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An Efficient Directional Denoising on Reproduced Frames for Poisson Noise Removal in Videos

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Abstract- With today requirement, video processing is challenging task with its rapid growth in multimedia technology. Videos are highly prone to distortions which are caused due to various factors. The discrete nature of photons which introduce Poisson noise is one of the major problems seen in videos. A noisy video has not only an unpleasant visual effect, but it also restricts the user to extract the true content. The aim of video denoising is to improve the perceptual quality by removing the noise, while preserving the signal features as much as possible. In this paper, the aim is to propose an efficient Poisson denoising model with both high computational efficiency and recovery quality. There exists a high correlation among the neighboring frames of a video, since the motions among such frames are small. Hence, video denoising techniques can be considered as an extension of image denoising techniques, by providing temporal filtering taking into account the correlation between the neighboring frames. The research paper propose a directional denoising scheme to estimate Linear Minimum Mean Square Error(LMMSE) for the noiseless and missing samples under the same framework of optimal estimation. The local statistics is adaptively calculated to guide the estimation process. For each noisy sample, the proposed work computes multiple estimates of it along with different directions and then fuses those directional estimates for a more accurate output. Compared with the conventional schemes, proposed method preserves the frame image edge structures. Thus combines the advantage of directional denoising for individual frame and frame reproduced by frame stitching to achieve better quality video with low computational complexity.

Keywords – photons, Poisson noise, denoising, Linear Minimum Mean Square, optimal estimation, local statistics, directional denoising.

1. INTRODUCTION

Preserving features of images or videos [1,4] while removing various types of noises such as Gaussian noise [1], [3], [5], impulse noise [6], mixed noise [7], and Poisson noise [8], [9] had been a challenge to video processing community in many real world image and video processing applications. The detailed review of various techniques and their qualitative and quantitative comparisons are included in [1]. For any application, the image or video has to be preprocessed and then used for further processing. Many of the literature show that the image or video used in applications are assumed to be clean. But in real, they are prone to various artifacts. The crucial subject of poisson noise cannot be ignored and had been a challenge to researchers. The task of image denoising with Poisson noise is particularly interesting in vast real applications [10]–[12]. Due to the physical mechanism, the strength of the Poisson noise depends on the image intensity and is therefore not additive, alluding to the fact that Poisson denoising is generally quite different from the usual case of the additive noise. Till now, a variety of Poisson denoising algorithms has been proposed in [8], [9], [13], and [14]. Rough classification shows two major contributions: 1) with variance stabilizing transformation (VST) and 2) without VST. The approaches in the first class preprocess the input data by applying a nonlinear VST such as Anscombe [15], [16] or Fisz [17] which removed the signal-dependency property of the Poisson noise. The noise variance is estimated and then the transformed data is made to have a Gaussian nature noise which can be further removed using filters. In most of the literature wavelets with hard and soft thresholding have been used to remove the unwanted Gaussian noise [5]. Finally, the estimate of the underlying noise-free image is obtained by applying an inverse VST [18]–[21] to the denoised transformed data. Using the well-known BM3D algorithm [22] for Gaussian noise removal, the resulting Poisson denoising algorithm leads to state-of-the-art performance. However, the VST is accurate only when the measured pixels have relative high intensity. In order to deal with the above deficiency of the VST operation, several authors [23]–[25] have investigated denoising strategies without VST, which rely directly on the statistics of the Poisson noise. Salmon et al. [23] [26] [27] used a direct approach to achieves state-of-the-art results for images suffering from a high noise level. There are two versions involved in this method: the nonlocal PCA and the nonlocal sparse PCA (NLSPCA). Similarly, to overcome the deficiency of VST, the data fidelity term originated from Poisson noise statistics is adopted in [8], [25], and [28]. Some other work done by researchers included in [29], where the author developed a robust noise parameter estimation technique for Poisson corrupted images by combining variance stabilization and AWGN-based noise variance estimation. Poisson distribution characteristics to estimate the photon count from relative illumination data, under simple hypotheses was given in [30]. That allowed them to use variance-stabilizing methods on standard digital photographs [31] presented a unified framework to deal with video denoising problems by adopting a two-steps process, namely the video epitome and sparse coding.

2. OUR CONTRIBUTIONS

Lei Zhang, Xin Li, and David Zhang [32] in their work had suggested an efficient directional denoising technique to remove poisson noise and preserved edges during interpolation. The process of directional denoising and interpolation were simultaneously applied to reduce computational complexity. The optimal estimation was modeled to estimate noiseless and missing samples. For each noisy sample, they computed multiple estimates of it along different directions and then fuse those directional estimates for a more accurate output.

Many frame stitching techniques are used by researchers in the literature. This research paper propose a novel frame stitching technique using a 3x3 window from a current frame to locate in 7x7 neighborhood in the next frame, assuming that there is little deflection of the object features in the next frame with respect to the current frame. The main idea behind stitching two consecutive frames is to eliminate poisson noise of the current frame by reproducing the current frame from the next frame. Results showed high peak signal to noise (psnr) ratio when directional estimate using LMMSE is made on the reproduced frame. Therefore our contribution is reproducing current from the successive or next frame and applying directional denoising.

3. FRAME REPRODUCTION

To achieve greater block matching accuracy, the block size of the source (current frame) frame was taken to be 3x3. Considering camera movement to be little in the destination frame (successive or next frame) the source block is searched in a neighborhood of 7x7 window around the central block with same spatial coordinates as that of the source block. The successive frame is padded with border elements so as to create a neighborhood of 7x7 around the border elements. Figure 1 below shows both the source and the destination blocks from current and the next frame respectively.

	(m,n)	

	1	2	3	4	5	
	6	7	8	9	10	
	11	12	(m,n)	14	15	
	16	17	18	19	20	
	21	22	23	24	25	

Figure 1- The source and the destination blocks

The source block is compared with all the 25 destination blocks situated around the 25 elements. The distance error is calculated as

$E = \text{avg}(\text{abs}(B_s-D_s))$

Where B_s represents all the nine elements of source block and D_s represents all the nine elements of the destination block. Individual elements are subtracted and the mean value is calculated. Thus we have 25 values corresponding to 25 blocks in the destination. Further the block index corresponding to the minimum distance is found. Here no thresholding is used, simply the block from destination whose distance is at least out of 25 blocks is considered. It may happen that more than one block have same distance value and that to be the minimum. The

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following conditions are applied for the best matching block.

1. If only one block is found to be having the minimum value, its index is stored.
2. If more than one block have the same minimum distance and block 13 (central block) is one of them, then block 13 is taken into account and rest are neglected.
3. If block 13 is not present, then the immediate neighbors 7, 8, 9, 12, 14, 17, 18 1nd 19 are searched in sequence. For example, if block 7 is found to have minimum distance, it is taken into account. Any one is considered and that to in sequence.
4. If none of the immediate block has minimum distance then remaining blocks 1, 2, 3, 4, 5, 6, 10, 11, 15, 16, 20, 21, 22, 23, 24 and 25 are searched again in sequence. This will result in motion error so the index is accompanied by an infinity value is stored. This will be corrected later when the camera alignment is calculated. For example if 11, 22 and 25 are the blocks with same minimum distance, then 11 is stored with infinity, whereas 22 and 25 are stored for future correction.

Now the total count for each index is calculated except for the block 13. This is done because block 13 has the same spatial coordinates as that of the source block. The block with the maximum count will give us the camera motion. For example if block 17 has the maximum count then the camera is deflected 215^0 with respected to the current frame. Now the step 4 above index is corrected. At step 4, index 11 was stored, but as per camera movement, now it is corrected and replaced by index 22, since it is in the vicinity of 17.

The above frame reproduction is done after converting the frame from RGB color space to gray scale. Once the blocks are localized, the new frame is reproduced form the destination frame pixel value and finally all the components (R, G and B) are acquired from the same spatial coordinated of the destination frame. Figure 2 shows the current frame and the next successive frame and **Figure 2:** Shows the current frame with the reproduced frame.

Figure 3: The current frame and the successive frame

Figure 4: The current frame and the frame reproduced by block matching technique

Directional Denoising

The noisy frame I_n containing poisson noise can be represented as $I_n=I+n$; Where, I is the noiseless frame, n is the poisson noise.

Consider a noisy pixel $I_n(m,n)$, the goal is to estimate the noiseless value I’(m,n) of it using it neighbors $I_v(m,n)$. We had utilized the technique mentioned in [32] to estimate I’(m,n) nearer to original pixel I(m,n). Optimal estimation technique such as the LMMSE [33] is used to find the estimate I’(m,n) of the original pixel I(m,n). If a 3×3 window around I’(m,n) is used, $S_v$will be a 9×1 variable vector and its variance matrix var(S_v) is a 9×9 matrix. The inverse of the 9×9 matrix var(S_v) will cost much computation. So, we divide the estimation of into several sub-problems, each of which yields a

directional estimate of I'(m,n), and then fuse those directional estimates into a more robust one.
Refer to Figure 4, we partition the nine noisy samples within the 3×3 window centered on (m, n) into three groups along different directions: horizontal/vertical, diagonal and the noisy sample I_v(m,n). The red circle represents the noiseless pixel to be estimated and the blue circles represent the available noisy measurements. Each of the first two groups has four elements and the last group has one member only. With the three groups, we are able to calculate three directional estimates of I'(m,n). The three estimates can then be adaptively fused to obtain a more robust and accurate estimation of I' (m,n).

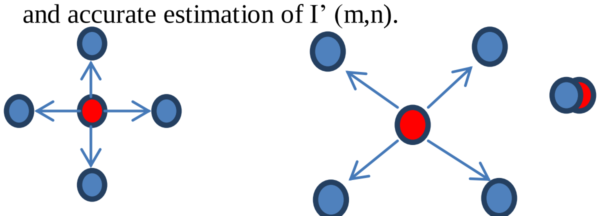

Figure 5 - Partition of the nine measurements into 3 groups to estimate the unknown noiseless sample.

Considering four neighbors of I'(m,n) above, then the LMMSE can be calculated by finding mean, variance and covariance for all the three groups separately. The above mean, variance and covariance are calculated by considering a training window around the 3x3 matrix under consideration as suggested in [32]. The training window centered on the 3x3 window considered is of 5x5. The directional estimates are then fused to find the actual estimate. The brief estimation can be found in [32]. Here we had not taken into account the weight vectors they had calculated for interpolation.

4. METHODOLOGY& RESULTS

1. Read the video.
2. Store the frames in memory.
3. Select any two consecutive frames.
4. LMMSE using directional denoising to current frame.
5. Frame stitching
6. LMMSE using directional denoising to reproduced frame.

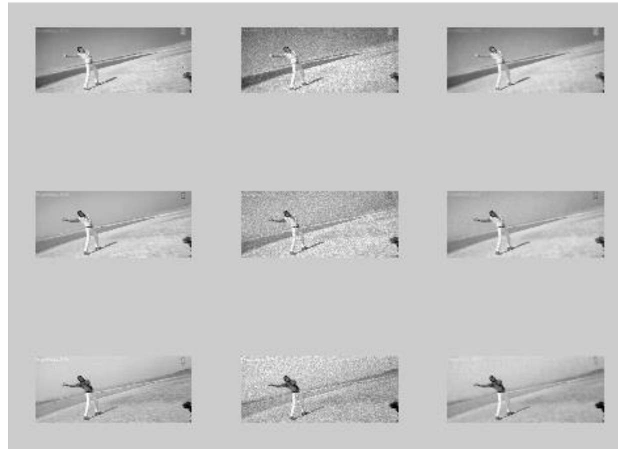

Figure 6 – Results of Directional denoising to R, G and B components of current frame. First column represents original R, G and B frames. Second column represents frames with poisson noise and the third column is the result after denoising.

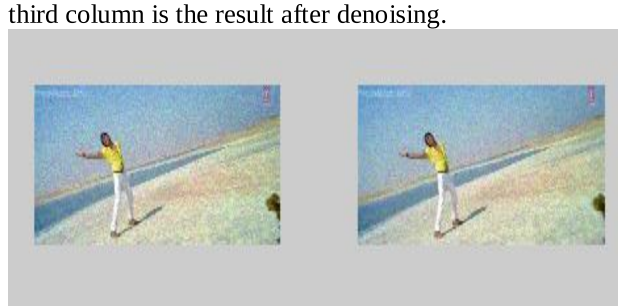

Figure 7 – First frame is the RGB frame with poisson noise and the second frame is the result of directional denoising. Second frame is the combined view of all components.

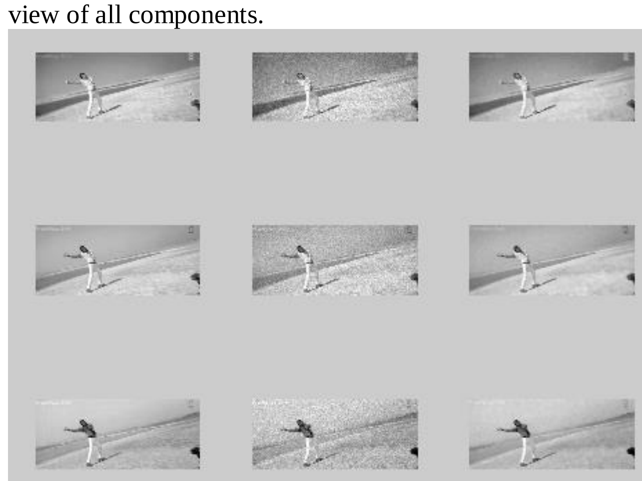

Figure 8 – Results of Directional denoising to R, G and B components of reproduced frame. First column represent original R, G and B frames. Second column

represent frames with Poisson noise and the third column is the result after denoising.

Figure 9 – First frame is the original RGB frame and the second frame is the result of directional denoising. Second frame is the combined view of all reproduced R, G and B components.

The results can be better understood from signal to noise ratios.

Table 1- Comparison of SNR value when denoising is applied to the components of original frame and the reproduced frame with same parameters.

Sr. No.	**Frames**	**SNR using Current Frame**	**SNR using Reproduced Frame**
1	R	25.5981	37.1343
2	G	26.0527	38.2425
3	B	24.8511	36.5725

5. CONCLUSIONS

Figure 6 and 8 clearly shows the difference in visual context. The reproduced frame when applied for directional denoising produces much better results than applying denoising to the frame itself. The SNR values for all the components independently as seen from table 1 are remarkable as compared to the SNR value obtained when denoising is applied to the frame itself. The edges as seen in figure 8 are preserved with small amount of loss. The computational complexity of the denoising and the frame reproduction is low. The color perception has been degraded to some extent but as far as poisson noise is concerned it is worth. Also if video is concerned it may not be an issue when high frame rate. Further work will be focused on enhancing the image quality with better SNR values. Also we have not used minimum threshold value in block matching, which may have represented an incorrect block from the successive frame to the source block. The block matching algorithm can be modified to improve the performance.

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