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A New Detail Preserving Neural Median Filter with Reduced Streaking and False Alarm for Impulse Noise Suppression in Images

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Abstract: A new impulse detection algorithm is proposed which can successfully remove impulse noise from corrupted images while preserving image details; streaking is also reduced. The algorithm is an appropriate combination of impulse detection algorithm and a Recursive Weighted Median [RWM] filter whose weights are calculated by back propagation algorithm based on universal approximation theorem. The main advantage of the algorithm is that it detects both positive and negative impulses with high accuracy while reducing the probability of falsely detecting image details as impulses. Results show that the proposed algorithm is more effective in terms of visual appreciation, noise suppression and mean squared error performance compared with standard median filtering, general recursive weighted median filtering and adaptive length median filtering.

Key words: Recursive weighted median filter, back propagation algorithm, universal approximation theorem, impulsive noise, adaptive window, noise removal

INTRODUCTION

It is well known that linear filtering techniques are not effective in the removal of impulse noise with minimum signal distortion. Median based filters are the best-known and most widely used non-linear digital filters for removal of impulse noise[1]. General Median filters often exhibit blurring for large window sizes, or insufficient noise suppression for small window sizes. Many different techniques were proposed to detect impulse noise with reduced blurring and improved noise rejection, namely, weighted median filters[2], recursive weighted median filters[3-5], median filter with adaptive length[6-8]. Weights are selected based on optimization techniques or threshold decomposition technique. These techniques are generally complex and often damage original samples while suppressing noise. This study proposes an RWM filter whose weights are calculated by a back propagation technique based on universal algorithm. It is shown that the proposed algorithm produces better results qualitatively and quantitatively than standard median filters, general RWM filters and adaptive length median filters.

Generally adaptive length median filter algorithm is derived from deterministic, statistical properties of the median filter. Lin[7] proposed an adaptive window size median filter algorithm, which can achieve a high degree of noise suppression while preserving image sharpness. Unlike certain nonlinear edge preserving adaptive algorithms[4] based on edge detection, Lin's algorithm is based on impulse noise detection. The positive and negative impulses are removed separately. The adaptive scheme exhibits a significant improvement over median filters, general weighted median filters and recursive weighted median filters. However, the problem of false alarm exists. A negative impulse noise can be incorrectly detected as positive impulse noise and vice versa. As mentioned in[7], the algorithm also performs poorly for mixed impulse noise. In order to overcome these problems, this algorithm has been modified by Huang[6]. The modified algorithm takes both positive and negative impulses in account and removes them simultaneously. The problem of false alarm still exists.

In this study a more efficient algorithm is derived for the suppression of high density impulse noises. The algorithm simultaneously removes both positive and negative impulses; it reduces streaking and also acts as edge detector; the proposed filter performs better in removing high density impulsive noise while preserving fine details and also considerably reduces false alarm.

Recursive weighted median filter: One of the main problems in the design of linear recursive filters is stability under the Bounded-Input Bounded-Output (BIBO) criterion, which establishes certain constrains on the filter feedback coefficients. Unlike linear filters, recursive WM filters are guaranteed to be stable under the BIBO criterion. Earlier researchers suggested many

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new algorithms for the determination of the weights of RWM filters, which are more complex to compute. Problem of optimal weighted median filter with structural constraints can be formulated as a non linear programming problem in general. However, its high computational complexity and poor performance due to its non convex nature prohibit the available RWM filters from practical applications.

Selection of weights for RWM filter using back propagation by universal approximation theorem: The weights for the RWM filter are calculated by back propagation algorithm. A multilayer perceptron trained with the back propagation algorithm provides a powerful device for approximating a nonlinear input-output mapping of a general nature. The Back propagation algorithm has lower mean square error and recognition rate is higher at the output stage as given in Fig 1. Hence the weights calculated by back propagation algorithm will be approximately useful for the RWM filtering operation. The weights used in BP network are approximated according to number of samples present in the RWM filtering windows. Each weight in the back propagation algorithm is calculated by adaptive learning rate techniques[9,10]. The number of hidden layers and the output layers are determined by the universal approximation theorem[1,11] so that the number of weights needed in the RWM filters is equal to the window size. Suppose the window size is 3×3, then the number of weights required for RWM filtering is 9. By using the universal approximation theorem, the number of hidden layers and output layers are adjusted to the number of weights required for the filtering process. The theorem states that a single hidden layer is sufficient for a multilayer perceptron to compute a uniform ε approximation into a given training set represented by the sets of inputs x_1, $x_2 \ldots x_{n0}$ and desired output denoted by $f(x_1, x2 \ldots x_{n0})$. Similarly, the weights in back propagation are adjusted to the number of weights required in the RWM filtering operation. The weight is calculated by using below equations:

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

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

The weights for the RWM filters are calculated by threshold decomposition techniques, optimization techniques, LMS, LMA optimization[2,3,5].

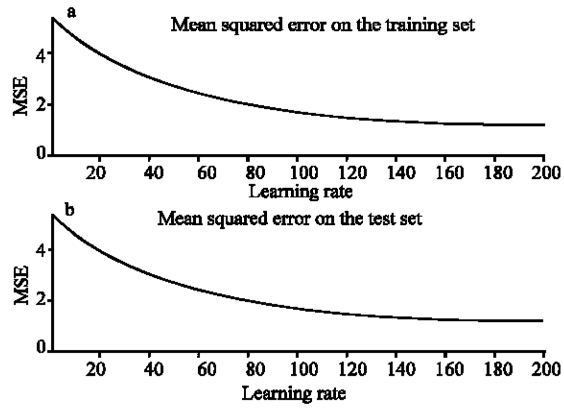

Fig. 1: (a) Table with least MSE of Training set and Test set. and gradient (b) graph of MSE on Training set and Test set with different iterations

$$\frac{\partial E^{**}}{\partial w_{ij}}(n)=\frac{\partial E^{*}}{\partial w_{ij}}(n)+\text{decay}*w_{ij}(n)$$

$$\Delta w_{ij}(n)=-\varepsilon_{ij}(n)*\frac{\partial E^{**}}{\partial w_{ij}}(n)+\alpha_{ij}(n)*\Delta w_{ij}(n-1)$$

$$\alpha_{max}=1.75$$
$$\varepsilon_0=0.55$$
$$\text{Decay}=0.0004$$

$$\tilde{\alpha}_{ij}(n)=\frac{\dfrac{\partial E^{**}}{\partial w_{ij}}(n)}{\dfrac{\partial E^{**}}{\partial w_{ij}}(n-1)-\dfrac{\partial E^{**}}{\partial w_{ij}}(n)}$$

$$\tilde{\alpha}_{ij}(n)=\alpha_{max},\quad \text{if } \tilde{\alpha}_{ij}(n)>\text{infinite}$$
$$\text{V } \tilde{\alpha}_{ij}(n)>\alpha\,\text{max}$$
$$\text{V } \tilde{\alpha}_{ij}(n)*\Delta w_{ij}(n-1)*\frac{\partial E^{**}}{\partial w_{ij}}(n)>0.0$$
$$\alpha_{ij}(n)=\tilde{\alpha}_{ij}(n),\quad \text{else}$$

MSE training set	MSE test set	|G|
0.244223	0.242637	5.4720
0.210788	0.209377	5.0726
0.181143	0.179914	4.6578
0.156248	0.155191	4.2607
0.135454	0.134554	3.8912

New algorithm for adaptive RWM filter: The algorithm is derived from deterministic properties of the median filters instead of calculating local statistics of pixels. If the window length is (2n + 1) the RWM filter can remove 'n' impulses. The algorithm should detect the width of the impulse noise and then apply an RWM filter having appropriate length. The block diagram description of the proposed algorithm is shown in Fig. 2.

Step by step operation of the new algorithm:

X_{n-3}	X_{n-2}	X_{n-1}	X_n	X_{n+1}	X_{n+2}	X_{n+3}

1. Select the maximum window length, L=7;
2. Read pixels values from the window.
3. Find the maximum and minimum pixel values of the window.
4. If X_n=max or X_n=min
   then
   X_n is corrupted pixel
   Go to next step
   Else, X_n is uncorrupted pixel;
   X_n is the output sample.
5. Find 'n' where 'n' is the number of impulses (max and min) present inside the window. Depending upon the value of n (n<=3) the window size is taken as (2n+1)
6. Apply Recursive Weighted median filter operation and calculate Weights by Back propagation algorithm using Universal Approximation theorem.

The algorithm for RWM filter is

- Calculate the threshold

$$T_0 = (1/2)\left(\sum_{i=1}^{N}|Al| + \sum_{k=0}^{M}|Bk|\right)$$

- Jointly sort the 'signed' past output samples sgn(Al)Y(n-l) and the 'signed' input observations sgn(Bk)X(n+k).
- Sum the magnitudes of the weights corresponding to the sorted 'signed' samples beginning with the maximum and continuing down in the order.
- If $2T_0$ is an even number, the output I 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 $\geq T_0$.

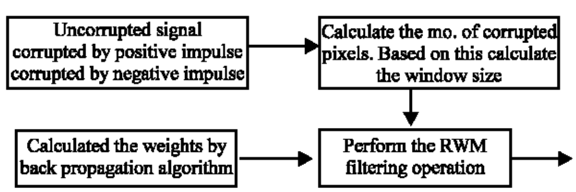

Fig. 2: Block diagram of the proposed algorithm

RESULTS

Among the commonly tested 256-by-256 8 bit gray scale images, the Lena image with homogeneous region and the high activity are selected for processing the proposed algorithm. In the simulations, images will be corrupted by "salt"(with value 255) and "pepper"(with value 0) noise with equal probability. Also a wide range of noise levels varying from 10% to 60% are selected. The restoration performances are quantitatively measured by mean square error

$$MSE = tN\sum_{j=0}^{N-1}(X_j - X_j)^2$$

Where Xj is the reconstructed image, ~~X~~j is the original image and N is the size of the image. By using the proposed algorithm, the window size is adjusted so that the detection and removal of impulsive noise of the filter is better. The weight calculation for the RWM filter is adjusted by the universal approximation theorem. The learning rate for the back propagation is adaptive to the each weight calculated. Figure 3 and 4 show the denoising results of different filters. Figure 3a is Lena image corrupted with 25% salt and pepper noise and Fig. 4a is the Lena image corrupted with 50% salt and pepper noise. Figure 3b and 3b are the median filtered images which are not clear; the high frequency noises are found at the edges, Fig. 3c and 4c show the results of General Weighted median filter using optimization technique for weight calculations. The optimization techniques have many structural constraints and also not used for reducing the streaking property of the image. Figure 3d and 4d are the results of adaptive RWM filter based on lin's algorithm .In lin's algorithm still some false alarms exist at the output for high density noises. Figure 3e and 4e are the results of the proposed adaptive RWM filter using back propagation algorithm. The new algorithm produces better result by reducing the streaking and the high frequency noises at the edges . Perceptually, we observe that proposed algorithm is capable of removing streaks very efficiently and at the same time preserves detail information and features of the images. In addition, there is no blurring of images even at 50% of noise level. False alarm generally implies selection of black pixels as white pixels and vice versa. False alarm can be observed in Fig. 3 [b-e] and 4 [b-e] Absence of false alarm can be noticed in Figs 3f and 4f, which are the results of the proposed algorithm. Figure 5 shows the comparison graph of different filters including the new algorithm.

Fig. 3: Denoising results of different filters. (a) Original image (b) corrupted Lena image with 25% salt and pepper noise (c) median filter image (d) Gen. Weighted median filter using optimization. (e) Adaptive (lin's) RWM filter (f) new adaptive RWM filter using back propagation algorithm

Fig. 4: Denoising results of different filters. (a) Original image (b)corrupted Lena image with 50% salt and pepper noise (c) median filter image (d) Gen. Weighted median filter using optimization. (e) adaptive(lin's) RWM filter (f) new adaptive RWM filter using back propagation algorithm

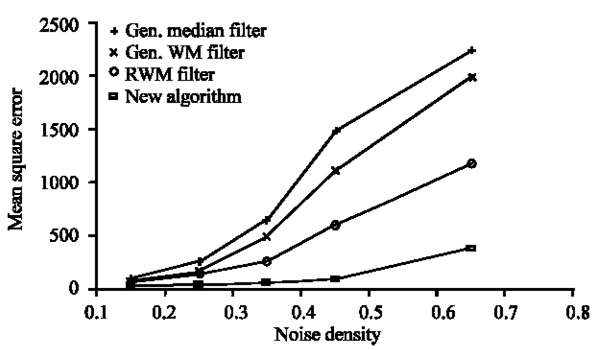

Fig. 5: Mean Square Error for the Lena image at various noise levels for different algorithms

CONCLUSION

In this study a neural based adaptive, detail preserving algorithm for image restoration is proposed. The proposed RWM filter removes salt (positive) and pepper (negative) noises simultaneously. It is shown that even at a higher noise level (<= 50%), the texture, details and edges are preserved; streaking and false alarm are also reduced. Further work is on to improve these results by using different noise detectors and regularization functional that are tailored to different types of noises, such as the random-valued noises or impulse and Gaussian noises.

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