comprehension of the morphology of images and their applications, image improvement, image rendering, etc.

Over the years, a plethora of approaches for image processing has been suggested in this context. Here, an evaluation of these techniques has been provided, focusing on the representative techniques that performed better in this area. These strategies have been divided into groups based on the natural processes they employ. These categories include picture de-noising techniques based on the median, statistical modeling, derivative, fuzzy logic, and mathematical morphology. In the following section of the remaining work, these categories are explored one at a time, and the conclusion is provided at the end.

Methods for Median-Based Image De-noising

The pillars of image cancellation techniques used in contemporary image processing are median-based filters or de-noising techniques. The Median Filter was first presented by Tukey, and since then, great efforts have been made to optimize, enhance, and refine it. All of the image's pixels, whether damaged or not, were subjected to the standard median filters that were displayed. Weighted Median Filters (WMF) and Switching Median Filters (SMF) were suggested as a solution to this disadvantage. By giving the middle pixel more weight, WMF lessened the smoothing impact, maintained the sharpness of the image, and handled all of the pixels like a typical median filter. It was suggested to use Weighted Order Statistics Median Filters (WOSFs) [9]. A WMF design that accepts complicated and negative weights is given. The steer ability idea was presented, and its use was discovered [10].

By distinguishing between corrupted and uncorrupted pixels and leaving the uncorrupted pixels unaltered, SMF decreased the amount of pixels that were submitted to filtration. The median filter and SMF extensions have been given. There are current instances of noise adaptable methods [11,12,13]. Window size, shape, or rank is examples of parameters that can be used as input functions for the adaptive technique. When used with Gaussian Noise or a mix of the two, Directional Weighted Median (DWM) introduced an iterative filtering method to address this flaw. To solve the issues raised, Hsing suggested switching bilateral filters based on a median-based detection approach. The output of a nonlinear median filter and current pixel value were used to create a linear combination in partition-based approaches that have been researched. It is possible to look into a few hybrid linear-nonlinear filtering techniques. Based on a combination of the Local Outlier Factor (LOF) [14], Boundary Discriminative Noise Detection (BDND), and Directional Weighted Median Filter, Wang and Lu [15] presented LOFBDND as an effective SMF.

Image De-noising Based on Statistical Modeling

Over the past 10 years, multiresolution image representation has received a lot of interest for probabilistic modeling due to its sparseness property in non-Gaussian statistics for wavelet coefficients. Additionally, multiresolution and sparse domains like Discrete Wavelet Transform (DWT) [16], Discrete Complex Wavelet Transform (DCWT) [17], Discrete Contour let Transform (DCT) [18], and Discrete Curve let Transform accurately capture the statistical properties of images (DCUT) [19]. Three steps make up sparse domain image denoising: (a) converting noisy observation into signal; (b) estimating the picture from transformed coefficients; and (c) synthesis step that involves performing an inverse transformation on a subset of coefficients. There are various forms of image estimating functions derived from the transformed coefficients, including hard and soft thresholding, firm and garrote thresholding. Leptokurtic peaked and heavy-tailed are two properties of wavelet coefficients' marginal histograms. Some techniques for picture de-noising appear to take use of the wavelet coefficients' marginal histograms' properties and apply straightforward shrinking algorithms. Inter scale dependency is another feature of wavelet coefficients. Local parameters of the probability density function describe this phenomenon. It has been found that algorithms that employ local parameters perform better than those that use global parameters. Additionally, a study of joint wavelet coefficient histograms has been provided [20]. The Gaussian scale mixture (GSM) has undergone recent modifications. There have been some statistical models for wavelet coefficient estimation in the sparse domain [21,22].

Image De-noising Based on Derivatives

Over the past ten years, partial differential equations have been widely used in edge preservation image de-noising. Nonlinear diffusion and energy functional minimization are two different forms of these techniques; nonlinear diffusion is an axiomatic approach to nonlinear scale space, and energy functional minimization is a variation technique. PDE models have been presented in a sizable number of papers over the past few years; some representative models are described here.

Axiomatic Method

The initial PDE model was put forth by Witkin [23] and was based on a linear heat equation that diffused in all directions and destroyed the edges. This restriction enlightened new approaches for researchers, such directing diffusion speed, adding a fidelity term, or combining these approaches. By regulating the diffusion speed and putting forth the nonlinear adaptive diffusion process known as anisotropic diffusion, Perona and Malik [24] were the first to introduce such a scheme. In order to improve the controlling speed function, Catte [25], You and Kaveh [26]each suggested PDE image denoising models that used an evolving Laplacian picture rather than a gradient image. Chen introduced linked nonlinear diffusion model, in which the controlling function is smoothed by diffusion equation, whereas Black offered a new controlling function based on statistical interpretation of anisotropic diffusion termed edge halting function. While Tschumperlé and Deriche introduced a unifying expression for vector-valued images to regularise PDE to achieve desired smoothing behaviors by summarising the existing PDE-based formalisms, Sapiro and Ringach [27] combined speed and direction of diffusion for the improvement of the controlling function. Based on research into the numerical scheme of an anisotropic diffusion filter and its extension to the matrix of anisotropic diffusion, Vosburg suggested a method [28] for removing speckle noise from ultrasonic images. Wang and Zhang employed the local variance to regulate the diffusion both forward and backward.

Variation Strategy

By providing the fidelity term a straightforward shape and describing it as a dynamic value, Rudin established the Total Variation Denoising (TVD) model [27]. Fidelity functions were non convex functions with the fidelity term fixed to a constant value. In the situation of extremely high noise density, Nikolova described the use of non convex functions to reduce the goodness of fit to the polluted data and stabilize the denoising. Processing for TV deblurring issues, Abubakar developed a multiplicative regularisation approach, in which the regularisation parameter is regulated by an optimum processing for the preservation of texture and some image features, Gilboa presented the pyramidal texture structure-texture decomposition and analysis. Denoising in various image regions was controlled by spatially variable fidelity factors. Wang merged the pixel and wavelet domains, using shrinkage and TV as appropriate regularizers in each domain. The quasi-Newton method for TV regularisation was introduced by Chart and. Bae presented the graph cuts-based TV minimization technique. Due to the fact that existing approaches treated corrupted and uncorrupted pixels equally in cases of high noise densities and fewer iterations left the corrupted pixels, Wu and Tang distinguished the pixels as edge, noise, and interior pixels and defined the speed function and fidelity term based on these definitions. In order to address issues with TV-based image restoration, Zuo [23] introduced the GAPG (generalised accelerated approximation gradient) approach.

Image De-Noising Based on Fuzzy Logic

Since their origin, neural networks and fuzzy systems have the ability to handle uncertainty and learn from examples, respectively. With observable fuzziness as a result of the presence of fuzziness in the image signal and tainted signal, image denoising is unquestionably a filtering system. Fuzzy systems have thus become a significant area of contemporary research. Russo [23] has evaluated traditional approaches, fuzzy weight filters, and fuzzified FIRE filters in relation to applications, filters, and advancements in fuzzy systems. Zhang suggested employing long-range correlation among several image sections to detect and remove impulse noise on a fuzzy basis. Examples of expanding applications for fuzzy systems are provided. Image denoising has also been done with the use of neuro-fuzzy systems, which were created by fusing neural networks and fuzzy systems. Lee proposed a fuzzy filter that used genetic learning, while Yuksel created a hybrid filter that incorporated an internal parameter adaptive optimization process with training by combining an edge detector, median filter, and neuro-fuzzy network. For the purposes of identifying and removing noise, Schulte and others suggested fuzzy derivative estimation and fuzzy smoothing. Although these methods require more memory and compute, they perform better. Liang suggested two-stage neuro-fuzzy methods for removing impulse noise. Toh and Isa [24] devised the Cluster-based Adaptive Fuzzy Switching Median (CAFSM) to remove all types of noise and salt and pepper, respectively, in order to deal with uncertainties existing in local information. Applications for type-2 fuzzy logic systems (FLSs) have grown significantly in recent years. Type-1 [25] FLSs have scalar membership functions, whereas type-2 FLSs have fuzzy membership functions. Type-2 FLSs are more effective as a result of the double degree of fuzziness. Due to the unpredictability in picture data and the fuzzy nature of image filtering, fuzzy logic-based algorithms have demonstrated promising outcomes.

Image De-noising Based on Mathematical Morphology

In image processing, mathematical morphology is about shapes and structures; it is a geometrical approach with a solid mathematical foundation. Recently, scholars have been more interested in picture de-noising based on mathematical morphology. The goal of the project is to create a nonlinear operator that can extract geometric and topological data from photographs.

A lattice theory application to spatial structures is mathematical morphology. The morphological method that can modify the local context of the signal is adaptive mathematical morphology [26]. There are various morphological filter types available, including soft morphological filters, hybrid operator-based morphological filters, and multi-structure elements-based morphological filters. These methods enhanced the effectiveness of image denoising. Key methods for building morphological hybrid filters are morphological dual operators.

Transform Techniques in Image De-noising

From the original spatial domain approaches to the current transform domain methods, image denoising techniques have evolved gradually. Initially derived from the Fourier transform, transform domain approaches have now evolved to include the cosine transform, wavelet domain methods [27,28], block matching, and three dimensional filtering (BM3D) [29]. The characteristics of image information and noise are different in the transform domain, which is an observation used by transform domain approaches.

BM3D

The most widely used denoising technique is BM3D, which was suggested by Dabov et al. [29] as an efficient and potent extension of the NLM methodology. In the transform domain, BM3D is a two-stage non-locally collaborative filtering technique. By using block matching, related patches are piled into 3D groups in this technique, which then undergoes a wavelet domain transformation. Then, in the wavelet domain, hard thresholding or coefficient-based Wiener filtering is used. Finally, all estimated patches are combined to rebuild the entire image following an inverse transform of coefficients. However, as the noise level gradually rises, BM3D's denoising effectiveness significantly declines and artifacts start to appear, particularly in flat areas.

There have been numerous upgraded versions of BM3D released to improve denoising performance [30,31].In order to extend BM3D to volumetric data, Maggioni et al. [31] Recently suggested the block-matching and 4D filtering (BM4D) approach. It makes use of voxel cubes that have been piled into a 4-D group. The group's 4-D transform concurrently takes advantage of the voxel local and non-local correlations. As a result, the group's spectrum is exceedingly sparse, which enables coefficient shrinkage to effectively separate the signal from the noise.

CNN-Based De-noising Methods

The model-based optimization algorithms that determine the best ways to reassemble the de-noised image include the variation denoising techniques that were previously addressed. These techniques, however, frequently entail time-consuming iterative inference. The convolutional neural network (CNN)-based denoising techniques, on the other hand, make an effort to learn a mapping function by optimising a loss function on a training set that includes clean-degraded image pairs [32,33].

In recent years, CNN-based techniques have been rapidly developed and have excelled at many simple computer vision applications. When a five-layer network was created, a CNN was first employed for picture denoising. Numerous CNN-based denoising techniques have been suggested recently [32,34,35,36]. The performance of these approaches has significantly increased when compared to that of ref. Deep learning techniques and multi-layer perception (MLP) models are two subcategories of CNN-based denoising techniques.

MLP Models

Xie et al. [37] and Vincent et al. [38] both presented auto-encoders for MLP-based image de-noising models. The trainable non-linear reaction-diffusion (TNRD) model, which was proposed by Chen et al. [32], was a feed-forward deep network that produced better de-noising results. There are various benefits to this class of techniques. Because there are fewer ratiocination processes, these strategies are first effective. Furthermore, these techniques are easier to grasp because optimization algorithms may determine the discriminative architecture. Interpretability, however, may raise the cost of performance; for instance, the MAP model [34] limits the use of learned priors and inference techniques.

Deep Learning-Based De-noising Methods

Modern deep learning denoising techniques frequently rely on CNNs. Deep learning-based denoising techniques have received a lot of interest because of their exceptional denoising capacity. For the first time, residual learning and batch standardisation were brought into image denoising by Zhang et al. [34] Additionally; they presented feed-forward denoising CNNs (DnCNNs).

The model uses a residual learning formulation to learn a mapping function, and it combines it with batch normalisation to speed up the training process while increasing the denoising outcomes. These are the two key properties of DnCNNs. Particularly, it turns out that batch normalisation and residual learning can complement one another, and their integration is effective in accelerating training and enhancing denoising performance. A trained DnCNN can manage interpolation and compression errors as well, but the trained model under is not appropriate for other noise variances.

The denoising technique should allow the user to adaptively choose between noise suppression and texture protection when the noise level is uncertain. To achieve these desired qualities, the fast and flexible denoising convolutional neural network (FFDNet) [35]was developed. FFDNet's ability to operate on down-sampled sub-images accelerates training and testing while enlarging the receptive field, which is another significant contribution. FFDNet is hence extremely adaptable to various noises.

Although this system is quick to implement and efficient, the learning process has a significant degree of time complexity. The learning of high-level features using a hierarchical network has improved with the emergence of CNN-based denoising algorithms.

Contrasting CNN-Based De-noising Techniques

Here, we contrast the denoising outcomes of the CNN-based approaches (DnCNN [34]and FFDNet [35]) with those of a number of recently developed efficient image denoising techniques, such as BM3D [29] and WNNM [39]. To the best of our knowledge, WNNM is a successful plan that has recently been developed, while BM3D has historically been the most common denoising technique. First, for a wide range of noise levels, FFDNet [35] outperforms WNNM [39] by about 0.2 dB and BM3D [29] by a significant margin. Second, while the noise level is low (e.g., 25), FFDNet somewhat underperforms DnCNN [34]; but, as the noise level rises (e.g., > 25), FFDNet steadily outperforms DnCNN. The fine textures are blurred by WNNM [39] and BM3D [29], however more textures are restored by the other two methods. This is due to Monarch's abundance of repeated structures, which NSS may take advantage of to good effect. These regions' contour margins are also crisper and appear more realistic. FFDNet [35]generates de-noised photos with the highest perceptual quality overall.

Conclusions

Image denoising has grown in complexity and requirements, thus there is still a great demand for research in this area. In this study, we have reviewed the advantages and disadvantages of numerous picture denoising techniques that have recently undergone advancements. Nonlinear denoising methods have traditionally been the most sophisticated. The processes involve a variety of noise types. All noise types including impulse, Gaussian white noise, and speckle as well as the proper denoising methods have been considered. Each approach has its own performance indicators for the issues it focuses on, some of which might not be sufficient to address other issues. Wavelet domain techniques have generally fared pretty well due to their noise adaptability and sparsity. Although spatial domain computations are more challenging and time-consuming, median-based techniques have excelled at restoring images because of their nonlinearity. Fuzzy logic-based techniques have led to hopeful outcomes. Recent improvements in image denoising techniques include sparse representation, low-rank, and CNN (more precisely deep learning)-based denoising approaches as a result of the rise of NLM, which has recently supplanted the conventional local denoising model. Despite the widespread usage of picture sparsity and low-rank priors in recent years, CNN-based approaches, which have been shown to be successful, have grown rapidly over this period.

In conclusion, the purpose of this study is to provide a synopsis of the different denoising techniques. The examination of noise can be helpful in creating new denoising schemes because different types of noise call for different denoising techniques. We must first investigate how to handle various kinds of noise, particularly those that exist in real life, in order to prepare for future work.

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