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A MULTIPLE-OUTPUT NONLINEAR FILTER FOR IMAGE DENOISING

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Abstract: A multiple-output nonlinear filter for impulse noise removal from image data is presented. The proposed technique is based on the subsequent activation of two recursive filtering algorithms that operate on different subsets of input data. As a result, two pixel values are updated at each processing step producing a very effective cancellation of noise pulses. Impulse noise removal is based on rank ordered filtering. A nonlinear mechanism for error correction is also provided in order to avoid detail blur. Validation of the method is carried out by evaluating the quality of the filtered data with respect to two conflicting performance indexes: effectiveness of the noise cancellation and accuracy of detail preservation. Experimental results show that the proposed approach performs significantly better than well-known nonlinear methods in the literature including state-of-the-art operators.
Keywords: measurement of electrical quantities, noise cancellation.

1 INTRODUCTION

Images have become a very important class of data for instrumentation and measurement [1,2]. Hence, the development of appropriate techniques for image denoising plays a very relevant role in digital processing of this kind of measurement information. As is known, the quality of image data is often degraded by impulse noise caused by noisy sensors and/or channel transmission errors. Nonlinear approaches have been shown to be very attractive in addressing this issue [3]. Indeed, a variety of nonlinear filters have been proposed encompassing classical methods and emerging technologies as well [4,5]. In this work a nonlinear filter based on a multiple-output architecture is presented. The new filter includes two serial sub-units that recursively process different groups of rank ordered data. Key features of the proposed approach are the ability to deal with highly corrupted images, few parameter settings and better performance than state-of-the-art filters. This paper is organized as follows. Sect.2 describes the multiple-output structure, Sect.3 analyzes the filtering action, Sect.4 focuses on the validation of the method and, finally, Sect.5 reports conclusions.

2 THE MULTIPLE-OUTPUT ARCHITECTURE

Let us suppose we deal with digitized images having L gray levels. Let $x(\mathbf{m})$ be the pixel luminance at location $\mathbf{m}=[m_1,m_2]$ in the noisy image. Let $x(\mathbf{n})$ be the pixel luminance at location $\mathbf{n}=[n_1,n_2]$, where $n_1=m_1+1$ and $n_2=m_2+1$. The filter operates on a 4x4 pixel window as shown in Fig.1. The window scans the input image from the upper-left corner to the bottom-right corner. Let the pixels in the window be grouped into three subsets A, B and C as depicted in the same figure.

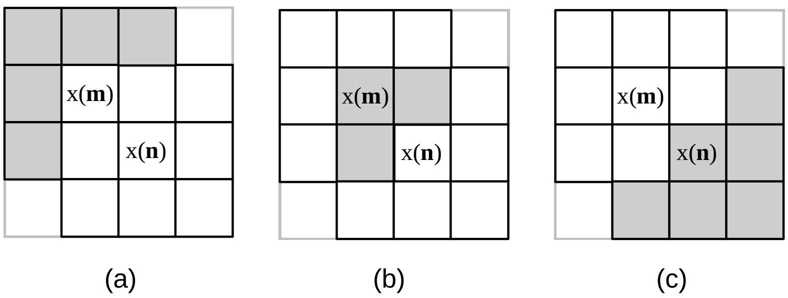

Fig.1 - Definition of pixel subsets in the window: (a) subset A, (b) subset B, (c) subset C.

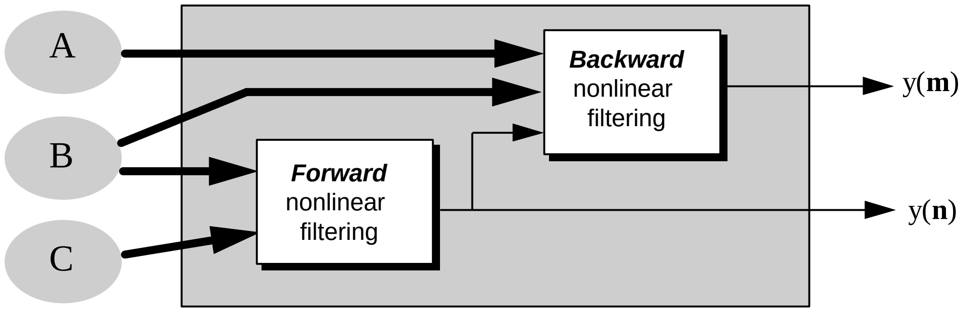

Fig.2 - Multiple-output filtering architecture.

These subsets constitute the inputs of the filter according to the scheme represented in Fig.2. The filter includes two sub-units that have the same structure and size. Let us focus on the sub-unit devoted to "forward" filtering. As a first step, the pixel values in the neighborhood of $x(\mathbf{n})$ are ordered by rank, i.e. arranged in ascending order of magnitude:

$$x_1 \le x_2 \le x_3 \le \ldots \le x_8. \tag{1}$$

Let us consider the pair of ordered values: $x_a = x_4$ and $x_b = x_5$. Then, the output $y(\mathbf{n})$ is evaluated as follows:

$$y(\mathbf{n}) = x(\mathbf{n}) + \alpha(x_a, x) - \beta(x_b, x) \tag{2}$$

where and α and β represent nonlinear mappings that aim at estimating the noise ($0 \le \alpha \le L-1$, $0 \le \beta \le L-1$). These mappings are defined by the following relationships:

$$\alpha(x_a, x) = \begin{cases} x_a - x & x_a - x > p_1 \\ \dfrac{p_1}{p_1 - \gamma}(x_a - x - \gamma) & \gamma < x_a - x \le p_1 \\ 0 & x_a - x \le \gamma \end{cases} \tag{3}$$

$$\beta(x_b, x) = \begin{cases} x - x_b & x - x_b > p_1 \\ \dfrac{p_1}{p_1 - \gamma}(x - x_b - \gamma) & \gamma < x - x_b \le p_1 \\ 0 & x - x_b \le \gamma \end{cases} \tag{4}$$

$$\gamma(\delta) = \begin{cases} p_2 & \delta \le p_3 \\ p_2\left[1 - 2\dfrac{(\delta - p_3)^2}{p_4^2}\right] & p_3 < \delta \le p_3 + \dfrac{p_4}{2} \\ 2p_2\left[1 - \dfrac{\delta - p_3}{p_4}\right]^2 & p_3 + \dfrac{p_4}{2} < \delta \le p_3 + p_4 \\ 0 & \delta > p_3 + p_4 \end{cases} \tag{5}$$

where $\delta = \left|x - \frac{L}{2}\right|$ and p_1, p_2, p_3 and p_4 are parameters ($p_1 > p_2$). As above mentioned, the filtering is recursive, i.e. the new value $y(\mathbf{n})$ is immediately assigned to $x(\mathbf{n})$ and re-used for further processing.

The operation performed by the second sub-unit devoted to "backward" filtering is very similar to the previous one. The output value y(**m**) is immediately assigned to x(**m**). Since the processing is recursive, the "backward" filtering sub-unit operates on data that have already been processed by the "forward" filtering sub-unit. As a result, noise pulses (possibly) still present in the image data can be eliminated.

3 ANALYSIS OF THE FILTERING ACTION

The accuracy of the filtering action depends on both cancellation of noise pulses and preservation of image details. The basic mechanism for the removal of noise operates as follows. As a first step, let γ be a constant value. The detection of a negative noise pulse is performed by considering the difference x_a-x (see eq.(3)). It should be observed that the rank-ordered element x_a plays the role of a first estimate of the noise-free luminance value. Three cases are considered. If $x_a - x > p_1$, a negative noise pulse is very likely to occur. Then a full correction is performed. Since $\beta=0$ and $\alpha=x_a-x$, relation (2) yields: $y=x_a$. If $\gamma<x_a-x\leq p_1$, either a negative noise pulse or an image detail could occur. According to (3), the noise correction is gradually reduced as the difference x_a-x approaches the lower limit γ. Finally, if $x_a-x>\gamma$, no noise pulse should be present. Hence, no correction is performed in order not to blur the image details. The detection of a positive noise pulse is a very similar process that takes into consideration the difference x-x_b (see eq.(4)). The detail-preserving mechanism can easily be controlled by gradually varying γ according to relation (5): $0\leq\gamma\leq p_2$. In particular, when $\gamma=0$, full correction is enabled, regardless of the estimated amplitude of the noise. This behavior can be exploited to reduce the filtering errors caused by the presence of small-amplitude noise pulses in the bright and dark areas of the image. The choice of parameter values is not a critical process. Good results can generally be obtained with the following settings: $80<p_1<190$, $p_2>15$.

4 VALIDATION OF THE METHOD

In order to analyze the performance of the method, different image data have been considered. For this purpose we have chosen some well-known 256×256 test pictures having 256 gray levels: "Lena" and "Boats" (Fig.3).

(a)

(b)

Fig.3 – Test images: (a) “Lena”, (b) “Boats”.

These images have been corrupted by superimposing impulse noise with probability 0.35. For a comparison, the results yielded by the 3×3 median filter, the 5×5 median filter [3] and the very powerful SD-ROM technique [6] have been considered. The overall performance of the proposed method and other techniques has been evaluated by resorting to the mean square error (MSE) of the processed images with respect to the uncorrupted data. The corresponding MSE values are reported in the second column of Tab.I and II. It is known, however, that the MSE value by itself is not sufficient to represent the visual quality of an image. In order to highlight the different behavior with respect to noise cancellation and detail preservation, the MSE evaluation has been split into two different components called MSE_{nc} and MSE_{dp}. The former is evaluated into the class of pixels that have been corrupted by noise pulses, the latter is evaluated in the class of pixels that have not been corrupted by noise. These components are defined by the following relationships:

$$MSE_{nc} = \frac{1}{N_1} \sum_{\mathbf{k} \in C_1} \left(y(\mathbf{k}) - z(\mathbf{k}) \right)^2 \tag{6}$$

$$MSE_{dp} = \frac{1}{N_2} \sum_{\mathbf{k} \in C_2} \left(y(\mathbf{k}) - z(\mathbf{k}) \right)^2 \tag{7}$$

where $z(\mathbf{k})$ is the pixel luminance at location $\mathbf{k}=[k_1,k_2]$ in the noise-free image, C_1 is the set of coordinates that denotes the group of N_1 pixels corrupted by impulse noise ($x(\mathbf{k}) \neq z(\mathbf{k})$) and C_2 is the set of coordinates that denotes the group of N_2 uncorrupted pixels ($x(\mathbf{k})=z(\mathbf{k})$) in the noisy image. According to (6-7), the overall MSE is given by:

$$MSE = \frac{N_1}{N} MSE_{nc} + \frac{N_2}{N} MSE_{dp} \tag{8}$$

where $N=N_1+N_2$. It should be observed that the MSE_{nc} value addresses corrupted pixels only. Hence, it characterizes the ability to remove noise pulses (noise cancellation). On the contrary, the MSE_{dp} value deals with the class of uncorrupted pixels. Thus, it characterizes the ability to avoid detail blur (detail preservation). The list of MSE_{nc} e MSE_{dp} values are reported Tab.I and II. The superior performance of the proposed method is apparent. A sample of the processed images is also depicted in Figs.4-5.

	MSE	MSE_{nc}	MSE_{dp}
3x3 median filter	571.3	1051.6	319.9
5x5 median filter	188.7	220.0	172.0
SD-ROM filter	167.2	372.2	58.3
proposed filter	69.6	199.2	0.6

Tab. I - MSE values ("Lena" image).

	MSE	MSE_{nc}	MSE_{dp}
3x3 median filter	676.7	1086.3	405.9
5x5 median filter	314.4	359.0	290.7
SD-ROM filter	206.3	420.9	92.2
proposed filter	107.0	308.1	0.1

Tab. II - MSE values ("Boats" image).

(a) (b)

Fig.4 – (a) “Lena” corrupted by impulse noise with probability 0.35,
(b) result of the application of the proposed filter.

(a) (b)

Fig.5 – (a) result yielded by the 5×5 median filter,
(b) result yielded by the SD-ROM technique.

5 CONCLUSIONS

A new method for impulse noise removal from image data has been presented. The multiple-output structure of the proposed filter is based on subsequent activation of two recursive sub-units that operate on different groups of rank ordered data. A nonlinear algorithm aims at preventing detail blur during noise removal. As a result, restoration of highly corrupted data can effectively be performed. Validation of the method has been carried out by splitting the filtering errors into two different components: errors due to incomplete removal of noise pulses and errors caused by detail blur during the filtering action. Experimental results have been shown that the proposed multiple-output nonlinear filter performs significantly better than other nonlinear techniques in the literature including state-of-the-art methods.

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