A FAST SWITCHING FILTER FOR IMPULSIVE

NOISE REMOVAL FROM COLOR IMAGES

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**ABSTRACT** 

In this paper, we present a fast switching filter for impulsive noise removal from color images. The filter

exploits the HSL color space, and is based on the peer group concept, which allows for the fast detection of

noise in a neighborhood without resorting to pairwise distance computations between each pixel.

Experiments on large set of diverse images demonstrate that the proposed approach is not only extremely

fast, but also gives excellent results in comparison to various state-of-the-art filters.

Keywords: color image processing, nonlinear vector filter, impulsive noise, HSL color space, switching filter, peer

group, S-CIELAB

1. Introduction

The growing use of color images in diverse applications such as content-based image retrieval, medical

image analysis, biometrics, remote sensing, watermarking, and visual quality inspection has led to an

increasing interest in color image processing. These applications need to perform many of the same tasks as

their grayscale counterparts, such as edge detection, segmentation and feature extraction [1]. However,

images are often contaminated with noise which is often introduced during acquisition or transmission. In

particular, the introduction of bit errors and impulsive noise into an image not only lowers its perceptual

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quality but also makes subsequent tasks such as edge detection and segmentation more difficult. Therefore, the removal of noise from an image is often a necessary preprocessing step for these tasks. Modern image filtering solutions can eliminate noise without significantly degrading the underlying image structures such as edges and fine details [2]. Recent applications of color image denoising include enhancement of cDNA microarray images [3,4], virtual restoration of artworks [5,6], and video filtering [7-10].

Numerous filters have been proposed in the literature for noise removal from color images [11-14]. Among these, nonlinear vector filters have proved successful in dealing with impulsive noise while preserving edges and image details [13]. These filters treat pixels in a color image as vectors to avoid color shifts and artifacts. An important class of nonlinear vector filters is the one based on robust order-statistics with the vector median filter (*VMF*) [15], the basic vector directional filter (*BVDF*) [16], and the directional-distance filter (*DDF*) [17] being the most well-known examples. These filters involve the reduced ordering [18] of a set of input vectors within a window to compute the output vector.

The fundamental order-statistics based filters (*VMF*, *BVDF*, and *DDF*) as well as their fuzzy [19,20] and hybrid [21] extensions share a common deficiency in that they are implemented uniformly across the image and tend to modify pixels that are not corrupted by noise [22]. This results in excessive smoothing and the consequent blur of edges and loss of fine image details. In order to overcome this, intelligent filters that switch between a robust order-statistics based filter such as the *VMF* and the identity operation have been introduced [22-37]. These filters determine whether the pixel under consideration is noisy or not in the context of its neighborhood. In the former case, the pixel is replaced by the output of the noise removal filter; otherwise, it is left unchanged to preserve the desired (noise-free) signal structures. Such an approach is computationally efficient considering that the expensive filtering operation is performed only on the noisy pixels, which often comprise a small percentage of the image.

In this paper, we introduce a new switching filter for the removal of impulsive noise from color images. The proposed filter exploits the *HSL* color space [13], and is based on the concept of a *peer group* [22], which allows for the fast detection of noise in a neighborhood without resorting to pairwise distance

computations between each pixel. The center pixel in a neighborhood is considered as noise-free if it has a certain number of pixels that are similar to it. In this case, it remains intact. Otherwise, it is replaced by the *VMF* output, i.e. the pixel that minimizes the sum of distances to all other pixels in the neighborhood. The method is tested on a large set of images from diverse domains. The results demonstrate that the proposed filter is not only extremely fast, but also gives excellent results in comparison to various state-of-the-art filters.

The rest of the paper is organized as follows. Section 2 describes the proposed method and the motivation behind the choice of the *HSL* space for the calculation of the similarity metric. Section 3 presents the experimental results. Finally, section 4 gives the conclusions.

## 2. Proposed Method

Let y(x):  $Z^2 o Z^3$  denote an RGB color image that is comprised of a two-dimensional array of three component samples. Although natural images are often nonstationary, filters operate on the assumption that they can be subdivided into small regions that are stationary [12]. This is accomplished using a small window that slides through the individual image pixels while performing the filtering operation locally. The most commonly used window is a square-shaped window  $W = \{x_i | i = 1, 2, ..., n\}$  of a finite size n, where  $x_1, x_2, ..., x_n$  is a set of pixels centered around  $x_{(n+1)/2}$  which determines the position of the window.

Most vector filters operate by ordering the vectors inside the filter window. However, calculating the aggregate distances used in the ordering criterion may limit the use of these filters in real-time applications. One way to reduce the computational requirements of a nonlinear vector filter is to limit the number of comparisons that are performed between the center pixel and the neighboring pixels in the window. The Fast Peer Group Filter (*FPGF*) [31] uses the concept of the *peer group* [22] to determine the output vector according to the following rule:

$$x_{FPGF} = \begin{cases} x_{(n+1)/2} & \text{if } \left| \left\{ x_j \in W \mid j \neq (n+1)/2 \text{ and } \left\| x_{(n+1)/2} - x_j \right\|_p \le Tol \right\} \right| \ge m \\ x_{VMF} & \text{otherwise} \end{cases}$$
(1)

where Tol is the distance threshold, m is the size of the  $peer\ group$ ,  $\|\cdot\|$  is the set cardinality,  $\|\cdot\|_p$  is the  $L_p$  (Minkowski) norm, and  $x_{VMF}$  denotes the VMF output given by:

$$x_{VMF} = \underset{x_i \in W}{\operatorname{argmin}} \sum_{j=1}^{n} \left\| x_i - x_j \right\|_{p} \qquad (2)$$

Essentially, the *peer group* of a pixel represents the neighboring pixels in the window that are sufficiently 'similar' to it according to a particular measure. This concept is due to Lee [38] and has been used extensively in the design of various filters, often under the name of *extended spatial neighborhood* [31].

The FPGF is much faster than the well-known vector filters mentioned in the previous section because it declares the center pixel to be noise-free as soon as m pixels in the window are determined to be sufficiently similar to it. If m is low, and the level of noise in the image is not very high, this allows for a dramatic reduction in the number of distance computations that need to be performed. In particular, the minimum and maximum number of distance calculations necessary to classify a pixel equal m and n-m, respectively. Therefore, on the average, the number of distance calculations performed by the FPGF is much lower than that performed by the VMF, i.e. n(n-1)/2. However, due to the nature of the  $L_2$  norm, the distance computations performed in highly correlated spaces such as RGB remain expensive. On the other hand, if the image is transformed into a color space which decouples chromaticity and luminance, the distance between two color vectors can be evaluated without such a computation. In this study, we adopted the HSL color space in order to accomplish this.

The HSL (hue, saturation and lightness) color space is an intuitive alternative to the RGB space [13]. It uses approximately cylindrical coordinates, and is a non-linear deformation of the RGB color cube (Figure 1a). The hue  $H \in [0,360]$  is a function of the angle in the polar coordinate system and describes a pure color. The saturation  $S \in [0,100]$  is proportional to radial distance and denotes the purity of a color. Finally, the

lightness  $L \in [0,255]$  is the distance along the axis perpendicular to the polar coordinate plane and represents the brightness. The distance between two vectors  $x_i = (h_i, s_i, l_i)$  and  $x_j = (h_j, s_j, l_j)$  in the *HSL* space is given by:

$$D(x_i, x_j) = D_{HSL}(x_i, x_j) = \sqrt{s_i^2 + s_j^2 - 2s_i s_j \cos(h_i - h_j) + (l_i - l_j)^2}$$
(3)

#### **INSERT FIGURE 1 HERE**

Building upon the idea of the *peer group* in much the same way as the *FPGF*, we propose a new filtering algorithm called the Fast *HSL*-based Switching Filter (*FHSF*). First, the *RGB* image is transformed to the *HSL* space [13]. The output vector in a window is then determined according to the following rule:

$$x_{FHSF} = \begin{cases} x_{(n+1)/2} & \text{if } \left| \left\{ x_j \in W \mid j \neq (n+1)/2 \text{ and } S(x_{(n+1)/2}, x_j) = 1 \right\} \right| \geq m \\ x_{VMF} & \text{otherwise} \end{cases}$$

$$S(x_i, x_j) = \begin{cases} 1 & \text{if } \left| h_i - h_j \right| \leq Ht \text{ and } \left| s_i - s_j \right| \leq St \text{ and } \left| l_i - l_j \right| \leq Lt \\ 0 & \text{otherwise} \end{cases}$$

$$(4)$$

where  $(h_i, s_i, l_i)$  and  $(h_j, s_j, l_j)$  denote the hue, saturation, and lightness of the pixels  $x_i$  and  $x_j$ , respectively. Ht, St, and Lt are the thresholds for the hue, saturation, and lightness, respectively.

The *FHSF* algorithm works as follows. First, it checks whether the center pixel is noisy or not. If the pixel is determined to be noisy, it is replaced by the *VMF* output. Otherwise, it remains untouched. A noise-free pixel is one which has a minimum of *m* peers that are sufficiently similar to it. The similarity is determined by the function *S*, which checks to see if the hue, saturation and lightness of the pixel are close to those of the center pixel.

The similarity function S is clearly cheaper to evaluate when compared to the  $L_2$  norm in the RGB space. The superficial similarity between the S function and the  $L_1$  norm can be discounted by the fact that the former operates in the decorrelated HSL space as opposed to the correlated RGB space, and consequently the conjunction involved in this function allows for *short-circuit* evaluation. That is, for instance, as long as

two color vectors differ in hue, the remaining two conditions need not be evaluated. On the other hand, in the  $L_I$  norm the absolute differences between the R, G, and B components always need to be calculated. Table 1 shows the number of elementary operations required by each function. It can be seen that in the worst case, since COMPs and ADDs have the same complexity [39], the S function has the same number of operations as the  $L_I$  norm.

#### **INSERT TABLE 1 HERE**

# 3. Experimental Results

#### 3.1 Noise Model and Error Metrics

Several simplified color image noise models have been proposed in the literature [10,11,13]. In this study, the correlated impulsive noise model originally proposed in [10] is adopted. In order to evaluate the filtering performance the following error metrics are used: *MAE* (Mean Absolute Error) [13], *MSE* (Mean Squared Error) [13], *NCD* (Normalized Color Distance) [13], and *PCD* (Perceptual Color Distance) [40-42]. *MAE* and *MSE* are based on the *RGB* color difference and measure the detail preservation and noise suppression capability of a filter, respectively. *NCD* and *PCD* are perceptually oriented metrics that measure the color preservation capability of a filter. *NCD* is based on the *CIELAB* color difference whereas *PCD* is based on the *S-CIELAB* color difference, which is a spatial extension of the former [43]. It should be noted that, to the best of the authors' knowledge, *PCD* has not been used in the color image filtering literature to date. It is included because it takes into account both the spatial and color sensitivity of the human visual system [41].

#### 3.2 Parameter Selection

There are four parameters involved in the proposed filter: m (the peer group size), Ht (Hue Threshold), St (Saturation Threshold) and Lt (Lightness Threshold). Appropriate ranges for these parameters need to be

determined to ensure a good filtering performance on a variety of images. Since the filtering operation is very fast, a simple grid search procedure can be used for this task. In order to do this, the parameter space should first be quantized.

The parameters m, Ht, St, and Lt were restricted to  $[1,8]^1$  (step size  $\Delta=1$ ), [6,20] ( $\Delta=2$ ), [4,16] ( $\Delta=2$ ), and [32,64] ( $\Delta=4$ ), respectively. The sizes of the intervals for the Ht, St, and Lt parameters follow the relative importance of the individual components of the HSL space. This is because the human visual system is most sensitive to changes in hue, followed by saturation, and then lightness [44]. For example, the hue threshold Ht is restricted to the [6,20] interval because for noise removal purposes, two colors that have more than  $20^{\circ}$  of hue difference can safely be considered as dissimilar (see Figure 1b).

A set of 100 images was collected from the World Wide Web to be used in the grid search. These included images of people, animals, plants, buildings, aerial maps, man-made objects, natural scenery, paintings, sketches, as well scientific, biomedical, and synthetic images and test images commonly used in the color image processing literature. Figure 2 shows several representative images from this set.

#### **INSERT FIGURE 2 HERE**

The PCD measure was used to quantify the goodness of a particular set of parameters  $\{m, Ht, St, Lt\}$ . Figure 3 shows the minimum PCD values obtained during the grid search at each m value for several images that are contaminated with 5%, 10%, 15% and 20% impulsive noise.

#### **INSERT FIGURE 3 HERE**

As explained in Section 2, the filtering operation is faster for lower values of m. In fact, the performance of the proposed filter (in terms of both the effectiveness and the efficiency) will approach that of the VMF at

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<sup>&</sup>lt;sup>1</sup> Assuming a 3x3 window

high values of m. It can be seen from Figure 3 that m = 3 provides a good compromise between effectiveness and efficiency. This is in line with the observations of Smolka and Chydzinski [31].

The ranges for the remaining three parameters, Ht, St and Lt, were determined as follows. For each test image, the parameters were varied in the above-mentioned intervals and the corresponding PCD values were calculated. Considering the diversity of the images, it is unreasonable to expect the same parameter combination to give the lowest PCD value for each image. Therefore, the parameter combinations that achieved the lowest 5% PCD values for each image were recorded. It is expected that a parameter combination that will perform well on a variety of images would appear somewhere in these top 5% lists. The intersection of these lists revealed that the following ranges perform well on the test images,  $Ht \in [8,12]$ ,  $St \in [8,14]$ , and  $Lt \in [40,56]$ . For comparison with other filters, the following default values are used: Ht = 10, St = 10, and Lt = 48.

Note that the full range of H is [0,360] and thus acceptable values for Ht lie between 2.22% and 3.33% of this range. Similarly, the range of S is [0,100] and values for St lie between 8.00% and 14.00%. Finally, the range of L is [0,255] and values for Lt lie between 15.62% and 21.87%. This is in line with the above-mentioned fact that the human visual system is most sensitive to changes in hue, followed by saturation, and then lightness [44]. Figure 4 shows an example of this phenomenon wherein a zoomed section of the parrots image is corrupted with 10% noise and then filtered using a parameter configuration in which two of the thresholds are fixed while the other one is relaxed. Figure (c) is the filtering result with the default parameters, (d) is with Ht relaxed by 5% (Ht = 28), (e) is with St relaxed by 10% (St = 20) and (f) is with Lt relaxed by 12.5% (Lt = 80). It can be seen that although the change in the hue threshold is the smallest, the degradation in the filtering result is the greatest. On the other hand, the change in the lightness threshold is the largest, but the filtering result is better than those of (d) and (e).

## **INSERT FIGURE 4 HERE**

#### 3.3 Comparison with State-of-the-Art Filters

The proposed filter is compared with recent switching filters such as the peer group filter (PGF) [22], the adaptive vector median filter (AVMF) [26], the fast fuzzy noise reduction filter (FFNRF) [32], the fast peer group filter (FPGF) [31], the vector sigma filters based on the mean and lowest ranked vectors ( $SVMF_{mean}$ ,  $SVMF_{rank}$ ) [33], and their adaptive counterparts ( $ASVMF_{mean}$ ,  $ASVMF_{rank}$ ) [33]. The traditional filters mentioned in Section 1 (VMF, BVDF, and DDF) are also included in this comparison to highlight the merits of the switching technique. Finally, for comparison purposes, the FHSF version that uses the 3D distance function in the HSL space ( $FHSF_{HSL}$ ) and the  $L_I$  version of the FPGF ( $FPGF_I$ ) are also considered in the experiments. In the following discussion, the standard versions of the FHSF and the FPGF are denoted as  $FHSF_S$  (Equation 4) and  $FPGF_2$  (Equation 1 with p = 2), respectively.

Figure 5 shows the filtering results for a zoomed section of the cat image. Parts (c) and (d) show the outputs of the non-switching filters, i.e. the VMF and the DDF. It can be seen that even though these filters suppress the noise very well, this comes at the expense of the blurring of image details, e.g. the whiskers. On the other hand, the switching filters, i.e. the  $FPGF_2$ , the FFNRF, the PGF, and the  $FHSF_S$  preserve the details satisfactorily. Among these, the  $FHSF_S$  strikes the best balance between noise removal and detail preservation.

#### **INSERT FIGURE 5 HERE**

Figure 6 shows the filtering results for a section of the pig image and the corresponding difference images. In order to obtain the difference images, the pixelwise absolute differences between the original and the filtered images are multiplied by 5 and then negated. As expected, the VMF and the DDF outputs show significant differences when compared to the original image. In contrast, the switching filters show a clear improvement in restoring the original image. Among these, it can be seen that the AVMF, the PGF, and the  $FHSF_S$  give the best performance.

## **INSERT FIGURE 6 HERE**

Tables 2-4 compare the filters using the criteria described in Section 3.1, i.e. MAE, MSE, NCD, PCD and the execution time<sup>2</sup> in seconds. It can be seen that the  $FHSF_S$  compares favorably with the best filters in terms of filtering effectiveness, as assessed by the first four criteria. The execution time is also a very important factor which determines the practicality of a noise removal filter. From this perspective, due to their high computational requirements, the non-switching filters in general are not appropriate for denoising large images that are common in domains such as astronomy, remote sensing and biology. Regarding the remaining filters, as the image size increases, the computational advantage of the  $FHSF_S$  over the others becomes apparent. In general, the  $FHSF_S$  is almost twice as fast as the next fastest filter, i.e. the  $FPGF_J$ . Note that the timing for the  $FHSF_S$  includes the RGB to HSL transform, although this is negligible<sup>3</sup>.

#### **INSERT TABLE 2 HERE**

#### **INSERT TABLE 3 HERE**

#### **INSERT TABLE 4 HERE**

In summary, the experiments demonstrate that the  $FHSF_S$  combines simplicity, excellent filtering performance and significant computational efficiency, which makes it a practical method for impulsive noise removal from color images.

## 4. Conclusions

In this paper, we introduced a fast switching filter for the removal of impulsive noise from color images.

The proposed filter exploited the *HSL* color space in conjunction with the concept of a *peer group* in order

 $<sup>^2</sup>$  C language, GCC 3.4.4 compiler, Intel Centrino 1.6GHz processor  $\,$ 

 $<sup>^{3}</sup>$  On a 4096x4096 image that contains 16 million unique colors, the *RGB* to *HSL* transform takes 45 nanoseconds per pixel. On a typical 1024x1024 image, the total transformation time is less than 0.05 seconds.

to allow for the fast detection of noise in a neighborhood. The method was tested on a large set of images from diverse domains, as well as classical images used in the color image processing literature. The experiments demonstrated that the new method is much faster than state-of-the-art filters and that the filtering quality is also excellent.

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# **Figure Legend**

- Figure 1. (a) HSL double hexcone (b) Hue circle
- Figure 2. Representative images from the image set
- **Figure 3.** m vs. minimum *PCD* at noise levels (a) 5%, (b) 10%, (c) 15% and (d) 20%
- Figure 4. Filtering results for the parrots image using different parameter configurations
- **Figure 5.** Filtering results for the cat image corrupted with 10% noise
- **Figure 6.** Filtering results for the pig image corrupted with 10% noise and the corresponding absolute difference images

# **Table Legend**

- **Table 1.** Number of elementary operations
- **Table 2.** Comparison of the filters on the test images at 5% noise level
- **Table 3.** Comparison of the filters on the test images at 10% noise level
- **Table 4.** Comparison of the filters on the test images at 15% noise level

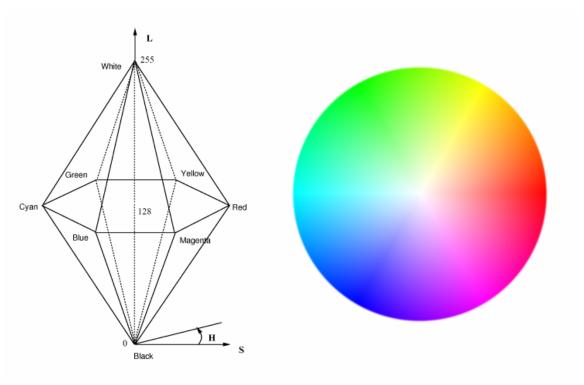
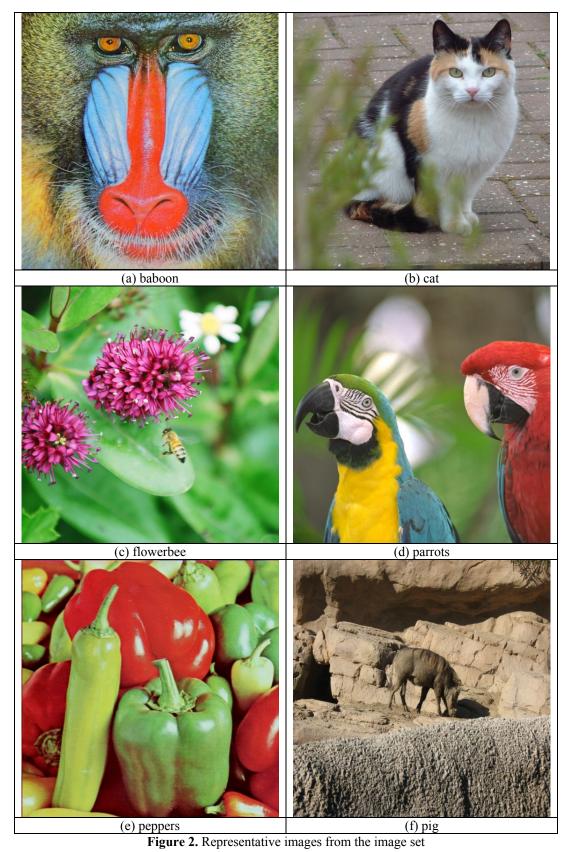


Figure 1. (a) HSL double hexcone (b) Hue circle



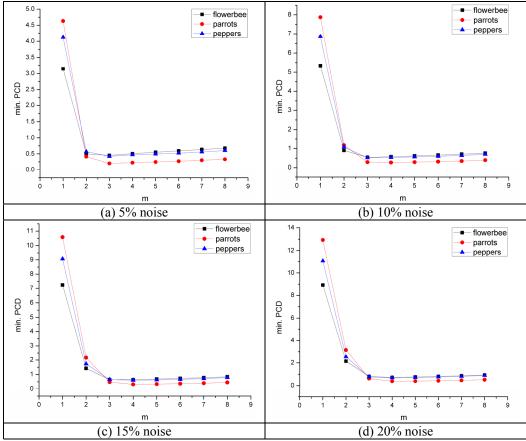
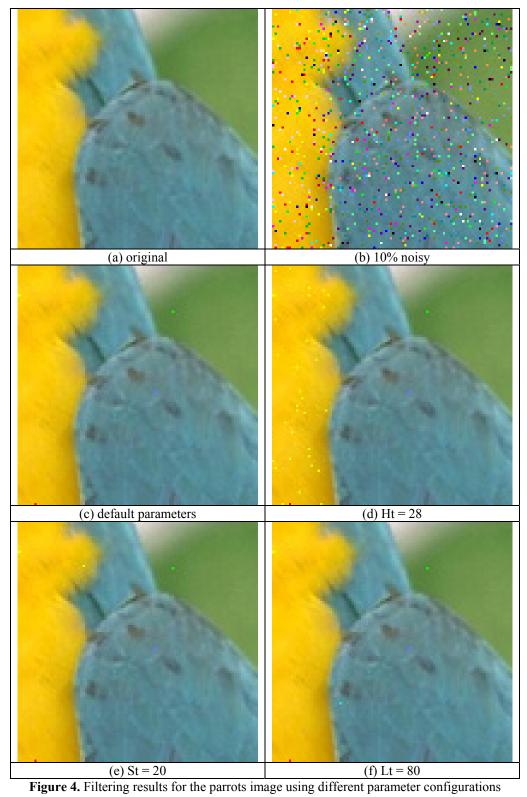
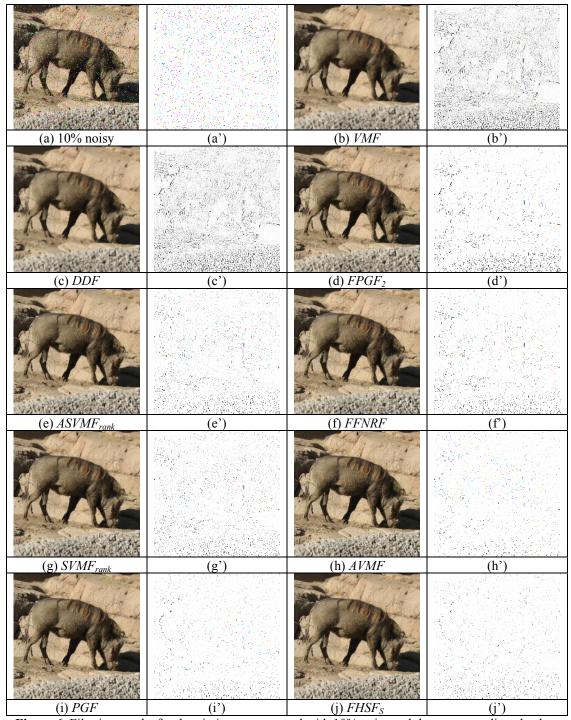


Figure 3. m vs. minimum *PCD* at noise levels (a) 5%, (b) 10%, (c) 15% and (d) 20%







**Figure 6.** Filtering results for the pig image corrupted with 10% noise and the corresponding absolute difference images

**Table 1.** Number of elementary operations

Function	ABS	ADD	SUB	COMP	MULT	COS
$L_{I}$	3	2	3	1	1	-
$L_2$	-	2	3	1	3	-
$D_{HSL}$	-	2	3	1	6	1
S	max. 3	-	max. 3	max. 3	-	-

**Table 2.** Comparison of the filters on the test images at 5% noise level

			Jonipariso	ii or tiic	THE TO	
BABOON (512 x 512 pixels)						
Filter	MAE	MSE	NCD	PCD	Time	
NONE	3.021	444.912	0.054147	3.190	-	
ASVMF <sub>mean</sub>	5.288	213.915	0.034924	2.245	0.265	
ASVMF <sub>rank</sub>	4.752	203.662	0.031785	2.189	0.672	
AVMF	1.909	114.535	0.017017	1.263	0.828	
BVDF	11.270	379.708	0.07534	3.363	8.281	
DDF	10.293	315.996	0.068711	3.069	8.765	
FFNRF	4.044	218.383	0.027072	1.984	0.375	
FHSF <sub>HSL</sub>	5.120	202.901	0.034014	2.132	0.359	
FHSF <sub>S</sub>	2.443	102.198	0.016858	1.269	0.093	
FPGF <sub>2</sub>	4.416	201.745	0.028855	2.060	0.234	
FPGF <sub>1</sub>	7.164	271.991	0.046831	2.660	0.266	
PGF	1.483	69.330	0.010498	0.998	0.250	
SVMF <sub>mean</sub>	4.015	169.237	0.026675	1.930	0.359	
SVMF <sub>rank</sub>	4.010	169.825	0.026523	1.927	0.594	
VMF	10.570	316.689	0.071926	3.171	0.624	
PARROTS (153	36 x 1024)					
Filter	MAE	MSE	NCD	PCD	Time	
NONE	3.065	472.017	0.061343	4.685	-	
ASVMF <sub>mean</sub>	0.179	3.110	0.002168	0.1465	1.187	
ASVMF <sub>rank</sub>	0.181	3.653	0.002350	0.147	3.547	
AVMF	0.359	22.315	0.007956	0.251	4.390	
BVDF	0.861	8.135	0.007753	0.384	39.719	
DDF	0.583	3.936	0.005536	0.290	43.391	
FFNRF	0.101	2.449	0.001768	0.107	1.906	
FHSF <sub>HSL</sub>	0.082	1.220	0.000946	0.108	1.204	
FHSF <sub>S</sub>	0.065	0.855	0.000741	0.097	0.407	
FPGF <sub>2</sub>	0.107	2.263	0.001714	0.103	0.735	
FPGF <sub>1</sub>	0.125	2.332	0.001708	0.111	0.547	
PGF	0.104	2.608	0.001832	0.106	1.485	
SVMF <sub>mean</sub>	0.123	2.042	0.001472	0.120	1.922	
SVMF <sub>rank</sub>	0.105	1.178	0.001072	0.111	3.500	
VMF	0.540	2.609	0.005351	0.267	3.500	

PEPPERS (512 x 480)						
Filter	MAE	MSE	NCD	PCD '	Time	
NONE	3.068	489.064	0.047504	4.138	-	
ASVMF <sub>mean</sub>	0.506	6.389	0.004151	0.534	0.172	
ASVMF <sub>rank</sub>	0.507	7.089	0.004236	0.542	0.641	
AVMF	0.419	21.954	0.006366	0.613	0.750	
BVDF	2.150	30.059	0.018474	1.254	7.704	
DDF	1.730	15.445	0.014379	0.922	8.047	
FFNRF	0.212	4.908	0.002637	0.436	0.329	
FHSF <sub>HSL</sub>	0.233	3.021	0.002206	0.441	0.235	
FHSF <sub>S</sub>	0.208	2.672	0.002091	0.430	0.078	
$FPGF_2$	0.220	3.885	0.002388	0.440	0.125	
$FPGF_1$	0.266	4.260	0.002657	0.471	0.109	
PGF	0.207	4.337	0.002422	0.431	0.234	
SVMF <sub>mean</sub>	0.380	4.911	0.003151	0.489	0.312	
SVMF <sub>rank</sub>	0.335	3.642	0.00265	0.475	0.562	
VMF	1.680	10.600	0.014163	0.866	0.563	
FLOWERBI	EE (3088	x 2048)				
Filter	MAE	MSE	NCD	PCD	Time	
NONE	3.066	480.868	0.046835	1.717	-	
ASVMF <sub>mean</sub>	0.578	5.952	0.003608	0.272	5.094	
ASVMF <sub>rank</sub>	0.559	6.543	0.003593	0.278	14.687	
AVMF	0.376	20.639	0.005393	0.354	17.359	
BVDF	1.814	11.650	0.010962	0.426	184.969	
DDF	1.655	9.473	0.009879	0.394	201.374	
FFNRF	0.167	2.630	0.001547	0.174	7.891	
FHSF <sub>HSL</sub>	0.175	1.718	0.001219	0.173	4.907	
FHSF <sub>S</sub>	0.144	1.313	0.00107	0.163	1.453	
FPGF <sub>2</sub>	0.160	2.149	0.001369	0.166	2.969	
FPGF <sub>1</sub>	0.180	2.168	0.001383	0.173	2.281	
PGF	0.167	2.807	0.001518	0.171	5.969	
SVMF <sub>mean</sub>	0.439	4.209	0.002671	0.243	8.344	
SVMF <sub>rank</sub>	0.417	3.390	0.002406	0.235	14.047	
VMF	1.697	9.660	0.010444	0.397	14.094	

Table 3. Comparison of the filters on the test images at 10% noise level

	1	able 5.	zompariso	n or u	ie iiitei
BABOON (51	2 x 512 pix	els)			
Filter	MAE	MSE	NCD	PCD	Time
NONE	6.168	914.459	0.109563	5.505	-
ASVMF <sub>mean</sub>	5.014	210.446	0.035257	2.233	0.281
ASVMF <sub>rank</sub>	4.619	205.536	0.033701	2.196	0.657
AVMF	2.680	149.962	0.026662	1.644	0.797
BVDF	11.650	397.573	0.078111	3.508	8.172
DDF	10.564	324.853	0.070965	3.153	8.813
FFNRF	4.485	231.183	0.031609	2.161	0.375
FHSF <sub>HSL</sub>	5.768	222.239	0.038852	2.333	0.375
FHSF <sub>S</sub>	3.151	127.181	0.022178	1.539	0.109
FPGF <sub>2</sub>	5.205	224.401	0.034677	2.310	0.235
FPGF <sub>1</sub>	7.770	287.367	0.051368	2.819	0.281
PGF	2.288	98.839	0.016958	1.356	0.329
SVMF <sub>mean</sub>	4.006	172.698	0.028911	1.978	0.422
SVMF <sub>rank</sub>	4.041	173.619	0.028697	1.984	0.656
VMF	10.813	326.192	0.073878	3.256	0.641
PARROTS (1:	536 x 1024)				
Filter	MAE	MSE	NCD	PCD	Time
NONE	6.119	941.234	0.122676	7.956	-
ASVMF <sub>mean</sub>	0.310	10.874	0.005117	0.222	1.250
ASVMF <sub>rank</sub>	0.336	12.633	0.005785	0.221	3.610
AVMF	0.718	44.311	0.015853	0.419	4.250
BVDF	0.935	9.100	0.008498	0.412	40.797
DDF	0.646	4.444	0.006251	0.313	43.906
FFNRF	0.218	6.047	0.003981	0.160	1.953
FHSF <sub>HSL</sub>	0.149	3.201	0.001901	0.161	1.344
FHSF <sub>S</sub>	0.132	3.448	0.001691	0.162	0.485
FPGF <sub>2</sub>	0.214	4.490	0.003445	0.144	0.905
FPGF <sub>1</sub>	0.227	4.236	0.003273	0.150	0.718
PGF	0.226	6.976	0.00403	0.177	1.531
SVMF <sub>mean</sub>	0.238	7.857	0.003813	0.196	2.047
SVMF <sub>rank</sub>	0.170	3.210	0.002165	0.149	3.265
VMF	0.616	3.247	0.006174	0.296	3.250

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PEPPERS (512 x 480)						
Filter	MAE	MSE	NCD	PCD	Time	
NONE	6.184	983.288	0.094969	6.764	-	
ASVMF <sub>mean</sub>	0.646	15.608	0.006727	0.618	0.203	
ASVMF <sub>rank</sub>	0.679	18.524	0.007333	0.646	0.578	
AVMF	0.845	44.461	0.01275	0.851	0.703	
BVDF	2.378	40.246	0.021017	1.488	7.703	
DDF	1.888	17.109	0.016101	0.970	7.953	
FFNRF	0.439	11.573	0.005574	0.555	0.328	
FHSF <sub>HSL</sub>	0.3923	6.046	0.003907	0.523	0.235	
FHSF <sub>S</sub>	0.370	6.098	0.003869	0.508	0.079	
FPGF <sub>2</sub>	0.429	7.772	0.004726	0.527	0.157	
FPGF <sub>1</sub>	0.477	7.680	0.004843	0.555	0.140	
PGF	0.432	10.999	0.005185	0.533	0.250	
SVMF <sub>mean</sub>	0.539	13.218	0.005628	0.575	0.344	
SVMF <sub>rank</sub>	0.461	8.509	0.004435	0.529	0.563	
VMF	1.842	13.163	0.015854	0.924	0.547	
FLOWERB	EE (3088 x	2048)				
Filter	MAE	MSE	NCD	PCD	Time	
NONE	6.129	960.795	0.093671	2.851	-	
ASVMF <sub>mean</sub>	0.6449	12.948	0.005325	0.326	5.250	
ASVMF <sub>rank</sub>	0.655	15.074	0.005739	0.346	14.797	
AVMF	0.762	41.588	0.010859	0.566	17.595	
BVDF	1.925	13.044	0.01177	0.452	183.641	
DDF	1.737	10.189	0.010584	0.411	192.375	
FFNRF	0.348	6.361	0.003401	0.235	8.016	
FHSF <sub>HSL</sub>	0.307	4.138	0.002272	0.217	5.578	
FHSF <sub>S</sub>	0.274	3.904	0.002131	0.209	1.828	
FPGF <sub>2</sub>	0.328	4.430	0.002792	0.212	3.813	
FPGF <sub>1</sub>	0.348	4.121	0.002714	0.218	2.938	
PGF	0.355	7.583	0.003343	0.233	6.625	
SVMF <sub>mean</sub>	0.524	9.415	0.004118	0.284	8.859	
SVMF <sub>rank</sub>	0.470	5.194	0.003169	0.252	14.235	
VMF	1.778	10.406	0.011118	0.417	14.156	

Table 4. Comparison of the filters on the test images at 15% noise level

BAROON (512	BABOON (512 x 512 pixels)						
Filter MAE MSE NCD PCD Time							
NONE	9.212		0.163820		-		
ASVMF <sub>mean</sub>	5.043		0.039034	2.319	0.234		
ASVMF <sub>rank</sub>	4.726	219.993	0.038661	2.285	0.610		
AVMF	3.522	190.028	0.037089	1.957	0.719		
BVDF	12.032	417.613	0.080963	3.640	8.109		
DDF	10.846	335.445	0.073274	3.246	8.672		
FFNRF	5.017	251.577	0.037636	2.341	0.344		
FHSF <sub>HSL</sub>	6.483	246.382	0.044302	2.519	0.360		
FHSFs	3.937	157.523	0.028343	1.805	0.110		
$FPGF_2$	6.042	249.839	0.040849	2.524	0.281		
FPGF <sub>1</sub>	8.400	305.442	0.056120	2.959	0.312		
PGF	3.135	132.236	0.023939	1.679	0.328		
SVMF <sub>mean</sub>	4.205	189.528	0.03397	2.106	0.391		
SVMF <sub>rank</sub>	4.258	189.290	0.033357	2.086	0.594		
VMF	11.066	337.448	0.075857	3.343	0.594		
PARROTS (153	66 x 1024)						
Filter	MAE	MSE	NCD	PCD T	Γime		
NONE	9.216	1419.074	0.184092	10.680	-		
ASVMF <sub>mean</sub>	0.536	25.797	0.010298	0.379	1.297		
ASVMF <sub>rank</sub>	0.597	29.275	0.011644	0.368	3.500		
AVMF	1.086	66.930	0.023909	0.585	4.187		
BVDF	1.017	11.178	0.009398	0.456	41.063		
DDF	0.716	5.083	0.007065	0.343	44.156		
FFNRF	0.362	11.560	0.006896	0.236	1.984		
FHSF <sub>HSL</sub>	0.237	8.304	0.003368	0.276	1.547		
FHSF <sub>S</sub>	0.225	9.875	0.00328	0.304	0.563		
FPGF <sub>2</sub>	0.328	6.961	0.005292	0.192	1.094		
FPGF <sub>1</sub>	0.338	6.384	0.004945	0.198	0.906		
PGF	0.376	14.717	0.006867	0.311	1.703		
SVMF <sub>mean</sub>	0.449	22.600	0.008443	0.391	2.172		
SVMF <sub>rank</sub>	0.287	9.150	0.004406	0.244	3.375		
VMF	0.697	4.048	0.007065	0.331	3.360		

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PEPPERS (512 x 480)							
Filter	MAE	MSE	NCD	PCD '	Гіте		
NONE	9.200	1465.480	0.141325	9.101	-		
ASVMF <sub>mean</sub>	0.902	32.168	0.010989	0.812	0.187		
ASVMF <sub>rank</sub>	0.962	36.363	0.012038	0.843	0.578		
AVMF	1.240	64.149	0.018588	1.097	0.687		
BVDF	2.623	57.374	0.023845	1.812	7.657		
DDF	2.039	19.385	0.017644	1.043	7.953		
FFNRF	0.691	20.228	0.009018	0.709	0.328		
FHSF <sub>HSL</sub>	0.590	14.166	0.006159	0.680	0.249		
FHSFs	0.566	14.178	0.006134	0.676	0.094		
$FPGF_2$	0.645	11.784	0.007078	0.632	0.172		
$FPGF_1$	0.691	11.280	0.00703	0.663	0.156		
PGF	0.677	20.420	0.008287	0.735	0.281		
SVMF <sub>mean</sub>	0.803	29.786	0.009688	0.79	0.344		
SVMF <sub>rank</sub>	0.659	17.584	0.007142	0.668	0.547		
VMF	1.987	15.428	0.017381	0.996	0.563		
FLOWERBI	EE (308	8 x 2048)					
Filter	MAE	MSE	NCD	PCD ′	Гіте		
NONE	9.179	1439.494	0.140248	3.808			
ASVMF <sub>mean</sub>	0.841	27.884	0.008753	0.441	5.312		
ASVMF <sub>rank</sub>	0.888	31.652	0.009704	0.483	14.469		
AVMF	1.148	62.520	0.016352	0.763	17.250		
BVDF	2.048	15.394	0.012673	0.484	176.156		
DDF	1.825	11.110	0.011324	0.430	186.750		
FFNRF	0.551	12.041	0.005667	0.304	7.875		
FHSF <sub>HSL</sub>	0.458	9.270	0.003634	0.270	6.250		
FHSF <sub>S</sub>	0.427	9.834	0.003582	0.268	2.124		
$FPGF_2$	0.502	7.020	0.004282	0.254	4.421		
$FPGF_1$	0.523	6.352	0.00410	0.259	3.501		
PGF	0.568	15.801	0.005609	0.309	7.157		
SVMF <sub>mean</sub>	0.727	23.667	0.007241	0.384	8.907		
SVMF <sub>rank</sub>	0.600	11.385	0.004855	0.300	13.906		
VMF	1.864	11.356	0.011815	0.437	13.875		