VIDEO DENOISING ALGORITHMS: A DETAILED STUDY

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Abstract— Video is a sequence of images, forming a moving picture and plays an important role in the area of digital image processing. The main challenging factor in video denoising is removal of noise from an image while preserving its details. Noise creates a barrier. It affects the performance by decreasing the resolution, image quality, image visuality and the object recognizing capability in images. Image restoration generally refers to the reconstruction of the true image based on its corrupted version. The reconstructed video can be used in applications like video communication, forensics, CCTV surveillance etc. The video denoising method can be mainly classified into spatial domain and transform domain denoising. This paper is a detailed study of different video denoising algorithms and its advantages and disadvantages

Index Terms—Denoising, PSNR, Spatial filtering, Transform domain filtering.

I. INTRODUCTION

Video denoising [1] is the process of removing noise from a video signal. Denoising is one of the most important problem in video processing. The ubiquitous use of relatively low-quality smart phone cameras has also led to the increasing importance of video denoising. Recovering high-quality video also improves robustness in high-level vision tasks. Video denoising methods [2] can be divided into spatial domain and transform domain filtering. In spatial video denoising methods, image noise reduction is applied to each frame individually and in transform-domain denoising methods, typically assume that the true signal can be well approximated by a linear combination of few basis elements.

Noise is random signal and destroy most part of image information. Gaussian noise, Poisson noise, Speckle noise, Salt and Pepper noise are the commonly found noises affecting images. These noises are coming from faulty memory locations or may be introduced due to imperfections in image capturing devices like cameras, misaligned lenses, weak focal length, scattering etc. This paper is an exhaustive literature survey, based on the concepts of noise theory, different video denoising methods and its classification, comparison between the various video denoising methods and briefing its advantages and disadvantages.

A. Different Types of Noises

Noise is the unwanted information in digital images. Noise produces undesirable effects such as artefacts, unrealistic edges, unseen lines, corners, blurred objects and disturbs background scenes. To reduce these undesirable effects, prior learning of noise models is

essential for further processing. Digital noise may arise from various kinds of sources such as Charge Coupled Devices (CCD) and Complementary Metal Oxide Semiconductor (CMOS) sensors. There are basically 2 types of noise models:

- ➢ Additive Noise Model
- ➢ Multiplicative Noise Model

In additive noise model, the noise gets added to the original video to generate the resultant noisy video. In the multiplicative model, the noisy video is generated by multiplication of the original video frames and the noise signal. The most common noise types found in videos are Gaussian Noise, Salt & Pepper Noise and Speckle Noise.

a. *Salt and Pepper Noise*

It is also called as impulse noise [2]. Impulse noise effects the image or video during its transmission. The impulse noise doesn't affect the image as a whole, but it drastically changes certain pixel values in the image. Image pixel values are replaced by corrupted pixel values (either 0 or 1). The maximum or minimum values for a 0 and 1 are dependent upon the number of bits used. Impulse noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. The salt and pepper noise are generally caused by faulty pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. Elimination of impulse noise can be done by using dark frame subtraction and interpolating around bright pixels.

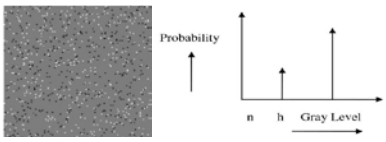


Fig.1: Salt and pepper Noise and its Probability distribution function

b. *Gaussian Noise*

It is a type of additive noise having probability density function (PDF) equal to that of the normal distribution. This normal distribution is also known as the Gaussian distribution. This is also known as electronic noise because it mainly arises in amplifiers or detectors. Gaussian noise [2] is independent at each pixel and signal intensity. It is caused by thermal noise and affects each and every pixel of an image. The probability distribution function of Gaussian noise is bell shaped as shown in figure 2.

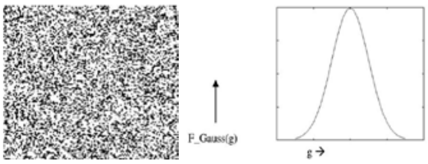


Fig.2: Gaussian Noise and its Probability distribution function

c. *Speckle Noise*

Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar (SAR) images. In conventional radar, speckle noise results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean gray level of a local area. Speckle noise is a type of multiplicative noise.

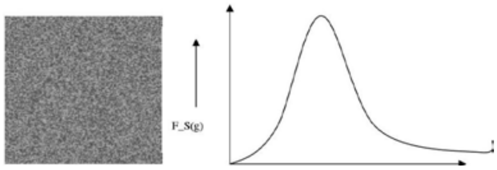


Fig.3: Speckle Noise and its Gamma distribution function

This paper is structured as follows: Section II describes different denoising methods and its comparative study, Section III describes experimental results and Section IV concludes the paper.

II. DENOISING TECHNIQUES

Denoising is the process of removal of noise. It is extremely essential to apply the denoising methods over the noisy images or on the affected area of the images for eliminating the noise from the image. It is also used to extract the features of the image.

A. *Spatial Domain Denoising*

A traditional way to remove noise from image data is to employ spatial filters. Spatial filtering [3] is the method of choice in situations when only additive noise is present. It can be further classified into two categories, linear and nonlinear. In linear denoising, the output will change linearly on changing the input and in non-linear denoising, there will be a non-linear change in the output with the changing inputs.

a. *Linear Filters*

It is mainly done for additive noise. It includes Mean filter and Wiener filter [3]. The mean filter is the optimal linear filter for Gaussian noise in the mean square error sense. But it blurs sharp edges, destroy lines, other fine details of image and perform poorly in the presence of signal-dependent noise. The Wiener filtering method requires the information about the spectra of the noise and the original signal, and it works well only if the underlying signal is smooth. Wiener method implements spatial smoothing and its model complexity control corresponds to choosing the window size [3].

i. Mean filter

Mean filter is an averaging filter [4]-[6]. This filter provides smoothness in an image by reducing the intensity variations between the adjacent pixels. It applies mask over each pixel in the signal. Therefore, to make a single pixel, each pixel which falls under mask are averaged. The main disadvantage is that edge preserving criteria is poor in Mean filter.

ii. Wiener Filter

It is a statistical approach [7] to filter out noise from a corrupted signal by taking the estimate of the desired signal, provide an optimal solution to filtering problem. This filter helps to minimize the mean square error. It plays a central role in applications like linear prediction, echo cancellation, signal restoration, channel equalization and system identification

b. Non-Linear Filters

This filtering is mainly used in case of multiplicative noise. The main drawback of spatial filtering is blurring of edges. To overcome this demerit, nonlinear filters were introduced. A common example of nonlinear filter is median filter. Some types of median filters are weighted median [8], rank conditioned rank selection filter [9] and relaxed median filter [10].

i. Median Filter

A nonlinear filter in which filtering is done by finding the median value across the window, and then replacing the center pixel by the median value of pixels within the window. If the window has entries of odd number, middle value is taken. But, for an even number of entries, there is more than one possible median. It is a robust filter. It is mainly used for smoothening and helps to preserve the edges.

B. Transform Domain Filtering

Transform domain filtering can be divided according to the choice of basic functions. They are mainly classified as non- data adaptive transform and data adaptive transform domain filtering.

a. Spatial Frequency Filtering

The process [11] involves low pass filtering using Fast Fourier Transform. The noise is removed by choosing the appropriate cut-off frequency and adapting a frequency domain filter, when the components of noise are decorrelated from useful signal. The main disadvantage of Fast Fourier Transform (FFT) is that the edge information is spread across frequencies and time information is lost, hence low pass filtering results in smearing of the edges.

b. Wavelet Domain Filtering

Discrete Wavelet Transform (DWT) [12] make the signal energy concentrate in a small number of coefficients, hence, the DWT of the noisy image consists of a small number of coefficients having high Signal to Noise Ratio (SNR) while relatively large number of coefficients is having low SNR. After removing the coefficients with low SNR (i.e., noisy coefficients) the image is reconstructed by using inverse DWT. So, by this technique noise gets removed. A major advantage of wavelet based denoising is that it provides time and frequency localization simultaneously. Moreover, wavelet methods characterize such signals much more efficiently than either the original domain or transforms with global basis elements such as the Fourier transform.

c. Wavelet Based Thresholding

It is a signal estimation technique [13] that exploits the capabilities of wavelet transform for signal denoising. It removes noise by killing coefficients that are irrelevant relative to some threshold that turns out to be simple and effective. The choice of this threshold determines, to a great extent, the efficiency of denoising.

d. Thresholding Method

The two main important techniques for thresholding are hard and soft thresholding [14]. Hard thresholding which is based on keep and kill rule is more instinctively appealing. However, it introduces artefacts in the recovered images. Soft thresholding is based on shrink and kill rule. It shrinks the coefficients above the threshold in absolute value. In practice, soft thresholding has been used over hard thresholding because it gives more visually pleasant images as compared to hard thresholding and reduces the abrupt changes that occur in hard thresholding. Normally hard thresholding is used for compression and soft thresholding for denoising.

e. Data-Adaptive Transforms

The Independent Component Analysis (ICA) [15] method is mainly used for denoising non-gaussian data. One exceptional merit of using ICA is its assumption of signal to be Non-Gaussian which helps to denoise images with Non-Gaussian as well as Gaussian distribution. The main disadvantage of ICA method is its computational cost, as it uses a sliding window and it requires samples of noise free data or at least two image frames of the same scene. Hence, in some applications ICA cannot be used, because of unknown training data.

f. Non local means

A patch-based filtering method [16]-[18] in which each output pixel is formed as a weighted sum of the center pixels of neighboring patches, within a given search window. The weights are based on similarity with respect to the reference patch. Normally, the similarity is measured by patch intensity vector distances. Pixels from patches with higher similarity (lower vector distances) are given more weight, using a negative exponential weighting. The advantage of this method is that it provides greater post-filtering clarity and less loss of detail in the image but it is computationally complex.

g. Denoising by optical flow estimation

A denoising method [19]-[20] compromising of motion estimation and patch based denoising, in which the groups of patches are denoised by the image fusion technique called Principal Component Analysis (PCA) [21], which ensure preservation of fine structure and details. This method includes two iteration stage, denoised image of first stage is used in the second stage for improving the denoised result. The similarity between two patches is computed in the first denoised image, and the transformed coefficients are used to drive the thresholding in the second iteration. The main steps of these algorithms are motion compensation, choice of similar patches and denoising of similar patches. One of the disadvantages of this method is output blurring.

h. Sliding 3D DCT domain

The SW-DCT [22] is performed in the 3D space, and the use of a temporal redundancy of video which can improve the filtering performance. It operates in the spatial domain of each video frame and in the temporal direction 1D sliding DCT [23] can be similarly applied along the temporal axis. SW-DCT performance is significantly improved when transform operate over a highly correlated signal. However, pixels along the temporal axis may be uncorrelated due to dynamical nature of a video signal. Here video data are locally filtered by sliding 3d window and their selection is done by applying block matching. Denoising is performed by hard thresholding and estimates are reconstructed using weighted average of locally estimates of overlapping patches.

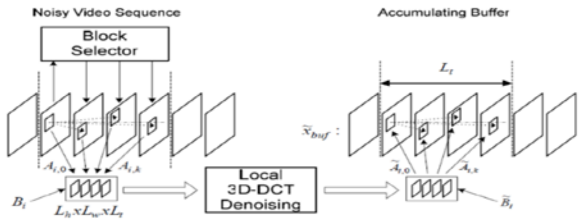


Fig.4: Block diagram of 3D-DCT denoising algorithm

i. KSVD

K-SVD [24] is a dictionary learning algorithm for creating a dictionary for sparse representations, via a singular value decomposition approach. KSVD is a generalization of the k-means clustering method, and it works by iteratively alternating between sparse coding the input data based on the current dictionary [25], and updating the atoms in the dictionary to better fit the data. The goal of dictionary learning is to learn an overcomplete dictionary matrix D ϵ $R^{n\times K}$ that contains K signal-atoms. A signal vector [26,27] y ϵ R^{n} can be represented, sparsely, as a linear combination of these atoms; to represent y, the representation vector x should satisfy the exact condition y=Dx, or the approximate condition y≈Dx, made precise by requiring that $\|y-Dx\|_p \le \varepsilon$ for some small value ε and some Lp norm. The vector x ϵ R^{k} contains the representation coefficients of the signal y. Typically, the norm is selected as $L1$, $L2$, or $L\infty$.

If $n < k$ and D is a full-rank matrix, an infinite number of solutions are available for the representation problem. Hence, constraints should be set on the solution. Also, to ensure sparsity, the solution with the fewest nonzero coefficients is preferred. Thus, the sparsity representation is the solution of either

$$\boldsymbol{min_x}\|\boldsymbol{x}\|_0 \quad \text{subject to } y=Dx$$

Or

$$\boldsymbol{min_x}\|\boldsymbol{x}\|_0 \quad \text{subject to } \|y-Dx\|_2 \le \varepsilon$$

Where the $\|x\|_0$ counts the nonzero entries in the vector.

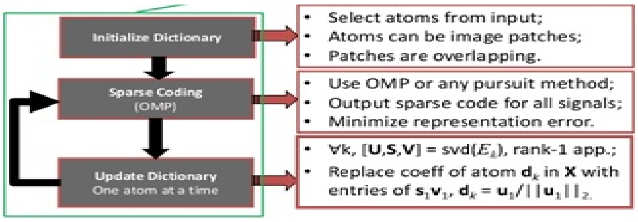


Fig.5: KSVD Algorithm

The main disadvantage of this method is choosing an appropriate "dictionary" for a dataset is a non-convex problem, and KSVD operates by an iterative update which does not guarantee to find the global optimum.

j. VBM3D

VBM3D [28] is block matching technique on video and depends on sparse representation of image in the transform domain. In BM3D the sparsity is enhanced by grouping similar 2D fragments into 3D data array depending on similarity measure with respect to a reference block forming a group. This exploits the potential similarity (correlation, affinity, etc.) between grouped blocks to estimate the true signal in each of them by producing a highly sparse representation in 3D transform domain, so that the noise is removed by wavelet shrinkage. This approach of exploiting similarity and estimating the original signal is called as *collaborative filtering* [29]. Collaborative filtering has three successive steps: firstly for each reference patch, find similar patches from the input image by classifying them according to some similarity criteria and transform them into a 3D data array by grouping the matched 2D blocks and shrinking of the coefficients in transformed 3D spectrum is applied to attenuate the noise and finally apply inverse 3D transform to the shrunken coefficients and return the obtained 2D estimates of the grouped blocks to their original positions. As the grouped 2D blocks are similar, the transformation can achieve a very high sparse representation of the original signal. The main advantage of this method is preserving finest details shared by grouped blocks by preserving the unique features of each individual block.

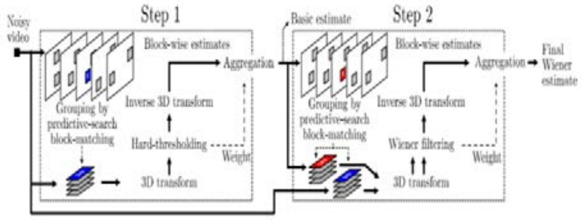


Fig.6: Flowchart of VBM3D denoising algorithm

It is not effective when a large number of matching blocks is not found i.e., in case of highly dynamic videos this method introduces artefacts and doesn't perform as well. The main limitation of BM3D is during filtering could not distinguish between the spatial and temporal patches and artefacts are introduced, especially in flat areas.

k. VBM4D

It is an extension of the VBM3D [28] filter to volumetric data. The two main process are grouping and collaborative filtering. In this method, mutually similar d-dimensional patches are stacked together in a (d + 1) dimensional array and jointly filtered in transform domain. While in BM3D the basic data patches are blocks of pixels and here cubes of voxels, which are stacked into a four-dimensional group. The 4D transform [30] applied on the group simultaneously exploits the local correlation present among voxels in each cube and the nonlocal correlation between the corresponding voxels of different cubes. The spectrum of the group is highly sparse, leading to very effective separation of signal and noise through coefficients shrinkage. BM4D is implemented in two cascading stages, namely a hard-thresholding and a Wiener-filtering stage. Each comprising three steps: grouping, collaborative filtering, and aggregation. The main disadvantage of this method is it is a nonconvex problem

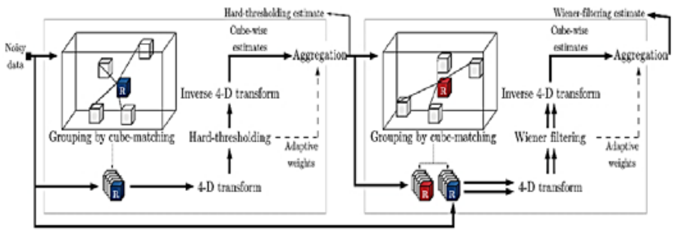


Fig.7: Flowchart of VBM4D algorithm

l. Video denoising via online sparse and low rank matrix decomposition

It is also called as Layering Denoising [31,32,33], in which the noisy video is split in to "low-rank" layer and the "sparse layer". Low-rank layer means that the matrix formed by each image of this layer, arranged as a column vector is low-rank. The main processing stage are initialization, splitting phase and denoising phase. Firstly, initialization stage and then splitting the given video and finally applying the denoising algorithm. Splitting of video is done by a batch technique called principal components pursuit (PCP) and a recently proposed online and dynamic technique called Recursive Projected Compressive Sensing (ReProCS) [34]. It is faster and has better separation performance for videos where the sparse layer is either correlated over time. This is followed by VBM3D on each of the two layers and helps to find more matched blocks to filter over. The main disadvantage of this method, is only applicable to small videos.

m.LASSO

It is an online dictionary technique [35]. In the real-world scenario as the size of the input data might be too big to fit it into memory, where denoising can be done in a streaming fashion. The main steps in this process are first of all choosing a dictionary, then sparse coding and updating the dictionary. In this approach, the optimization problem is formulated as:

$$\boldsymbol{min}_{r\in R^n}\{\ \|\boldsymbol{r}\|_1\}\ \text{subject to}\ \|\boldsymbol{X}-\boldsymbol{DR}\|_F^2\ \ <\boldsymbol{\epsilon}$$

Where ϵ is the permitted error the reconstruction LASSO [35]. It finds an estimate of r_i by minimizing the least square error subject to a L^1-norm constraint in the solution vector, formulated as:

$$\mathbf{min}_{\mathbf{r}\in\mathbf{R}^n}\ \frac{\mathbf{1}}{\mathbf{2}}\ \|\mathbf{X}-\mathbf{Dr}\|_F^2+\boldsymbol{\lambda}\|\mathbf{r}\|_1$$

Where $\boldsymbol{\lambda}>\mathbf{0}$ $\boldsymbol{\lambda}>\mathbf{0}$ controls the trade-off between sparsity and the reconstruction error. This gives the global optimal solution. But its solution is a nonconvex problem and NP hard.

n. VIDOSAT

This is the first online data adaptive algorithm for denoising. The video denoising framework processes noisy frames in an online, sequential fashion to produce streaming denoised video frames. The algorithms [36] require limited storage of a few video frames, and modest computation, scaling linearly with the number of pixels per frame. This method handles high definition or high rate video enabling real-time output with controlled delay, using modest computational resources. The online transform learning technique [37] exploits the spatio-temporal structure of the video patches using adaptive 3D transform-domain sparsity to process them sequentially. Overlapping patches are used in this framework. The streaming scheme then outputs the oldest frame from the FIFO input buffer, are given to minibatch denoising process. The patches output by the mini-batch denoising algorithms are deposited at their corresponding spatio-temporal locations in the fixed-size FIFO output buffer. The denoised estimate is obtained by normalizing pixel-wise by the number of occurrences of each pixel in the aggregated patches. Here the frame is denoised together with both past and future adjacent frames, which are highly correlated. Once these patches are denoised, by aggregation into the output buffer to the final denoised frame to reconstruct the streaming video frames. This approach involves cheap computation and limited memory requirements. Compared to popular techniques for online synthesis dictionary learning, the online adaptation of sparsifying transforms allows for cheaper and exact updates, and is thus well suited for high- dimensional data applications.

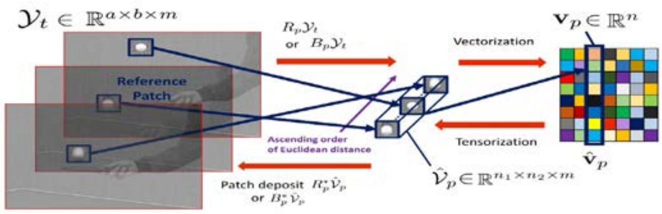


Fig.8: Diagrammatical representation of VIDOSAT.

i. VIDOSAT-BM

The method followed here is same as VIDOSAT [38] except here incorporating video denoising along with video blockmatching.in previous method only video denoising is done in the successive video frames taking the adjacent patches as constant. But here using the various motions like translation, rotation, scaling of each adjacent frame and using block matching technique to denoise the noised video. Comparatively high PSNR value is obtained and a high quality denoised video streams. Table I shows the comparative study between different denoising algorithm based on their principle involved, advantages and disadvantages.

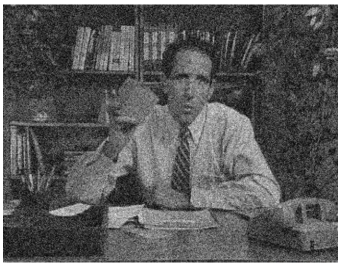
III. EXPERIMENTAL RESULTS AND INFERENCES

To evaluate the performance metrices of video denoising methods, PSNR is used as representative quantitative measurement:

Given an original image as x, the PSNR of a denoised image $\hat{x}$ is defined by

$$\text{PSNR}(x, \hat{x}) = 10.log_{10}\left(\frac{255^2}{\|x-\hat{x}\|_2^2}\right).$$

The typical values of PSNR in image and video compression are in between 30 to 50 dB.


(a)

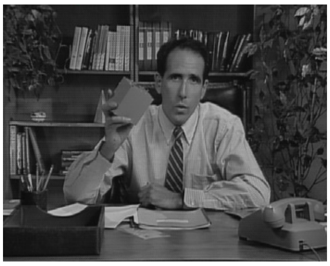

(b)

Fig.9: (a) Noisy Video of Salesman and (b) Denoised Video by using VIDOSAT-BM

Table I: PSNR value comparison of different denoising methods

Data				
σ	**10**	**15**	**20**	**50**
Mean Filter	28.29	24.71	22.16	13.91
Wiener Filter	35.67	33.97	32.72	21.30
Wavelet Domain Filtering	36.55	35.08	33.18	24.82
KSVD	37.37	35.15	33.59	28.79
3D DCT	37.14	34.73	33.03	27.59
RNLF	37.21	35.21	33.72	28.58
VBM3D	37.25	35.44	34.04	28.65
VBM4D	37.30	35.25	33.79	27.76
VIDOSAT	37.77	36.15	34.49	29.24
VIDOSAT-BM	**38.17**	**36.72**	**34.53**	**29.63**

a. Inference

Figure 9 (a)shows the noisy frame of salesman video, here the additive gaussian noise is added and(b) is the denoised frame using VIDOSAT-BM. From Table II it is noted that, compared with existing denoising methods that is, spatial filtering methods and other methods of transform domain VIDOSAT-BM, sparse transform based online video denoising method provides an improved PSNR value and a better quality of denoised output.

IV. CONCLUSION

During image acquisition and transmission, noise is seen in images. This is characterized by noise model. So, study of noise model is very important part in image processing. On the other hand, video denoising is necessary action in image processing operation. Without the prior knowledge of noise model, we cannot elaborate and perform denoising actions. Hence, here reviewed and presented various noise models and various denoising techniques including spatial and transform domain filtering, its advantages and disadvantages available in digital images. Online video denoising based on efficient high-dimensional sparsifying transform learning, transforms are learned in an online manner from appropriately constructed 3D(spatio-temporal) patches. This method outperforms all compared methods, like spatial filtering, learned synthesis dictionaries, VBM3D and VBM4D methods. Compared to other method this method provides an improved value of PSNR and obtained high quality denoised outputs. The reconstructed video can be used in video application, CCTV surveillance, forensics etc.

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