A HYBRID FILTER FOR IMAGE ENHANCEMENT

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ABSTRACT

In this paper, we present a new hybrid filter design methodology. Our hybrid filter consists of a nonlinear impulsive noise filter and a fuzzy weighted linear filter. This hybrid filter can efficiently remove large amounts of mixed Gaussian and impulsive noise while preserving the image details. The performance and robust stability of the proposed filter are compared to linear filters and nonlinear filters theoretically and experimentally.

1. INTRODUCTION

Image enhancement and restoration in a noisy environment are fundamental problems in image processing. Various filtering techniques have been developed to suppress noise in order to improve the quality of images. Many filters for image processing are designed assuming a specific noise distribution. For example, linear techniques are used to remove Gaussian noise, and order statistic techniques are used to remove impulsive noise. Hybrid filters have been developed to remove either Gaussian or impulsive noise. These include the L-filter [1], the FIR-WOS filter [2], and the neural filter [3]. These filters use combinations of order statistics to generate the output and can be trained to remove either Gaussian or impulsive noise. Other filters have been introduced to remove a combination of Gaussian and impulsive noise. The filter in [4] removes a small amount of impulsive noise (5%) mixed with Gaussian noise. In this paper we introduce a new hybrid filter structure which removes significantly larger amounts of mixed noise. A second advantage of our filter structure is its reduced complexity and robustness. Compared to neural filters or other hybrid filters, we require fewer operations while removing larger amounts of noise.

The proposed filter uses the following two step approach to remove both impulsive and Gaussian noise from an image. First, order statistics techniques are used to remove the large magnitude impulsive noise. This procedure is essential for the following step because of the weak robust stability of the linear filter to signal outliers. By removing the outliers before performing linear filtering, it is possible to better protect the image information. To effectively remove the outliers, we use an iterative selective-peeling procedure in the local area of an image to detect and peel out the outliers.

The second part of our hybrid filter uses a weighted average linear filter to remove additive Gaussian noise and small ripple impulsive noise. Our weighted linear filter differs from the classical weighted linear filter. Traditionally, a crisp function has been used to generate the weights. Instead we use fuzzy clustering [5] to accurately measure the gray level differences in the filter neighborhood. With this approach the structure of the filter is simple and the implementation is straightforward. Test results show that the proposed filter effectively removes large amounts of mixed Gaussian and impulsive noise.

2. FILTER DESIGN

2.1. Image signal and noise model

Images can be corrupted with different kinds of noises. The observed image is a nonlinear combination of the true image signal and noise. The noise could be described by the combination of many different distributions depending on the source of corruption. In image processing, the common source of noise can be described using Gaussian and/or impulsive noise distributions. In this paper, we assume the images are corrupted by the combination of Gaussian noise with mean equal to zero and variance equal to σ^2, $(0,\sigma^2)$, and impulsive noise with probability p and height h. Let X_{MM} denote an $M \times M$ noisy image. The pixel x at location (i,j) can be described by:

$$x(i,j) = \begin{cases} s(i,j) + n_G(i,j) + h & \text{for probability } p \\ s(i,j) + n_G(i,j) & \text{otherwise,} \end{cases} \tag{1}$$

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where $s(i, j)$ denotes the original gray level image signal and $n_G(i, j)$ denotes the Gaussian noise. Our goal is to remove both Gaussian noise and impulsive noise from signal $x(i, j)$ while maintaining the resemblance of the estimated image signal, $\hat{s}(i, j)$, with the original signal, $s(i, j)$.

2.2. Robust stability of filters

The optimal filter for removing Gaussian noise is the linear filter [1]. If only Gaussian noise appears in the image, the linear weighted average filter could be used to remove the Gaussian noise while preserving image details. From robust stability analysis of the linear filter [7], it has been shown that linear filters have good robust stability to Gaussian noise, however they are not robust to outliers (impulsive noises).

To describe the robustness of a filter operating in the presence of impulsive noise, we use the breakdown point and breakdown probability. The breakdown point is defined as the reliability limit of a defined estimator [1]. The breakdown probability is the measure of an outlier existing in the output of the estimator. In filter design, the breakdown point should be large while the breakdown probability should be small.

The mathematical concept of breakdown point is introduced in [7]. The mathematical definition of the breakdown point is based on the notion of the Prohorov distance between two signal distributions F and G.

Definition : Assume F and G denote two probability distributions. The Prohorov distance of these two probability distributions is defined as

$$d(F, G) = \inf\{\nu; F(A) \leq G(A^\nu) + \nu \text{ for all events A}\}.$$

The breakdown point ν^* of the filter $\{S_n; n \geq 1\}$ at distribution F is defined as

$$\nu^* = \sup_{n \to \infty} \{\nu \leq 1;\ \exists\ r_\nu \quad \text{s.t.} \quad d(F, G) < \nu \quad \text{implies} \quad G(\{|S_n| \leq r_\nu\}) \to 1\}$$

The median filter, commonly used for impulsive noise filtering, has a breakdown point of $\nu^* = \frac{1}{2}$ [6]. Thus, even with 50% outliers (or 50% impulsive noise in an image), the median filter still performs well. 50% is the critical point for reliability of the median filter. In contrast, the linear average filter has $\nu^* = 0$. A single outlier can destroy the reliability of the average filter.

2.3. Design procedure

The median filter effectively removes impulsive noise and the linear average filter effectively removes Gaussian noise. When both impulsive and Gaussian noise appear, neither the linear average filter nor the median filter perform well. Thus, it is necessary to use a hybrid filter. Since impulsive noise, randomly appears in the image with independent amplitude, we can design a peeling algorithm to remove the impulsive noise from the image. Then a linear filter can be used to remove the Gaussian noise.

The proposed filtering process is divided into two steps as shown in Fig 1. The filter consists of an impulse removal filter followed by a fuzzy weighted averaging filter. The operation of the filter can be described as follows.

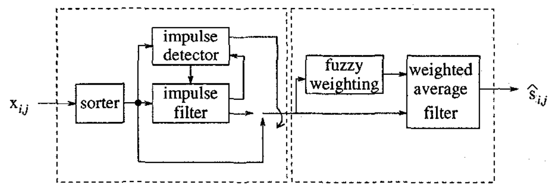

Figure 1: Block diagram of the proposed hybrid filter

Step 1. A selective-peeling procedure removes impulsive noise using the following iterative approach. Define the local area or neighborhood of a pixel, $x_{m,n}$, as a window of pixels of size $(2N + 1) \times (2N + 1)$, where $x_{m,n}$ is located at the center of the window. Sort the local window. For each pixel value from the maximum (minimum) to the median do the following. Measure the absolute distance from the current pixel value to the median. If this distance exceeds a threshold, impulse noise is detected and peeled from the local neighborhood. Peeling occurs by replacing the current pixel value with the median value. The peeling process continues until all possible outliers are detected and replaced in the local window.

Step 2. After the selective-peeling procedure, the following linear weighted average filter is used to remove Gaussian noise. Let $x'_{i,j}$ represent the pixels in the image after applying step 1. The output pixel, $\hat{s}_{m,n}$, is estimated by averaging over the local neighborhood of pixels as follows.

$$\hat{s}_{m,n} = \frac{\sum_{i=-N}^{N} \sum_{j=-N}^{N} w(\Delta x'_{i,j}) x'_{i,j}}{\sum_{i=-N}^{N} \sum_{j=-N}^{N} w(\Delta x'_{i,j})}, \tag{2}$$

where $\Delta x'_{i,j} = x'_{m,n} - x'_{i,j}$ is the gray level difference of the center pixel with a neighboring pixel, and $w(\Delta x'_{i,j})$ is a weight function which depends on the gray level differences of the surrounding pixels. A normal weighted average would use a threshold function to determine each of the weights where $w(\Delta x'_{i,j})$ either has value of 1 corresponding to a small gray level difference or value of 0 corresponding to a large gray level difference. This is equivalent to a crisp membership function. However, thresholding does not work well in the image processing case where the separation of objects is ambiguous. Replacing the binary thresholding function with a fuzzy clustering membership function provides support for a continuous thresholding decision which generates significantly better results. This membership function allows us to better describe the "big difference" and the "small difference" between gray levels. In this paper, we use a fuzzy membership function $w(\Delta x'_{i,j})$ trained from part of the Lena image by using a LMS (Least Mean Square) algorithm [8].

3. EXPERIMENTAL RESULTS

The designed filter was tested using several noise conditions. Fig. 3 shows one set of results. The original image is corrupted with Gaussian noise with distribution $(0, 10^2)$ and four levels of Salt and Pepper noise with densities 24.41%, 12.21%, 6.1% and 1.22%. The different impulsive noise densities demonstrate the robustness of the filter. The filter was trained using the original Lena image and the noise corrupted image.

The identical filter was used to filter several other images. In Table 1 we list MSE (mean square error), MAE (mean absolute error) and PSNR (peak signal to noise ratio) of the result of the proposed filter compared to other filters. The MSE, MAE, and the PSNR are defined as follows:

$$MSE := \frac{1}{N \times N} \sum_{i=1}^{N} \sum_{j=1}^{N} (x_{i,j} - s_{i,j})^2$$

$$MAE := \frac{1}{N \times N} \sum_{i=1}^{N} \sum_{j=1}^{N} |x_{i,j} - s_{i,j}|$$

$$PSNR := 10log10 \frac{(255)^2}{\frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} (x_{i,j} - s_{i,j})^2} dB$$

Our filter gives significantly better results in all cases. Furthermore it has a reduced complexity compared to other filters [2, 3].

	MSE				MAE				PSNR			
	Noisy	Our flt.	Ave. flt.	Med. flt.	Noisy	Our flt.	Ave. fl	Med. flt.	Noisy	Our flt.	Ave. flt.	Med. flt.
LENA	1847.4	64.3	270.7	162.6	18.53	5.84	12.02	7.93	15.47	30.05	24.19	26.02
BRIDGE	1833.9	89.1	473.5	299.5	12.14	6.48	16.63	11.49	15.5	28.63	21.57	23.37
LAKE	2070.0	142.3	703.6	421.8	20.55	9.39	20.71	14.19	14.96	24.46	20.21	21.88
ZELDA	2004.2	236.3	489.4	287.6	25.11	13.15	19.10	14.29	15.11	24.39	23.16	23.54
BINARY	15224	13282	12719	13170	91.65	87.97	92.59	87.78	6.31	6.89	7.08	6.93

Table 1: MSE, MAE and PSNR for several filtering methods.

In Fig. 3, we show the results of several other filters, including the linear moving average filter, the linear adaptive FIR filter, the median filter, the L filter and Arakawa's [5] fuzzy filter. In the mixed noise environment, neither the linear filter nor the nonlinear filter,acting alone, effectively remove mixed Gaussian noise or the impulsive noise. The linear filter is optimal in removing short tailed noise while the nonlinear filter is better at removing long tailed noise. This is demonstrated in Fig. 3. This result shows that the combination of linear and nonlinear filters is necessary to remove mixed noise.

Table 2: Measured MSE, MAE and PSNR vs. impulse percentage in input image for the proposed and the median filter.

	MSE		MAE		PSNR	
%	Prop.	Med	Prop.	Med	Prop.	Med
5	39.0	125.2	3.16	5.75	32.22	27.15
9	45.5	129.7	3.38	5.89	31.55	27.0
12	49.4	132.5	3.52	5.97	31.19	26.9
16	56.1	140.5	3.73	6.14	30.64	26.65
20	63.0	145.7	3.94	6.28	30.13	26.5
24	74.8	157.4	4.23	6.49	29.39	26.16
29	86.8	169.6	4.54	6.74	28.73	25.84
35	109.5	190.6	5.01	7.09	27.74	25.33
40	133.2	216.4	5.51	7.53	26.89	24.78
45	170.0	252.4	6.08	8.01	25.83	24.11
50	216.8	304.3	6.7	8.62	24.77	23.3
54	295.5	392.5	7.61	9.54	23.42	22.19
59	465.2	588.0	9.26	11.35	21.45	20.44
65	781.4	947.1	12.21	14.16	19.20	18.37
69	1282	1502	16.5	19.31	17.05	16.36

To determine the breakdown probability and breakdown point, we tested a highly impulsive noise corrupted image with our filter, the median filter, and the L filter. The results are shown in Table 2. In Fig. 2, we plot the relationship of the MSE, MAE and PSNR of the Lena image corrupted with different percentages of impulsive (Salt-n-Pepper) noise. The median filter has a breakdown point at 50%. The breakdown point of our filter is much higher than 50% since our peeling process decreases the breakdown probability significantly.

From the theoretical and experimental results, we can conclude that the proposed filter can remove large amounts of mixed Gaussian noise and impulsive noise. Furthermore its implementation complexity is low. The breakdown point of the proposed filter is higher than 50%. The MSE, MAE are lower than other filters and the PSNR is higher than other filters.

4. REFERENCES

[1] I. Pitas, A.N. Venetanopoulos, "Nonlinear Digital Filters",Boston: Kluwer, 1989.

[2] L. Yin, Y. Neuvo, "Fast Adaptation and Performance Characteristics of FIR-WOS Hybrid Fil-

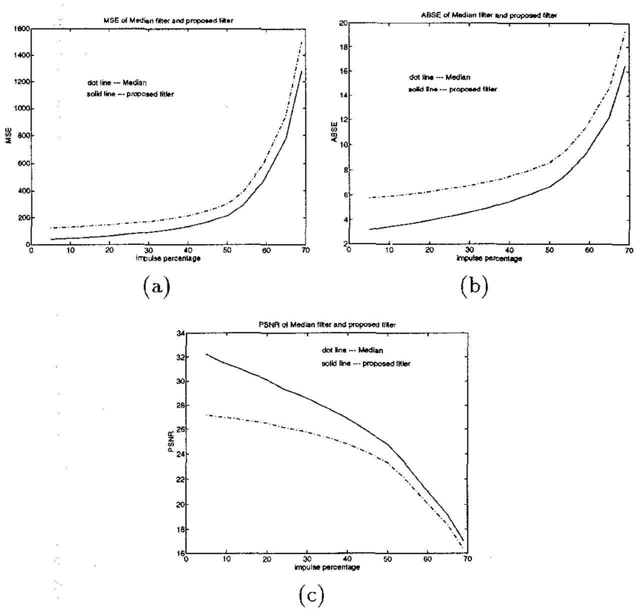

Figure 2: (a) MSE vs. impulse percentage, (b) MAE vs. impulse percentage, (c) PSNR vs. impulse percentage.

ters," *IEEE Trans. on Signal Processing*, pp. 1610-1628, July 1994.

[3] L. Yin, J. Astola, and Y. Neuvo, "A New Class of Nonlinear Filters – Neural Filters," *IEEE Trans. on Signal Processing*, pp. 1201-1222, Mar. 1993.

[4] M. Karczewicz, M. Gabbouj, and J. Astola, "Robust B-Spline Image Smoothing", *Proc. of IEEE Int'l Conf. on Image Processing*, Nov. 1994.

[5] K. Arakawa, Y. Arakawa, "A Nonlinear Digital Filter Using Fuzzy Clustering," *Proc. Int'l Conf. on Acoustics, Speech, and Signal Proc.*, pp.IV309-IV312, 1992.

[6] P. J. Huber, *Robust Statistics*, Wiley Series in Probability and Mathematical Statistics, John Wiley & Sons, Inc, 1981.

[7] F. Hampel, E. M. Ronchetti, P. Rousseuw, W. A. Stahel, *Robust Statistics - The Approach Based on Influence Functions*, Wiley Series in Probability and Mathematical Statistics, John Wiley & Sons, Inc, 1986.

[8] S. Peng, L. Lucke, "Fuzzy Filtering for Mixed Noise Removal during Image Processing," *IEEE Int'l Conf. on Fuzzy Systems*, Orlando, Florida, June, 1994.

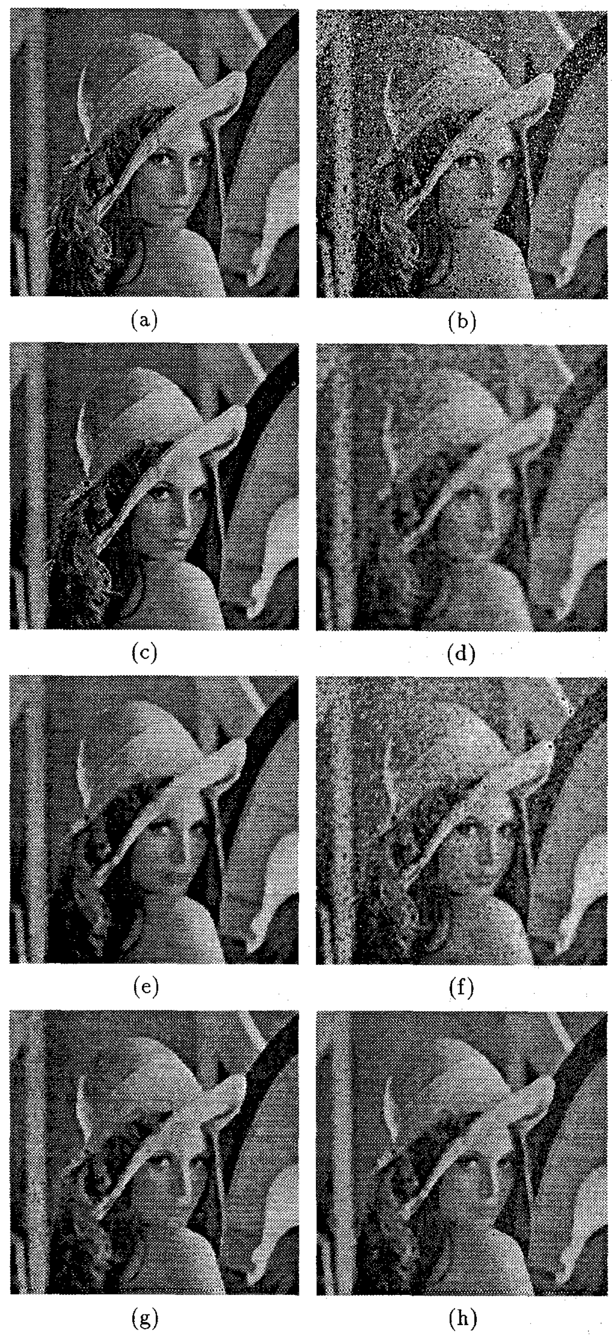

Figure 3: (a) Original Lena image, (b) Lena image corrupted by Gaussian noise $(0, 10^2)$ and varying impulsive noise, (c) Proposed filtering result, (d) Linear moving average filtering result, (e) Median filtering result, (f) Trained FIR filtering result, (g) L filtering result, (h) Arakawa proposed filtering result.