Study of the Accuracy of the Color Peak Signal-to-Blur Ratio (CPSBR)

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Abstract—The most critical issue in the restoration of color pictures from noise is the preservation of the useful information embedded in the image data. The Color Peak Signal-to-Blur Ratio (CPSBR) is a new full-reference method that measures the color/detail preservation yielded by a color image denoising filter. The approach is based on a simple and effective algorithm for the estimation of the filtering blur that operates in the RGB color space. An extensive study of the accuracy of the CPSBR is provided in this paper focusing on two key paradigms for image denoising: the family of order-statistics smoothers and the class of nonlinear weighted average filters. In this framework, the exact values of color distortion and detail blur produced by weighted vector medians, scalar and vector bilateral filters are theoretically evaluated and used for a comparison in order to validate the method. Results of many computer simulations dealing with color images corrupted by different amounts of Gaussian and impulse noise show that the novel CPSBR is a very accurate measure of color/detail preservation.

***Keywords*—**Color images, image denoising, image filtering, image analysis.

I. Introduction

Very often, color pictures are degraded by noise generated by noisy image sensors and/or noisy transmission channels. For this reason, the development of noise reduction filters for color images has become one of the most important research and application fields in digital image processing. Removing noise without destroying the information in the image data is a challenging issue for any image denoising technique [1-6]. Therefore, accurate metrics for quantitative evaluation of color distortion and detail blur are necessary in order to validate any new filter and to analyze the behavior of the available ones. For the sake of simplicity, validation of denoising algorithms for color images is often limited to the luminance channel only. In this case, metrics for monochrome images are adopted and the chroma information is ignored. Many different metrics are available in the literature for grayscale pictures. In this framework, some recently proposed methods have shown to overcome the limitations of classical and human perception-based metrics in assessing the quality of a filtered image [7-10]. Indeed, classical metrics (e.g., MSE and PSNR) cannot distinguish between noise cancellation and detail preservation and the same limitation affects metrics that try to mimic human perception [11-15], because different combinations of unfiltered noise and detail blur can lead to the same score. A smaller number of metrics is available for color image processing applications, such as the *normalized color difference* (NCD) [16], the *color PSNR* (CPSNR) [17], the *color quality index* (CQI) [18] and the *mean pixel distance* (MPD) [19]. However, although these methods take into account the chroma information, they are scalar indexes and then cannot separate residual noise from filtering distortion. In order to address this issue, a collection of six new metrics operating in the YC_bC_r color coordinate system was proposed in [20-21] in order to address different classes of filtering errors affecting the luminance and the chroma information of a filtered picture. The aim of this paper is twofold: to present a simpler but effective approach that does not require any color space transformation, and to provide an in-depth analysis of its accuracy considering some of the most important families of noise reduction filters for color images. The novel method, namely *color peak signal-to-blur ratio* (CPSNR) operates in the RGB color coordinate system that is commonly adopted for image display, storage and processing [22-24]. It extends to color image processing our previously proposed measure of detail preservation for grayscale pictures [10]. The accuracy of the proposed approach is evaluated considering the results yielded by denoising techniques belonging to the classes of order statistics filters and nonlinear weighted average smoothers as well. For the first time, the *exact* values of color distortion and detail blur are theoretically evaluated for weighted vector median, scalar and vector bilateral filters [25-28] and adopted for a comparison.

The rest of the paper is organized as follows. Section II describes the CPSBR, Section III presents a complete study of the accuracy of the method, Section IV discusses the results of many computer simulations and, finally, Section V reports the conclusions.

II. The novel CPSBR

Formally, let $\mathbf{r}(i,j)=[r_1(i.j), r_2(i.j), r_3(i.j)]^T$, be the vector (in the RGB space) representing the pixel at spatial position (i,j) in the original noise-free image (i=1,…, N_1; j=1,…, N_2), where r_1, r_2 and r_3 briefly denote the R, G and B components, respectively. Let each component be digitized by adopting L different levels: $0 \le r_k \le L-1$ (L=256 for a 24-bit RGB color picture). In a similar way, let $\mathbf{x}(i,j)=[x_1(i.j), x_2(i.j), x_3(i.j)]^T$ and $\mathbf{y}(i,j)=[y_1(i.j), y_2(i.j), y_3(i.j)]^T$ be the corresponding pixels in the noisy and in the filtered image.

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Let the overall *color peak signal-to-noise ratio* (CPSNR) be expressed by the following relationship:

$$\mathrm{CPSNR} = 10\log_{10}\frac{(L-1)^2}{\frac{1}{3N_1N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}\sum_{k=1}^{3} e_k^2(i,j)} \qquad (1)$$

where $e_k(i,j) = y_k(i,j) - r_k(i,j)$ is the filtering error in the k-th image channel (k=1,2,3). Thus, we shall define the *color peak signal-to-blur ratio* (CPSBR) as follows:

$$\mathrm{CPSBR} = 10\log_{10}\frac{(L-1)^2}{\frac{1}{3N_1N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}\sum_{k=1}^{3}\left[\hat{e}_k^{(b)}(i,j)\right]^2} \qquad (2)$$

where $\hat{e}_k^{(b)}(i,j)$ is an estimate of the error component $e_k^{(b)}(i,j)$ dealing with the color/detail blur. Clearly we have:

$$\mathrm{CPSNR}=\mathrm{CPSBR}-\mathrm{CD} \qquad (3)$$

where CD can be interpreted as a measure of the (color) degradation caused by noise:

$$\mathrm{CD} = 10\log_{10}\frac{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}\sum_{k=1}^{3} e_k^2(i,j)}{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}\sum_{k=1}^{3}\left[\hat{e}_k^{(b)}(i,j)\right]^2} \qquad (4)$$

In fact, if no noise is present, we have CD=0 and then CPSNR=CPSBR. The estimates $\hat{e}_k^{(b)}(i,j)$ in eq.(2) are evaluated exploiting the information that is obtained by filtering the noise-free reference image. Formally, let $\mathbf{b}(i,j)=[b_1(i.j), b_2(i.j), b_3(i.j)]^T$ be the pixel at location (i,j) in the picture that is obtained applying to the reference pixel $\mathbf{r}(i,j)$ *exactly* the same processing adopted for the noisy pixel $\mathbf{x}(i,j)$. Thus, in our approach, the estimates $\hat{e}_k^{(b)}(i,j)$ are evaluated as follows:

$$\hat{e}_k^{(b)} = \begin{cases} y_k(i,j) - r_k(i,j) & \text{if } r_k(i,j) < y_k(i,j) \le b_k(i,j) \\ y_k(i,j) - r_k(i,j) & \text{if } b_k(i,j) \le y_k(i,j) < r_k(i,j) \\ b_k(i,j) - r_k(i,j) & \text{if } r_k(i,j) < b_k(i,j) \le y_k(i,j) \\ b_k(i,j) - r_k(i,j) & \text{if } y_k(i,j) \le b_k(i,j) < r_k(i,j) \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

As an example, condition $r_k(i,j)<y_k(i,j)\le b_k(i,j)$ means that filtering a noisy pixel yields a smaller error than filtering a noise-free pixel. Hence, the error $y_k(i,j)-r_k(i,j)$ is very likely to represent blur only: $\hat{e}_k^{(b)}(i,j) = y_k(i,j) - r_k(i,j)$. A similar situation occurs for negative errors, if $b_k(i,j)\le y_k(i,j)<r_k(i,j)$. Conversely, condition $r_k(i,j)<b_k(i,j)\le y_k(i,j)$ means that filtering a noisy pixel yields a larger error than filtering the corresponding noise-free pixel. Since, in this case, the blur is only a fraction of the overall error, a reasonable choice is: $\hat{e}_k^{(b)}(i,j) = b_k(i,j) - r_k(i,j)$. A similar situation occurs when $y_k(i,j)\le b_k(i,j)<r_k(i,j)$. In all other cases, the filtering error is constituted by unfiltered noise only, so no filtering blur is present.

III. Study of the Accuracy

The accuracy of the method is here investigated evaluating the *true value* of CPSBR (namely $\mathrm{CPSBR_T}$) for vector and scalar implementations of the bilateral filter, and for weighted vector medians.

A. Vector Bilateral Filtering

The bilateral filter is a well-known nonlinear operator that is specifically designed to smooth out short-tailed noise distributions, such as Gaussian and uniform noise. The true error component $e_k^{(b)}(i,j)$ can be theoretically obtained as follows. The bilateral filter is a nonlinear weighted average filter whose weights depend upon the spatial distance and intensity distance with respect to the central pixel [25-26]. Formally, let $\mathbf{y}^{(VB)}(i,j)$ be the output of a $(2N+1)\times(2N+1)$ vector bilateral operator

$$\mathbf{y}^{(VB)}(i,j) = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w(i,j,u,v)\,\mathbf{x}(i-u,j-v)}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w(i,j,u,v)} \qquad (6)$$

where:

$$w(i,j,u,v) = w^{(D)}(u,v)\,w^{(R)}(i,j,u,v) \qquad (7)$$

$$w^{(D)}(u,v) = e^{-\frac{u^2+v^2}{2\sigma_d^2}} \qquad (8)$$

$$w^{(R)}(i,j,u,v) = e^{-\frac{\left\|\mathbf{x}(i,j)-\mathbf{x}(i-u,j-v)\right\|^2}{2\sigma_r^2}} \qquad (9)$$

and $\left\|\mathbf{x}(i,j)-\mathbf{x}(i-u,j-v)\right\|$ is the Euclidean distance of two vector pixels $\mathbf{x}(i,j)$ and $\mathbf{x}(i-u,j-v)$. The smoothing behavior is easily controlled by the parameters σ_d and σ_r. Now, let $n_k(i,j)$ be the noise amplitude affecting the pixel at location (i,j):

$$x_k(i,j) = r_k(i,j) + n_k(i,j) \qquad (10)$$

The filtering error $e_k(i,j) = y_k^{(VB)}(i,j) - r_k(i,j)$ can be expressed as follows:

$$e_k(i,j) = e'_k(i,j) + e''_k(i,j) \tag{11}$$

where $e'_k(i,j)$ and $e''_k(i,j)$ represent the (signed) error components dealing with the filtering distortion and the remaining noise, respectively:

$$e'_k(i,j) = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w(i,j,u,v)\, r_k(i-u,j-v)}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w(i,j,u,v)} - r_k(i,j) \tag{12}$$

$$e''_k(i,j) = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w(i,j,u,v)\, n_k(i-u,j-v)}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w(i,j,u,v)} \tag{13}$$

Once the signed error components $e'_k(i,j)$ and $e''_k(i,j)$ are available, the *resulting* filtering blur $e_k^{(b)}(i,j)$ is evaluated as follows:

1) if ($e'_k(i,j) \geq 0$ and $e''_k(i,j) \geq 0$) or ($e'_k(i,j) \leq 0$ and $e''_k(i,j) \leq 0$) then $e_k^{(b)}(i,j) = e'_k(i,j)$;

2) if $e'_k(i,j) \geq 0$, $e''_k(i,j) \leq 0$ and $\left|e'_k(i,j)\right| \geq \left|e''_k(i,j)\right|$ then $e_k^{(b)}(i,j) = e_k(i,j)$;

3) if $e'_k(i,j) \geq 0$, $e''_k(i,j) \leq 0$ and $\left|e'_k(i,j)\right| < \left|e''_k(i,j)\right|$ then $e_k^{(b)}(i,j) = 0$;

4) if $e'_k(i,j) \leq 0$, $e''_k(i,j) \geq 0$ and $\left|e'_k(i,j)\right| \geq \left|e''_k(i,j)\right|$ then $e_k^{(b)}(i,j) = e_k(i,j)$;

5) if $e'_k(i,j) \leq 0$, $e''_k(i,j) \geq 0$ and $\left|e'_k(i,j)\right| < \left|e''_k(i,j)\right|$ then $e_k^{(b)}(i,j) = 0$.

Finally, the $CPSBR_T$ is computed by means of the following relationship:

$$CPSBR_T = 10\log_{10}\frac{(L-1)^2}{\frac{1}{3N_1N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}\sum_{k=1}^{3}\left[e_k^{(b)}(i,j)\right]^2} \tag{14}$$

B. Scalar Bilateral Filtering

In this approach, scalar bilateral filters are applied to each channel separately. It is known that this choice typically destroys the correlation between color components and yields more filtering errors than using a vector method. Formally, let $\mathbf{y}^{(SB)}(i,j)$ be the output of a $(2N+1)\times(2N+1)$ scalar bilateral filter. The k-th component is given by the following relationships:

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$$y_k^{(SB)}(i,j) = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w_k(i,j,u,v)\, x_k(i-u,j-v)}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w_k(i,j,u,v)} \tag{15}$$

$$w_k(i,j,u,v) = w^{(D)}(u,v)\, w_k^{(R)}(i,j,u,v) \tag{16}$$

$$w_k^{(R)}(i,j,u,v) = e^{-\frac{\left|x_k(i,j)-x_k(i-u,j-v)\right|^2}{2\sigma_r^2}} \tag{17}$$

where $\left|x_k(i,j) - x_k(i-u,j-v)\right|$ is the absolute difference of pixel luminances $x_k(i,j)$ and $x_k(i-u,j-v)$ in the k-th channel. In this case, the filtering error in the k-th channel is $e_k(i,j) = y_k^{(SB)}(i,j) - r_k(i,j)$ and its signed components $e'_k(i,j)$ and $e''_k(i,j)$ become:

$$e'_k(i,j) = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w_k(i,j,u,v)\, r_k(i-u,j-v)}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w_k(i,j,u,v)} - r_k(i,j) \tag{18}$$

$$e''_k(i,j) = \frac{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w_k(i,j,u,v)\, n_k(i-u,j-v)}{\sum_{u=-N}^{N}\sum_{v=-N}^{N} w_k(i,j,u,v)} \tag{19}$$

After the evaluation of the signed components $e'_k(i,j)$ and $e''_k(i,j)$, the resulting blur $e_k^{(b)}(i,j)$ is computed as in the previous case.

C. Weighted Vector Median Filtering

Weighted vector median filters are well-known nonlinear operators for the removal of impulse noise from color images [27-28]. Let us consider a $(2N+1)\times(2N+1)$ window centered on $\mathbf{x}(i,j)$. Let W be the set of vector pixels inside the window: $W=\{\mathbf{x}_1, \mathbf{x}_2, .., \mathbf{x}_M\}$, where $M=(2N+1)^2$.

(a) (b) (c) (d) (e) (f)

Fig.1 – 24-bit color images: (a) "Venice" (b) "Bridge", (c) "Baboon", (d) "Lighthouse", (e) "Airplane", (f) "Houses".

Formally, the output of the weighted vector median filter $\mathbf{y}^{(WVM)}$ is the vector pixel $\mathbf{x}_m$ (from the input set W) chosen as follows:

$$\sum_{i=1}^{M} w_i \left\| \mathbf{x}_m - \mathbf{x}_i \right\| = \underset{j=1,2,\ldots M}{\mathrm{MIN}} \left\{ \sum_{i=1}^{M} w_i \left\| \mathbf{x}_j - \mathbf{x}_i \right\| \right\} \qquad (20)$$

where and w_1, w_2, …, w_M are nonnegative integer weights. The *center weighted vector median* (CWVM) filter with control parameter k ($1 \leq k \leq (M+1)/2$) is obtained by setting the weights according to the following relationship [27]:

$$w_i = \begin{cases} M - 2k + 2 & \text{if } i = (M+1)/2 \\ 1 & \text{otherwise} \end{cases} \qquad (21)$$

The amounts of smoothing (and thus of detail preservation) depends upon the value of k and can range from identity filter (k=1) to vector median (k=(M+1)/2).

Now, let (i–p,j–q) be the coordinates of the vector pixel $\mathbf{x}_m$ ($-N \leq p \leq N$, $-N \leq q \leq N$). Thus, the output of the CWVM filter can be expressed as follows:

$$\mathbf{y}^{(CWVM)}(i,j) = \mathbf{x}(i-p, j-q) \qquad (22)$$

In this case, the filtering error in the k-th channel is $e_k(i,j) = y_k^{(CWVM)}(i,j) - r_k(i,j)$ and its signed components $e_k'(i,j)$ and $e_k''(i,j)$ become:

$$e_k'(i,j) = r_k(i-p, j-q) - r_k(i,j) \qquad (23)$$

$$e_k''(i,j) = n_k(i-p, j-q) \qquad (24)$$

The resulting blur $e_k^{(b)}(i,j)$ can be obtained as in the previous cases.

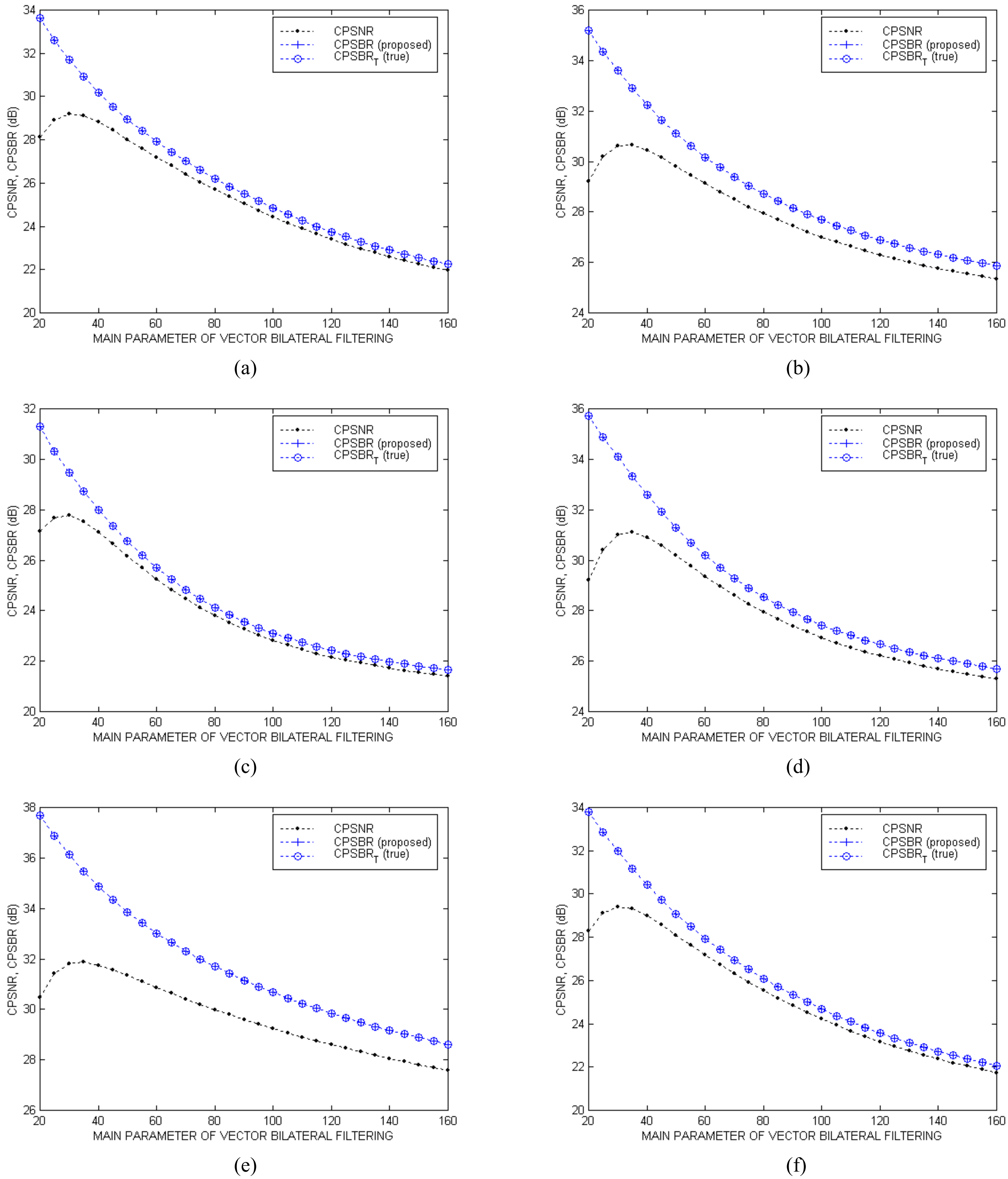
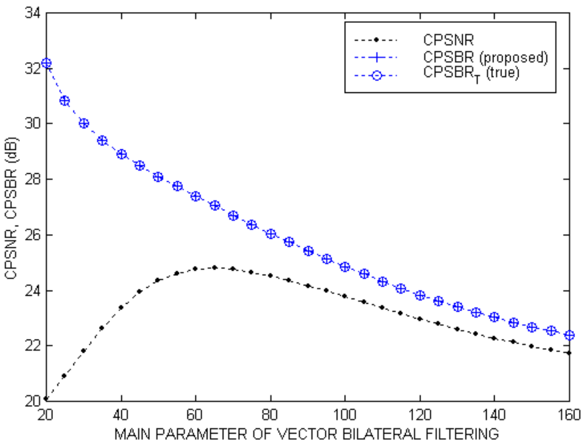


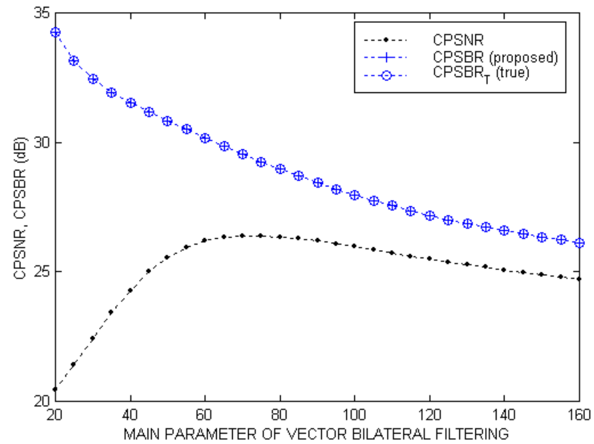
Fig.2 – CPSBR and CPSNR evaluations for color images corrupted by Gaussian noise (σ=15) and processed by vector bilateral filtering: (a) “Venice” (b) “Bridge”, (c) “Baboon”, (d) “Lighthouse”, (e) “Airplane”, (f) “Houses”.

IV. RESULTS OF COMPUTER SIMULATIONS

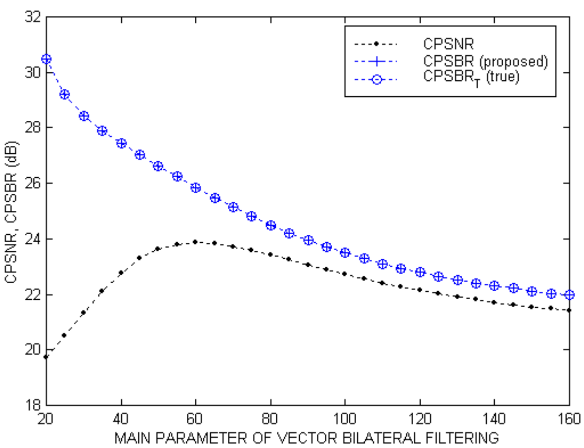
We shall report in this section the results of many groups of tests dealing with the following color pictures: “Venice”, “Bridge”, “Baboon”, “Lighthouse”, “Airplane” and “Houses” (Fig.1). All of these pictures are 24-bit color images whose size is 512-by-512 pixels. In the first group of tests, we corrupted these images adding different amounts of Gaussian noise and we processed the noisy data adopting a (2N+1)×(2N+1) vector bilateral filter.



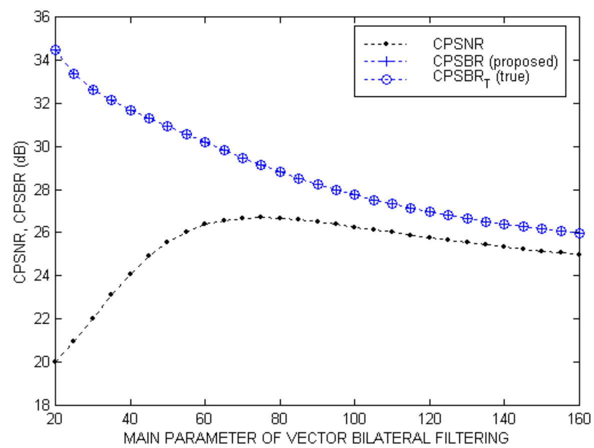
(a)



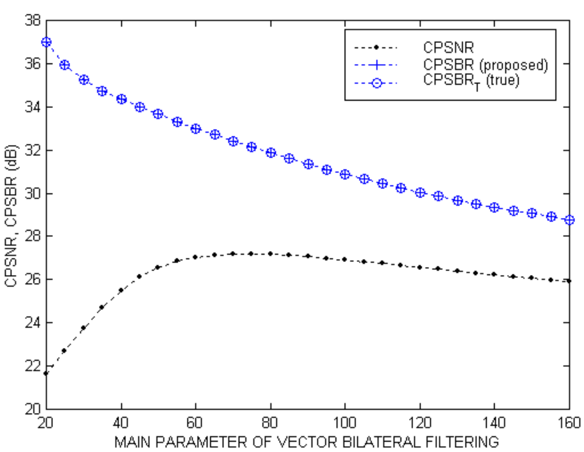
(b)



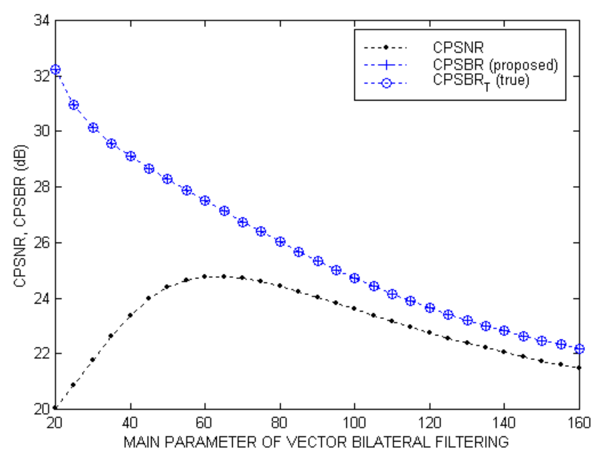
(c)



(d)



(e)



(f)

Fig.3 – CPSBR and CPSNR evaluations for color images corrupted by Gaussian noise (σ=30) and processed by vector bilateral filtering: (a) "Venice" (b) "Bridge", (c) "Baboon", (d) "Lighthouse", (e) "Airplane", (f) "Houses".

We adopted the following parameter settings: N=3, σ_d=5, $20 \leq \sigma_r \leq 160$. It is known that, as the value of the main parameter σ_r increases, both the noise cancellation and the filtering distortion increase. In this first experiment, we generated six noisy images adding zero-mean Gaussian noise with standard deviation σ=15. The corresponding values of CPSNR and CPSBR are graphically depicted in Fig.2. In order to assess the accuracy of the proposed method, we considered the theoretical results obtained in the previous section. It can be observed that, in all cases, the proposed CPSBR is in

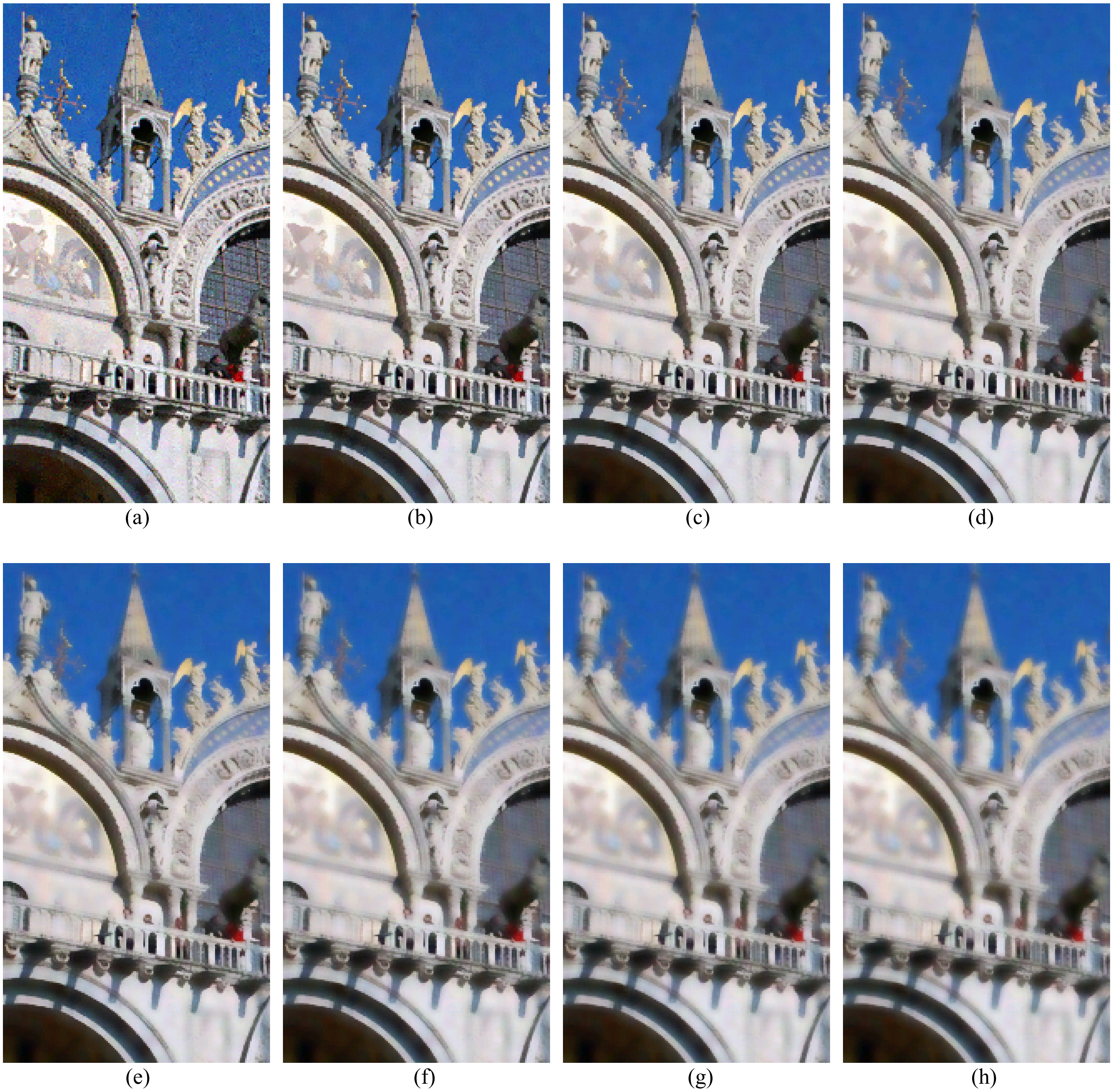


Fig.4 – Portions of the 24-bit color picture "Venice" corrupted by Gaussian noise (σ=15) and processed by 7×7 vector bilateral filtering (σ_d=5) with increasing values of the main parameter σ_r: (a) σ_r=20, (b) σ_r=40, (c) σ_r=60, (d) σ_r=80, (e) σ_r=100, (f) σ_r=120, (g) σ_r=140, (h) σ_r=160.

perfect agreement with the theoretical values. As expected, the $CPSBR_T$ (and so the CPSBR) decreases as the value of the main parameter σ_r increases (lower values of $CPSBR_T$ denote worse preservation of detail/color information during noise smoothing). In the second experiment we increased the amount of noise corruption (σ=30). The values of CPSNR and CPSBR are shown in Fig.3. It can be seen again that the proposed PSBR perfectly estimates the $CPSBR_T$. A sample of the processed data ("Venice" picture corrupted by Gaussian noise with σ=15) is reported in Fig.4 for visual inspection.

The filtering blur is clearly perceivable as the value of the main parameter σ_r becomes larger. In the second group of tests we adopted scalar bilateral filtering. Clearly, a scalar approach cannot take into account the correlation among color components. Hence an increase of filtering errors is expected with respect to the vector method. The values of CPSNR and CPSBR for images corrupted by Gaussian noise with σ=15 and σ=30 are reported in Fig.5 and Fig.6, respectively. In any case, the proposed CPSBR yields results that are in very good agreement with the theoretical values.

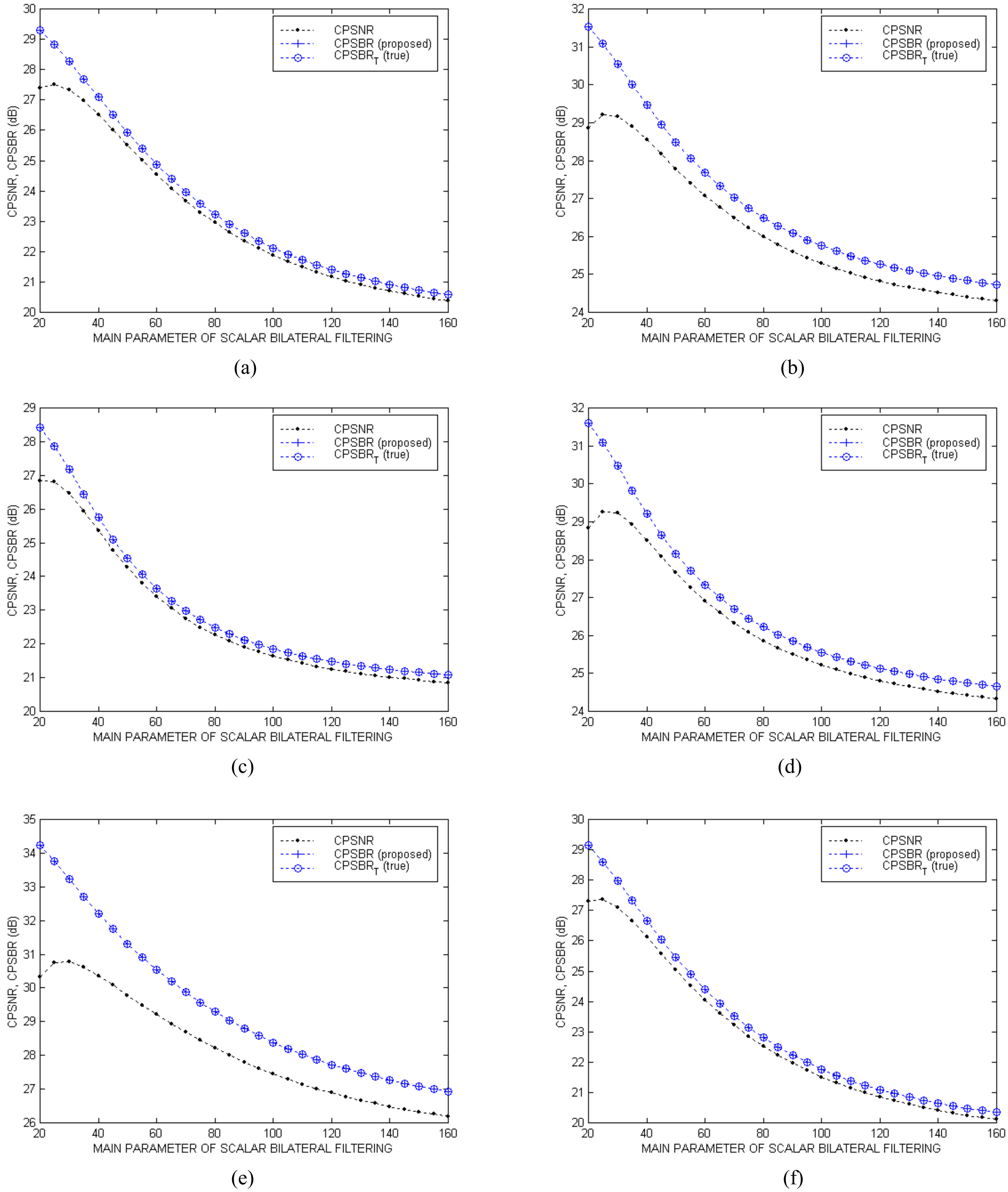
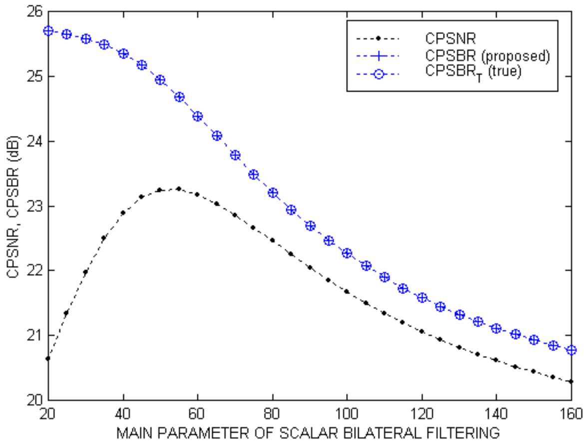
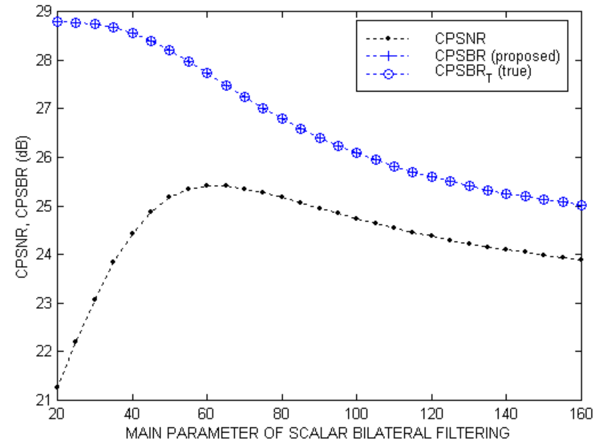


Fig.5 – CPSBR and CPSNR evaluations for color images corrupted by Gaussian noise (σ=15) and processed by scalar bilateral filtering: (a) “Venice” (b) “Bridge”, (c) “Baboon”, (d) “Lighthouse”, (e) “Airplane”, (f) “Houses”.

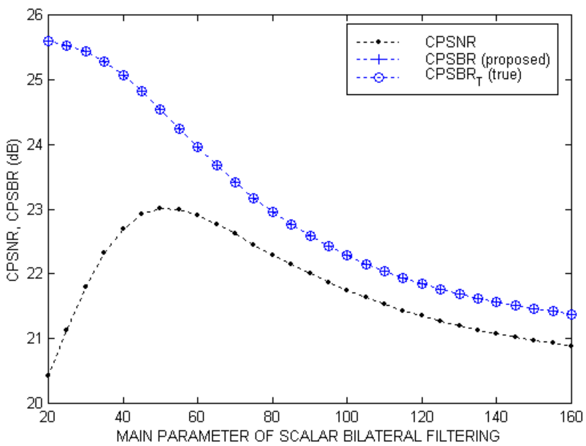
In the third group of experiments we considered the case of impulse noise and the application of a (2N+1)×(2N+1) center weighted vector median filter with the following parameter settings: N=2, $1 \le k \le 13$. We corrupted the test pictures by superimposing impulse noise with probability 10%. The corresponding values of CPSNR and CPSBR are reported in Fig.7. According to the algorithm described in Section III, the maximum detail preservation (and so the maximum value of CPSBR) occurs for k=1. The detail preservation decreases for larger values of k.



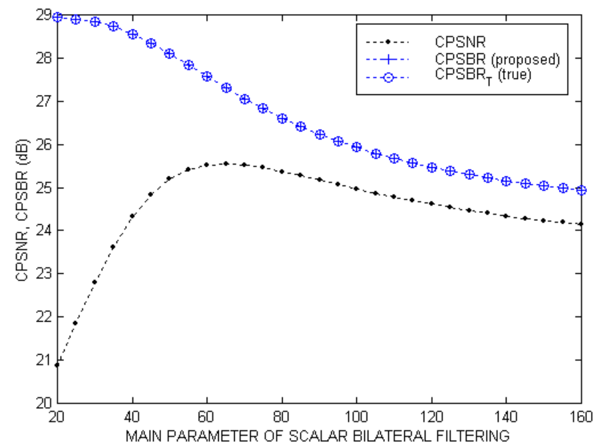
(a)



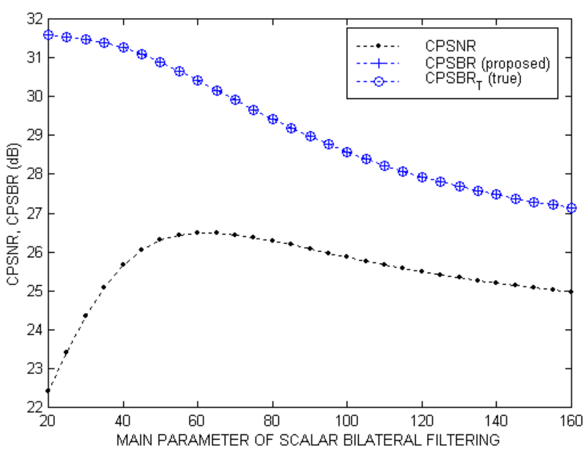
(b)



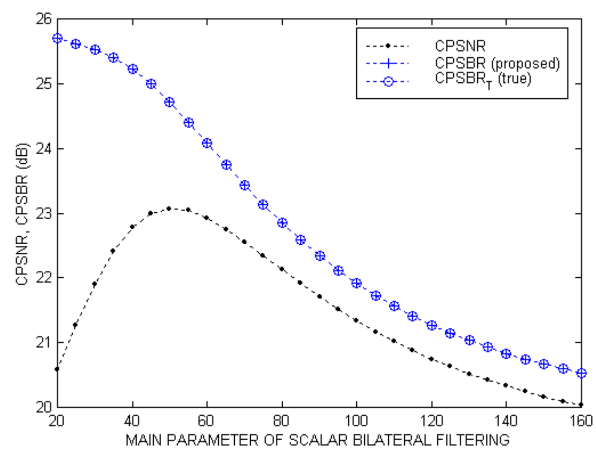
(c)



(d)



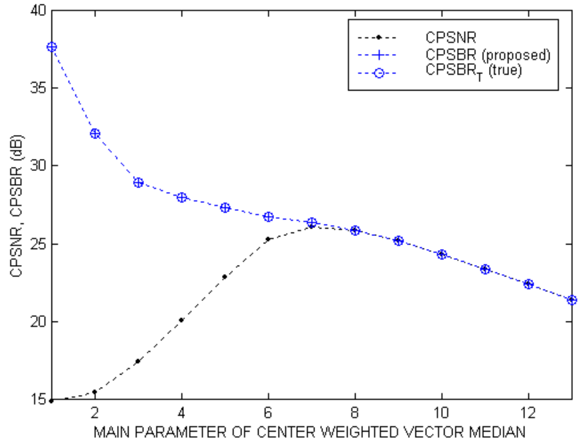
(e)



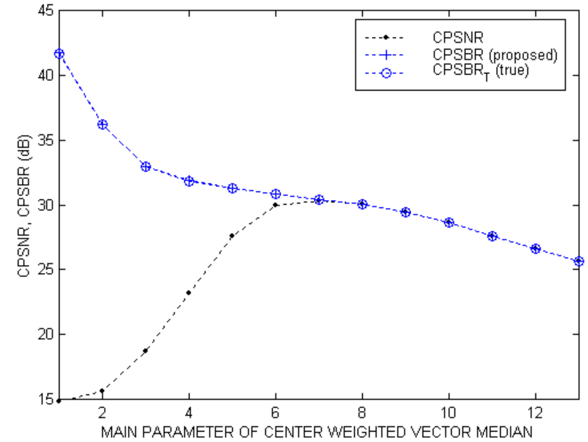
(f)

Fig.6 – CPSBR and CPSNR evaluations for color images corrupted by Gaussian noise (σ=30) and processed by scalar bilateral filtering: (a) “Venice” (b) “Bridge”, (c) “Baboon”, (d) “Lighthouse”, (e) “Airplane”, (f) “Houses”.

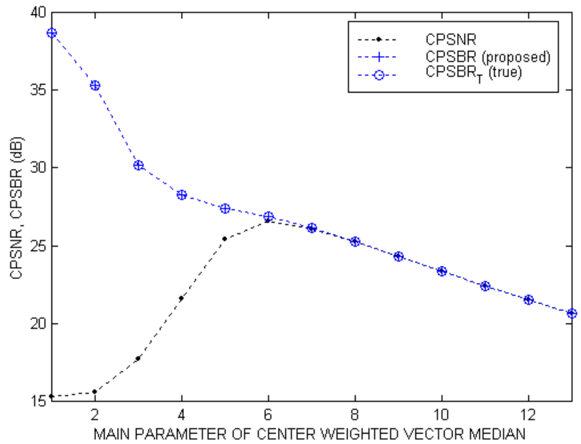
It can be observed that for k>7 almost all noise pulses are removed and the remaining effect is filtering distortion only (CPSBR=CPSNR). The good performance of the CPSBR is apparent for this group of tests too. It perfectly estimates the true CPSBR$_T$. A sample of the processed images (“Baboon”) is reported in Fig.8. We see that the filtering blur increases for growing values of k. Indeed, the image details (and some unfiltered noise pulses) are clearly perceivable in Fig.8a (k=4), Conversely, the noise has been completely removed in Fig.8d, at the price of some annoying detail blur (k=13).



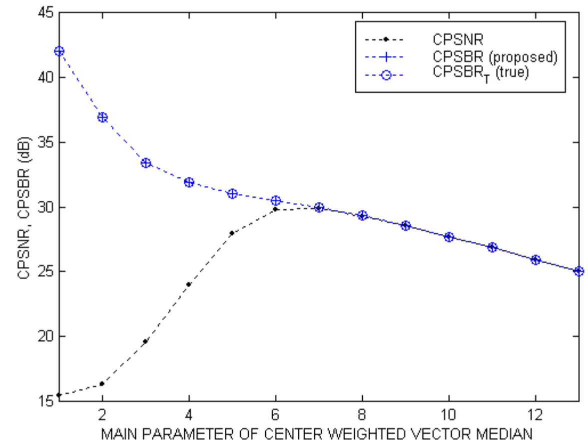
(a)



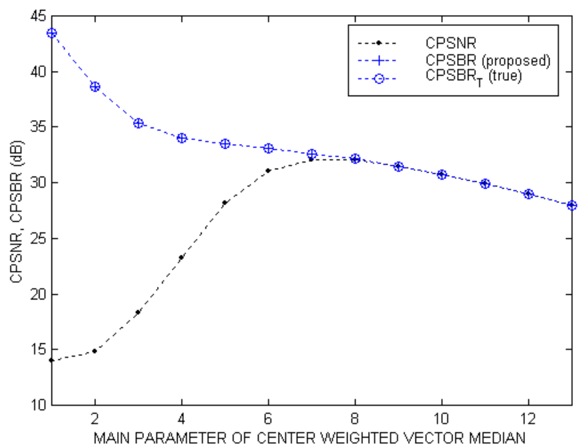
(b)



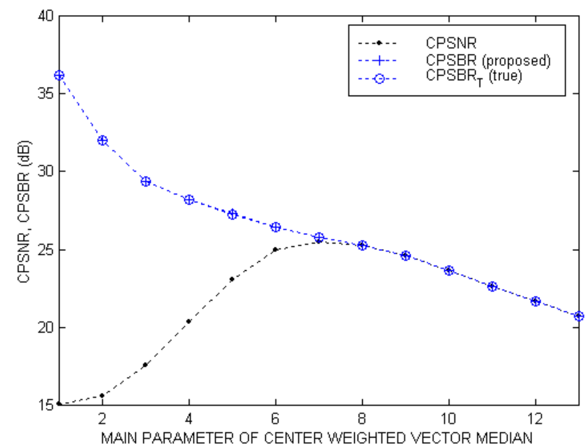
(c)



(d)



(e)



(f)

Fig.7 – CPSBR and CPSNR evaluations for color images corrupted by impulse noise with probability 10% and processed by center weighted vector median filtering: (a) “Venice” (b) “Bridge”, (c) “Baboon”, (d) “Lighthouse”, (e) “Airplane”, (f) “Houses”.

V. Conclusions

The novel CPSBR offers a simple and effective method for the validation of color image denoising filters. It operates in the widespread adopted RGB color space and measures how good a filter is at providing color and detail preservation during noise removal. The method does not adopt color space transformations and is computationally lighter than our previously proposed metrics.

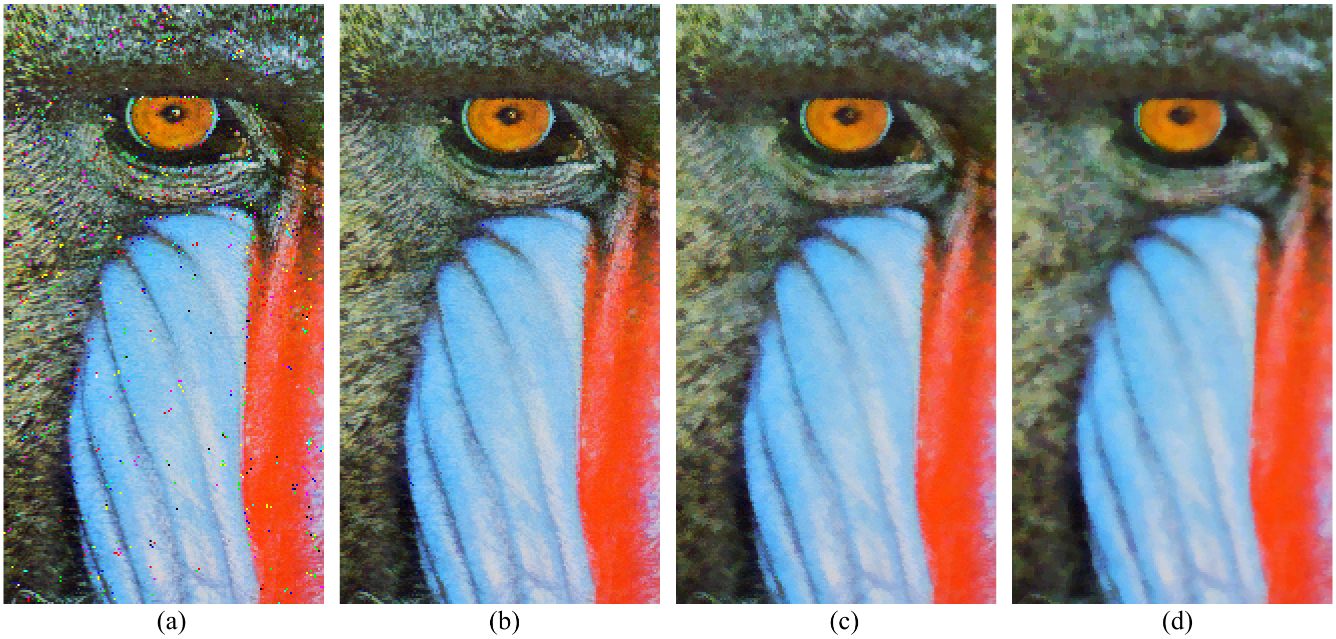


Fig.8 – Portions of the 24-bit color picture “Baboon” corrupted by impulse noise with probability 10% and processed by a 5×5 center weighted vector median filter with increasing values of the main parameter k: (a) k=4, (b) k=7, (c) k=10, (d) k=13.

In order to assess the accuracy of the CPSBR, we have considered widespread used nonlinear techniques for noise removal such as weighted vector medians, scalar and bilateral filters. We have theoretically evaluated the true values of CPSBR for all these filters and used this information for a comparison. Results of many computer simulations considering images corrupted by different amounts of Gaussian and impulse noise have shown that the novel CPSBR yields very accurate estimates of such theoretical values and then can represent a powerful resource for the validation of noise reduction filters for color images.

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