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Gradient Histogram Based De-Noising for Videos using Additive White Gaussian Noise

Sangeeta Khatarkar[1], Sumeet Dhillon[2]

Research Scholar, Computer Science & Engineering, Samrat Ashok Technological Institute, Vidisha (M.P.), India[1]

Asst. Professor, Computer Science & Engineering, Samrat Ashok Technological Institute, Vidisha (M.P.), India[2]

Abstract: Image and video denoising is very popular and governs the performance of many other algorithms. In this paper gradient histogram method is applied on the frames of the video i.e. images for denoising and hence the complete video is denoised. Gradient histogram approach has one advantage in addition to other approach; it also improves visual quality of denoised image. In this paper gradient histogram method is applied after applying additive white Gaussian noise to the images retrieved from video. It is found that PSNR of denoised video is 17.4 which is more as compared to previous approaches which has maximum of 16.

Keywords: Gradient histogram, image denoising, spatial domains, transforms domains, psnr.

I. INTRODUCTION

Images and videos have become an integral part of our life in recent times. Applications now extend from more general documentation of an event and visual communication to more serious surveillance and medical fields. This has raised the massive demand for images with high accuracy and visual quality. However, digital images captured by modern cameras often get corrupted by noise at the time of image acquisition (digitization) and/or transmission. This form of corruption may result in degradation of visual appearance of an image. The efficiency of imaging sensors is affected by a number of factors, such as environmental conditions during image acquisition and by the quality of the sensing elements themselves. For example, in acquiring images with a CCD camera, sensor temperatures and light levels are major factors that can affect the amount of noise in the resulting image. The corruption in images may also occur during transmission. Reason being the interference in the channel used for transmission. For instance, an image transmitted through a wireless medium might be corrupted due to lighting effects or other atmospheric disturbance. Image denoising is a well explored topic in the field of image processing where the prime objective is to improve the visual quality of an image by reducing noise from its given noisy version. Numerous image denoising techniques have been developed to minimize the effect of noise(s) occurred due to any of the above mentioned noise sources. A major challenge is to preserve the image details and local geometries while removing the undesirable noise. And for video denoising it will be converted into images by taking each and every frames and by applying denoising for all the frames.

II. IMAGE NOISE

Image noise is a random variation of brightness or color information in images and is usually an aspect of electronic noise. As earlier mentioned, the principal sources of noise in digital images arise during image acquisition and/or transmission. Image noises can be broadly classified in two categories viz. spatially independent noise and spatially dependent noise.

General Classification of Image Denoising Techniques

During the last few decades, a large number of image denoising approaches have been added to the literature. Also, the surveys on these approaches have been provided by various authors. Recently, Shao et al. (2014) presented the taxonomy of image denoising methods, while Jain and Tyagi (2014) have mainly focused to provide survey on most promising edge-preserving image denoising methods. Generally, image denoising methods have been with adaptive clipping, and spatial noise reduction with the NLM denoising filter.

In 2014 another approach is proposed in [13] which also enhances low light video to HDR video broadly classified into spatial domain methods and transform domain methods. In [12] 2014, is aimed to develop a novel framework to enhance video from extremely low-light environments. It consists of an effective motion adaptive temporal filter based on the Kalman filter framework, a tone-mapping by histogram adjustment.

Spatial Domain Methods

A traditional way to remove noise from image data is to employ spatial filters. Spatial domain filtering methods take the original noisy image into consideration and apply filtering process on it. Spatial filters are direct and high speed processing tools of images.

Spatial filters can be further classified into linear and nonlinear filters. Some conventional spatial domain filters have been elaborated in [1].

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Transform Domain Methods

In contrast with spatial domain filtering methods, transform domain filtering methods first obtain some transform of given noisy image and then apply denoising procedure on transformed image. The transform domain filtering methods were subdivided according to the choice of the basis transform functions which may be data adaptive or non-data adaptive

III. RELATED WORK

Generally, image denoising methods can be grouped in two categories: model-based methods and learning-based methods. Most denoising methods reconstruct the clean image by exploiting some image and noise prior models, and they belong to the first category. Learning-based methods attempt to learn a mapping function from the noisy image to the clean image [2], and have been receiving considerable research interests [3]. Numerous image denoising algorithms have been proposed, and here we only review those model-based denoising methods related to our work from a viewpoint of natural image priors. Studies on natural image priors aim to find suitable models to describe the characteristics or statistics (e.g., distribution) of images in some transformed domain.

One representative class of image priors is the gradient priors based on the observation that natural images generally have a heavy tailed distribution of gradients. The use of gradient prior can be traced back to 1990s, when Rudin et al. [4] proposed a total variation (TV) model for image denoising, where the gradients are actually modeled by Laplacian distribution. Another well-known prior model, the mixture of Gaussians (GMM), can also be used to approximate the distribution of gradient magnitude [5, 6]. In addition, the hyper-Laplacian model can more accurately model the heavy-tailed distribution of gradients, and has been widely applied to various image restoration tasks [7, 8]

Denoising with gradient histogram preservation (GHP)
Given a clean image x, the noisy observation y of x is usually modeled as

$$y = x + v \qquad (1)$$

Where v is the additive white Gaussian noise (AWGN) with zero mean and standard deviation σ. The goal of image denoising is to estimate the desired image x from y. One popular approach to image denoising is the variational method, in which the denoised image is obtained by

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \left\{ \frac{1}{2\sigma^2} \|\mathbf{y} - \mathbf{x}\|^2 + \mu \cdot R(\mathbf{x}) \right\}$$

Where R(x) denotes some regularization term and μ is a positive constant. The specific form of R(x) depends on the used image priors.

One common problem of image denoising methods is that the image fine scale details such as texture structures will be over-smoothed. An over-smoothed image will have much weaker gradients than the original image. Intuitively, a good estimation of x without smoothing too much the textures should have a similar gradient distribution to that of x. With this motivation, we propose a gradient histogram preservation (GHP) model for texture enhanced image denoising (TEID).

Additive white Gaussian noise (AWGN) is a basic noise model used in Information theory to mimic the effect of many random processes that occur in nature. The modifiers denote specific characteristics:

- Additive because it is added to any noise that might be intrinsic to the information system.
- White refers to the idea that it has uniform power across the frequency band for the information system. It is an analogy to the color white which has uniform emissions at all frequencies in the visible spectrum.
- Gaussian because it has a normal distribution in the time domain with an average time domain value of zero.

Peak signal to noise ratio (PSNR)

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality [9]. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not.

SSIM is used for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measurement or prediction of image quality is based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods such as peak signal-to-noise ratio (PSNR) and mean squared error (MSE)[10], which have proven to be inconsistent with human visual perception.

Non-local means is an algorithm in image processing for image denoising. Unlike "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel [11]. This result in much greater post-filtering clarity and less loss of detail in the image compared with local mean algorithms.

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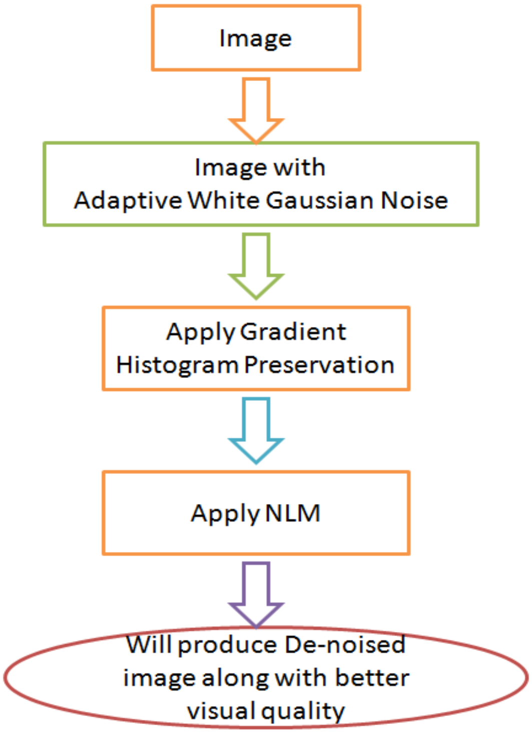
VI. PROPOSED APPROACH:



Step 1: get the low light video as input.

Step 2: perform the temporal noise reduction using the Kalman filtering algorithm to estimate the exact pixel values using inter frame relations. Using state transition and observation equations:

$$\begin{cases} X_t = M_t X_{t-1} + S_t, \\ Y_t = X_t + V_t, \end{cases} \quad \text{where} \quad \begin{cases} S_t \sim N(0, Q_t^{-1}), \\ V_t \sim N(0, C_t^{-1}), \end{cases}$$

Where X_t and Y_t are clear image frame and noisy image frame at time t respectively. They are rearranged as column vectors in lexicographic order.

M_t Denotes a motion matrix and S_t accounts for the difference between the previous and current frame, Q_t^{-1} reflects the amount of motion estimation error.

V_t Represents the Gaussian noise during acquisition of current frame.
C_t^{-1} Denotes the variance of measurement noise.
Step 3: perform the tone mapping using gamma correction in each color plane as follows:

$$\begin{cases} \lambda_{low,c} = \arg\max_{\lambda}(h(\lambda)), \\ \lambda_{high,c} = \arg\min_{\lambda}\left(\sum_{x=0}^{\lambda} h(x) \geq \alpha \cdot M\right), \end{cases} \quad \text{for } c \in \{r, g, b\},$$

Where $\lambda_{low,c}$ and $\lambda_{high,c}$ are low and high thresholds for eachcolor channel, respectively. h(x)is the histogram for the normalized intensity value x. Since most of pixels assigned to intensities below the peak of histogram are noisy ones, the low clipping threshold is set at the peak of histogram.

Step 4: perform the Gradient Histogram Preservation (GHP) for the image to enhance the texture information of the filtered image received from step 2. The GHP model can be formulated as:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x},F}\left\{\frac{1}{2\sigma^2}\|\mathbf{y}-\mathbf{x}\|^2 + \lambda\sum_i \left\|\boldsymbol{\alpha}_i - \boldsymbol{\beta}_i\right\|_1 + \mu\|F(\nabla\mathbf{x}) - \nabla\mathbf{x}\|^2\right\}$$

Where $\hat{x}$is the estimated GHP image. y Represents the noisy image. λ and μ are the weight constants.

∇Represents the gradient operator.α_i is The sparse coding vector and $\beta_i$is defined as weighted average of α_i.

Step 5: Finally the Non-Local Mean filtering is performed to remove the remaining noise.

Experimental setup and Results
MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment and fourth-generation programming language.

A proprietary programming language developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, Fortran and Python.

Although MATLAB is intended primarily for numerical computing, but has lots of support for image processing and video also

In this paper GHP is applied using MATLAB. The table below represents PSNR for standard video sets Malm, Kuang, Shang, Kim, Lee. It is clear that PSNR is improved.

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Table 1: Comparison of image denoising techniques

De-noising technique	PSNR	SSIM	Visual quality
Model based	Increases (2 to3%)	Increases (10 to15%)	No improvement
Learning based	Increases (3 to6%)	Increases(15 to20%)	No improvement
GHP based	Increases (2 to4%)	Increases(10 to20%)	increases

Table 2: Comparison of PSNR for proposed method

Metric	Input	Malm [3]	Zhang [6]	Kuang [33	Shan [34]	Kim [35]	Lee [36]	Previous	Proposed
PSNR	11.9	15.9	15.7	12.3	12.2	14.7	15	16.5	17.5511
SSIM	0.23	0.47	0.37	0.21	0.19	0.3	0.28	0.59	0.6582
MI	0.14	0.48	0.33	0.16	0.16	0.17	0.22	0.68	0.8005

V. CONCLUSION

In this paper Gradient histogram preservation is applied on videos for smoothing and it is clear from table 1, PSNR is considerably improved by proposed technique. Video is denoised using images taken by extracting frames. First of all to the noisy images retrieved from video additive white Gaussian noise is added. Then Gradient histogram preservation is applied.

VI. FUTURE WORK

In future supporting techniques like spatial noise removal , kalman filter which are used with non local means and Gradient histogram can also be used. Edge smoothing can further be studied to improve visual quality of the images. There are number of filtering approaches like Gabor filtering which can be applied to further increase the PSNR of the given work. Texture image denoising can also be applied.

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