MULTICHANNEL FILTERING FOR COLOR IMAGE PROCESSING

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ABSTRACT

This paper addresses the problem of noise attenuation for multichannel data, such as color images. The proposed filter utilizes adaptive data dependent non-parametric techniques. Simulation results indicate that the new filter suppresses impulsive as well as Gaussian noise and preserves edges and details.

1. INTRODUCTION

A number of multichannel filters have been proposed to date for color image filtering [1]. Among them are the Vector Median Filter (*VMF*), the Vector Directional Filters (*VDF*) [2] and the Fuzzy Vector Filter (*FVF*) [3]. The large number of filters available poses some difficulties to the practitioner, since most of them are designed to perform well in a specific application and their performance deteriorates rapidly under different operational scenarios. Thus, a nonlinear adaptive filter, which performs equally well in a wide variety of applications, is of great importance. Our goal is to devise a simple, computationally efficient and reliable filter structure, which will deliver acceptable results without making any assumption about signal or noise characteristics.

2. ADAPTIVE MULTICHANNEL FILTER

Consider the following model for the color image degradation process, $\mathbf{y_j} = \mathbf{x_j} + \mathbf{n_j}$ where $\mathbf{x_j}$ is a *three-dimensional* uncorrupted image vector, $\mathbf{y_j}$ is the corresponding noisy vector to be filtered and $\mathbf{n_j}$ is an additive noise vector. It is assumed that the image vectors are deterministic and that the noise vectors result from an **i.i.d** process.

Let us denote with $\hat{x}(y)$ the minimum variance estimator of the color vector $\mathbf{x}$ given the noisy measurement vector $\mathbf{y}$. The expected square error in the filter when the image vectors are corrupted by additive noise as above, can be written as follows:

$$V = \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} (x-\hat{x}(y))(x-\hat{x}(y))^{\tau} f(x|y)\, dx\right) f(y)\, dy \tag{1}$$

where z^{τ} denotes the transpose of z. Since $\hat{x}(y)$ does not enter into the outer integral and $f(y)$ is always positive, it is sufficient for the optimal minimum variance estimator to minimize the expected value of the estimation cost (conditional Bayesian risk), given the observation $\mathbf{y}$. Thus, it is sufficient to minimize the quantity:

$$V_{BR} = \int_{-\infty}^{\infty} (x-\hat{x}(y))(x-\hat{x}(y))^{\tau} f(x|y)\, dx \tag{2}$$

The optimal minimum variance estimator which minimizes the above cost is then known to be [4]:

$$\hat{x}(y)_{mv} = \int_{-\infty}^{\infty} x f(x|y)\, dx = \int_{-\infty}^{\infty} \frac{x f(x,y)}{f(y)}\, dx \tag{3}$$

with $f(y) = \int_{-\infty}^{\infty} f(x,y) f(x)\, dx$.

If the densities in (3) are known and a training record of the sample pairs $(\mathbf{x}, \mathbf{y})$ is available, the minimum variance estimator can be derived. Unfortunately, in a realistic image processing scenario, no a-priori knowledge about the noise process or the image itself is available. Thus, a non-parametric estimator must be utilized to approximate the probability density functions (PDF) in (3). Let us assume a window of finite length n centered around a noisy vector $\mathbf{y}$. Through this window a set of multivariate noisy samples $W = (y_1, y_2, y_3, ..., y_n)$ become available. Based on the W set, an adaptive data dependent multivariate kernel estimator can be devised to approximate the densities in (3). The form of the adaptive kernel estimator selected, is as follows [5]:

$$\hat{f}(x,y) = (n^{-1})\sum_{l=1}^{n}(h_l)^{-M}K(\frac{y-y_l}{h_l}) \quad (4)$$

where y_l is the l^{th} training vector, with $l = 1,2,3,...,n$, $M = 3$ is the dimensionality of the measurement space and h_l is the data dependent smoothing parameter which regulates the shape of the kernel. The function h_l could be any function of the sample size n [6]. In this paper, the smoothing factor is defined as a function of the aggregate distance between the local observation under consideration and all the other vectors inside the W set, excluding the point at which the density is evaluated. Thus,

$$h_l = n^{\frac{-k}{M}}A_l = n^{\frac{-k}{M}}(\sum_{j=1}^{n}|y_j - y_l|) \quad (5)$$

with $y_j \neq y_l$ for $\forall y_j$ $j = 1,2,...,n$, $|y_j - y_l|$ is the absolute distance (L_1 metric) between the two vectors and k is a parameter to be determined with the multiplier $n^{\frac{-k}{M}}$ adopted from [6]. For the simulation studies in this paper the multivariate extension of the exponential kernel $K(z) = exp(-|z|)$ was selected [6].

Given (3)-(5), the non-parametric estimator can be defined as:

$$\hat{x}(y)_{np} = \int_{-\infty}^{\infty}\frac{x\hat{f}(x,y)}{\hat{f}(y)}\,dx \quad (6)$$

$$\hat{x}(y)_{np} = \sum_{l=1}^{n}x_l(\frac{(n^{-1})h_l^{-M}K(\frac{y-y_l}{h_l})}{\sum_{l=1}^{n}(n^{-1})h_l^{-M}K(\frac{y-y_l}{h_l})}) \quad (7)$$

$$\hat{x}(y)_{np} = \sum_{l=1}^{n}x_l(\frac{(n^{-1})h_l^{-M}K(\frac{y-y_l}{h_l})}{(n^{-1})\sum_{l=1}^{n}h_l^{-M}K(\frac{y-y_l}{h_l})}) \quad (8)$$

$$\hat{x}(y)_{np} = \sum_{l=1}^{n}x_l(\frac{h_l^{-M}K(\frac{y-y_l}{h_l})}{\sum_{l=1}^{n}h_l^{-M}K(\frac{y-y_l}{h_l})}) = \sum_{l=1}^{n}x_l w_l(y) \quad (9)$$

where $y_l \in W$ and $w_l(y)$ is a weighting function defined in the interval [0,1].

To obtain the required estimate we must assume that, in the absence of noise, discrete sample points x_l are available. In a real time image processing application however, that is not the case. Therefore, alternative suboptimal solutions are introduced. In a first approach, we substitute the vectors x_l in (7) with their noisy measurements. The resulting Adaptive Non-parametric Multichannel Filter (hereafter ANMF) is solely based on the available noisy vectors and the form of the minimum variance estimator. Thus, the form of the ANMF is as follows:

$$\hat{x}(y)_{ANMF} = \sum_{l=1}^{n}y_l(\frac{h_l^{-M}K(\frac{y-y_l}{h_l})}{\sum_{l=1}^{n}h_l^{-M}K(\frac{y-y_l}{h_l})}) \quad (10)$$

3. APPLICATION TO COLOR IMAGES

The new filter is compared quantitatively with the widely used *Vector Median Filter* (VMF), the *Arithmetic Vector Mean Filter* (AVMF) and *chromaticity* based filters, such as the the *Generalized Vector Directional Filter* (GVDF) and the *Distance Directional Filter* (DDF) [2].

The *RGB* color 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) defined as:

$$NMSE = \frac{\sum_{i=0}^{N1}\sum_{j=0}^{N2}||(y(i,j) - \hat{y}(i,j)||^2}{\sum_{i=0}^{N1}\sum_{j=0}^{N2}||(y(i,j)||^2} \quad (11)$$

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 has been used as quantitative measure for evaluation purposes (see Tables II, III).

In many application areas, such as multimedia, telecommunications (e.g. TV), production of motion pictures, printing industry and graphic arts, greater emphasis is given to perceptual image quality. Consequently, the perceptual closeness (alternatively perceptual difference or error) of the filtered image to the uncorrupted original image is ultimately the best measure of the efficiency of any color image filtering method. This leads us to the question of how to estimate the perceptual error between two color vectors. Precise quantification of the perceptual error between two color vectors is one of the most important and open research problem. RGB is the most popular color space used conventionally to store, process, display, and analyze color images. However, the human perception of color cannot be described using the RGB model. Therefore, measures such as the Normalized Mean Square Error (NMSE) defined in the RGB color space are not appropriate to quantify the perceptual error between images. Thus, it is important to use color spaces, which are closely related to the human perceptual characteristics and suitable for defining appropriate measures of perceptual error between color vectors. A number of such color spaces are used lately in areas such as computer graphics, motion pictures, graphic arts, and printing industry. Among these, perceptually uniform color spaces are the most appropriate to define simple yet precise measures of perceptual error.

The *Commision Internationale de l'Eclairage* (CIE) standardized two color spaces, $L^*u^*v^*$ and $L^*a^*b^*$, as perceptually uniform. The $L^*a^*b^*$ color space is chosen in this paper for our analysis.

In a uniform color space, such as $L^*a^*b^*$, we computed the Normalized Color Difference (NCD) which is estimated according to the following formula:

$$NCD = \frac{\sum_{i=0}^{N1} \sum_{j=0}^{N2} \|\Delta E_{ab}\|}{\sum_{i=0}^{N1} \sum_{j=0}^{N2} \|E_{ab}^*\|} \qquad (12)$$

where E_{ab}^* is the square of *norm* or *magnitude* of the uncorrupted original image pixel vector in the $L^*a^*b^*$ space and ΔE_{ab} is the difference between the original image and the filtered result at the specific image location (i,j) defined as follows:

$$\Delta E_{ab}(i,j) = (L(i,j) - \hat{L}(i,j))^2$$

$$+ (a(i,j) - \hat{a}(i,j))^2 + (b(i,j) - \hat{b}(i,j))^2 \qquad (13)$$

Tables IV-V summarize the results obtained for the test image 'Lenna'.

In addition to the quantitative evaluation presented above, a qualitative evaluation is necessary since, ultimately, the visual assessment of the processe d images is the best subjective measure of any method's efficiency. Therefore, we present sample processing results in Fig. 1-2. Fig. 1 shows the colour 'Lenna' image corrupted with (4%) impulsive noise. Fig. 2 shows results of the *ANMF* filter.

In conclusion, an adaptive multichannel filter based on non-parametric density estimators was introduced. The filter smoothes noise under different scenarios, outperforming other widely used multichannel filters. Moreover, the new filter preserves the chromaticity component, which is very important in visual perception of color images.

4. REFERENCES

[1] A.N. Venetsanopoulos, K.N. Plataniotis, 'Multichannel image processing', Proceedings of the IEEE Workshop on Nonlinear Signal Processing, pp.2-6, 1995.

[2] D.G. Karakos, P.E. Trahanias, 'Combining vector median and vector directional filters: The directional-distance filters, ' Proceedings of the IEEE Conf. on Image Processing, ICIP-95, pp. 171-174, 1995.

[3] K.N. Plataniotis, D. Androutsos, A.N. Venetsanopoulos, 'Colour Image Processing Using Fuzzy Vector Directional Filters', Proceedings of the IEEE Workshop on Nonlinear Signal Processing, pp. 535-538, 1995.

[4] A.P. Sage, J.L. Melsa, *Estimation Theory with Applications to Communication and Control*, R.E. Krieger Publishing Co., Huntington N.Y., 1979.

[5] L. Breiman, W. Meisel, E. Purcell, Variable kernel estimates of multivariate densities', Technometrics, vol. 19, no. 2, pp. 135-144, may 1977.

[6] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, Academic Press, Second Edition, London, 1990.

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 $3X3$

No	$ANMF$	$GVDF$	DDF	VMF	$AVMF$
1	0.8710	1.46	1.524	1.60	0.696
2	0.2005	0.30	0.3255	0.19	0.818
3	0.3746	0.6238	0.6483	0.5404	0.616
4	1.0438	1.982	2.1646	1.6791	1.29

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

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

No	$ANMF$	$GVDF$	DDF	VMF	$AVMF$
1	0.5908	1.08	1.0242	1.17	0.599
2	0.7318	0.5126	0.58	0.6656	0.665
3	0.3936	0.459	0.6913	0.5172	0.570
4	0.6455	1.1044	1.3048	1.0377	0.889

Table 4: NCD for the 'Lenna' image, $3X3$

No	$ANMF$	$GVDF$	DDF	VMF	$AVMF$
1	0.020	0.0305	0.0355	0.043	0.0165
2	0.03245	0.00397	0.0063	0.0333	0.0155
3	0.00815	0.0110	0.0143	0.0153	0.0123
4	0.02248	0.0344	0.047	0.048	0.0275

Figure 2: $ANMF$ of (1) using *3X3 window*

Table 5: NCD for the 'Lenna' image, $5X5$

No	$ANMF$	$GVDF$	DDF	VMF	$AVMF$
1	0.0118	0.0156	0.0213	0.0268	0.0109
2	0.0519	0.0055	0.0059	0.00617	0.0112
3	0.0072	0.0081	0.0103	0.0118	0.0097
4	0.0125	0.0175	0.023	0.0284	0.0164