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Review of Filter-Based Image Denoising Methods

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ABSTRACT

Image denoising is one of the fundamental tasks in the field of digital image processing. In tasks such as object detection, the effectiveness of image denoising plays a crucial role in the accuracy of the detection results. As image acquisition devices and technologies continue to advance, various types of noise, such as Gaussian noise and salt-and-pepper noise, are commonly present in images. These types of noise have a detrimental impact on the quality and visual fidelity of the images. Consequently, the research and application of image denoising techniques hold significant importance in improving image quality, enhancing fine details, and accurately analyzing image content. Among the myriad of image denoising methods, filter-based approaches have garnered notable attention due to their simplicity, efficiency, and ease of implementation. This paper aims to provide a comprehensive overview and reference for researchers in the field by reviewing the research progress and potential breakthrough directions of filter-based image denoising methods.

KEYWORDS

Image denoising; Digital image processing; Filter-based approaches

1. INTRODUCTION

With the widespread application of digital images in various domains, the demand for image quality has become increasingly significant. However, image quality often suffers degradation due to various interferences and noise during the processes of image acquisition and transmission. These noises originate from the perceptual limitations of image acquisition devices, sensor noise, interferences during signal transmission, as well as image storage and compression processes [1]. From both human visual perception and subsequent image processing and analysis perspectives, these noises have detrimental effects on the visual effects and information extraction of the images.

Figure 1. The image data with noise.

The presence of noisy image data, as depicted in Figure 1, significantly impacts subsequent image processing. Therefore, research and application of image denoising techniques have become crucially important. The goal of image denoising is to restore the original information of an image by reducing or eliminating the influence of noise, resulting in a clearer image with enhanced details and improved suitability for subsequent processing and analysis [2]. Among numerous image denoising methods, filter-based approaches have garnered considerable attention due to their simplicity, efficiency, and ease of implementation [3].

Filter-based image denoising methods aim to enhance image quality by designing and applying various filters. These filters can be linear, such as the mean filter [4], median filter [5], and Gaussian filter [6], or they can be nonlinear, such as adaptive filters [7] and wavelet filters [8], among others. These methods are based on signal processing and filtering theory, utilizing filters to perform local or global operations on the image, thereby reducing the influence of noise while preserving the image's structure and details.

In this paper, we aim to provide a systematic review of the research progress and current applications of filter-based image denoising methods. We will cover commonly used filter-based image denoising techniques, such as linear filters, adaptive filters, and wavelet denoising methods. We will delve into the principles, characteristics, and applicable scenarios of these methods, while also discussing the current challenges and future directions. Additionally, beyond traditional filter-based denoising methods, we will explore the potential novel applications of Kalman filters and their variants in image denoising, which hold promise for achieving more efficient denoising effects in the future.

2. COMMON FILTER-BASED IMAGE DENOISING METHODS

2.1. Mean Filter

The mean filter [9] is a commonly used image filter employed to smooth images and reduce noise. Its principle involves replacing the value of each pixel with the average value of its surrounding neighborhood pixels, aiming to achieve noise removal. The relevant formula is presented below:

$$Output(x, y) = \big(1/(k * k)\big) * \Sigma\Sigma Input(i, j) \tag{1}$$

Where, $i = -k/2,\ j = -k/2,\ Output(x, y)$ represents the filtered output pixel value, $Input(i, j)$ represents the input pixel value in the neighborhood, k denotes the size of the filter (typically an odd number), and Σ denotes the summation operation.

The mean filter is effective in removing simple types of noise such as Gaussian noise, salt and pepper noise, and it can smooth the image, reducing its details and textures. Additionally, it serves as a fundamental step in various image processing algorithms, including edge detection [10] and image segmentation [11].

However, the mean filter also has certain limitations. For instance, it is ineffective in handling salt and pepper noise and preserving image details [12] When applied to images containing subtle structures and edges, the mean filter may cause a blurring effect.

2.2. Median Filter

The median filter is commonly used for removing salt and pepper noise from images. Unlike the mean filter, the median filter first defines a fixed-size filtering window and then replaces the value of each pixel with the median value of its surrounding neighborhood pixels. This process aims to smooth the image and reduce noise. The relevant formula is presented below:

$$Output(x, y) = Median(Input(i, j)) \tag{2}$$

where, $Output(x, y)$ represents the filtered output pixel value, $Input(i, j)$ represents the input pixel value in the neighborhood, and $Median$ denotes the calculation of the median value of the neighborhood pixel values. k represents the size of the defined filtering window.

The median filter excels in removing salt and pepper noise by effectively replacing noisy pixels with the median value of the neighboring pixels, while minimizing the impact on image details and edges. In comparison to the mean filter, the median filter better preserves the edge information within the image [13].

However, the median filter also has its own limitations. For instance, it performs poorly in handling certain types of noise, such as Gaussian noise. Moreover, when dealing with large filter window sizes (i.e., larger values of k), the median filter can result in blurring of image details.

2.3. Gaussian Filter

The Gaussian filter is commonly employed for image denoising and high-frequency noise removal. It utilizes the Gaussian function to perform a weighted average on the image, and it can also be used to create image blurring effects [14]. The Gaussian filter first defines a two-dimensional Gaussian function and then computes the output value for each pixel in the image by performing a weighted average of its neighboring pixels. The weights assigned to the neighboring pixels depend on their spatial distance from the current pixel. The relevant formula is presented below:

$$Output(x, y) = \left(1/(2\pi\sigma^2)\right) * \Sigma\Sigma Input(i, j) * exp\left(-(i - x)^2/(2\sigma^2) - (j - y)^2/(2\sigma^2)\right) \tag{3}$$

where, $Output(x, y)$ represents the filtered output pixel value, $Input(i, j)$ represents the input pixel value in the neighborhood, σ denotes the standard deviation of the Gaussian distribution, k represents the size of the filter (usually an odd number), exp represents the exponential function, and Σ denotes the summation operation.

The Gaussian filter effectively reduces high-frequency noise in the image and can enhance image clarity while making it smoother. However, the denoising performance of the Gaussian filter heavily relies on parameter settings. For instance, a larger Gaussian standard deviation can lead to the loss of fine image details.

2.4. Adaptive Filter

The adaptive filter differs from traditional fixed filters in that it determines the weight of each pixel based on the image's statistical information and the characteristics of local pixels, aiming to achieve more accurate image denoising and enhancement effects [15]. It first defines a filtering window and then dynamically updates the weights for each pixel within the window based on the statistical information of all the pixels in the window. The relevant formula is presented below:

$$Output(x,y) = Mean\big(Input(x,y)\big) - c * \Big(Mean\big(Input(x,y)\big) - Input(x,y)\Big) \tag{4}$$

where, $Output(x,y)$ represents the filtered output pixel value, $Input(x,y)$ represents the pixel value of the input image, $Mean$ denotes the calculation of the mean value of the pixels within the window, and c is a known constant.

The effectiveness of the adaptive filter is determined by the size of the filtering window and the selection of parameters. A larger filtering window can provide more accurate estimations but may result in the loss of image details [16]. Therefore, the denoising performance of the adaptive filter heavily relies on parameter values, which often requires iterative tuning or manual intervention.

2.5. Wavelet Denoising

Wavelet denoising is an image signal processing technique based on wavelet transform [17]. It aims to remove noise while preserving the essential features of the signal. Unlike the previous denoising methods mentioned, wavelet denoising involves decomposing the signal or image into different scales of frequency bands and then performing denoising on each individual band. Finally, the denoised frequency bands are synthesized together [18].

Compared to the filtering techniques mentioned earlier in this paper, wavelet denoising requires consideration of several relevant parameters. For instance, the selection of wavelet basis functions, the number of decomposition levels, and the appropriate thresholding functions for each frequency band. Similarly, the denoising effectiveness of wavelet denoising is influenced by these parameters. Compared to traditional denoising methods, wavelet denoising is relatively more complex. However, with appropriate parameter selection, it can achieve superior denoising results.

3. PROSPECTS OF KALMAN FILTER APPLICATION IN IMAGE DENOISING

In the field of state tracking, one of the most commonly used methods is the Kalman filter (KF) [19]. It is highly efficient and easy to implement and has achieved successful applications in various domains such as control, navigation, and communication. The Kalman filter utilizes mathematical modeling and observation data to achieve optimal estimation of the state. In the field of motion tracking, the mathematical modeling is based on approximated motion equations. However, in the domain of image denoising, it is challenging to accurately approximate the model.

Compared to the traditional image denoising techniques mentioned earlier, if the Kalman filter can be successfully applied in the field of image denoising, it has the potential to significantly improve the accuracy compared to the aforementioned methods. However, in relative terms, the computation of the Kalman filter is slightly more complex compared to traditional denoising methods. In this section, we will discuss the challenges of applying the Kalman filter to image denoising, considering the aspects of model approximation and computational complexity.

3.1. Modeling Challenges

The Kalman filter utilizes the observed data and its own mathematical modeling to dynamically weigh the predicted results and generate an optimal estimation. However, the modeling process requires prior specification. For instance, consider the following simple model of uniform linear motion:

$$x = x^0 + v^0 * t + (1/2) * a * t^2 \tag{5}$$

While the aforementioned approach can be used for modeling approximations in simple motion models, it becomes challenging to achieve high-precision modeling approximations for complex images [20]. Even if modeling is possible, the computational time required would be far from reaching the level required for large-scale applications.

When applying the Kalman filter to image denoising, the image needs to be treated as pixel curve data for filtering. For each pixel curve, it is difficult for the Kalman filter to achieve an accurate modeling approximation, thereby hindering the calculation of corresponding parameters for updating the filtering gain. Although the extended Kalman filter (EKF) [21] can address nonlinear model problems, it still cannot overcome the challenges associated with modeling difficulties in image denoising.

3.2. Computational Complexity Issues

In this section, we assume that the modeling issue of the Kalman filter has been addressed in the context of image denoising. However, even in this case, the Kalman filter can only perform filtering on pixel curves. When traditional RGB images are processed by computers, they are divided into separate color channel images for R, G, and B. The Kalman filter needs to perform pixel curve filtering on each channel image. The specific process can be referred to in Figure 2.

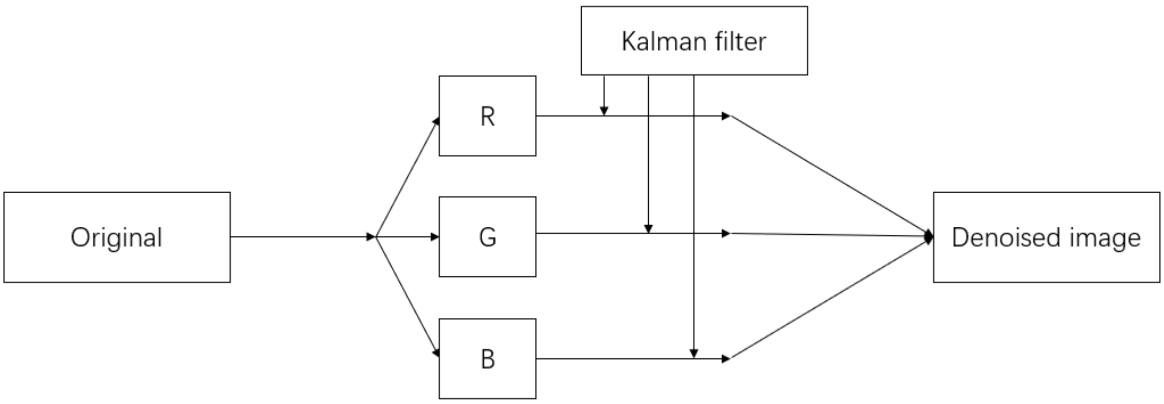

Figure 2. Illustration of Kalman Filter Processing RGB Images

The filtering process of the Kalman filter is depicted as follows [22]:

$$\hat{\boldsymbol{x}}_{k+1,k} = \boldsymbol{F}_{k+1,k}\hat{\boldsymbol{x}}_k + \boldsymbol{B}_k\boldsymbol{u}_k \tag{6}$$

$$\boldsymbol{P}_{k+1,k} = \boldsymbol{F}_{k+1,k}\boldsymbol{P}_k\boldsymbol{F}_{k+1,k}^T + \boldsymbol{Q}_k \tag{7}$$

$$\boldsymbol{K}_{k+1} = \boldsymbol{P}_{k+1,k}\boldsymbol{H}_{k+1,k}^T\left(\boldsymbol{H}_{k+1,k}\boldsymbol{P}_{k+1,k}\boldsymbol{H}_{k+1,k}^T + \boldsymbol{R}_k\right)^{-1} \tag{8}$$

$$\hat{\boldsymbol{x}}_{k+1} = \hat{\boldsymbol{x}}_{k+1,k} + \boldsymbol{K}_{k+1}\left(\boldsymbol{y}_{k+1} - \boldsymbol{H}_{k+1,k}\hat{\boldsymbol{x}}_{k+1,k}\right) \tag{9}$$

$$\boldsymbol{P}_{k+1} = \left(I - \boldsymbol{K}_{k+1}\boldsymbol{H}_{k+1,k}\right)\boldsymbol{P}_{k+1,k} \tag{10}$$

in the given equations, $\boldsymbol{y}_{k+1}$ represents the input image pixel curve, $\widehat{\boldsymbol{x}}_{k+1}$represents the filtered curve (denoised pixel curve), and $\boldsymbol{K}_{k+1}$ represents the filter gain matrix. Based on equations (6)-(10), it can be observed that compared to traditional denoising methods, the computational approach of the Kalman filter is overly complex and involves numerous parameters. While the Kalman filter offers higher precision compared to traditional denoising filters, it also introduces increased computational complexity. In the context of future applications in image processing, there is a need for simpler modeling and computational approaches.

4. SUMMARY AND OUTLOOK

Image denoising techniques are crucial problems in the field of digital image processing and find extensive applications in computer vision and object detection. High-quality denoised images greatly facilitate subsequent image processing and related tasks such as object recognition. This article aims to introduce several commonly used filter-based image processing methods, discussing their advantages and suitable scenarios. Additionally, we explore the prospects and technical challenges of applying the Kalman filter to image denoising. Resolving these technical challenges in the future would significantly enhance the effectiveness of image denoising.

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