HOMOGENEITY-BASED DIRECTIONAL WIENER FILTERING OF VIDEO NOISE

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ABSTRACT

This paper proposes a method for the reduction of white Gaussian video noise. The method achieves a maximum gain of 5.6 dB and is capable of preserving image content. It adapts window size, weighting and behavior to both image content and noise level in order to optimize the filtering. It starts by detecting the intensity-homogeneous direction from 8 different candidates. A variant of the Wiener filter is then applied directionally. The filtering is performed along homogeneous areas and not across edges. For noisy images, the filtering is increased automatically by using a larger kernel size. The proposed filter achieves better image preservation by turning off gradually for less noisy images. It works well for both highly noisy and good-quality images.

1. INTRODUCTION

Video processing applications continuously increase in volume and complexity. The presence of noise can significantly impact the performance of these algorithms. Different applications bring forth different requirements for the noise reduction filter. In general, however, a noise reduction filter should be able to work well with variable noise level while still preserving high frequency image content such as fine details and structures.

A number of spatial adaptive filters have been proposed over the years. The method in [1] introduced a spatial filter that is based on the Sigma probability. This filter is known as the Sigma Filter (SF) and is widely used as a benchmark for testing spatial adaptive filters against. It selects which pixels to include in or exclude from the averaging process based on the noise level. The filter presented in [2], defined a Recursive Sigma Filter (RSF) that adds a number of modifications to the Sigma Filter. These modifications include changing the shape of the kernel, making the filtering recursive and using a tri-level weighting function. A criteria to measure homogeneity and a Homogeneity-based Filter (HF) that is applied to the intensity most homogeneous direction were introduced in [3].

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A classical approach to spatial noise filtering is the spatial Wiener Filter (WF) [4]. It produces a relatively high gain for noisier images, however, it does not handle images with low noise levels well despite being noise level adaptive. It also introduces some blurring and is computationally more complex than other methods.

In this paper, we integrate the spatial Wiener filter [4] with adaptive directional filtering to create a structure-oriented adaptive Wiener filter. The contributions of the proposed approach include 1) increased gain by using a noise-adaptive kernel size and using an automatically determined number of homogeneous directions and 2) increased preservation of image content by applying Wiener filtering directionally along edges and not across them.

The remainder of the paper is as follows. Section 2 presents the proposed approach theoretically and gives an interpretation of its good performance. Objective simulation results are presented and discussed in Section 3. Finally, Section 4 concludes the paper.

2. PROPOSED APPROACH

Video signals are spatially correlated in nature. In unstructured areas, low-pass filtering can reduce spatially uncorrelated noise while preserving the original signal. On the contrary, structured areas with fine details like edges and corners gets blurred with such filtering.

The principle idea of the proposed approach is to adapt filtering to noise level by increasing the filtering action for noisy images to achieve higher gain and to adapt it to image content by filtering along edges and not across them to avoid blurring. Controlling the filtering action is accomplished by controlling the kernel size and number of homogeneous directions used in filtering. To control where filtering is performed in order to preserve structure, we detect image activity in the area surrounding the processed pixel. The main steps of the proposed method are:

1. Adapt window size W to noise level using

$$W(\sigma_\eta) = \begin{cases} 5 & : \sigma_\eta > t_\eta \\ 3 & : otherwise \end{cases}. \qquad (1)$$

2. Measure homogeneity along eight candidate directions of the $W(\sigma_\eta)$ window.

3. Apply adaptive Wiener filtering in [4] to selected homogeneous directions.

The detection of image structure is done using eight intensity-homogeneity analyzers as in [3] (see Fig. 1). These analyzers work as directional Laplacian operators with the coefficients $\{-1, -1, .., W-1, .., -1, -1\}$, where W is a positive odd integer (e.g., $W = 3$). The output of applying these operators to the pixels with close intensity values is close to 0.

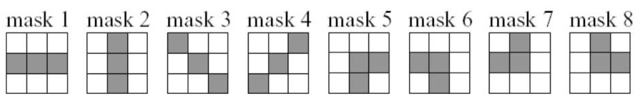

Fig. 1. Homogeneous-intensity analyzer masks [3].

For highly noisy images, however, using a kernel of $W = 5$ achieves theoretically higher gain than with $W = 3$. On the other side, using a kernel of $W = 5$ introduces blurring in good-quality images. This is evident in Fig. 4 where a $W = 3$ kernel is compared to a $W = 5$ kernel. To combine the benefits of both kernel sizes, we propose to adapt it to the noise level. The noise level is estimated using the approach in [5]. Fig. 4 suggests how the selection of the window size can be determined by defining a threshold to decide at what noise level the switch from a $W = 5$ to $W = 3$ kernel is made. The point the 3×3 and 5×5 kernel sizes intersect corresponds to a noise level of 28 dB($\sigma_\eta = 10.13$) which is selected as t_η.

To measure homogeneity along directions, define σ_η to be the estimated noise standard deviation and ϵ_i the output of applying $mask_i$ of size $W = 3$ to the currently processed pixel $I_{(n,m)}$ with spatial coordinates n and m where $i = 1, 2, ..., 8$ is the mask index. Depending on which i gives the minimum ϵ_i, the input-output relationship for a simple directional filter is given by

$$I^o_{(n,m)} = \frac{w_{\sigma_\eta} I_{(n,m)} + \sum\limits_{a,b \in \{-1,0,1\}} f(i) I_{(n+a,m+b)}}{w_{\sigma_\eta} + 2}, \quad (2)$$

where $f(i)$ is a 1 or 0 based on the direction detected to be the most homogeneous and w_{σ_η} is the central pixel weight equal to $r \cdot \sigma_\eta$ where $0 < r < 1$. As can be seen from (2), $\sum_{a,b \in \{-1,0,1\}} I_{(n+a,m+b)}$ defines a 3×3 neighborhood around the center pixel $I_{(n,m)}$. $f(i)$ will select a subset from the 3×3 population by choosing pixels that make up a homogeneous direction. For example, if $mask_1$, i.e., the horizontal direction, was detected to be the most homogeneous, (2) reduces to

$$I^o_{(n,m)} = \frac{w_{\sigma_\eta} I_{(n,m)} + I_{(n,m-1)} + I_{(n,m+1)}}{w_{\sigma_\eta} + 2}. \quad (3)$$

We propose a directional Wiener filter by applying directionally the Wiener filter through defining the mean, μ_i, along the direction i (see Fig. 1) using

$$\mu_i = \frac{\sum\limits_{a,b \in [1-W(\sigma_\eta), W(\sigma_\eta)-1]} f(i) I_{(n+a,m+b)}}{W-1}. \quad (4)$$

Similarly, the variance, σ_i^2, along directions is calculated using

$$\sigma_i^2 = \frac{\sum\limits_{a,b \in [1-W(\sigma_\eta), W(\sigma_\eta)-1]} f(i)(I^2_{(n+a,m+b)} - \mu_i^2)}{W-1}. \quad (5)$$

The input-output relationship of the proposed method based on (4) and (5) is given by

$$I^o_{(n,m)} = \sum_{i \in \{1,2,..D\}} \frac{\max(\sigma_i^2 - \sigma_\eta^2, 0)}{D\sigma_i^2} (I_{(n,m)} - \mu_i) + \mu_i, \quad (6)$$

where D is the number of directions used. D is decided by the behavior of the Wiener weighting function. If the direction is homogeneous, the local directional variance σ_i^2 will be less than the estimated noise variance σ_η^2 causing (6) to reduce to $I^o_{(n,m)} = \mu_i$. If σ_i^2 is larger than σ_η^2, indicating a direction with high activity, (6) will reduce to $I^o_{(n,m)} = I_{(n,m)}$ which will ensure that no filtering takes place along that direction. This behavior is different from that of the classical Wiener filter where the entire window is considered in the local mean and variance calculation causing outlier pixels to be included in the averaging process which will eventually increase blurring.

Fig. 2 shows the change in the shape of the kernel at different noise level ranges between the directional filter and the proposed filter. In Fig. 2(a,b), all pixels in the homogeneous direction are assumed to belong to one population and are included in the averaging process. Fig. 2(c,d) illustrates how the proposed method adapts kernel size, shape and weighting to frame and noise characteristics.

The justification of using a larger kernel for noisy images is to increase the number of samples used in the averaging process, thus increasing the probability of the mean giving a closer approximation to the noise free pixel value.

The main reason the proposed method outperformed the reference adaptive methods in [1], [2], [4] and [3] is that the number of used directions is adapted to image content and noise level. This means that full filtering action can be achieved in case of a totally homogeneous region and no filtering in case of a highly structured region. To ensure that the new ideas do not decrease the real-time speed of the proposed filter due to the variable kernel size, the method is designed to work for $W = 5$ with the two outermost pixels given extra binary weights of 1 or 0 based on the determined kernel size. This way those pixels can be turned off completely, thus

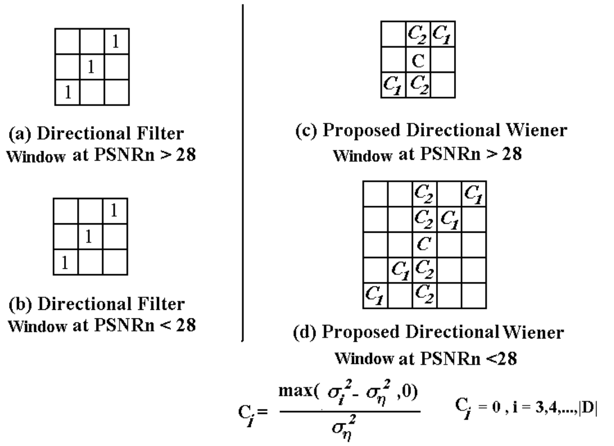

Fig. 2. Fixed directional filter versus proposed variable kernel shape and direction at different noise levels.

effectively reducing the kernel size to $W = 3$ without much complexity.

3. RESULTS

To validate the proposed approach, 8 images (Fig 3(a-h)) and 4 video sequences (Fig. 3(i-l)) were used in simulation. The images were corrupted by noise levels ranging from 20-40 dB PSNR in steps of 5 dB and the video sequences with levels 20-40 in steps of 10 dB.

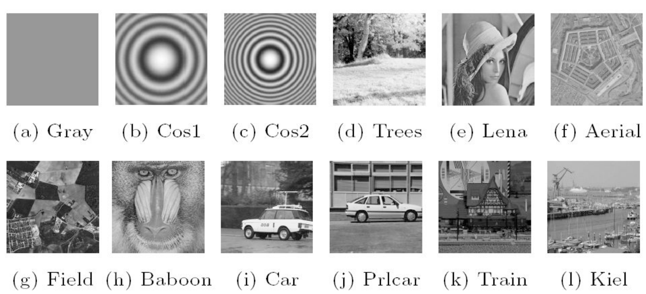

Fig. 3. Images and Video Sequences used in Simulation.

Fig. 4 shows how the threshold of $t_\eta = 28$ was determined at the intersection of the fixed $W = 3$ and $W = 5$ curves. A comparison of the gain achieved by the proposed and reference methods at different noise levels is shown in Fig. 5 (for the test images) and Fig. 6 (for the test video sequences). The proposed method outperforms all reference methods. It also outperform the WF in preserving non-noisy images while still giving good gain for noisier images. The average gain (in dB) over time for the proposed and reference methods is shown in Fig. 7 for the *Train* and *Prlcar* sequences with 25dB noise. It can be seen that the proposed algorithm

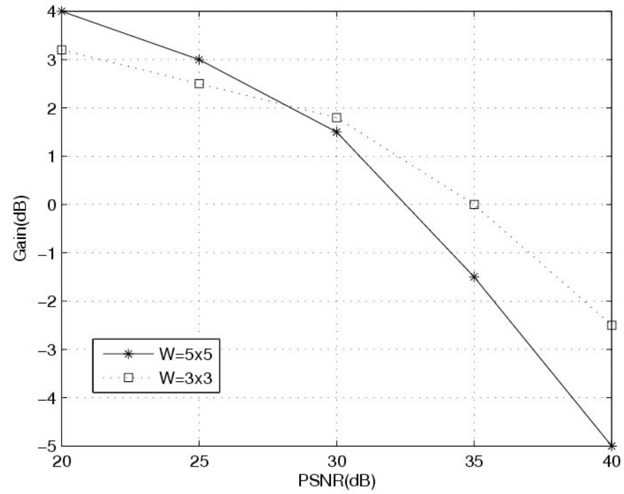

Fig. 4. Average gain at different noise levels with a $W = 3$ and $W = 5$ kernels with t_η selected at intersection $t_\eta = 28$ dB

outperforms the reference methods and also more stable over time.

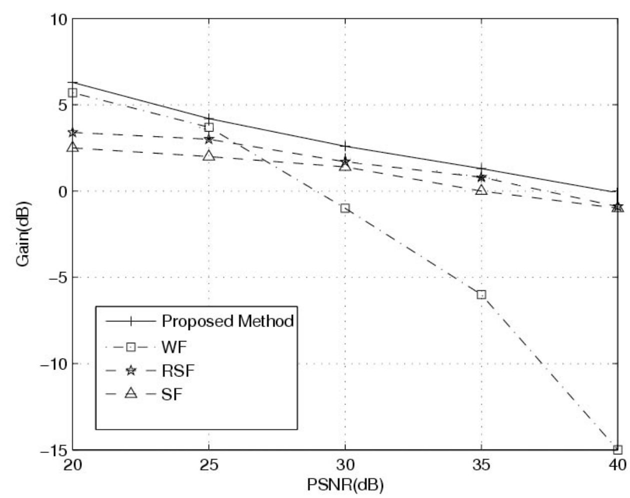

Fig. 5. Average gain achieved by proposed method, SF[1], RSF[2] and WF[4] when applied to images in Fig. 3(a-h). Note the gain of 2.31 dB of the proposed filter compared to the 0.62 of WF in the 25-30 dB range

Table 1 shows the average time needed by each method to process a 512×512 frame when implemented using C++ under an Intel(R) Xeon(TM) CPU 2.40GHz machine running Linux. As can be seen, the proposed method lags behind the methods in [3]. The time complexity of the algorithm can be tolerated with the almost daily advances in processing power. The proposed method is still faster than the standard Wiener filter.

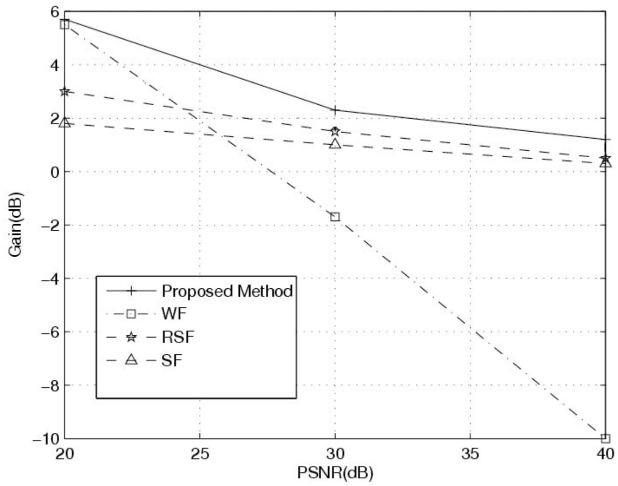

Fig. 6. Average gain achieved by by proposed method, SF[1], RSF[2] and WF[4] when applied to videos in Fig. 3(i-l) where the proposed method clearly outperforms the classical Wiener filter

Table 1. Time Complexity Comparison.

Algorithm	(seconds/512x512 frame)
HF[3]	0.13
RSF[2]	0.23
Proposed Method	0.30
WF[4]	0.37

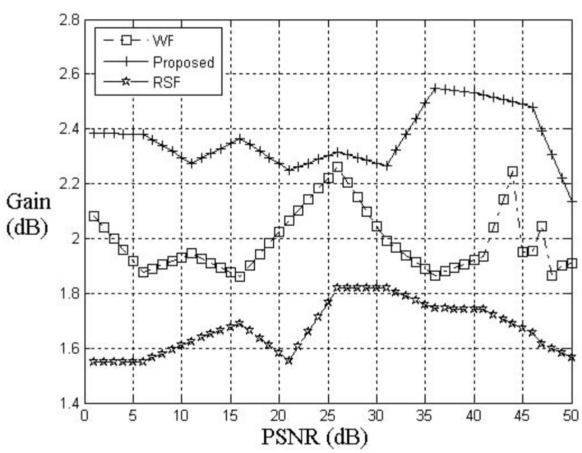

Fig. 7. Gain (in dB) over time achieved from applying proposed and reference methods to 25dB noisy *Train* and *Prlcar*.

Fig. 8 shows the proposed filter's ability to preserve image structure while reducing noise. Note the blurring introduced by the Wiener filter in high structured areas such as the hair in the *Lena* image.

(a) 25dB Noisy Lena. (b)Wiener filter[4] (c)Proposed method

Fig. 8. Improved structure-preservation in the directional Wiener filter over the classical Wiener filter. Note obvious blurring in the Wiener filter in high structure areas.

4. CONCLUSION

This paper proposed a new method for spatial noise reduction of white Gaussian noise that is good at preserving image contents while still achieving high gain in quality. The method uses the Wiener filter for directional smoothing along homogeneous areas and not across edges. The proposed method achieves a maximum gain of 5.6 dB by increasing the filtering through expansion of kernel size and including more homogeneous directions in filtering. Hence, it adapts behavior to image content and noise level. Simulations show that the proposed method achieves higher noise reduction gain than reference methods.

5. REFERENCES

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