A NEURAL LUM SMOOTHER

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Abstract

In this paper a design of neural LUM smoother is presented. The LUM smoother distinguishes by a number of smoothing characteristics done by the filter parameter. However, the tuning parameter for smoothing is fixed for whole image. The new method realises adaptive control of the level of smoothing by neural networks. The well-known and very popular backpropagation algorithm is used. The analysis of the new method is presented. Performance of the proposed methods is evaluated through subjective and objective criteria and compared with the traditional LUM smoother.

Keywords

LUM filters, neural networks, backpropagation, impulsive noise, smoothing, adaptive control

1. Introduction

The LUM smoothers, a subclass of a lower-upper-middle (LUM) filters [2-4] is designed for impulsive noise smoothing and outliers rejection. The name of these filters follows since a lower- and upper-order statistics are compared with the middle sample in the filter window to determine the output. The LUM smoother can take on a range of smoothing characteristics. The level of smoothing done by LUM smoother can range from no smoothing to that of the median. Thus, by desirable level of smoothing can be achieved the best balance between noise suppression and detail preservation.

However, the traditional approach processes a whole image with the fixed level of smoothing. Thus, the excessive or insufficient smoothing can be performed. Some adaptive methods were introduced [3,10]. In this paper, the problem of adaptive control is solved by an neural network. Thus, the appropriate smoothing is determined by the output of neural network.

The remainder of this paper is organised as follows. The used noise and test images are described in the next section. In Section 3, the LUM smoother is defined. The new method is presented in the next section, where the two approaches are introduced. Properties of the methods are summarised in the conclusion, where the directions of next research are mentioned.

2. Noise Description

Various test images were used to demonstrate the performance of the proposed methods, but the objective results are presented for images Lena and Bridge, only. The test images have a resolution of 256 x 256 pixels with 8 bits/pixel grey-scale quantization. Image Bridge contains a number of problem areas (high frequency elements, e.g. edges, image details). Image Lena Fig.2a is more easily (more monotonous fields) and in this case the better results are expected. Two types of variable impulsive noise were used (5% and 10%). Fig.2b shows the image Lena corrupted by the I10 noise. For objective comparison the well-known mean absolute error (MAE) and mean square error (MSE) are used.

Table 1 Evaluating of distorted images

Noise	5%		10%	
Image	*MAE*	*MSE*	*MAE*	*MSE*
Lena	3.540	374.3	7.018	759.0
Bridge	3.568	398.9	7.221	807.6

3. LUM Smoother

A structure of LUM smoother is based on tuning parameter k for the smoothing. Varying this parameter changes the level of the smoothing from no smoothing (i.e. identity filter for k=1, where $y^*=x^*$) to the maximum amount of smoothing (i.e. median, $k=(N+1)/2$).

Thus, the smoothing function is created by a simply comparing of processed sample x^* to the lower- and upper-order statistics. If x^* lies in a range formed by these order statistics it is not modified. If x^* lies outside this range it is replaced by a sample that lies closer to the median.

The output of LUM smoother is given by

$$y^* = med\{x_{(k)}, x^*, x_{(N-k+1)}\}, \quad (1)$$

where y^* is an estimate of the processed sample x^*, $x_{(k)}$ and $x_{(N-k+1)}$ are lower and upper order statistics of the ordered set. The k ($1 \leq k \leq (N+1)/2$) is the tuning parameter for smoothing.

Thus, the LUM smoother achieves the best balance between noise smoothing and signal-detail preservation. However, the excessive or insufficient smoothing can be performed by the LUM smoother with fixed level of smoothing. The typical example of excessive smoothing is shown in the Fig.2c. The blurring is nearly more objectionable than the original noise. On the other hand, the Fig.2d shows the insufficient smoothing case for LUM with k=3, where the presence of some impulses is observed.

Table 2 LUM smoother - image Lena

Noise	5%		10%	
Image	*MAE*	*MSE*	*MAE*	*MSE*
Identity	3.540	374.3	7.018	759.1
LUM k=2	**1.443**	73.3	3.051	202.9
LUM k=3	1.640	**35.4**	**2.254**	64.3
LUM k=4	2.711	48.3	3.059	**59.6**
Median	4.563	85.4	4.888	94.3

Table 3 LUM smoother - image Bridge

Noise	5%		10%	
Image	*MAE*	*MSE*	*MAE*	*MSE*
Identity	3.568	398.4	7.221	807.6
LUM k=2	**1.936**	96.5	3.836	245.5
LUM k=3	2.631	**59.4**	**3.561**	**108.4**
LUM k=4	4.552	88.3	5.097	112.6
Median	7.644	157.2	8.042	173.7

From Table 2-3 is evident, that the blurring introduced by median multiplies deviation from origin. Through this result, it can be noticed that the median filter smoothes out the noise as well as the image details.

On the other hand, the traditional LUM smoother for k=2,3,4 achieves the best balance between noise smoothing and details preservation. However, the best results can be obtained by adaptive change of level of smoothing. In this paper, the adaptive control is realised by neural network, where the well-known backpropagation algorithm was used.

4. Neural LUM Smoother

The neural LUM smoother (Fig.1), the proposed method is based on the traditional LUM smoother controlled by neural network (NN) [8,9]. Two approaches are possible.

The first one is based on LUM smoother with full control by the neural network. In the first step, the outputs of LUM smoother for each possible tuning parameter are computed. Clearly, for the 3x3 operation window, the five outputs are obtained (1). Next, the normalised outputs of LUM smoother are supplied to the neural network. The denormalised output of neural network corresponding to the output of neural LUM smoother. The neural network consists of four layers (5-20-10-1 neurons).

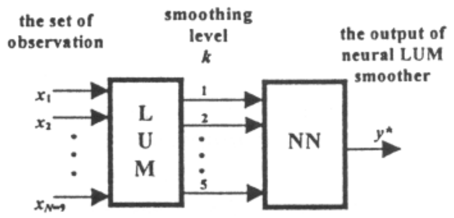

Fig.1 3x3 neural LUM smoother

The results obtained by this method are summarised in Table 4. It is evident that the neural LUM smoother (Fig.2e) performed the better approximation of origin images than the traditional LUM smoother. In addition, the excellent MSE value was obtained by this method. The worse results of the image Bridge were caused by the training of neural network on the image Lena.

Table 4 Full neural LUM smoother

Noise	5%		10%	
Image	*MAE*	*MSE*	*MAE*	*MSE*
Lena	1.413	21.4	1.810	31.3
Bridge	2.853	52.1	3.505	76.6

The second approach is more composite. The identical filter is determined by impulse detector [1,5-7,11] and spare outputs of LUM filter (corresponding to the level of smoothing k=2,3,...,5) are on the input of neural network. The neural network consists of four layers (4-15-10-1). The sigmoidal activation function was used like the first approach. The neural network was trained on the image Lena, again. The obtained image is shown in Fig.2f. These results (Table 5) are characterised by the topping detail preservation (MAE) done by the impulse detector. The very efficient LUMsm detector [4,11] was used. The noise suppression (MSE) done by the neural network is excellent performed, too.

Table 5 Neural LUM smoother with impulse detector

Noise	5%		10%	
Image	*MAE*	*MSE*	*MAE*	*MSE*
Lena	0.915	26.3	1.371	37.0
Bridge	1.860	55.7	2.593	80.9

5. Conclusion

A new method, the neural LUM smoother has been developed, presented and compared to the well-known median and the traditional LUM smoothing filters. The proposed method has excellent performance of noise reduction in the environments corrupted by an impulsive noise with variable random value.

The traditional LUM smoother performs the noise reduction with the fixed level of smoothing for the whole image. Thus, the excessive or insufficient smoothing can be performed.

In the proposed methods, the output value is determined by the neural network. Two approaches were developed. The first one, all possible outputs of LUM smoother are supplied to the network. In the second approach, the identical filter is determined by LUMsm impulse detector and spare outputs of LUM filter are on the input of neural network. Both approaches have excellent properties of the noise suppression and the detail preservation.

Future work will concentrate on the expansion of the LUM smoother to the color image processing.

(a) (b) (c)

(d) (e) (f)

Fig.2 (a) Original image (b) Noisy image (10% impulsive noise) (c) Median filter (d) LUM k=3 (e) New method – neural LUM smoother (f) New method –neural LUM smoother with impulse detector

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