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# Video Colour Denoising using Fuzzy and Directional Techniques

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## 1. Introduction

Different classes of filters have been proposed for removing noise from gray scale and colour images (Astola & Kuosmanen, 1997; Bovik, 2000; Kotropoulos & Pitas, 2001). They are classified into several categories depending on specific applications. Linear filters are efficient for Gaussian noise removal but often distort edges and have poor performance against impulsive noise. Nonlinear filters are designed to suppress noise of different nature, they can remove impulsive noise and guarantee detail preservation. Rank order based filters have received considerable attention due to their inherent outlier rejection and detail preservation properties (Astola & Kuosmanen, 1997; Bovik, 2000; Kotropoulos & Pitas, 2001, Plataniotis & Venetsanopoulos, 2000).

In the last decade, many useful colour processing techniques based on vector processing have been investigated due to the inherent correlation that exists between the image channels compared to traditional component-wise approaches (Plataniotis & Venetsanopoulos, 2000). The fuzzy filters are designed by fuzzy rules to remove noise and to provide edge and fine detail preservation (Russo & Ramponi, 1994). The fuzzy filter depends on the fuzzy rules and the defuzzification process, which combines the effects of applied rules to produce an only output value (Russo & Ramponi, 2004, Schulte et al., 2007). The vector directional filters employ the directional processing taking pixels as vectors, and obtaining the output vector that shows a less deviation of its angles under ordering criteria in respect to the other vectors (Trahianas & Venetsanopoulos, 1996).

This chapter presents the capability features of Fuzzy Directional (FD) filter to remove impulse noise from corrupted colour images (Ponomaryov, et al., 2010). The FD filter uses directional processing, where vectorial order statistics are employed, and fuzzy rules that are based on gradient values and angle deviations to determine, if the central pixel is noisy or present local movement. Simulation results in colour images and video sequences have shown that the restoration performance is better in comparison with other known filters. In Addition, we present the Median M-Type L- (MML) filter for the removal of impulsive noise in gray-scale and colour image processing applications (Gallegos-Funes et al., 2008, Toledo-Lopez et al., 2008). The proposed scheme is based on modification of L- filter that uses the MM (Median M-type) -estimator to calculate the robust point estimate of the pixels within the filtering window. The proposed filter uses the value of the central pixel within the filtering window to provide the preservation of fine details and the redescending M-

estimators combined with the calculation of the median estimator to obtain the sufficient impulsive noise rejection. Influence functions into the  $M$ -estimator can be used to provide better impulsive noise suppression. Simulation results in gray-scale and colour images have demonstrated that the proposed filters consistently outperform other filters by balancing the tradeoff between noise suppression, fine detail preservation, and color retention.

## 2. Proposed filters

### 2.1 Fuzzy Directional filter

In the proposed Fuzzy Directional filter, a  $3 \times 3$  sliding window is used in the centre of a bigger one of size  $5 \times 5$ . Last window is employed to calculate values in different directions with respect to neighbour pixels in the initial  $3 \times 3$  window. Each a neighbour of a central pixel  $x_c^\beta = (x_c^R, x_c^G, x_c^B)$  (in the RGB colour space) corresponds to one of the eight directions, as it is illustrated in Figure 1. We introduce the basic gradient values  $\nabla_{(k,l)}^\beta x(i,j)$  for central pixel and its neighbours as follows (Ponomaryov, et al., 2010),

$$\nabla_{(k,l)}^\beta x(i,j) = \nabla [x_C^\beta(i,j), x^\beta(i+k, j+l)] = |x_C^\beta(i,j) - x^\beta(i+k, j+l)| \quad (1)$$

where each one of the  $(k,l)$  pairs corresponds to each one of eight directions of  $(i,j)$  point,  $k, l \in (-1, 0, +1)$ , and  $\beta = (R, G, B)$ .

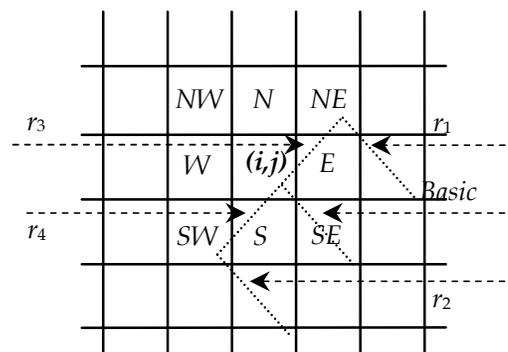


Fig. 1. Basic and related  $(r_1, r_2, r_3, r_4)$  gradient values.

We introduce subindex  $\gamma = (N, E, S, W, NW, NE, SE, SW)$  the related gradient values can be calculated in relation to the basic gradient direction. According with Figure 1, the basic gradient value for  $SE$  direction is written as,

$$\nabla_{(1,1)}^\beta x(i,j) = \nabla_{SE}^\beta \quad (2)$$

and its four related gradients values are given by,

$$\nabla_{(0,2)}^\beta x(i-1, j+1) = \nabla_{SE(r_1)}^\beta, \quad \nabla_{(2,0)}^\beta x(i+1, j-1) = \nabla_{SE(r_2)}^\beta, \quad \nabla_{(-1,1)}^\beta x(i-1, j+1) = \nabla_{SE(r_3)}^\beta, \quad \text{and} \quad (3)$$

$$\nabla_{(1,-1)}^\beta x(i+1, j-1) = \nabla_{SE(r_4)}^\beta$$

We propose two fuzzy sets: the fuzzy set SMALL that characterizes the membership level for a gradient value when it is sufficiently small, this infers in membership value as a big value. So, if a membership level is  $\approx 1$  this implies that there is *no movement* and/or *noise*

presence in a sample to be processed. In opposite case, we use the fuzzy set BIG. We also introduce the fuzzy angular deviation for a single component leaving another two out of the calculus.

For example, for  $R$  component in  $SE$  direction, the basic angular deviation is written as,

$$\theta_{(1,1)}^R x(i, j) = \theta_{SE}^R \tag{4}$$

and its related angular deviations are given by,

$$\theta_{(0,2)}^R x(i-1, j+1) = \theta_{SE(r_1)}^R, \theta_{(0,2)}^R x(i+1, j-1) = \theta_{SE(r_2)}^R, \theta_{(-1,1)}^R x(i-1, j+1) = \theta_{SE(r_3)}^R, \theta_{(1,-1)}^R x(i+1, j-1) = \theta_{SE(r_4)}^R \tag{5}$$

To characterize the fuzzy gradients and fuzzy angular deviation values, the following Gaussian membership functions are employed (Ponomaryov, et al., 2007)

$$G(F_\gamma^\beta \text{SMALL}) = \begin{cases} 1, & F_\gamma^\beta < med_F \\ \exp\left\{-\left[\frac{F_\gamma^\beta - med_F}{2\sigma_F^2}\right]^2\right\}, & \text{otherwise} \end{cases} \tag{6}$$

$$G(F_\gamma^\beta \text{BIG}) = \begin{cases} 1, & F_\gamma^\beta > med_F \\ \exp\left\{-\left[\frac{F_\gamma^\beta - med_F}{2\sigma_F^2}\right]^2\right\}, & \text{otherwise} \end{cases} \tag{7}$$

We propose fuzzy rules that are based on gradient values and angle deviations to determine: if the central component is noisy or present local movement. Table 1 presents the proposed fuzzy rules employ in the FD filter (Ponomaryov, et al., 2010).

Fuzzy Rule 1 defines the fuzzy angular-gradient value $\nabla_\gamma^{\beta F} \theta_\gamma^{\beta F}$ .
By other words, the membership level of central pixel $x_c^\beta$ in fuzzy set BIG in $\gamma$ direction: <b>IF</b> $(\nabla_\gamma^\beta B \otimes \nabla_{\gamma(r_1)}^\beta S \otimes \nabla_{\gamma(r_2)}^\beta S \otimes \nabla_{\gamma(r_3)}^\beta B \otimes \nabla_{\gamma(r_4)}^\beta B) \otimes_1 (\theta_\gamma^\beta B \otimes \theta_{\gamma(r_1)}^\beta S \otimes \theta_{\gamma(r_2)}^\beta S \otimes \theta_{\gamma(r_3)}^\beta B \otimes \theta_{\gamma(r_4)}^\beta B)$ <b>THEN</b> $\nabla_\gamma^{\beta F} \theta_\gamma^{\beta F} B$
Fuzzy rule 2 defines the fuzzy noise factor as $r^\beta$ .
<b>IF</b> $\nabla_N^{\beta F} \theta_N^{\beta F} B \oplus \nabla_S^{\beta F} \theta_S^{\beta F} B \oplus \nabla_E^{\beta F} \theta_E^{\beta F} B \oplus \nabla_W^{\beta F} \theta_W^{\beta F} B \oplus \nabla_{SW}^{\beta F} \theta_{SW}^{\beta F} B \oplus \nabla_{NE}^{\beta F} \theta_{NE}^{\beta F} B \oplus \nabla_{NW}^{\beta F} \theta_{NW}^{\beta F} B \oplus \nabla_{SE}^{\beta F} \theta_{SE}^{\beta F} B$ <b>THEN</b> $r^\beta B$ .

Table 1. Fuzzy rules used in the proposed FD filter.

From Fuzzy rule 1, a central pixel is considered *noisy* or belongs to fuzzy set BIG if its basic values with respect to related values satisfy to:

$$\begin{aligned} G(\nabla_\gamma^\beta) \approx G(\nabla_{\gamma(r_3)}^\beta) \approx G(\nabla_{\gamma(r_4)}^\beta), G(\theta_\gamma^\beta) \approx G(\theta_{\gamma(r_3)}^\beta) \approx G(\theta_{\gamma(r_4)}^\beta), \\ G(\nabla_\gamma^\beta) \neq G(\nabla_{\gamma(r_1)}^\beta) \neq G(\nabla_{\gamma(r_2)}^\beta), \text{ and } G(\theta_\gamma^\beta) \neq G(\theta_{\gamma(r_1)}^\beta) \neq G(\theta_{\gamma(r_2)}^\beta) \end{aligned} \tag{8}$$

The value  $r^\beta$  in Fuzzy rule 2 denotes the noise level of central pixel formed with the neighbour components. The big membership levels are given in the fuzzy set BIG, so, this rule shows when a noisy or fine detail pixel is present. If  $r^\beta \geq R_0$  the filtering is realized

using fuzzy membership levels obtained for the fuzzy set BIG, otherwise output filtered pixel is:  $y_o^\beta = x_c^\beta$ . In these Fuzzy rules  $A \otimes B = A \text{ AND } B$ ,  $A \otimes_1 B = \min(A, B)$ ,  $A \oplus B = \max(A, B)$ , and PB and QS denote that value  $P$  is BIG and value  $Q$  is SMALL, respectively.

The fuzzy values are the weights for each a neighbour component and should be taken in consideration before using fuzzy membership levels. To obtain the fuzzy weights in the filtering algorithm, we propose to determine the membership level for the fuzzy set FREE (free noise) as:  $v_\gamma^{\beta F} = 1 - \nabla_\gamma^{\beta F} \theta_\gamma^{\beta F}$ . The weight value for central component in fuzzy set FREE is chosen as:  $v_\gamma^{\beta F} = 3\sqrt{1 - r^\beta}$ .

The filtering procedure is performed selecting one of the neighbour components to avoid the detail and edge smoothing. Besides, it is proposed the filtering of a sample using their fuzzy weights and according to their ordering properties. The component values of the 3x3 sample are ordered as follows:

$$x_\gamma^{\beta(1)} \leq x_\gamma^{\beta(2)} \leq \dots \leq x_\gamma^{\beta(9)} \quad \text{and} \quad v_\gamma^{\beta(1)} \leq v_\gamma^{\beta(2)} \leq \dots \leq v_\gamma^{\beta(9)} \quad (9)$$

Equation (9) permits to withdraw the components that are sufficiently far with respect to a central value. For this reason, we define  $sum^\beta = v_\gamma^{\beta(j)}$ , where  $j$  decreases from 9 to 1; decreasing of  $j$  is valid until  $sum^\beta > (\sum_\gamma v_\gamma^{\beta F} + 3\sqrt{1 - r^\beta})/2$ . When  $j$  satisfies this condition, the  $j$ -th ordered value is selected as the output filtered value,

$$x_\gamma^{\beta(j)} = y_o^\beta \quad (10)$$

Finally, the values for Gaussian membership functions were found according to optimal values of PSNR and MAE criteria, these values are given by:  $\sigma_1^2=1000$ ,  $med_1=60$  and  $med_2=10$  for fuzzy gradient sets BIG and SMALL, respectively,  $\sigma_2^2=0.8$ ,  $med_3=0.1$  and  $med_4=0.8$  for fuzzy angular deviation sets BIG and SMALL, respectively, and  $R_0=0.3$ .

## 2.2 Median M-type L-filter

To improve the robustness of L-filter, we propose to use the Median M-type (MM) - estimator (Gallegos-Funes et al., 2008),

$$\varepsilon_{\text{medM}} = \text{MED} \left\{ X_i \tilde{\psi} \left( X_i - \text{MED} \{ \tilde{\mathbf{X}} \} \right), i = 1, \dots, N \right\} \quad (11)$$

where  $X_k$  is data sample,  $\tilde{\psi}$  is the normalized influence function  $\psi : \psi(X) = X\tilde{\psi}(X)$ , and  $X_N$  is the primary data sample. The Median estimator provides good properties of impulsive noise suppression and the M-estimator uses different influence functions to provide better robustness, for these reasons it can be expected that the properties of combined MM-estimator could be better in comparison with Median and M- estimators.

The representation of L-filter is  $F_L = \sum_{i=1}^N a_i \cdot X_{(i)}$  where  $X_{(i)}$  is the ordered data sample,  $i=1, \dots, N$ ,  $a_i = \int_{i-1/N}^{i/N} h(\lambda) d\lambda / \int_0^1 h(\lambda) d\lambda$  are the weight coefficients, and  $h(\lambda)$  is a probability density function (Kotropoulos & Pitas, 2001).

To introduce the MM-estimator (11) in the scheme of  $L$ -filter, we present the ordered data sample of  $L$ -filter as function of an influence function (Gallegos-Funes et al., 2008),

$$\hat{F}_L = \sum_{i=1}^N a_i \cdot \psi(X_i) \cdot X_i \quad (12)$$

where  $N = (2L + 1)^2$  is the filtering window size,  $\psi(X_i) \cdot X_i$  is the ordered data sample,  $\psi(u) = \begin{cases} c, & |u| \leq r \\ 0, & \text{otherwise} \end{cases}$  is the influence function,  $c$  is a constant, and  $r$  is connected with the range of  $\psi(u)$ .

Therefore, the MML filter can be obtained by the combination of  $L$ -filter (12) and the MM-estimator (11) (Gallegos-Funes et al., 2008),

$$\hat{F}_{MML} = \frac{\text{MED} \left\{ a_i \cdot \left[ X_i \cdot \psi \left( X_i - \text{MED} \{ \vec{X} \} \right) \right] \right\}}{a_{\text{MED}}} \quad (13)$$

where  $X_i \psi(X_i - \text{MED}\{\vec{X}\})$  are the selected pixels in accordance with the influence function used in a sliding filter window and  $a_{\text{MED}}$  is the median of coefficients  $a_i$  used as a scale constant.

To improve the properties of noise suppression of MML filter we use an impulsive noise detector (IND) (Aizenberg et al., 2003),

$$\text{IND} = \begin{cases} \hat{F}_{MML}, & \text{if } [(D \leq s) \vee (D \geq N - s)] \wedge (|X_c - \text{MED}(\vec{X})| \geq U) \\ X_c, & \text{otherwise} \end{cases} \quad (14)$$

where  $X_c$  is the central pixel in the filtering window,  $s > 0$  and  $U \geq 0$  are thresholds,  $N$  is the length of the data, and  $D = \text{rank}(X_c)$  is the rank of element  $X_c$ .

The coefficients  $a_i$  are computed using the Laplacian and Uniform distribution functions in

$h(\lambda)$  and the simple cut  $\psi_{\text{cut}(r)}(X) = X \cdot 1_{[-r, r]}(X) = \begin{cases} X, & |X| \leq r \\ 0, & \text{otherwise} \end{cases}$  and Andrew's sine

$\psi_{\text{sin}(r)}(X) = \begin{cases} \sin(X/r), & |X| \leq r\pi \\ 0, & \text{otherwise} \end{cases}$  influence functions are used in the filtering scheme, where

the parameter  $r$  is connected with restrictions on the range of  $\psi(X)$ .

### 3. Experimental results

To compare the performance of noise suppression of various filters the *peak signal to noise ratio* (PSNR) was used, and for the evaluation of fine detail preservation the *mean absolute error* (MAE) was computed (Astola & Kuosmanen, 1997; Bovik 2000),

$$\text{PSNR} = 10 \cdot \log \left[ \frac{(255)^2}{\text{MSE}} \right] \text{ dB} \quad (15)$$

$$\text{MAE} = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} |f(i, j) - \hat{F}(i, j)| \quad (16)$$

where  $\text{MSE} = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [f(i, j) - \hat{F}(i, j)]^2$  is the *mean square error*,  $f(i, j)$  is the original image;  $\hat{F}(i, j)$  is the restored image; and  $M, N$  is the size of the image.

We also compute the *mean chromaticity error* (MCRE) for evaluation of chromaticity retention, and the *normalized color difference* (NCD) for quantification of color perceptual error (Plataniotis & Venetsanopoulos, 2000):

$$\text{MCRE} = \frac{\sum_{i=1}^{M_1} \sum_{j=1}^{M_2} \|p_{i,j} - \hat{p}_{i,j}\|_{L_2}^2}{M_1 M_2} \quad (17)$$

$$\text{NCD} = \frac{\sum_{i=1}^{M_1} \sum_{j=1}^{M_2} \|\Delta E_{Luv}(i, j)\|_{L_2}}{\sum_{i=1}^{M_1} \sum_{j=1}^{M_2} \|E_{Luv}^*(i, j)\|_{L_2}} \quad (18)$$

where  $p_{i,j}$  and  $\hat{p}_{i,j}$  are the intersection points of  $f(i, j)$  and  $\hat{F}(i, j)$  with the plane defined by the Maxwell triangle, respectively,  $\|\Delta E_{Luv}(i, j)\|_{L_2} = \left[ (\Delta L^*)^2 + (\Delta u^*)^2 + (\Delta v^*)^2 \right]^{1/2}$  is the norm of color error,  $\Delta L^*$ ,  $\Delta u^*$ , and  $\Delta v^*$  are the difference in the  $L^*$ ,  $u^*$ , and  $v^*$  components, respectively, between the two color vectors that present the filtered image and uncorrupted original one for each a pixel  $(i, j)$  of an image,  $\|E_{Luv}^*(i, j)\|_{L_2} = \left[ (L^*)^2 + (u^*)^2 + (v^*)^2 \right]^{1/2}$  is the norm or magnitude of the uncorrupted original image pixel vector in the  $L^*u^*v^*$  space, and  $\|\cdot\|_{L_2}$  is the  $L_2$ -vector norm.

### 3.1 Noise suppression in colour images using the FD filter

The FD filter has been evaluated, and its performance has been compared with INR (Schulte, et al., 2007), MMKNN (Ponomaryov, et al., 2007), AMNF, WMKNN, and ABSTMKNN (Ponomaryov, et al., 2005b), VMF\_SAR (Smolka, et al., 2003), WVDF1 (Lukac, 2003) and AVMF (Lukac, et al., 2004) filters.

The 320x320 colour images Lena and Mandrill, were corrupted by impulsive noise in wide range of intensity, from 5% to 30%. Tables 2 and 3 expose the criteria NCD and MAE, respectively. From these tables one can see that FD filter has the best chromaticity and fine details preservation performance in low and middle impulsive noise levels.

Figure 2 presents the processed images for image Mandrill illustrating visual filtering performance. Fig. 2b-c exhibit the filtered images produced by the VMF\_SAR and INR filters, respectively. Fig. 2d shows the proposed FD filtered image, where it appears to have a very good subjective quality in comparison with Fig. 2b-c.

### 3.2 Noise suppression in video colour sequences using the FD filter

Proposed 3D-FD filter uses two colour frames of a video sequence (past and present) which are processed agree to the movement and noise levels present by central sample pixel in

Algorithm	5%	15%	20%	30%
INR filter	1.66	1.76	1.84	2.14
MMKNN filter	1.68	1.91	2.06	2.51
AMNF filter	1.95	2.12	2.22	2.52
WMKNN filter	0.96	1.66	2.07	3.02
ABSTMKNN filter	2.03	2.26	2.40	2.83
VMF_SAR filter	0.44	1.34	1.78	2.78
LWVDF filter	1.87	2.34	2.65	3.62
WVDF1 filter	1.56	2.13	2.50	3.67
AVMF filter	0.96	1.40	1.65	2.35
Proposed FD filter	0.37	0.84	1.15	2.06

Table 2.  $NCD \times 10^2$  criteria in colour image "Lena" for different impulsive noise intensity.

Algorithm	5%	15%	20%	30%
INR filter	4.41	4.70	4.98	5.98
MMKNN filter	4.41	5.06	5.54	6.92
AMNF filter	5.03	5.45	5.74	6.69
WMKNN filter	2.55	4.75	6.12	9.23
ABSTMKNN filter	5.15	5.78	6.22	7.49
VMF_SAR filter	1.19	3.69	5.00	8.09
LWVDF filter	5.10	6.36	7.34	10.5
WVDF1 filter	4.27	5.82	7.03	10.9
AVMF filter	2.39	3.62	4.40	6.53
Proposed FD filter	0.91	2.17	3.11	5.96

Table 3. MAE criteria in colour image "Lena" for different impulsive noise intensity.

present frame. It is employed a  $5 \times 5 \times 2$  sliding window processing formed by past and present frames. Difference magnitude values between these frames are computed to obtain a parameter indicating pixel magnitude differences in central pixel respect to neighbouring pixels (Ponomaryov et al., 2009).

The same procedure developed in Section 2.1 should be repeated to compute the basic and four related values in any direction. As in 2D Fuzzy Directional Filter (Sec. 2.1), calculate the absolute difference directional values of a central pixel with respect to its neighbours as an angle variance value between present and past frames. Using angle variance value, we can present the absolute variance directional values to the *SE* (basic) direction only.

Let employ the same Gaussian membership functions for fuzzy values as in the equations 6 and 7, introducing the fuzzy gradient-directional difference values. Numerical experiments realized in this case have given the values used for the functions described in equations 6 and 7: with  $med3=0.1$ ,  $med4=0.01$  according to the best *PSNR* and *MAE* criteria results.

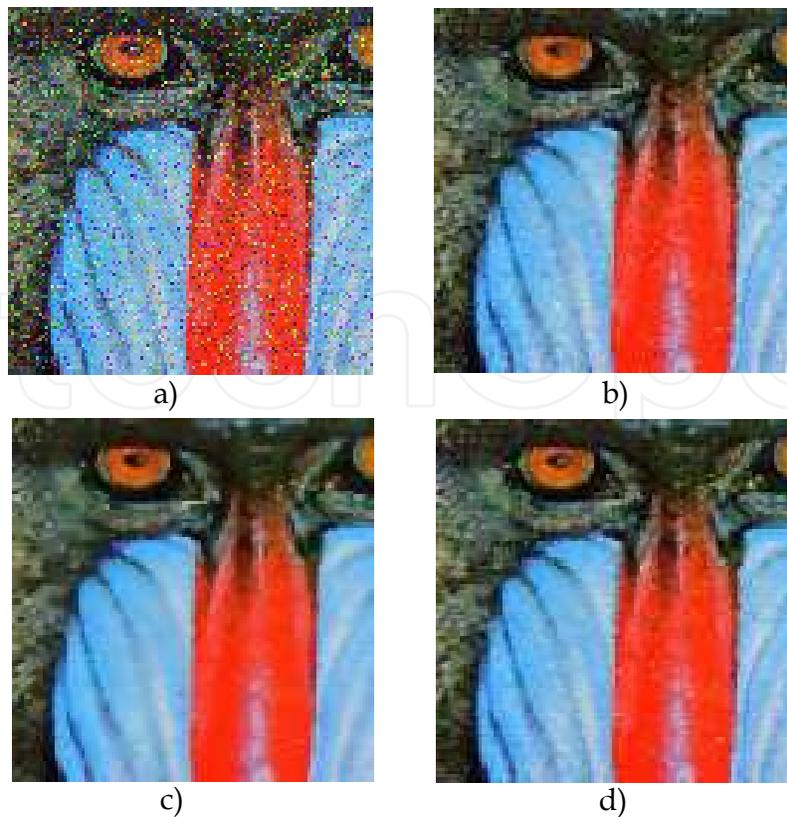


Fig. 2. Filtered images with 15% of impulsive noise: a) Degraded image, b) VMF\_SAR, c) INR, d) FD.

Designed fuzzy rules in processing video sequences are oriented to detect the movement and noise levels presence in central component pixel. First fuzzy rule characterizes the confidence in the movement and noise in a central component pixel due to neighbouring fuzzy values in any  $\gamma$  direction. Second fuzzy rule characterizes the confidence in the no movement and no noise in a central pixel in any  $\gamma$  direction. So, the distinctness of the different area (uniform region, edge or fine detail), where a current central pixel component belongs, can be realized using this rule. Third fuzzy rule characterizes the movement-noisy factor and estimate the movement and noise levels presence in a central pixel component using fuzzy values determined for all directions. Finally the fourth fuzzy rule is designed to characterize no movement-no noisy factor, allowing the estimation of no movement and no noise levels presence in a central component pixel using fuzzy values determined for all directions (Ponomaryov et al., 2009).

The parameters obtained using fuzzy rules can be applied efficiently in a decision scheme (Ponomaryov et al., 2009), where decisions if a central component pixel is noisy, or is in movement, or is a free one of both mentioned events, are treated in the denoising scheme. Fuzzy Rules from the first to the fourth determine the novel algorithm based on the fuzzy parameters. Filtering output of the scheme proposed consists of the  $j$ -th component pixel, which satisfies to the proposed conditions, guaranteeing that edges and fine details should be preserved according to the sort ordering criterion sketched in the scheme by the past and present frames.

Non-stationary noise left by this algorithm, should be processed with the application of the Proposed FD filter developed in Section 2.1. This application permits decreasing the

influence of the non-stationary noise left by the video processing scheme. As we are processing a video frame that is free from noise, the Proposed FD filter parameters changes slightly (Ponomaryov et al., 2009).

Algorithms used as comparative are robust and were obtained in literature presenting good results; the 3D-MF is an adaptation to process video sequences of the Median Filter, 3D-VMF is an adaptation of the Vector Median Filter (Astola et al., 1990). 3D-GVDF is a directional algorithm designed to process colour images; we present an adaptation of this filter in 3D environment (Trahanias et al., 1996). Finally the 3D-ATM is an adaptation of the Alpha-trimmed-mean algorithm in video colour sequence processing (Zlokolica et al., 2002). In Table 4 is shown the results of the proposed 3D filter, the best results are given for our design in MAE criterion for all noise level percentages, and in PSNR criterion the best results are present until 30% of impulsive noise. Video sequence used is the well known Flowers, and results are the averaging for 100 video frames forming Flowers video colour sequence. In Table 5, for Flowers video colour sequence in the averaging results, the best performance was obtained for our methodology. This criterion characterizes colour chromaticity properties preservation. For all noise levels is achieved the best results.

(%) noise	3D-FD filter		3D-MF		3D-VMF		3D-GVDF		3D-ATM	
	MAE	PSNR	MAE	PSNR	MAE	PSNR	MAE	PSNR	MAE	PSNR
5	2,13	29,52	6,65	26,83	6,63	26,78	7,44	25,56	6,80	26,85
15	3,37	27,76	7,19	26,22	7,14	26,20	7,71	25,29	7,35	26,27
30	6,08	25,04	8,59	24,77	8,49	24,69	9,74	23,24	8,88	24,79
40	9,15	22,82	10,8	22,82	10,6	22,70	11,4	22,08	11,5	22,85

Table 4. Averaging Criteria Results for Flowers sequence

(%)Noise	3D-FD filter	3D-MF	3D-VMF	3D-GVDF	3D-ATM
5	0,004	0,014	0,014	0,016	0,014
15	0,007	0,015	0,015	0,016	0,015
25	0,010	0,017	0,017	0,018	0,017
30	0,012	0,018	0,018	0,020	0,018

Table 5. Averaging NCD Criterion Results for Flowers sequence

In Figure 3, for 10<sup>th</sup> Miss America video frame, the best subjective results are perceived for our proposal, showing better chromaticity properties preservation as well as edge and fine details, against the other ones as can be perceived in zoomed face regions of the Miss America colour frame.

### 3.3 Noise suppression in gray scale images using the MML filter

The described MML filter was implemented with Simple cut (S) and Andrew's sine (A) influence functions, Laplacian (L) and Uniform (U) distribution functions, and with (D) and without (ND) impulsive noise detector and its performance has been compared with *adaptive center weighted median* (ACWM) (Chen & Wu, 2001), *rank order mean* (ROM) (Abreu

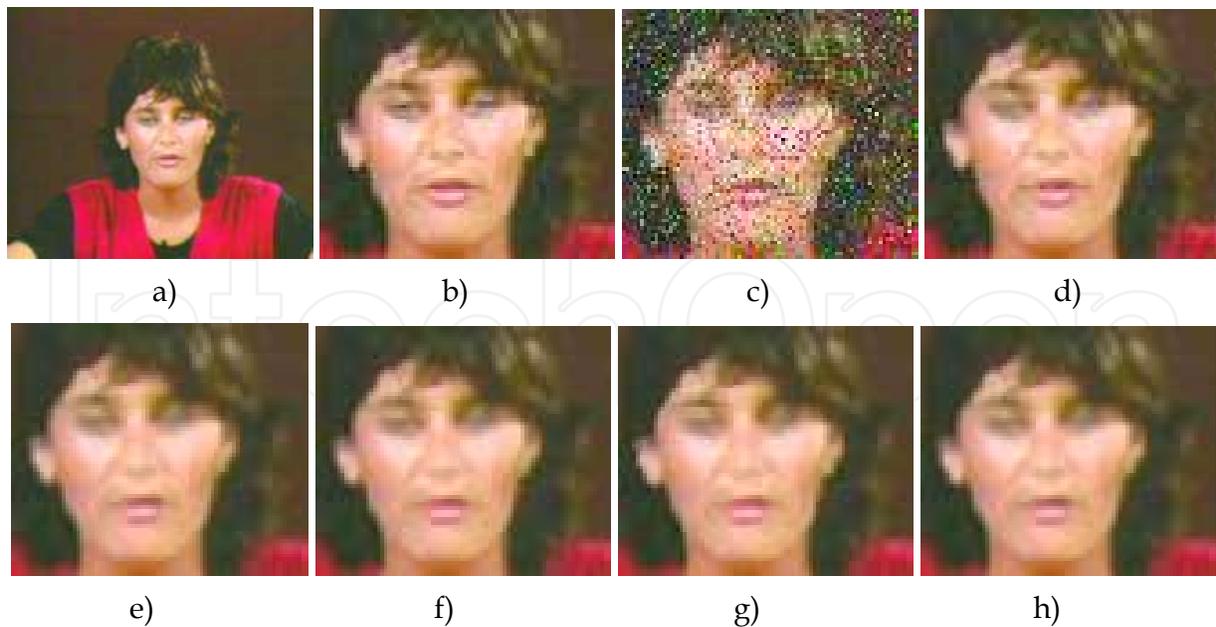


Fig. 3. a) 10<sup>th</sup> Miss America original image, b) Zoomed region analyzed, c) 15% of impulsive noise, d) Proposal 3D-FD filter, e) 3D-MF; f) 3D-VMF, g) 3D-GVDF, h) 3D-VATM.

Filters	Impulsive noise = 20%		Speckle noise = 0.1	
	PSNR	MAE	PSNR	MAE
ACWM	25.56	8.75	17.73	26.42
ROM	25.20	9.11	21.67	15.78
MFrost	21.62	15.80	22.52	12.82
NLMS-L	22.03	12.83	20.45	14.68
SFWO	23.01	10.24	22.07	14.20
MML (S,L,ND)	24.79	9.11	21.14	17.19
MML (S,U,ND)	25.59	7.38	22.84	13.48
MML (A,L,ND)	24.68	9.33	21.05	17.46
MML (A,U,ND)	25.59	7.40	22.82	13.49
MML (SA,L,D)	24.97	8.05	21.16	17.04
MML (S,U,D)	25.47	7.02	22.68	13.71
MML (A,L,D)	24.40	7.85	21.57	16.21
MML (A,U,D)	25.94	6.96	22.70	13.87

Table 6. Performance results in image "Lena" obtained by different filters.

et al., 1996), *Normalized Least Mean Squares L* (NLMS-L) (Kotropoulos & Pitas, 1996), *Sampled-Function Weighted Order* (SFWO) (Öten & De Figueiredo, 2002), and *Modified Frost* (MFrost) (Lukin et al., 1998) filters.

Table 6 shows the performance results for "Lena" image degraded with 20% of impulsive noise and  $\sigma^2=0.1$  of speckle noise. From Table 6, the proposed MML filter provides better

noise suppression and detail preservation than other filters in the most of cases. Figure 4 exhibits the filtered images in the case of 20% of impulsive noise. The restored image by proposed MML filter appears to have better subjective quality in comparison with other filters.

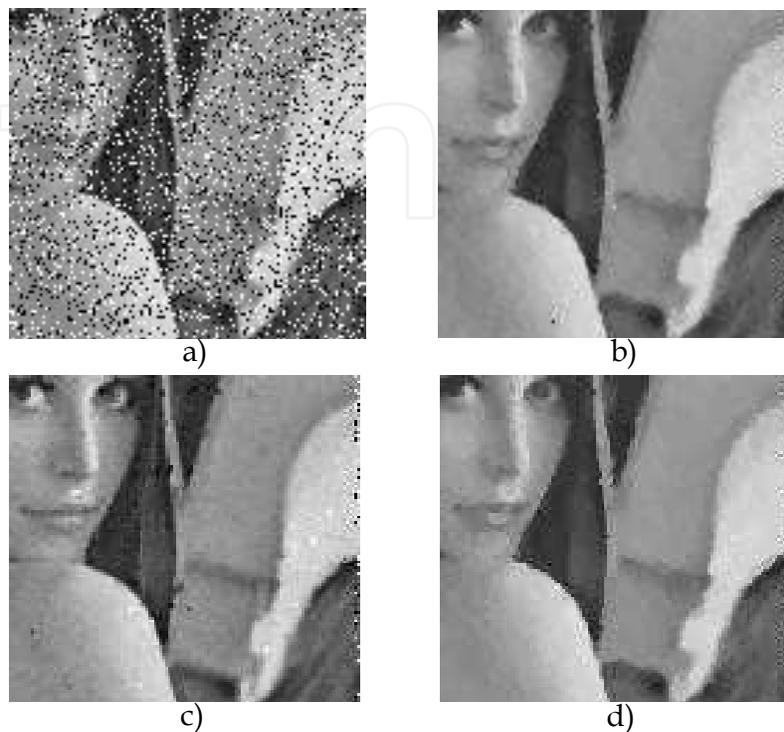


Fig. 4. Filtered images with 20% of impulsive noise: a) Degraded image, b) ROM, c) ACWM, d) MML (A,L,ND).

### 3.4 Noise suppression in colour images using the MML filter

The described MML filter was adapted to work in colour imaging (Toledo-Lopez et al., 2008). The proposed filter is called as Vector Median M-type L (VMML) -filter and its performance has been compared with *vector median* (VM), *basic vector directional* (BVD), *generalized vector directional* (GVD), *adaptive GVD* (AGVD), *double window GVD* (GVD\_DW), *multiple non-parametric* (MAMNFE) (Plataniotis et al., 1997) (Trahanias et al., 1996), *vector median M-type K-nearest neighbor* (VMMKNN) (Ponomaryov, et al., 2005), and *fast adaptive similarity VM* (FASVM) (Smolka et al., 2003) filters.

The 320x320 "Lena" color image was corrupted by 20% of impulsive noise. Table 7 shows that the performance criteria are often better for the proposed VMML filter in comparison when other filters in the most of cases. The visual results are given in Figure 5.

### 3.5 Noise suppression in colour SAR images using the MML filter

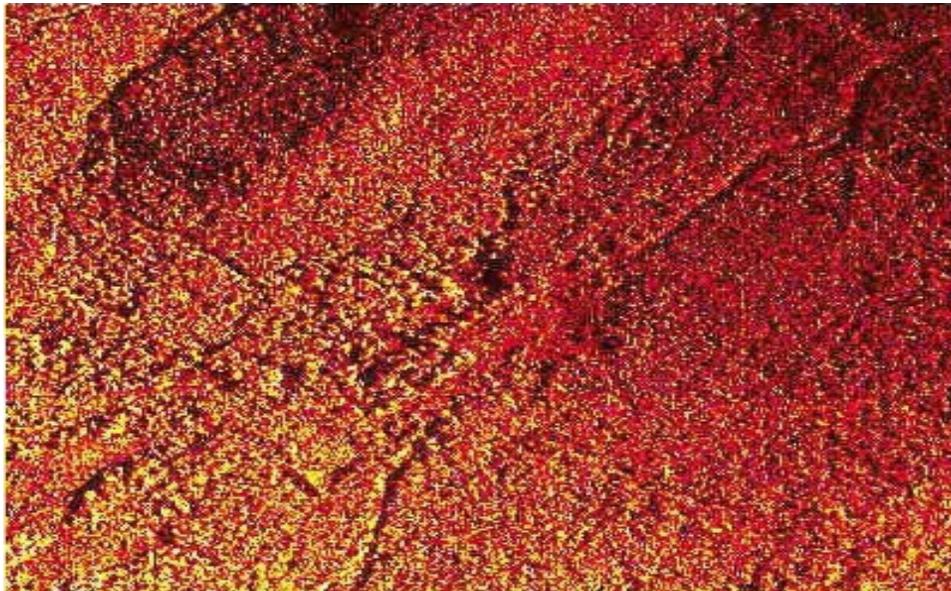
To demonstrate the performance of the proposed filtering scheme we applied it for filtering of SAR images, which naturally have speckle noise. The filtering results are presented in Figure 6 for "Rio Grande" SAR image. It is possible to see analyzing the filtering images that speckle noise can be efficiently suppressed, while the sharpness and fine feature are preserved using the proposed filter with and without noise detector.

Algorithm	PSNR	MAE	MCRE	NCD
VM	21.15	10.73	0.035	0.038
BVD	20.41	12.72	0.043	0.045
GVD	20.67	11.18	0.038	0.040
AGVD	22.01	11.18	0.028	0.036
GVDF_DW	22.59	10.09	0.028	0.039
MAMNFE	22.67	9.64	0.027	0.035
VMMKNN (S)	23.15	10.00	0.033	0.034
VMMKNN (A)	23.07	10.01	0.033	0.035
FASVM	24.80	5.00	0.025	0.017
VMML (S,L,ND)	25.81	6.49	0.026	0.016
VMML (S,U,ND)	25.88	5.53	0.026	0.026
VMML (A,L,ND)	25.88	7.00	0.026	0.015
VMML (A,U,ND)	26.52	5.36	0.022	0.015
VMML (S,L,D)	26.46	2.90	0.023	0.027
VMML (S,U,D)	26.47	2.79	0.023	0.025
VMML (A,L,D)	26.59	3.00	0.022	0.029
VMML (A,U,D)	26.73	2.74	0.021	0.025

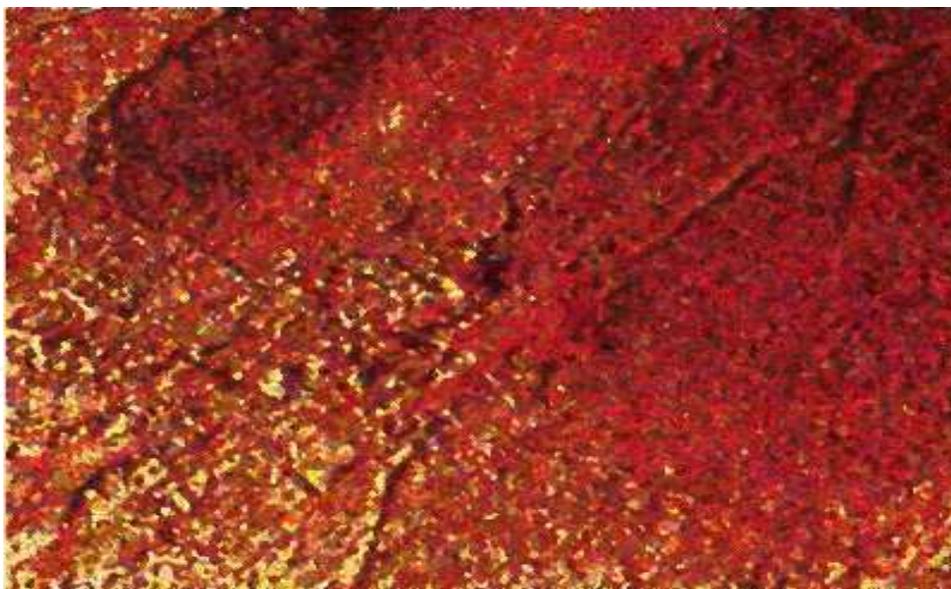
Table 7. Comparative restoration results for 20% impulsive noise for colour image "Lena"



Fig. 5. Subjective visual qualities of restored colour image "Lena", (a) Original test image "Lena", (b) Input noisy image (with 20% of impulsive noise), (c) FASVM filtering image, (d) VMMKNN filtered image, (e) Proposed VMML filtering image (S,E,ND), and (f) Proposed VMML filtering image (S,E,D).



(a)



(b)

Fig. 6. Visual results of despeckled SAR image. a) Original image “Manzano”, 2m resolution, Ku Band SAR, 15GHz, vertical polarization, source Sandia National Lab., b) Despeckled image from (a) with the proposed VMML filter (S,U,D).

## 4. Conclusions

The proposed FD filter connects two commonly used in colour imaging techniques: directional processing where vector order statistics are employed, and fuzzy logic procedures that applied membership values found for pixels to be processed. FD filter has presented good performance in terms of noise suppression, edge and fine detail preservation, and chromaticity preservation properties, as well in visual subjective analysis. The proposed MML filter is able to remove impulsive noise and preserve the edges and details in gray scale and colour imaging. The proposed MML filter uses the robust MM-estimator and utilizes an impulsive noise detector to provide better noise suppression, detail preservation, and in the case of colour imaging, provides better color retention. The VMML filter has demonstrated better quality of image processing, both in visual and analytical sense in comparison with different known colour image processing algorithms.

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## 6. References

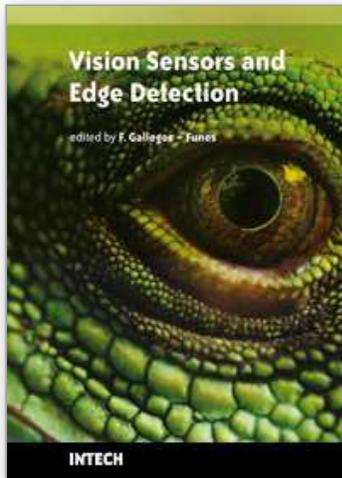
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