Proceedings of the 5th WSEAS Int. Conf. on SIGNAL, SPEECH and IMAGE PROCESSING, Corfu, Greece, August 17-19, 2005 (pp270-275)

Improved Performance of Adaptive Length Recursive Weighted Median Filter in the presence of High Density of Positive and Negative Impulses in Images

O.UMA MAHESHWARI ., DR. D. EBENEZER.
Digital Signal Processing Laboratory,
Department of Electronics and Communication Engineering,
College of Engineering, Anna University, Chennai. 600 025
INDIA
www.annauniv.edu

Abstract: - The problem considered is the design of an algorithm employing adaptive length recursive weighted median filter for removal of positive and negative impulses simultaneously in images. The weights for this algorithm are selected by optimization technique and the window length is determined by width of impulsive noise present in the input sample. The proposed algorithm achieves better clarity and significantly less Mean Square Error (MSE) than adaptive length recursive weighted median filter which remove positive and negative impulses separately.

Keywords: - Adaptive length recursive weighted median filter, impulsive noise, MSE, median filter, recursive weighted median filter, weighted median filter

1. Introduction

Median filters are well known for their ability to remove impulse noise in images while preserving edges [6,7]. The median filter exhibits blurring for large window size and insufficient noise suppression for small window size. Over the last two decades, there has been a large improvement in the development of various types of median filters. It was proved that recursive weighted median filter produces better result [1]-[3] when compared to non recursive type median filters, but results were available only for fixed window length. In some window, there may not be any noise. In such case the filter will reduce the signal level, which causes blurring.

In 1988 Lin propose an adaptive length median filter, [5] which achieve a high degree of noise suppression and preserve image sharpness. Unlike certain non linear edge preserving adaptive algorithm based on edge detection this algorithm is based on deterministic properties of median filter. Lin's algorithm removes positive impulse noise first and then removes negative impulse noise. So this algorithm performs poorly for mixed impulse noise. A negative impulse can be incorrectly detected as positive impulse and vice versa. So false alarm exists. In 1995 Huang propose an algorithm that removes positive and negative impulses simultaneously. But still false alarm exists.

To overcome the limitations of the adaptive length median filter and recursive weighted median filter an efficient algorithm is proposed which perform median filtering by adaptive length and recursive weights by which a better performance can be achieved in the presence of high density of mixed impulse noise. This filter is named as Adaptive Length Recursive Weighted Median Filter (ALRWMF).

In this paper a comparative results have been produced for ALRWMF, which removes positive and negative impulses separately and simultaneously. From the results ALRWMF that remove positive and negative impulses simultaneously give better result in the presence of high-density impulsive noise and significantly less MSE.

2. Recursive Weighted Median Filter (RWMF)

In case of Recursive Weighted Median (RWM) filter, the weights are chosen for the given window length. The window length need to be selected based on the amount of noise on the original signal. The window length is calculated by Lin's algorithm. After calculating the window length, RWM operation is performed. The weights can be selected by optimisation techniques. In optimization process, steepest decent algorithm produces better result. It was proved that negative weights in RWM filter gives good mean square error compared to positive or zero valued weights.

Recursive filters are comparatively advantageous over non-recursive filters. With same number of operations, they achieve more than non-recursive filters. The goal may be, for example, steepest possible transition between pass band and stop band. Stability can be achieved by applying negative feedback in the recursive part. The success of the median filters in image processing is based on two intrinsic properties: edge preservation and efficient attenuation of the impulsive noise.

The general weighted median filter structure admitting positive and negative weights is given by

$$B = \text{MEDIAN}\,(\,|W_1| \Diamond \text{sgn}(W_1)\,A\,W_1,\ |W_2| \Diamond \text{sgn}(W_2)\,A_2, \ldots\ |W_n| \Diamond \text{sgn}(W_n)\,A\,W_n\,) \quad \ldots\ldots\ldots(1)$$

with W_i € R for i = 1, 2, 3, 4,… n and

$\Diamond$ is the replication operator defined as

$$W_i \Diamond A_i = (A_i\,A_i\,A_i\,A_i \ldots A_i)\ W_i \text{ times.}$$

Admitting only positive weights, weighted median filter has low pass characteristics [2,4]. A large number of engineering applications require band pass or high pass characteristics. To overcome this limitation, a weighted median filter admitting negative weights were introduced.

The properties of the negative weights [4] are:

1. The output sample is strictly one of the input samples.

2. A negative indicates that the corresponding sample cannot appear in the output, and other samples of the same magnitude have a reduced sample selection probability. Again, other equally valued samples may appear in the output, provided that the sum of the relevant weights is positive.

3. A negative weight can also be said to favour samples with extreme magnitudes. That is, the minimum or maximum of the sample set, if their weights are positive.

The optimal WM filtering with structural constraints is formulated as

$$\text{Minimize} \sum_{i=1}^{N} Wi^{2} \qquad \text{subject to}$$

$$\sum_{i=1}^{N} Wi = 1 \qquad \ldots(2)$$

The general structure of the recursive weighted median filter[1] is given as

$$Y(n) = \text{MEDIAN}\,(\,|A1| \Diamond \text{sgn}(A1)\ Y(n\text{-}l))^{N} + |Bk| \Diamond \text{sgn}(X(n\text{-}k)\,|^{M2}) \quad \ldots.(3)$$

3. Adaptive Length Recursive Weighted Median Filter (ALRWMF)

In ALRWMF, the width of the impulsive noise is calculated and then from that the length of the window is calculated. For the selected window, the weights are given by optimization technique and recursive weighted median operation is done. The block diagram for ALRWMF is shown in figure.1.

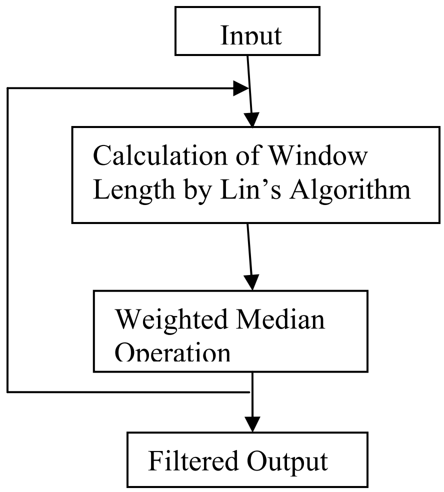

Fig.1 Block Diagram for ALRWMF

3.1 Algorithm for ALRWMF

Stage 1: Determination of the window size:

First the amount of the impulsive noise in the signal is determined and then length of the window is determined by using the Lin's algorithm.

The Lin's algorithm for Filter length decision is given by

Pixels inside window buffer:
$P_j = x(n+j-1)-x(n+j)$, for $j=1,2,3$;
$P_j = x(n+j+1)-x(n+j)$, for $j=-1,-2,-3$;

The conditions for the threshold values are as given in the [5].

Stage 2: Filtering operation:

After the determination of the window length, the recursive weighted median filtering operation is done. The algorithm for the RWM filtering is given as

1. Calculate the threshold

$$T_0 = (1/2)\left(\sum_{l=1}^{N} |A_l| + \sum_{k=-M1}^{M2} |B_k| \right)$$

Jointly sort the 'signed' past output samples sgn(Al)Y(n-l) and the 'signed' input observations sgn(Bk)X(n+k).

2. Sum the magnitudes of the weights corresponding to the sorted 'signed' samples beginning with the maximum and continuing down in the order.

3. If $2T_0$ is an even number, the output is the average between the signed sample whose weight magnitude causes the sum to become $\geq T_0$ and the next smaller signed sample; otherwise, the output is the signed sample whose weight causes the sum to become $\geq T_0$.

4. Results and Simulation

Using the above algorithm, the filtering operation is being done. After calculating the window length by Lin's algorithm, the RWM operation is performed by using the negative weights. And here it has been proved that the weights selected using the optimization technique give better result when compared to the other median algorithms. Fig2 and fig3 shows the result of ALRWMF. In these results fig2.c and fig4.c are the output of the ALRWMF which remove positive and negative impulse separately, has still some more impulses to be removed. But in fig2.d and fig4.d the output of the ALRWMF which remove positive and negative impulses simultaneously that impulse was further reduced to very minimum. It has been clearly shown in the fig3 and fig5, pixel distribution of any random row of the output image that fig3.c and fig5.c are the pixel distribution of ALRWMF which remove positive and negative impulse separately has some impulses that has been removed to very minimum in fig3.d and fig5.d the output of the ALRWMF which remove positive and negative impulses simultaneously. The mean square error and peak signal to noise ratio for the ALRWMF are calculated and tabulated in Table1 and table2. It is proved that the proposed design procedure gives better result than ALRWMF, which removes positive and negative impulses separately.

5. Conclusion

Generally, the RWM filters are designed only for the fixed window length. In the fixed window length, the noise may absent in some windows. Under this condition, the filtering operation is done for the original sample, which causes the blurring in the output. To overcome this, a filter is designed where the window length is determined by the width of the impulsive noise presented in the input sample. The performance of the proposed algorithm is proved to be appreciable compared to ALRWMF, which removes positive and negative impulses separately. By including recursive weights to adaptive length, we achieve excellent filtering of impulsive noise. The mean square error and peak signal to noise ratio for the ALRWMF, which removes positive and negative impulses separately and ALRWMF, which removes positive and negative impulses simultaneously, are calculated and tabulated. It is proved that the proposed design procedure gives better result than ALRWMF, which removes positive and negative impulses separately.

Table 1. Comparison-MSE

Noise variance	ALRWMF	ALRWMF-Simultaneous noise removal
0.1	83	92.55
0.2	147.02	147.89
0.3	335.57	245.33
0.4	941.39	594.12
0.5	2224	1350
0.6	4662	3148
0.7	8107	6267

Table 2. Comparison-PSNR in db

PSNR	ALRWMF	ALRWMF-Simultaneous noise removal
0.1	4.84	4.40
0.2	2.39	2.37
0.3	-1.19	0.17
0.4	-5.67	-3.67
0.5	-9.41	-7.24
0.6	-12.62	-10.95
0.7	-15.023	-13.91

Fig.2 Lena image (a) Input image (b) Image corrupted with variance 0.1 (c)ALRWMF(d)ALRWMF-Simultaneous noise removal

Proceedings of the 5th WSEAS Int. Conf. on SIGNAL, SPEECH and IMAGE PROCESSING, Corfu, Greece, August 17-19, 2005 (pp270-275)

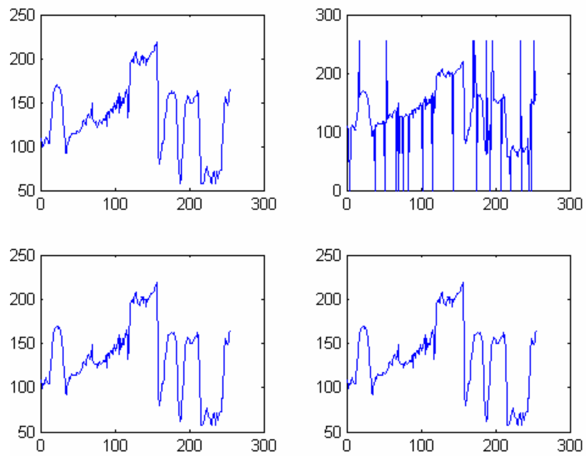

Fig. 3 Pixel distribution along 50th row (a) Input image (b) Image corrupted with variance 0.1 (c)ALRWMF(d) ALRWMF-Simultaneous noise removal

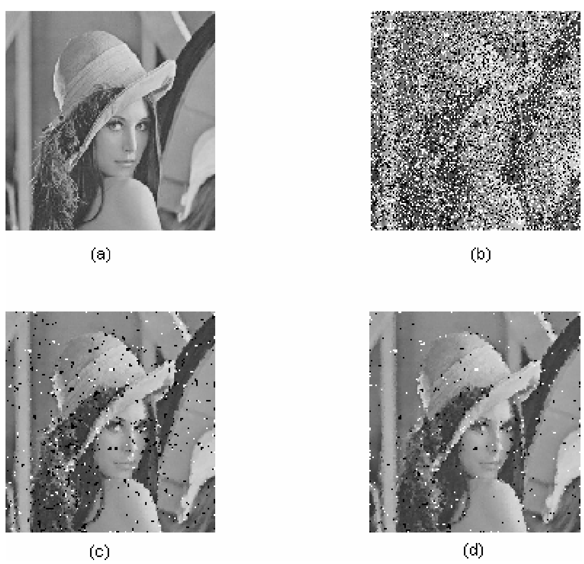

Fig.4 Lena image (a) Input image (b) Image corrupted with variance 0.4 (c)ALRWMF(d)ALRWMF-Simultaneous noise removal

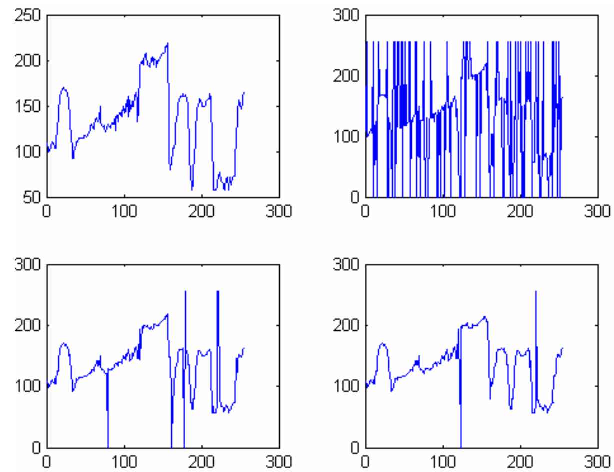

Fig.5 Pixel distribution along 50th row (a) Input image (b) Image corrupted with variance 0.4(c)ALRWMF(d)ALRWMF-Simultaneous noise removal

References:

[1] G. Arce, "A General Weighted Median Filter Structure Admitting Negative Weights", *IEEE Transaction. on Signal Processing.*, vol.46, Dec. 1998.

[2] G. Arce and J. Paredes, "Recursive Weighted Median Filters Admitting Negative Weights and Their Optimization", *IEEE Transaction. on Signal Processing.*, vol.48,nr.3, March 2000.

[3]O. Yli-Harja, J. Astola and Y. Neuvo, "Analysis of the Properties of Median and Weighted Median Filters Using Threshold Logic and Stack Decomposition", *IEEE Transaction Signal Processing.*, vol. 39,no. 2, pp. 395-410, Feb. 1991.

[4] O.Yli-Harja,Heikki Huttunen,Antti and Karen"Design of Recursive weighted median filters with negative weights" Signal Processing lab, Tampere University of Tech., Finland

[5] Ho-Ming LIN and Alan "Median filters with Adaptive Length", *IEEE transactions of the circuits and systems*,vol..35,no.6,June 1988.

[6]I.Pitas and A.N.Venetsanopoulos, *"Nonlinear digital filters Principles and applications"*, Kluwer academic publishers, Massachusetts, USA 1990

[7] Jakko Astola and Pauli,*"Fundamentals of nonlinear digital filtering" CRC Press,New York 2000.*

Biodata:

Mrs. O. Uma maheswari received her B.E and M.E Degree in Thiagarajar College of Engineering, Madurai in the year 1998 and 2000.Presently she is working as Lecturer in Department of Electronics and Communication Engineering, College of Engineering, Anna University, Chennai. She is doing her research in the area of non-linear digital filters.

Dr. D. Ebenezer is currently working as Assistant Professor in Department of Electronics and Communication Engineering, College of Engineering, Anna University, Chennai. His field of interest includes advanced digital signal processing and digital image processing. He is currently doing research in non-linear digital filter design.