Detection and Denoising of Impulsive noise using Vector-Marginal filter applied to color images

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Abstract: we present a vector-marginal filter for impulsive noise detection based on: 1) Fuzzy rank-ordered differences static (FROD) working on the color components and 2) Fuzzy detection phase on the separate components of the image using the City-block (L_1) distance. Also we present a denoising scheme for color images using angular criterion and the resulting detected noise.

Keywords. Color image processing, Vector filter, Marginal filter, Fuzzy Logic, Impulsive Noise.

1 Introduction

Digital image enhancement and analysis have played an important role in scientific, industrial, and military applications. In addition to these applications, image enhancement and analysis are increasingly being used in consumer electronics. Internet Web users, for instance, not only rely on built-in image processing protocols such as JPEG and interpolation, but they also have become image processing users equipped with powerful yet inexpensive software such as Photoshop. Image enhancement refers to processes seeking to improve the visual appearance of an image. Image enhancement is important because of its usefulness in virtually all image processing applications [1]. Color image processing techniques are commonly divided into two classes [2]: the first one Marginal (component-wise) methods that operate on each color channel separately, due to the independent processing ignores the correlation that exists between the color channels giving in some cases, the projection of the separate outputs into the color image usually results in perceivable color artifacts; and the second one Vector methods, that process the input samples as a set of vectors. Because no new color are introduced into the image, this kind of filtering is much more effective and adequate in color image processing applications as suggested in [2].

The design of the proposed filter is focused in the reduction of the impulsive noise in color images. This type of noise is generally caused by the acquisition or transmission of digital images through sensors or communication channels [3,4]. Image transmission noise is caused by various sources, among others; there are manmade

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phenomena, such as car ignition systems, industrial machines in the vicinity of the receiver, switching transients in power lines, and various unprotected switches. In addition, natural causes, such as lightning in the atmosphere and ice cracking in the Antarctic region, can also affect the transmission process. This kind of noise can be modeled as impulsive noise. Two most common impulsive noises are fixed-value impulsive noise and random-value impulsive noise [5, 3, 6]. For example, if F_i^{col} denotes the input noisy image and O_i the original noise-free image in i-th pixel position, then we can express the impulsive noise as in Eq.(1)[7]:

$$F_i^{col} = \begin{cases} {O_i}^{col}, & with\ probability\ 1-\delta \\ {\zeta_i}^{col}, & with\ probability\ \delta \end{cases}, \tag{1}$$

The x and y indexes indicate 2-D pixel position and col the color component, respectively, with $col = \{R, G, B\}$. In this paper we consider two types of impulsive noise, random-value and fixed-value. The characteristic of the Random-value type is that ${\zeta_i}^{col}$ is an identically distributed, independent random process with an arbitrary underlying probability density function. For fixed-value, ${\zeta_i}^{col}$ has value of 0 or 255. .

This paper is organized as follows. In Section 2, the vector-marginal impulsive noise detector and the proposed filter are detailed. In Section 3, we present experimental results for the random and fixed valued impulsive noise. Finally, conclusions are presented in Section 4.

2 *Proposed Vector-Marginal Impulsive Noise Detector and Filter (FDDEMV)*

The proposed filter is divided in two, the noise detection which in turn is divided in two stages, namely, *marginal* and *vectorial* noise detection under which a fuzzy rule is implemented, and a fuzzy filter which uses the noise level results obtained from the detection phase above along with the angle computed between each pixel and its neighbors inside the sliding window. Detailed methodology is described in next section.

2.1 Vector-Marginal Impulsive Noise Detector

The detector is divided in two stages, *vectorial* and *marginal*. The *vectorial* stage is based on the Fuzzy rank-ordered differences static (FROD) [10]. The design of the *marginal* stage is based on the L_1(City-Block) distance followed by a fuzzy stage that uses fuzzy similarity between the central pixel and its neighbors.

The Vectorial stage

The fuzzy rank-ordered differences static (FROD) uses the fuzzy version of the Chess-board metric (L_∞), the M_∞ fuzzy metric. This fuzzy metric is defined as: $X = \{0,1,\dots,255\}$, and $K > 0$ which denote an 8-bit pixel according to equation (2). Let define $\boldsymbol{x}_i \in X^3$. In this way let define the M_∞ metric on X^3 as in Eq. (2)

$$M_\infty(x_a, x_b) = min_{l=1}^{3} \frac{\min\{x_a(l), x_b(l)\}+K}{\max\{x_a(l), x_b(l)\}+K}, \tag{2}$$

we use the value parameter of $K = 1024$ according to [10]. x_a and x_b are the pixels under consideration.

Consider a nxn window denoted as Ω_x over an image pixel $\boldsymbol{x}$ where each pixel $\boldsymbol{x}_j \in \Omega_x$ is associated to its RGB color components$(x_R, x_G, x_B) \in X^3$. Let denote by Ω_x^0 the set of neighbors of $\boldsymbol{x}$ in Ω_x that is $\Omega_x^0 = \Omega_x - \{\boldsymbol{x}\}$. Considering the usage of the M_∞ fuzzy metric to obtain the fuzzy distances $d_{x,x_i} = M_\infty(x, x_i), \boldsymbol{x}_i \in \Omega_x^0$, and we order the fuzzy distances in descending sequence so that $s_j(\boldsymbol{x})$ is the j-th largest d_{x,x_j} value $(s_1(\boldsymbol{x}) \geq s_2(\boldsymbol{x}) \geq \cdots \geq s_{n^2-1}(\boldsymbol{x}))$, the $FROD$ static is given by Eq. (3) as:

$$FROD(\boldsymbol{x}) = \prod_{j=1}^{m} s_j(\boldsymbol{x}). \tag{3}$$

With the m-th nearest neighbors the $FROD$ static provides the degree in which the vector $\boldsymbol{x}$ is similar to its m most similar neighbors in Ω_x^0, we selected $m = 3$. An impulsive noise pixel is not expected to be similar to its neighbors respect to its fuzzy metric, which implies a low value of $FROD(\boldsymbol{x})$, whereas noise-free pixels, even those close to image edges, are expected to have a $FROD(\boldsymbol{x})$ value close to the unity.

The Marginal stage

This algorithm is applied for each color channel in an independent way: measure the L_1 distance given in the equation (4) between the central pixel and its neighbors, where μ stands for each RGB channel, $j = 0, \dots, n^2 - 1$, with $n = 3$, P_c^μ and P_j^μ are the central pixel and a neighbor pixel respectively:

$$\Delta_j^\mu = \text{dist}^\mu\left(P_c^\mu, P_j^\mu\right) = \left|P_c^\mu - P_j^\mu\right|. \tag{4}$$

Obtain the degree of membership of each Δ_j^μ within the Large fuzzy set using Eq. (5), obtaining in this manner $r^\mu\left(\Delta_j^\mu\right)$, which indicates the level of similarity between the central pixel and its neighbors, if the pixels are similar, Large fuzzy set will be close to the unity, otherwise it should be close to zero.

$$r^{\mu}(\Delta_j^{\mu}) = \begin{cases} 1, & if\ \Delta_j^{\mu} \le \alpha \\ 1 - 2\left(\frac{\Delta_j^{\mu}-\gamma}{\gamma-\alpha}\right)^2, & if\ \alpha_{\zeta} \le \Delta_j^{\mu} < \frac{\alpha+\gamma}{2} \\ 2\left(\frac{\Delta_j^{\mu}-\gamma}{\gamma-\alpha}\right)^2, & if\ \ \frac{\alpha+\gamma}{2} < \Delta_j^{\mu} \le \gamma \\ 0, & si\ \Delta_j^{\mu} > \gamma \end{cases}, \tag{5}$$

with $\alpha = 20$ and $\gamma = 100$ are parameters of the membership function obtained under experimentation, that indicate the level in which $r^{\mu}(\Delta_j^{\mu})$ has a maximum value (≈ 1) or minimun value(≈ 0).

Next, we arrange these degrees of membership in a descending order then name this sequence Z_j^{μ}, doing this, we can obtain a fuzzy similarity function Eq. (6) that indicates the level of similarity between the central pixel and its most similar neighbors.

$$NF_{\mu} = \prod_{j=1}^{B} Z_j^{\mu}\ , \tag{6}$$

where B is the number of pixels taken into account in the product to obtain NF_{μ}.

Respect to Fuzzy Rule

After having obtained the detected noise by means of vectorial and marginal processing, the next step is to combine these two stages of the detection scheme to obtain a noise level for the vectorial stage. This is done by using the *fuzzy rule 1* (Eq. (7)):

$$\begin{aligned} &\boldsymbol{fuzzy\ rule\ 1}: \\ &if\ NF_{\mathrm{R}}\ is\ large\ and\ NF_{\mathrm{G}}\ is\ large\ and\ NF_{\mathrm{B}}\ is\ large\ and \\ &FROD(\boldsymbol{x})\ is\ large\ then\ TNF\ is\ large \end{aligned} \tag{7}$$

where TNF is the Total Noise-Free detected value produced by combination of the vectorial and marginal stages and represents the level of noise from the pixel under processing. NF_{R}, NF_{G} and NF_{B} are the Noise-Free values resulting of the marginal processing on the Red, Blue and Green channels.

2.2 Proposed filtering scheme

Let introduce a filtering switching scheme that uses the detected noise. The Fig. 1 shows a block diagram of the algorithm, applied to each pixel in an image. The first is a conditional block, if TNF value is less than a threshold, it is performed a filtering over the pixel been processed, otherwise, no operation is done and the pixel under processing remains intact.

In the first block of the filtering, it is obtained an aggregated angular distance α_i [8] given in Eq. (8), this parameter indicates how much a given pixel i present in the

sliding window is similar to all neighbors. This is done by calculating the angles between each of the pixels agree to Eq. (9).

$$\alpha_i = \sum_{j=1}^{9} \theta\left(Pixel_i, Pixel_j\right), \tag{8}$$

$$\theta\left(Pixel_i, Pixel_j\right) = cos^{-1}\left(\frac{R_i \cdot R_j + G_i \cdot G_j + B_i \cdot B_j}{\sqrt{{R_i}^2 + {G_i}^2 + {B_i}^2}\sqrt{{R_j}^2 + {G_j}^2 + {B_j}^2}}\right). \tag{9}$$

In the next block, an ascending ordering is done with respect to the aggregated angular distance of each pixel. After, ascending ordering of the five pixels with the less α respect to its NF value, another ascending ordering is done but respect to the $Noise$ value of the five pixels with the less aggregated angular distance. Finally, in the last block, median filter operating over the 3 pixel of the previous step with the less $Noise$ value, a median filter is done over the three pixels with the less NF value. By experiments, we saw that taking into account five pixels for the ascending ordering respect to α and three pixels for the median filter, we get the best results.

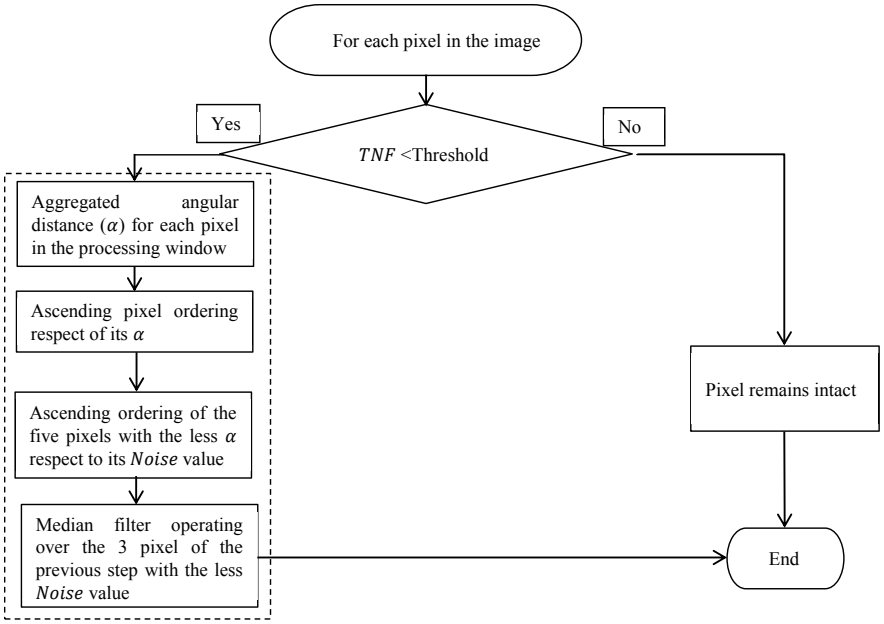


Fig. 1. Block diagram of the proposed filtering scheme.

3 Experimental Results

In this Section, we present the experimental results for the proposed filter. We compare several filters found in literature (Table 1) against the proposed filter using objective parameters. The parameters are: Peak Signal to Noise Ratio (PSNR) [1] Eq. (10) indicating noise suppression level, Mean Absolute Error (MAE) [1] Eq. (12), to measure fine details and edges preservation, and Mean Chromaticity Error (MCRE) [12] Eq. (13), characterizing the chromaticity error between the original and the filtered image.

$$PSNR = 10 \cdot log\left[\frac{255^2}{MSE}\right], \tag{10}$$

$$MSE = \frac{1}{3MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[(|R(x,y) - R'(x,y)|^2 + |G(x,y) - G'(x,y)|^2 + |B(x,y) - B'(x,y)|^2)], \tag{11}$$

$$MAE = \frac{1}{3MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[(|R(x,y) - R'(x,y)| + |G(x,y) - G'(x,y)| + |B(x,y) - B'(x,y)|)], \tag{12}$$

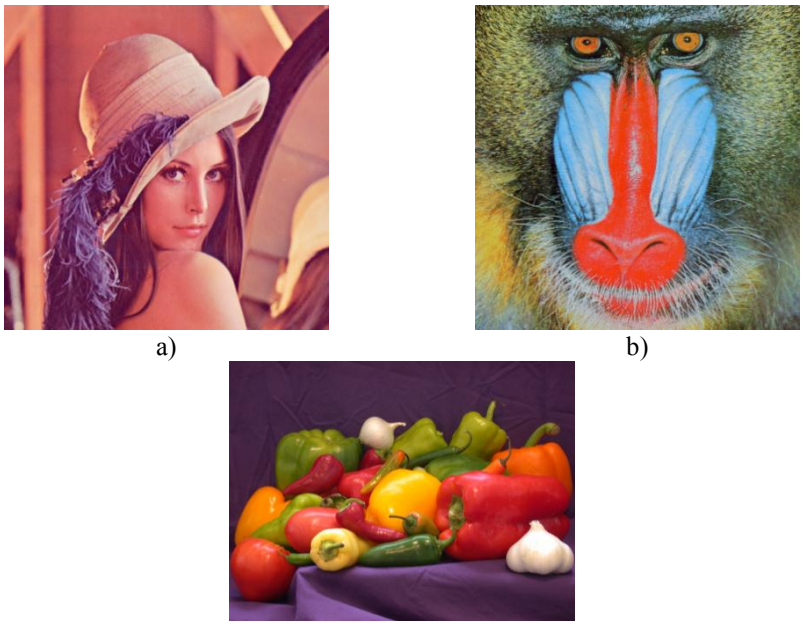
$$MCRE = \frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} C[f(x,y), f'(x,y)]}{MN}, \tag{13}$$

where M, N are the dimensions of the image, $R'(x,y)$, $G'(x,y)$, $B'(x,y)$ are the pixel position on each channel of the filtered image and $C[f(x,y), f'(x,y)]$ is the chromatic error between the vectors $f(x,y)$ and $f'(x,y)$.

Table 1. Filters found in the literature

Filter	Reference
α-trimmed	[9]
Basic Vectorial Directional filter (BVDF)	[8]
Fuzzy Two Step Color filter (FTSCF)	[11]
Fuzzy ROD Filter (FRF)	[10]
Vector Median filter VMF	[4]

We have used several standard images to contaminate with different densities and the two types of noise. The standard images that we have used are: Lenna, Mandrill (512x512 pixels) and peppers (512x384 pixels) all them shown in Fig. 2.



a) b) c)

Fig. 2. Standard test images used: a) Lenna, b) Mandrill and c) Peppers.

In Fig. 3, is displayed the PSNR results for Lenna contaminated with random-value impulsive noise, in Fig. 4 the MAE results for Mandrill contaminated fixed-value impulsive noise and in Fig. 5 are the MCRE results for the peppers image contaminated with fixed-value noise.

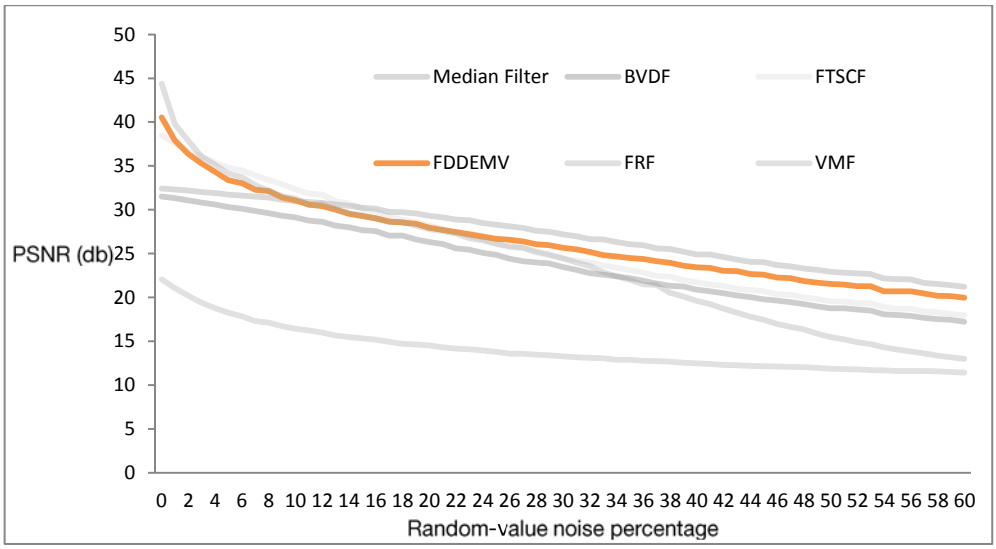


Fig. 3. PSNR results for Lenna contaminated with random-value impulsive noise

In the graphic in Fig. 3, we can note that the filter has a good performance respect to the others filters found in the literature in PSNR terms for low densities of random-value impulsive noise (<25%) and for high densities of noise (from 25 to 60%) is the second best.

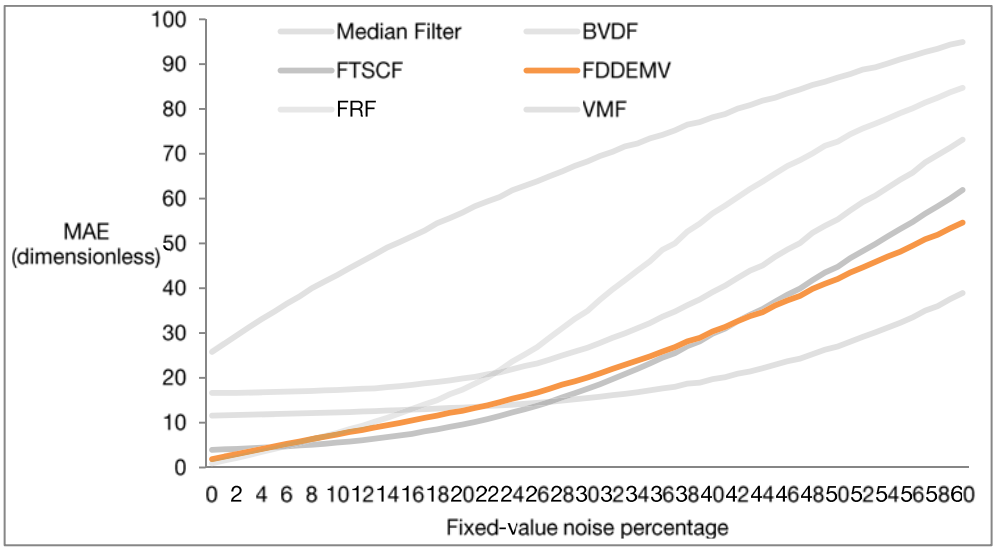


Fig. 4. MAE results for Mandrill image contaminated with "fixed-value" noise.

In the graphic in Fig. 4, we can note that the filter has a good performance respect to the others filters found in the literature in MAE terms for low densities of fixed-value impulsive noise (<10%) and for high densities of noise (from 40 to 60%)) is the second best.

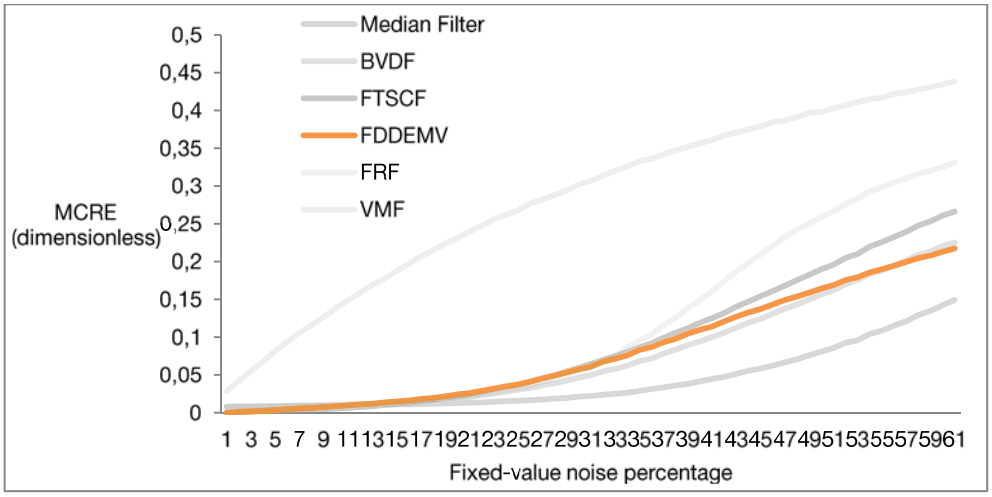


Fig. 5. MCRE results for Peppers image contaminated with "fixed-value" noise.

In the graphic in Fig. 5, we can note that the filter has a good performance respect to the others filters found in the literature in MCRE terms for low densities of fixed-value impulsive noise (<30%) and for high densities of noise (from 30 to 60%) maintains good performance.

Table 2 shows the results for PSNR, MAE and MCRE of Peppers using random-value impulsive noise.

Table 2. results for PSNR, MAE and MCRE of Peppers using random-value impulsive noise

% noise	Parameter	BVDF	VMF	Median Filter	FTSCF	FRF	**FDDEMV**
0	PSNR	35.37	26.46	38.94	47.69	50.54	46.02
	MAE	2.05	5.83	1.30	.03	.13	.03
	MCRE	.007	.029	.008	.000	.000	.000
5	PSNR	34.16	19.93	37.94	39.18	37.20	36.61
	MAE	2.34	9.83	1.46	.35	.54	.57
	MCRE	.0089	.0524	.0091	.0027	.0035	.0037
10	PSNR	32.55	17.58	36.56	34.86	33.95	33.63
	MAE	2.68	13.55	1.67	.73	1.04	1.8
	MCRE	.010	.074	.01	.005	.006	.007
15	PSNR	30.55	16.09	34.82	31.60	32.20	31.53
	MAE	3.14	17.13	1.91	1.20	1.50	1.58
	MCRE	.0127	.0931	.0115	.0090	.0090	.0103
20	PSNR	28.11	15.12	32.68	28.47	30.51	29.65
	MAE	3.87	20.20	2.26	1.90	2.01	2.20
	MCRE	.016	.11	.013	.013	.011	.014
25	PSNR	25.67	14.34	30.40	25.80	28.33	27.78
	MAE	4.86	23.11	2.72	2.84	2.63	2.96
	MCRE	.0213	.1255	.0164	.0199	.0144	.0186
30	PSNR	23.52	13.79	28.31	23.70	25.81	25.89
	MAE	6.22	25.63	3.35	4.04	3.52	3.98
	MCRE	.028	.138	.021	.027	.018	.024

We can see in the table that respect to PSNR, MAE and MCRE, the proposed filter has a competitive performance respect to the others filters found in the literature.

In Fig. 6, is displayed for subjective comparison Lenna corrupted with 5% fixed-value noise and the results from the filters found in the literature and the proposed filter.

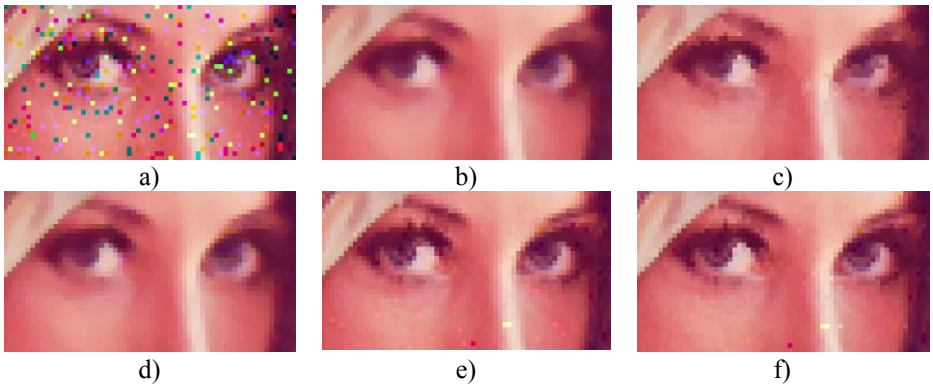


Fig. 6. a) Lenna corrupted with 5% fixed-value noise and the results of b)VMF, c)BVDF, d) Median Filter, e) FRF and f) proposed FDDEMV.

We can see in Fig. 6 that the proposed filter has good noise suppression that the rest of the filters, preservers better the image characteristics, also no color artifacts were introduced.

4 Conclusions

From the graphs and the tables, we can see that the proposal filter present good detail preservation, noise suppression and color preservation quality respect the other filters for the two types of noise, random-value and fixed-value at low densities of noise (<20%). With highest noise levels, the proposed filter is competitive respect to the others filters found in the literature.

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