NEAREST NEIGHBOUR MULTICHANNEL FILTERS FOR IMAGE PROCESSING

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ABSTRACT

This paper addresses the problem of noise attenuation for multichannel data. Two multichannel filters which utilize adaptively determined data dependent coefficients are introduced. The special case of colour image processing is studied as an important example of multichannel signal processing. Simulation results indicate that the new filters are computationally attractive and have excellent performance.

1 INTRODUCTION

Vector processing based on order statistics *(OS)* is one of the most effective methods available to filter out noise in multichannel signals, such as colour images [1]. In the multichannel case however, the concept of vector ordering has more than one interpretation and the centermost vector inside a filter window can be defined in more than one way depending on the distance function selected to measure dissimilarity among multivariate vectors[2]. A number of multichannel filters, such as the Vector Median Filter (*VMF*) [3], the Vector Directional Filter (*VDF*) [4] and the Fuzzy Vector Directional Filter (*FVDF*) [5] which utilize correlation among the multivariate vectors using distance measures, have been proposed. In this paper, two new adaptive nearest-neighbour filters based on ordering of multichannel vectors are introduced. The new filters can be seen as generalization of widely used multichannel nonlinear filters.

The rest of the paper is organized as follows. In section 2, two multichannel filters are introduced and analyzed. Motivation and implementation details are discussed in this section. The application of the new filters to colour image processing is considered in section 3. Finally, section 4 summarizes our conclusions.

2 MULTICHANNEL FILTERS FOR IMAGE PROCESSING

2.1 Adaptive Nearest Neighbour Multichannel Filter

The first filter discussed in this paper is a nearest neighbour adaptive filter with coefficients determined through distance transformations on a processing window. Let $y(x) : Z^l \rightarrow Z^m$, represent a multichannel signal and let $W \in Z^l$ be a window of finite size n (filter length). The noisy vectors inside the window W are denoted as x_j, $j = 1, 2, ..., n$. The filter structure is defined as a weighted average of all input vectors inside the window W. Therefore, the output at the window center is:

$$\hat{y} = \frac{\sum_{j=1}^{n} w_j x_j}{\sum_{j=1}^{n} w_j}. \quad (1)$$

Each one of the weights is a function of the distance between the vector under consideration and all other vectors inside the filter window. In this paper, a neighbour weighting function is utilized to assign weights to each one of the vector inputs. A function similar to the *k-NN* rule discussed in [6] is used to regulate the contribution of the vector located at pixel i is defined in the following way:

$$w_i = \frac{(d_{(n)} - d_{(i)})}{(d_{(n)} - d_{(1)})}, \quad (2)$$

where $d_{(n)}$ is the maximum distance in the filtering window, measured using an appropriate distance criterion, and $d_{(1)}$ is the minimum distance, which is associated with the centermost vector inside the window. The value of the weightin (2), expresses the degree to which the vector at point i is close to the ideal, centermost vector, and far away from the worst value, the outer rank. Both the optimal rank position $d_{(1)}$ and the worst rank $d_{(n)}$ are occupied by at least one of the vectors under consideration. It is evident that the outcome of the filter depends on the choice of the distance criterion selected as measure of dissimilarity. Since our primary objective is to apply the new filter to colour images, the so called *vector angle criterion* is used to calculate distances among the colour vectors [4]. This criterion considers the angle between two vectors as their distance. A scalar quantity

$$d_i = \sum_{j=1}^{n} A(x_i, x_j), \quad (3)$$

$$A(x_i, x_j) = cos^{-1}\left(\frac{x_i x_j^t}{|x_i||x_j|}\right), \quad (4)$$

is the distance associated with the noisy vector x_i inside the processing window of length n. An ordering of the d_i's

$$d_{(1)} \leq d_{(2)} \leq ... \leq d_{(n)}, \tag{5}$$

implies the same ordering to the corresponding x_i's:

$$x_{(1)} \leq x_{(2)} \leq ... \leq x_{(n)}. \tag{6}$$

The adaptive nearest neighbour multichannel filter (hereafter *ANNF*) performs smoothing of all vectors which are from the same region as the vector at the window center. It is reasonable to make the weights proportional to the difference, in terms of a distance measure, between a given vector and its neighbors inside the operational window. At edges, or in areas with high details, the filter only smooths pixels on the same side of the edge as the centermost vector, since vectors with relatively large distance values will be assigned smaller weights and will contribute less to the final filter output. Thus, edge or line detection operations, prior to filtering, can be avoided with considerable savings in terms of computational effort.

2.2 Double-window Adaptive Nearest Neighbour Multichannel Filter

In the *ANNF* filter proposed in the previous section the weights which regulate the contribution of each one of the nearest neighbours are determined using distance criteria among all the different vectors inside the processing window. In this section, a different form of the multichannel filter is introduced. The new filter has the same structure of (1) and its weights are determined adaptively using (2). In the new filter, however, the distance $d_{(i)}$ associated with the vector x_i inside the processing window is defined as the distance of this vector from a reference vector $\hat{x}_m$. Therefore, a scalar quantity

$$d_i = cos^{-1}(\frac{\hat{x}_m x_i^t}{|\hat{x}_m||x_i|}), \tag{7}$$

is the distance associated with the noisy vector x_i inside the processing window of length n, with reference point $\hat{x}_m$. As in the previous section an ordering of the new d_i's according to (5) implies the same ordering to the corresponding x_i's.

This form of ordering multidimensional vector signals is known as *R-ordering* [1]. Using the *R-ordering* scheme, ordering of vectors is reduced to one-dimensional (scalar) ordering. It is obvious that the performance of the *R-ordering* scheme and that of the new nearest neighbour filter utilizing the ordering process, depends on the choice of the appropriate reference vector. The ideal reference vector is the actual value of the multidimensional signal in the specific location under consideration. However, this signal is not available. Moreover, the noisy vector at the same location is not appropriate since any vector inside the window can be an outlier. Thus, a robust estimate of the location, usually evaluated in a smaller subset of the input vector set, is utilized as reference vector. The selection of this robust reference vector depends on the signal characteristics. Usually the median is the preferable choice since it smooths out impulsive noise and preserve edges and details. Moreover, unlike scalars, the centermost vector in a set of vectors can be defined in more than one way. Thus, the Vector Median Filter *VMF*, the Basic Vector Directional Filter *BVDF* [4] or the Marginal Median Filter *MAMF* operating in a *3x3* window centered around the current pixel can be used to provide the requested reliable reference point.

The new multichannel filter introduced in this paper can be viewed as a double-window two stage estimator. First the original image is filtered by a multichannel median filter in a small processing window in order to reject possible outliers and then an adaptive nonlinear filter with data dependent coefficients defined by (7) is used to provide the final estimates. Thus, the overall filter can be viewed as a combined multichannel median and vector directional operator. The algorithm is an extension to the multichannel case, of the double-window (*DW*) filtering structures extensively used for gray-scale image processing [7]. As in gray-scale processing, with this adaptive nearest neighbour filter, we can distinquish between two operators: (i) the computation of the median in the smaller window; and (ii) the adaptive averaging in a larger window. The performance of this double-window adaptive nearest neighbour multichannel filter (hereafter *DWANNF*) depends on the reference vector selected and the distance criterion used to generate the weights in (7). In our experiments the Marginal Median Filter (*MAMF*) operating in a *3x3* filtering window was selected to provide the reference vector. As in the first multichannel filter introduced in this paper, the *vector angle criterion* was used to calculate the distance between a given vector inside the operating window and the reference vector. However, any other multichannel median or different distance criteria, such as the *Euclidean* or the *Mahalanobis* distance can be used in the new filter.

The two proposed nearest neighbour filters differ in their structure and their computational complexity. It should be noted that the computational complexity of a given filter is a realistic measure of its practicality and usefulness, since it determines the required computing power and the associate processing time required for its implementation. The computationally intensive part of the adaptive schemes discussed here is the distance calculation part. In the *ANNF* the calculations for the determination of the weights involves measuring distances among all the vectors in the processing window. In the *DWANNF*, despite the fact that the calculation of the final weights is more computational attractive, additional calculations which involve ordering of multichannel images are required in the determination of the reference vector.

3 APPLICATION TO COLOUR IMAGES

The adaptive nearest-neighbour filters are compared quantitatively with the widely used Vector Median Filter (VMF) and the *chromaticity* based Generalized Vector Directional Filter (GVDF) [4]. The colour RGB test image 'Lenna' has been contaminated using various noise source models in order to assess the performance of the filters under different noise distributions (see Table I). The normalized mean square error (NMSE) has been used as quantitative measure for evaluation purposes. It is computed as:

$$NMSE = \frac{\sum_{i=0}^{N1} \sum_{j=0}^{N2} ||(y(i,j) - \hat{y}(i,j)||^2}{\sum_{i=0}^{N1} \sum_{j=0}^{N2} ||(y(i,j)||^2} \quad (8)$$

where $N1$, $N2$ are the image dimensions, and $y(i,j)$ and $\hat{y}(i,j)$ denote the original image vector and the estimation at pixel (i,j) respectively. Table II summarizes the results obtained for the test image 'Lenna' for a $3X3$ filter window. The results obtained using a $5X5$ filter window are given in Table III.

In addition to the quantitative evaluation presented above, a qualitative evaluation is necessary since the visual assessment of the processed images is, ultimately, the best subjective measure of the efficiency of any method. Therefore, we present sample processing results in Figs. 1- 4. Fig. 1 shows the colour image 'Lenna'. corrupted with (4%) impulsive noise. Figs. 2-4 present the results using the *GVDF*, *ANNF* and *DWANNF* filters respectively.

4 CONCLUSION

New adaptive nearest neighbour filters were introduced here. The filters smooth noise under different scenarios, outperforming other widely used multichannel filters. Moreover, the new filters preserve the chromaticity component, which is very important in visual perception of colour images. Future work in this area should address the development of nearest neighbour filters which utilize distance measures other than the angle criterion to weight nearest neighbours in the adaptive filter. Another double-window filter which utilizes an outlier rejection scheme instead of the median is currently under research investigation.

References

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Table 1: Noise Distributions

Number	Noise Model
1	Gaussian ($\sigma = 30$)
2	impulsive (4%)
3	Gaussian ($\sigma = 15$) impulsive (2%)
4	Gaussian ($\sigma = 30$) impulsive (4%)

Table 2: NMSE ($X10^{-2}$) for the 'Lenna' image, window $3X3$

Noise Model	$ANNF$	$DWANNF$	$GVDF$	VMF
1	0.8516	0.6591	1.46	1.60
2	0.2667	0.1930	0.30	0.19
3	0.3785	0.3264	0.6238	0.5404
4	1.0864	0.7988	1.982	1.6791

Table 3: NMSE ($X10^{-2}$) for the 'Lenna' image, window $5X5$

Noise Model	$ANNF$	$DWANNF$	$GVDF$	VMF
1	0.6242	0.5445	1.08	1.17
2	0.4269	0.2505	0.54	0.58
3	0.4367	0.3426	0.459	0.5172
4	0.7528	0.6211	1.1044	1.0377

Figure 1: 'Lenna' corrupted with 4% impulsive noise

Figure 3: ANFF: Filtered result of (1)

Figure 2: GVDF: Filtered result of (1)

Figure 4: DWANFF: Filtered result of (1)