Classification-based Hybrid Filters for Image Processing

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ABSTRACT

The paper proposes a new type of nonlinear filters, classification-based hybrid filters, which jointly utilize spatial, rank order and structural information in image processing. The proposed hybrid filters use a vector containing the observation samples in both spatial and rank order. The filter coefficients depend on the local structure of the image content, which can be classified based on the luminance pattern in the filter window. The optimal coefficients for each class are obtained by the Least Mean Square optimization. We show that the proposed classification-based hybrid filters exhibit improved performance over linear filters and order statistic filters in several applications, image de-blocking, impulsive noise reduction and image interpolation. Both quantitative and qualitative comparison have also been presented in the paper.

Keywords: hybrid filter, order statistic filter, pixel classification, de-blocking, noise reduction, image interpolation

1. INTRODUCTION

Linear filters estimate the output by using the weighted sum of the observation samples in the temporal or spatial order. They have good performance at eliminating Gaussian noise, but they are ineffective in removing impulsive noise. In order to solve the problem with linear filters, some non-linear filters which produce outputs based on the rank ordered observations, such as the most well known rank-order filter - the median filter[1–3] and its generalization - order statistic filters,[4,5] have been proposed. Such filters based on only order statistics have some advantages over linear filters. They are robust in environments with impulsive interference and they can track signal discontinuities without introducing smooth transient, as linear filters do. However, rank order information alone is not sufficient in many applications. To incorporate both spatial order and rank order information, many generalization of rank-order filters have been proposed. Good examples among them are combination filters,[6,7] permutation filters[8,9] and hybrid filters.[10] Different from the combination filters and the permutation filters which exhibit high complexity, the hybrid filter is relatively simple. The hybrid filter directly combines a linear filter and an OS filter. It exploits both spatial and rank information in the image content and is proposed to realize the advantages of OS filters in edge preservation and reduction of impulsive noise components while retaining the ability of the linear filter to suppress Gaussian noise. Nevertheless, the hybrid filter alone could not accommodate the optimal task for all different image structures, that is, it fails to utilize the important structure information from which more robust estimation can be constructed.

In this paper we propose a new type of nonlinear filters for image processing, classification-based hybrid filters. In the proposed method, the hybrid filters use a vector containing the observation samples in both spatial and rank order. To incorporate local structure information, the hybrid filter coefficients depend on the local structure of the image content, which can be classified based on the luminance pattern in the filter window. The classification method we employ is Adaptive Dynamic Range Coding (ADRC),[12] which is a simple and efficient way to identify the image structure. The optimal coefficients are obtained for each class by training the input and desired images as the training set and the optimization can be easily accomplished by the Least Mean Square algorithm. In

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the paper we present the evaluation of the proposed classification-based hybrid filters with other filters including linear filters and order statistic filters in several applications, image de-blocking, impulse noise reduction and image interpolation. Both quantitative (MSE) and qualitative comparisons have been provided in the result section. The experiments have shown that with the introduction of the structure classification information, the proposed classification-based hybrid filters demonstrate more flexibility and significant improvement over other filters.

The organization of this paper is as follows. Sect. 2 will introduce the hybrid filter and the optimization of the filter coefficients. We then present the proposed classification-based hybrid filters in Sect. 3. The evaluation of the proposed hybrid filters in several image processing application including image interpolation, image de-blocking and impulsive noise reduction is presented in Sect. 4. Finally, we draw our conclusion in Sect. 5.

2. THE HYBRID FILTER

In this section, we will provide the definition of the hybrid filter. Then we provide the optimization of its filter coefficients.

Let $X = (x_1, x_2, ..., x_n)^T$ be an observation containing n samples arranged by the spatial or temporal order in which the samples are observed. X^r is the sorted observation vector $X^r = (x_{(1)}, x_{(2)}, ..., x_{(n)})^T$ where $x_{(i)}$ is the ith largest sample in X, so that $x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(n)}$. Let the observation vector X be the input to the filter. For a linear filter, we have

$$y = w_1 x_1 + w_2 x_2 + ... + w_n x_n \tag{1}$$

where y is the output of the linear filter and $W = (w_1, w_2, ..., w_n)^T$ is the linear filter coefficient vector.

Then for an order statics filter, we have

$$y^r = w_{(1)} x_{(1)} + w_{(2)} x_{(2)} + ... + w_{(n)} x_{(n)} \tag{2}$$

where y^r is the output of the order statistic filter $W^r = (w_{(1)}, w_{(2)}, ..., w_{(n)})^T$ is the order statistic filter coefficient vector.

By concatenating X and X^r we can obtain an extended vector $X^h = (x_1, x_2, ..., x_n, x_{(1)}, x_{(2)}, ..., x_{(n)})^T$ contains spatial ordered and rank ordered samples. The output of the hybrid filter is a linear combination of both spatial ordered and rank ordered samples as shown in Equation 3.

$$y^h = w_1 x_1 + w_2 x_2 + ... + w_n x_n + w_{(1)} x_{(1)} + w_{(2)} x_{(2)} + ... + w_{(n)} x_{(n)} \tag{3}$$

where $W^h = (w_1, w_2, ..., w_n, w_{(1)}, w_{(2)}, ..., w_{(n)})^T$ is the hybrid filter coefficient vector.

As one can see from Equation 3, the hybrid filter is a direct combination of the linear and order statistic filter. If the coefficients for the spatial ordered or the rank ordered are constrained to be zero, the hybrid filter becomes equally the order statistic filter or the linear filter respectively.

Since Equation 3 is a linear equation, we can use the LMS algorithm to get the optimal coefficient for the hybrid filter. Suppose the total number of the observations $X_1, X_2, ..., X_M$ is M. Let y_m be the desired output and y^h_m be the output value of hybrid filter for the observation X_m. The sum square error then is:

$$e^2 = \sum_{m=1}^{M} (y_m - y^h_m) \tag{4}$$

Insert Equation 3 into Equation 4, then the sum square error becomes

$$e^2 = \sum_{m=1}^{M} [y_m - (w_1 x_{1,m} + w_2 x_{2,m} + ... + w_n x_{n,m} + w_{(1)} x_{(1),m} + w_{(2)} x_{(2),m} + ... + w_{(n)} x_{(n),m})]^2 \tag{5}$$

To get the minimal value of e^2 , let the first derivatives of e^2 to w_1, w_2 , ... ,w_n, $w_{(1)}$, $w_{(2)}$, ... ,$w_{(n)}$ equal zero.

$$\begin{aligned}
\frac{\partial e^2}{\partial w_1} &= \sum_{m=1}^{M} 2x_{1,m}[y_m - (w_1 x_{1,m} + ... + w_n x_{n,m} + w_{(1)}x_{(1),m} + ... + w_{(n)}x_{(n),m})] = 0 \\
&\cdots \\
\frac{\partial e^2}{\partial w_n} &= \sum_{m=1}^{M} 2x_{n,m}[y_m - (w_1 x_{1,m} + ... + w_n x_{n,m} + w_{(1)}x_{(1),m} + ... + w_{(n)}x_{(n),m})] = 0 \\
\frac{\partial e^2}{\partial w_{(1)}} &= \sum_{m=1}^{M} 2x_{(1),m}[y_m - (w_1 x_{1,m} + ... + w_n x_{n,m} + w_{(1)}x_{(1),m} + ... + w_{(n)}x_{(n),m})] = 0 \\
&\cdots \\
\frac{\partial e^2}{\partial w_{(n)}} &= \sum_{m=1}^{M} 2x_{(n),m}[y_m - (w_1 x_{1,m} + ... + w_n x_{n,m} + w_{(1)}x_{(1),m} + ... + w_{(n)}x_{(n),m})] = 0
\end{aligned} \tag{6}$$

Let

$$X_m = \begin{bmatrix}
\sum_{m=1}^{m} x_{1,m}x_{1,m} & \cdots & \sum_{m=1}^{M} x_{1,m}x_{n,m} & \sum_{m=1}^{m} x_{1,m}x_{(1),m} & \cdots & \sum_{m=1}^{m} x_{1,m}x_{(n),m} \\
\vdots & \vdots & \vdots & \vdots & & \\
\sum_{m=1}^{M} x_{n,m}x_{1,m} & \cdots & \sum_{m=1}^{M} x_{n,m}x_{n,m} & \sum_{m=1}^{m} x_{n,m}x_{(1),m} & \cdots & \sum_{m=1}^{m} x_{n,m}x_{(n),m} \\
\sum_{m=1}^{m} x_{(1),m}x_{1,m} & \cdots & \sum_{m=1}^{M} x_{(1),m}x_{n,m} & \sum_{m=1}^{m} x_{(1),m}x_{(1),m} & \cdots & \sum_{m=1}^{m} x_{(1),m}x_{(n),m} \\
\vdots & \vdots & \vdots & \vdots & & \\
\sum_{m=1}^{M} x_{(n),m}x_{1,m} & \cdots & \sum_{m=1}^{M} x_{(n),m}x_{n,m} & \sum_{m=1}^{m} x_{(n),m}x_{(1),m} & \cdots & \sum_{m=1}^{m} x_{(n),m}x_{(n),m}
\end{bmatrix} \tag{7}$$

$$Y = \left[\sum_{m=1}^{M} x_{1,m}y_m, \cdots, \sum_{m=1}^{M} x_{n,m}y_m, \sum_{m=1}^{M} x_{(1),m}y_m, \cdots, \sum_{m=1}^{M} x_{(n),m}y_m\right]^T \tag{8}$$

Equation 5 can be transformed into:

$$X_m \cdot W^h = Y \tag{9}$$

Please note that X_m is the sum of the correlation matrices of the combination vectors $X_1^c, X_2^c, ..., X_M^c$. Then the coefficients W^c can be solved by matrix inversion:

$$W^h = X_m^{-1} \cdot Y \tag{10}$$

3. THE CLASSIFICATION-BASED HYBRID FILTERS

The block diagram of the proposed classification-based hybrid filters is presented in Fig. 2. The local structure in the input image within the filter window is first classified by using Adaptive Dynamic Range Coding (ADRC). The 1-bit ADRC code of every pixel is defined by:

$$ADRC(x) = \begin{cases} 0, & if\ x < x_{av} \\ 1, & otherwise \end{cases} \tag{11}$$

where x is the value of pixels in the window and x_{av} is the average value of all pixels in the window. Figure 1. shows an example of ADRC operation over a 3×3 window. The concatenation of $ADRC(x)$ of all pixels in the

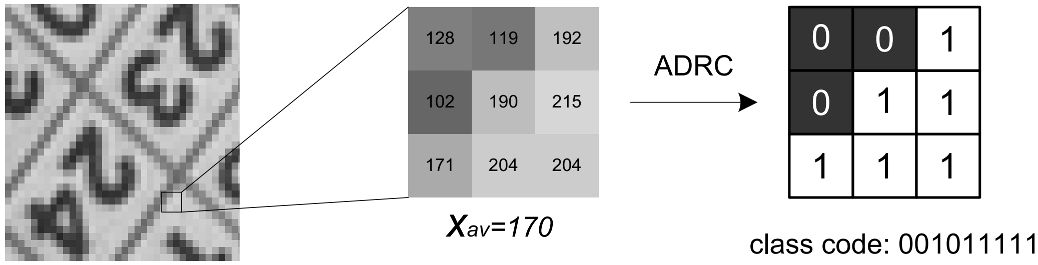

Figure 1. Adaptive Dynamic Range Coding: An example of a 3×3 aperture

window gives class code, c. The class, c, is used as the index to a Look-Up-Table (LUT) that contains a set of filter coefficients optimized for every class. The output pixel y^h then is computed by applying the hybrid filter of class c on its 3×3 aperture. This is shown in Equation 12.

$$y^h = w_{1,c}x_1 + w_{2,c}x_2 + ... + w_{9,c}x_9 + w_{(1),c}x_{(1)} + w_{(2),c}x_{(2)} + ... + w_{(9),c}x_{(9)} \tag{12}$$

where $w_{1,c}$, $w_{2,c}$, ... , $w_{9,c}$, $w_{(1),c}$, $w_{(2),c}$, ... , $w_{(9),c}$ are the hybrid filter coefficients for class c.

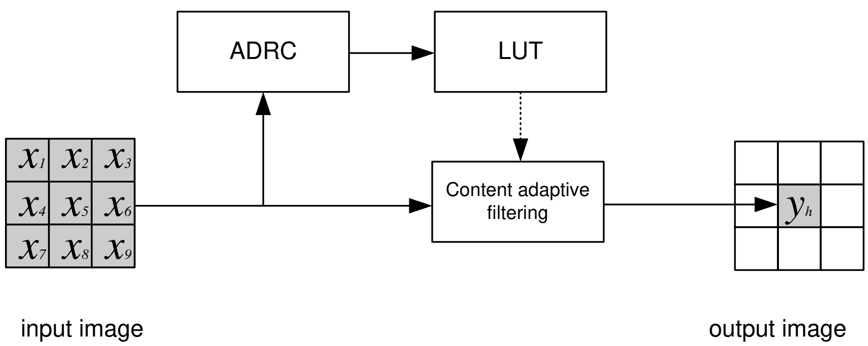

Figure 2. The block diagram of classification-based hybrid filters: the local image structure is classified using ADRC and the filter coefficients can be obtained from the LUT.

The optimization procedure of the classification-based hybrid filters is shown in Fig. 3. We use the input image and the output reference image as the training material. Before training, the input and output target pairs (X, y) are collected from the training material and are classified using ADRC on the input vector X. The pairs that belong to one specific class are used for the corresponding training, resulting in optimal coefficients for this class. The optimal coefficients can be obtained by using the LMS algorithm.

4. EXPERIMENTS AND RESULTS

In this section, the evaluation of the proposed hybrid filters in the application of image interpolation , image de-blocking and impulsive noise reduction are provided. In the evaluation, we compare the proposed hybrid filter with the linear filter and the OS filter, with and without ADRC classification, respectively. All the filters are trained on the same training material. The training material includes a variety of high quality natural images, including people, building, animals and landscapes. And the test materials used in our experiments are shown in Fig. 4. Note that these test material is not included in the training images.

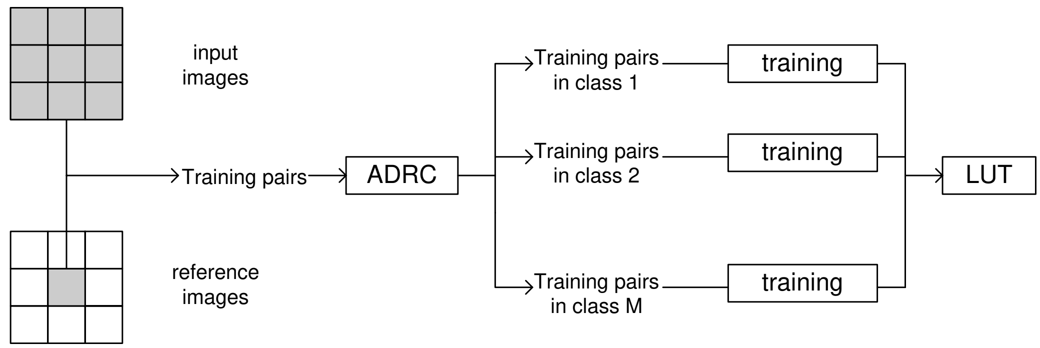

Figure 3. The training procedure of the classification-based hybrid filters. The input and output target pairs are collected from the training material and are classified by ADRC. The filter coefficients are optimized for specific classes.

Table 1. MSE scores for image interpolation

Sequence	Mean Square Error					
	Linear filters		OS filters		Hybrid filters	
	ADRC	no ADRC	ADRC	no ADRC	ADRC	no ADRC
Bicycle	47.4	71.2	153.6	301.4	45.0	71.2
Football	58.7	65.4	137.7	273.6	57.3	65.4
Lighthouse	98.8	106.3	170.5	356.8	97.2	106.3
Helicopter	32.2	34.1	133.9	324.3	30.1	34.2
Hotel	38.1	38.8	136.4	394.2	33.1	38.8
Siena	82.0	91.4	164.5	293.6	80.2	91.5
Average	59.5	67.9	149.4	324.0	57.1	67.9

4.1. Image Interpolation

For image interpolation, we apply the proposed filter with window size of 3×3 on the low resolution pixels to estimate the corresponding high resolution pixels using window flipping.[12] We adopt the same evaluation process as Zhao et al.[13]

In Table 1, the MSE score on some test images or video sequence are provided for in the image interpolation. Table 1 shows that the order statistic filters have the highest MSE score because they only use rank order information and fail to exploit the content structure. The MSE score for these filters with ADRC classification has a significant reduction compared to those without on every test image and sequence. Without ADRC classfication, the hybrid filters have similar performance as the linear filter because the hybrid filter cannot handle all the different image structures in the interpolation. With ADRC classification, the hybrid statistic filters demonstrate a somewhat more robust estimation and achieve a lower MSE score. For qualitative image quality comparison, some image fragments from the Bicycle sequence interpolated by these methods are shown in Fig. 5. The proposed hybrid filters produces the most satisfactory results. Comparing the image fragments (B) and (F), we can see that the linear filters with ADRC classification cause some blurring at the border of the letters while the proposed hybrid filters can reproduce the image edges more correctly.

4.2. Image De-blocking

In the experiment for image de-blocking, we test several sequences and images which have been compressed using JPEG compression at quality factor 20 (quality factor 100 is the best). The free baseline JPEG software from the Independent JPEG Group website (http://www.ijg.org/files/jpegsrc.v6b.tar.gz) is used for the JPEG

(A)Bicycle (B)Football (C)Lighthouse

(D)Helicopter (E)Hotel (F)siena

(G)Lena (I)Boat (J)Motor

Figure 4. The testing material used for evaluation.

encoding and decoding. We use a diamond shape filter window shown in Fig. 6 to keep the balance between performance and complexity.

From the MSE score shown in Table 2, we can see that the proposed hybrid filters achieve the best results. Figure 7 shows the image fragments from Lena processed by all the filters. We can see that the OS filters suppress the blocking artifacts more effectively that the linear filter in the smooth area while the linear filters show the better ability to preserve the details in the detailed area. The proposed hybrid filters then inherit the advantages from both linear and OS filters. They eliminate the blocking artifacts but retain the details.

4.3. Impulsive Noise Reduction

For impulsive noise reduction, several sequence and images corrupted by 20 percent of impulsive noise are tested. A 3×3 filter window centered at the pixel to be estimated is employed to eliminate the impulsive noise.

The MSE score performance of all the filters are listed in Table 3. As one can see, the proposed hybrid filters has MSE improvement over the linear filters and OS filters. The image fragments from restored Bicycle sequence

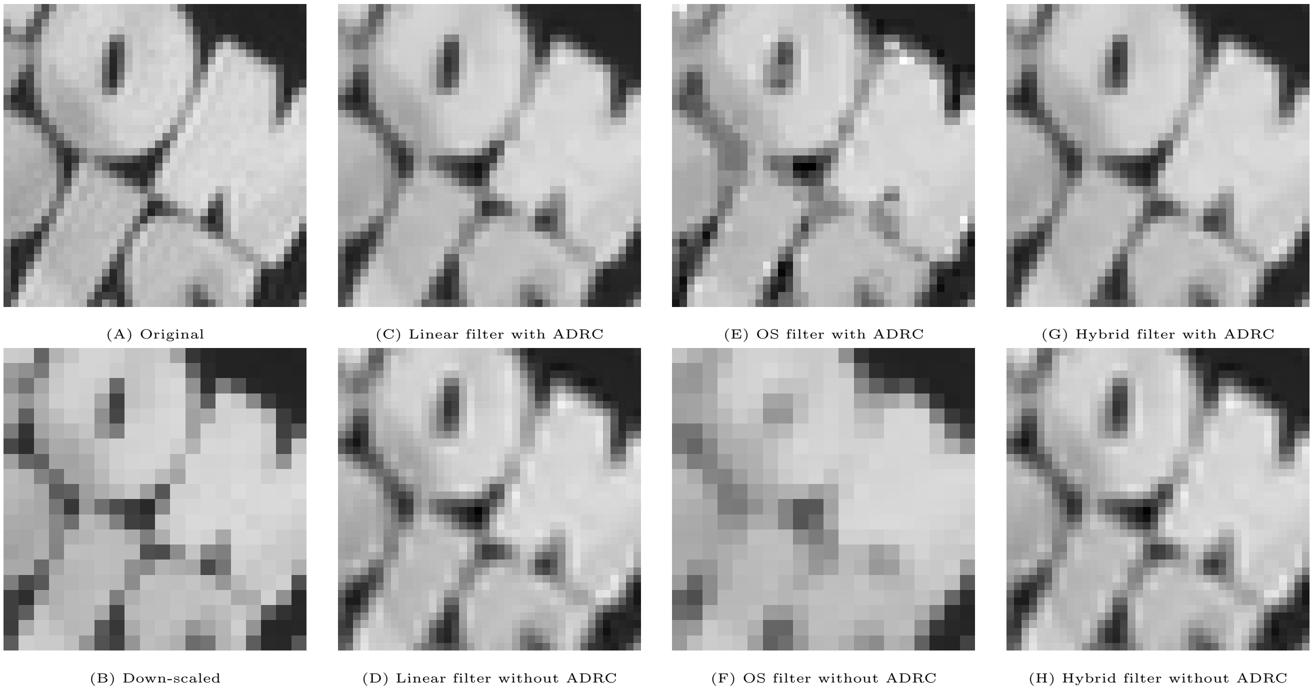

Figure 5. The image fragments from the Bicycle sequence interpolated by: (A) Original. (B)Down-scaled. (C)Linear filters with ADRC classification. (D) Linear filter without ADRC classification. (E) Order statistic filters with ADRC classification. (F) Order statistic filters without ADRC classification. (G) Hybrid filters with ADRC classification. (H) Hybrid filters without ADRC classification.

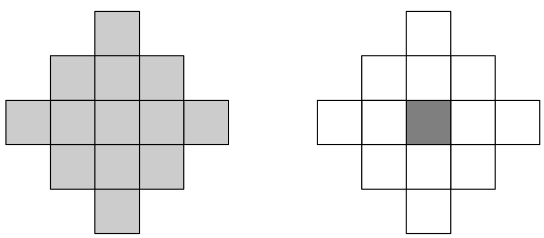

Figure 6. The diamond shape filter window for de-blocking: the estimated ouput is in the center of the window

Table 2. MSE scores for de-blocking

Sequence	Mean Square Error					
	Linear filters		OS filters		Hybrid filters	
	ADRC	no ADRC	ADRC	no ADRC	ADRC	no ADRC
Bicycle	44.5	52.7	46.6	90.5	41.2	49.3
Birds	11.1	11.6	11.8	17.5	10.6	11.5
Boat	61.1	63.9	63.5	87.8	59.3	62.4
Lena	29.7	31.7	30.8	39.5	28.7	31.0
Motor	87.4	94.9	92.2	157.3	84.3	91.9
Average	46.8	50.9	49.0	78.5	44.8	49.2

(A) Original | (C) Linear filter with ADRC | (E) OS filter with ADRC | (G) Hybrid filter with ADRC

(B) Compressed | (D) Linear filter without ADRC | (F) OS filter without ADRC | (H) Hybrid filter without ADRC

Figure 7. The image fragments from the Lena image processed by: (A) Original (B)Compressed (C) Linear filters with ADRC classification. (D) Linear filter without ADRC classification. (E) Order statistic filters with ADRC classification. (F) Order statistic filters without ADRC classification. (G) Hybrid filters with ADRC classification. (H) Hybrid filters without ADRC classification.

Table 3. MSE scores for impulsive noise reduction

Sequence	Mean Square Error					
	Linear filters		OS filters		Hybrid filters	
	ADRC	no ADRC	ADRC	no ADRC	ADRC	no ADRC
Bicycle	172.4	846.3	126.5	153.9	119.4	153.1
Hotel	148.0	787.4	99.4	124.2	98.7	123.6
Lena	138.1	541.0	71.2	73.9	71.1	73.4
Motor	216.0	709.8	153.1	186.3	149.7	184.3
Football	171.6	672.5	108.3	133.5	105.6	132.6
Average	169.2	711.4	111.8	134.4	108.9	133.4

by all the filters are shown in Fig. 8. The proposed hybrid filter have equivalently good performance as the OS filters. Furthermore, due to the additional spatial information offered by the linear part, the hybrid filters can restore the image structure better than the OS filter. We can see the text in the fragment processed by the hybrid has better contrast and is more legible than that by OS filters.

5. CONCLUSION

In this paper, we have introduced a new type of nonlinear filters for image processing, the classification-based hybrid filter. The proposed hybrid filters take a linear combination of both spatial ordered and rank ordered observation samples as the output, and the coefficients are based on the local structure classification. The optimization of the proposed hybrid filter is obtained with the LMS algorithm. With the joint utilization of spatial, rank order and structure information, the proposed hybrid filters have demonstrated more robust

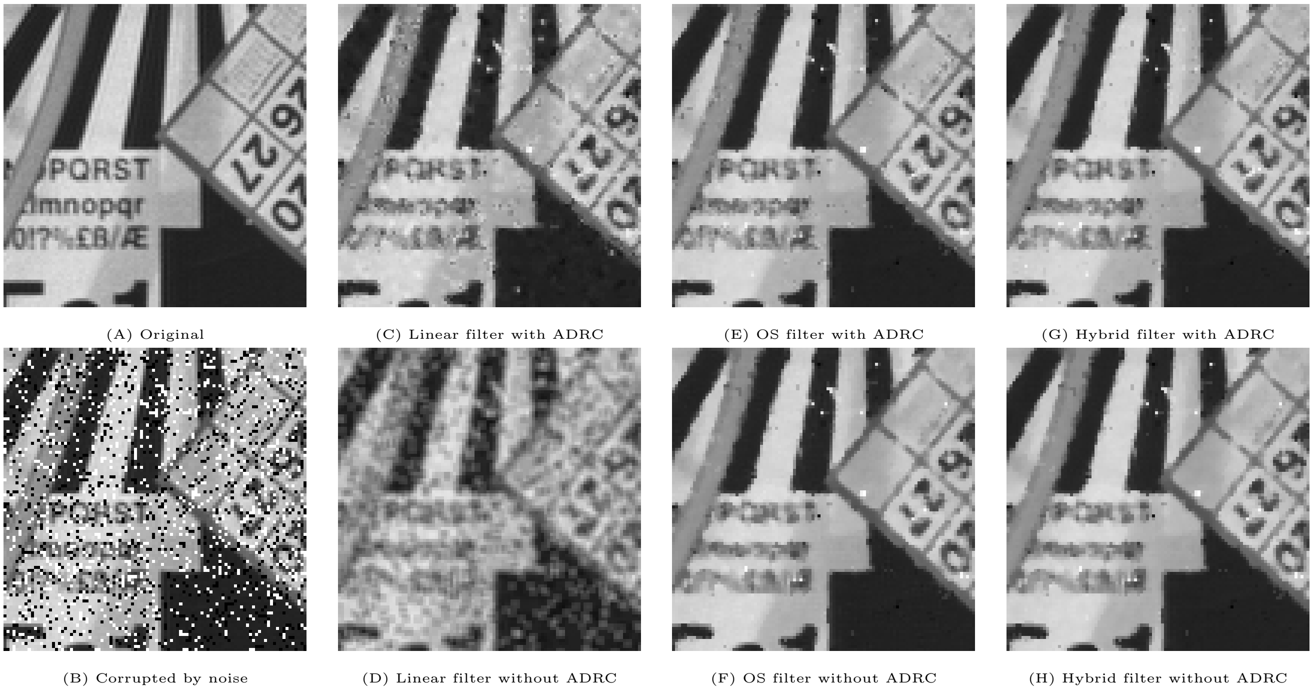

Figure 8. The image fragments from the restored Bicycle sequence by: (A) Original (B)Corrupted by noise (C)Linear filters with ADRC classification. (D) Linear filter without ADRC classification. (E) Order statistic filters with ADRC classification. (F) Order statistic filters without ADRC classification. (G) Hybrid filters with ADRC classification. (H) Hybrid filters without ADRC classification.

estimation and more flexibility over the linear and OS filters. In the evaluation in several image applications including image interpolation, image de-blocking and impulsive noise reduction, both quantitative and qualitative comparison showed that the proposed hybrid filters exhibit improved performance and merit further attention.

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