An image noise filter with emphasis on low frequency chrominance noise

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ABSTRACT

Chrominance noise appears as low frequency colored blotches throughout an image, especially in darker flat areas. The effect is more pronounced in lower light levels where the characteristic features are observed as irregularly shaped clusters of colored pixels that vary anywhere from 15 to 25 pixels across. This paper proposes a novel, simple and intuitive method of reducing chrominance noise in processed images while minimizing color bleeding artifacts. The approach is based on a hybrid multi scale spatial dual tree adaptive wavelet filter in hue-saturation-value color space. Results are provided in terms of comparisons on real images between the proposed method and another state of the art method.

Keywords: low frequency chrominance noise, dual tree wavelet, adaptive wavelet thresholding, chromaticity chart, image post processing.

1. INTRODUCTION

Assuming a sensor with a color filter array (CFA) in a typical color imaging processing pipeline, the sensor analog gains and possibly other digital gains must be adjusted as a result of color correction, white balance and other steps which may account for unequal sensor sensitivity on the different channels. According to the propagation of error formula, signal variance increases with the square root of the applied gain, thus regardless of the analog or digital domain where such a gain adjustment is performed, the net effect is a different signal standard deviation on the various channels. After color interpolation, when sensor channels are correlated, the described mechanism gives rise to what it is referred to as chrominance noise. This is further amplified when a non-spatially adaptive color correction is applied, as noted by others in [1-4], to become large, perceptually periodic groupings of 15 to 25 pixels across. For completion and an in depth, low level discussion on the various physical sources of noise in an imaging system, the reader is referred to Janesik [5].

Although utilizing a spatially adaptive color correction matrix will reduce chrominance noise, currently, the problem of post processing an image for this purpose remains an active research topic. Various more or less effective image de-noising methods have been developed ranging from bilateral filtering [6], anisotropic diffusion [7] and more recently wavelet coefficient thresholding or shrinkage [11-13] and de-noising in fractal frameworks [14].

This paper presents a solution which joins adaptive spatial filtering and adaptive coefficient thresholding in the wavelet domain to effectively reduce the perceived chrominance noise in images. The resulting noise in the luminance mimics a visually pleasing film-like grain effect. As the critical step in wavelet thresholding is the threshold parameter estimation, several methods have been proposed, for example, VisuShrink [11] and SureShrink [12] and, further improved by exploring inter-scale and intra-scale coefficient correlations [13, 15]. However due to the lack of shift invariance and directionality of the discrete wavelet transform (DWT), Kingsbury [16] proposed two radical transforms, the dual tree real (DTRWT) and dual tree complex (DTCWT) wavelet transforms to address the shortcomings of the DWT. It is within the context of the former, the dual tree real transform, that the solution proposed in this paper is formulated.

This paper is organized as follows: in section 2, we discuss the details of our solution and reference a previously developed method for parameter estimation; in section 3 we present our results and compare our solution with another state of the art method.

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2. PROPOSED SOLUTION

Removing the typical chrominance noise is relatively easy however costly. Since typical chrominance blotches are anywhere from 15 to 25 pixels across, any kernel filter that is relatively similar in size can be used to smooth the chrominance planes effectively. However if the implementation is not edge aware, color bleeding will occur. The rather large spatial requirement along with the need to design an adaptive filter that utilizes an edge stopping function renders this approach undesirable. To address this, we envisioned a solution in the form of a hybrid multi scale spatial dual tree wavelet filter. The general framework of the filter will be presented below.

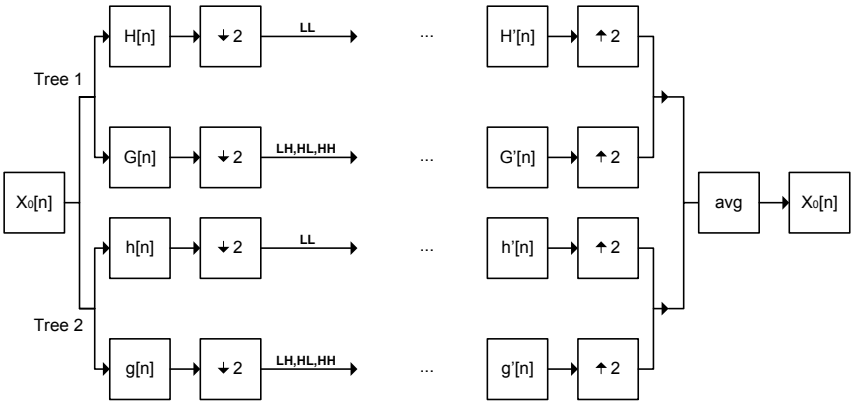


Figure 1: Dual tree one stage wavelet analysis and synthesis

Figure 1 illustrates a generic one stage dual tree wavelet analysis and synthesis filter pair. The input data is passed through two low pass filters depicted by $H_{[n]}$ and $h_{[n]}$ and similarly two high pass filters depicted by $G_{[n]}$ and $g_{[n]}$. A subsequent sub-sampling step yields six oriented high frequency detail sub-bands and two other low frequency ones. The synthesis step is the reverse of analysis, with the data corresponding to each tree passed again through a set of filters, up-sampled and averaged among the two tree outputs to yield the final synthesized data.

To achieve the same effect as a very large kernel we decompose the image using a dual tree wavelet transform and proceed to spatially filter the low frequency bands in the wavelet domain with a much smaller kernel. In addition, rather than convolving the chrominance channels with a kernel, we employ simple averaging in a modified hue saturation chromaticity space. Multi-scale bilateral filtering was also proposed by Zhang et al. in [8], however our approach here differs significantly as further explained. In [9] we introduced a bilateral filter technique and method of threshold estimation, based on a polyhedron classifier in three dimensions. We extend the idea presented there to infer edge locations in an image. Using the edge information from each low frequency sub-band and an estimate of local variance within a pixel neighborhood in the high frequency sub-bands, we build an adaptive threshold mechanism which we use to filter the wavelet coefficients in the high frequency chrominance and luminance sub-bands. The adaptability of the threshold around edges allows us to effectively eliminate the Gibbs phenomenon commonly encountered in wavelet image denoising. Furthermore, the nature of the dual tree wavelet transform, in terms of its directionality and near shift invariance, granted, at expense of additional data redundancy, permits us to also eliminate the typical checkerboard reconstruction artifacts which are present in regular wavelet transform methods.

In figure 2 we illustrate the details of our method within a one tree, one scale analysis – synthesis framework. Here, $S(n)$, $T(n)$ and $E(n)$ represent the spatial filtering, wavelet coefficient thresholding and edge information exchange respectively. In the subsections to follow, we discuss these operations further.

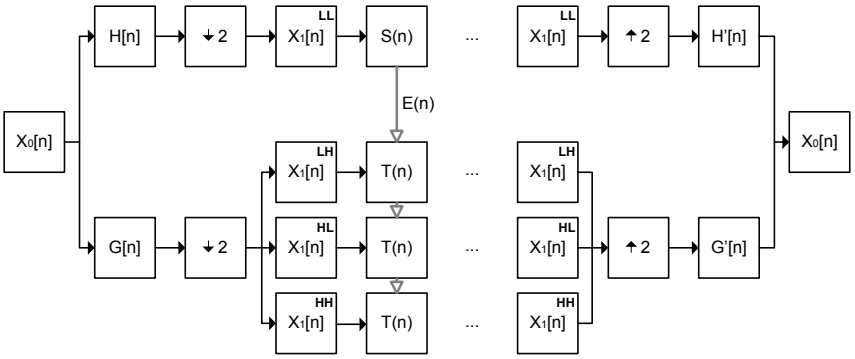


Figure 2: Hybrid multi scale spatial one stage wavelet analysis and synthesis filtering

2.1 LOW FREQUENCY SPATIAL FILTER

As mentioned before, to identify chrominance noise, we chose to use a hue-saturation 2D chromaticity diagram that makes this type of noise easy to categorize. To transform an RGB value into this space we utilize matrix A and respectively A^{-1} to transform back to RGB [10]:

$$A = \begin{bmatrix} 1 & 0 & 1/3 \\ -0.5 & 0.866 & 1/3 \\ -0.5 & -0.866 & 1/3 \end{bmatrix}$$

According to the illustration in figure 3, we term this space the xyV space, where x and y represent hue – saturation Cartesian coordinate equivalents, while V represents the corresponding value in hue saturation value (HSV) color space. As such, an absolute difference based polyhedron low pass classifier in xyV space can be described according to equation 1a below, for a $i \times j$ kernel. Allowing for an amount of band pass, a high pass classifier can also be described as a super structure encompassing the low pass classifier according to equation 1b.

$$Lp[n,m] = \begin{cases} |\Delta x[n,m]| \le Threshold_{l1} \;\&\& \\ |\Delta y[n,m]| \le Threshold_{l2} \;\&\& \\ |\Delta V[n,m]| \le Threshold_{l3} \;\&\& \\ |\Delta x[n,m]| + |\Delta V[n,m]| \le Threshold_{l4} \;\&\& \\ |\Delta y[n,m]| + |\Delta V[n,m]| \le Threshold_{l5} \;\&\& \\ |\Delta x[n,m]| + |\Delta y[n,m]| \le Threshold_{l6} \;\&\& \\ |\Delta x[n,m]| + |\Delta y[n,m]| + |\Delta V[n,m]| \le Threshold_{l7} \end{cases} \quad (1a)$$

, for $0 \le n \le i$ and $0 \le m \le j$,

, where $Lp[n,m]$ is set to 1 (i.e. low pass) if all seven conditions are met, or 0 otherwise.

$$Hp[n,m] = \begin{cases} |\Delta x[n,m]| > Threshold_{h1} \;\| \\ |\Delta y[n,m]| > Threshold_{h2} \;\| \\ |\Delta V[n,m]| > Threshold_{h3} \;\| \\ |\Delta x[n,m]| + |\Delta V[n,m]| > Threshold_{h4} \;\| \\ |\Delta y[n,m]| + |\Delta V[n,m]| > Threshold_{h5} \;\| \\ |\Delta x[n,m]| + |\Delta y[n,m]| > Threshold_{h6} \;\| \\ |\Delta x[n,m]| + |\Delta y[n,m]| + |\Delta V[n,m]| > Threshold_{h7} \end{cases} \quad (1b)$$

, for $0 \le n \le i$ and $0 \le m \le j$

, where $Hp[n,m]$ is set to 1 (i.e. high pass) if at least one of the seven conditions above are met.

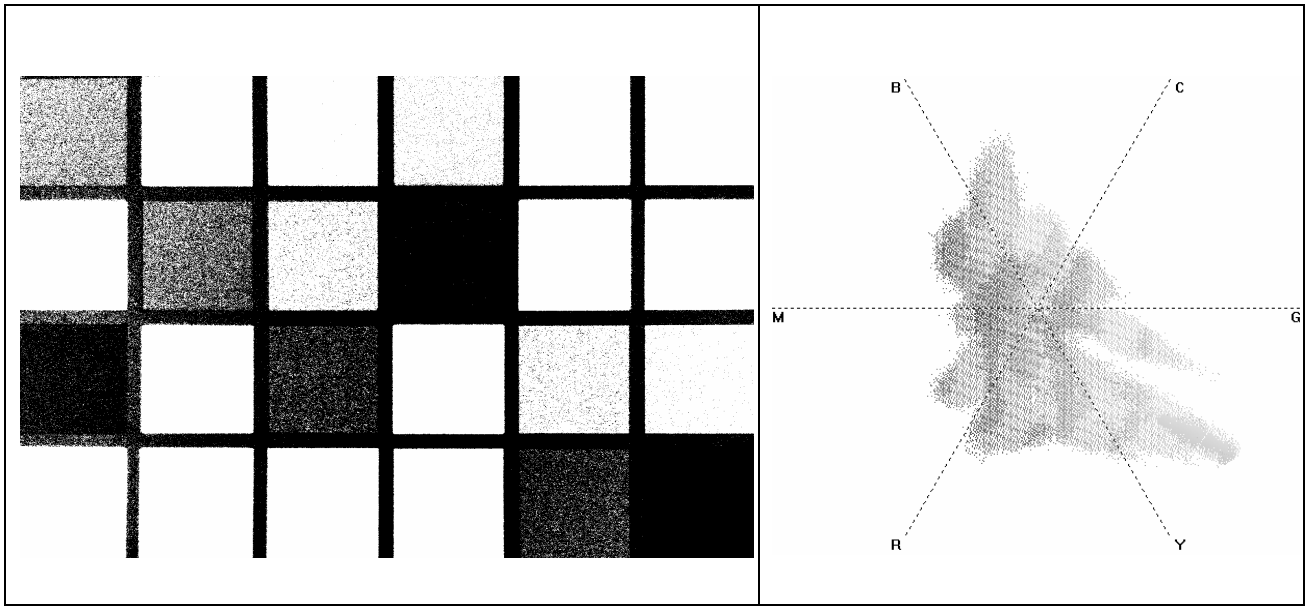


Figure 3: Chrominance noise on a Macbeth Color Checker chart (left – illustration is thresholded to enhance the noise in the print); corresponding 2D chromaticity diagram (right)

According to the pixel by pixel calculated mask, Lp we constrict the pixel neighborhood hue – saturation around its center of mass simply by replacing the current pixel with the average of the xy values taken from the masked neighborhood:

$$I(r,p)_{x,y} = avg\,(Lp[n+Kh, m+Kv] * I(r+n, p+m))_{x,y} \quad (2)$$

, where the average is calculated for $-Kh \le n \le +Kh$ and $-Kv \le m \le +Kv$

, with Kh and Kv being the horizontal and vertical kernel sizes, and r and p the current image coordinates neglecting the required image border extension.

As mentioned above, we need to provide edge information to our adaptive wavelet coefficient thresholding process. To achieve this, we define a scalar value to represent the strength of a pixel considered to be on an edge, based on the

constructed Hp mask and a Gaussian kernel, G as shown in equation 4. In figure 4 below we illustrate the edge strength map obtained from the *lighthouse* image.

$$E_{edge}(r,p) = \sum_{n,m=-Kh,-Kv}^{+Kh,+Kv} Hp[n+Kh, m+Kv] * K_{sharp} * G[n+Kh, m+Kv] \quad (3)$$

, where K_{sharp} represents an amplitude scalar

, with Kh and Kv being the horizontal and vertical kernel sizes, and r and p the current image coordinates neglecting the required image border extension.

If Kh and Kv are greater than three, we can impose an additional condition on the edge strength calculation, such that we prevent single blemish pixels that have been missed by previous processing from being classified as edges, effectively reducing such artifacts in the form of:

$$E_{edge}(r,p) = 0 \quad (4)$$

, if $\sum_{n,m=-Kh,-Kv}^{+Kh,+Kv} Hp[n+Kh, m+Kv] = 1$ when $n+Kh > 1$, $m+Kv > 1$ and $n < +Kh$ respectively $m < +Kv$.



Figure 4: Edge strength map (right) obtained from the *lighthouse* image (left)

2.2 HIGH FREQUENCY BANDS ADAPTIVE WAVELET THRESHOLDING

A key factor in any image denoising algorithm via wavelet coefficient shrinkage is threshold selection. The shrinkage problem consists of defining a coefficient thresholding transformation $T(.,\lambda)$ such that the mean square error, $MSE = E\left[\left\|X - \hat{X}\right\|^2\right]$, between the input X and output $\hat{X}$, is minimized.

In previous work [11] Dohono et al. proposed two operators, the hard and soft operators, $T_h(.,\lambda)$ and $T_s(.,\lambda)$ respectively.

$$T_h(y,\lambda) = \begin{cases} y, & if|y| \geq \lambda \\ 0, & otherwise \end{cases}$$

$$T_s(y,\lambda) = \begin{cases} y-\lambda, & if|y| \geq \lambda \\ y+\lambda, & if|y| \leq -\lambda \\ 0, & otherwise \end{cases}$$

Within the context of minimizing the MSE, the threshold value λ, can be specified as the product of the noise standard deviation, σ_n, or an estimate of it, $\hat{\sigma}_n$, and a constant C that is optimized with respect to the underlying image class:

$$T(y,\lambda) = T(y, C\hat{\sigma}_n)$$

While there are several methods in the literature for calculating an adaptive wavelet coefficient threshold, grouped mainly into three categories: algorithms which explore inter-scale coefficient statistical dependencies, others that explore intra-scale dependencies or those that do both, our solution explores the spatial correlation, at the same scale, between the low frequency and high frequency sub-bands to determine a threshold adaptation parameter. Furthermore, it utilizes an estimate of the intra-scale local variance within a coefficient neighborhood to supplement the threshold parameter adaptation.

To estimate the noise variance, σ_n^2, we use a robust median estimator as proposed by Dohono et al.:

$$\hat{\sigma}_n^2 = median(|X_{HH}(r,p)|)/0.6745$$

, where $X_{HH}(r,p)$ are the wavelet decomposition coefficients in the HH band in the first decomposition stage.

Furthermore to obtain an estimate of the local variance for a coefficient $X(m,n)$, we calculate a weighted local variance, as shown in equation 5, in an n x n context neighborhood, N, when the conditions imposed by equation 1a are met. For the set of weights, w, we utilize a two dimensional Gaussian. Note that we must subtract the noise variance since $X(m,n)$ is a noisy observation and noise is independent of the signal.

$$\sigma_l[m,n]^2 = \frac{\sum_{i,j \in N} w_{i,j}(X[i,j]^2 - \hat{\sigma}_n^2)}{\sum_{i,j \in N} w_{i,j}} \quad (5)$$

We can then define our mechanism for adapting the constant C on a coefficient by coefficient basis:

$$C[m,n] = \sigma_l Ww(E_{edge}) \quad (6)$$

, where $Wv(E_{edge})$ is an exponential decay function used to weigh the influence of the estimated local variance.

As such the mechanism is intuitively defined to allow for the largest influence of the estimated local variance in flat areas, and hence a larger threshold. Conversely, in textured or edge areas where the local variance is larger, the

exponential decay function of E_{edge}, weighs down the influence of the local variance and insures a smaller or near zero threshold.

3. RESULTS

In the implementation we utilized the wavelets described by the filters of Abdelnour [17] with a decomposition of two scales. For the chrominance portion we utilized a 7x7 kernel in the first scale decomposition and a 3x3 in the second.

To illustrate the effect of the filter, more specifically the chrominance part, we ran the algorithm on a Macbeth chart imaged with a 1.75 um pixel pitch CMOS sensor, under tungsten illumination at 50 lux. The left portion of figure 5 below illustrates the chromaticity diagram for the unfiltered image, while the right diagram shows the constricting of the hues in the filtered image before filtering the luminance or V channel.

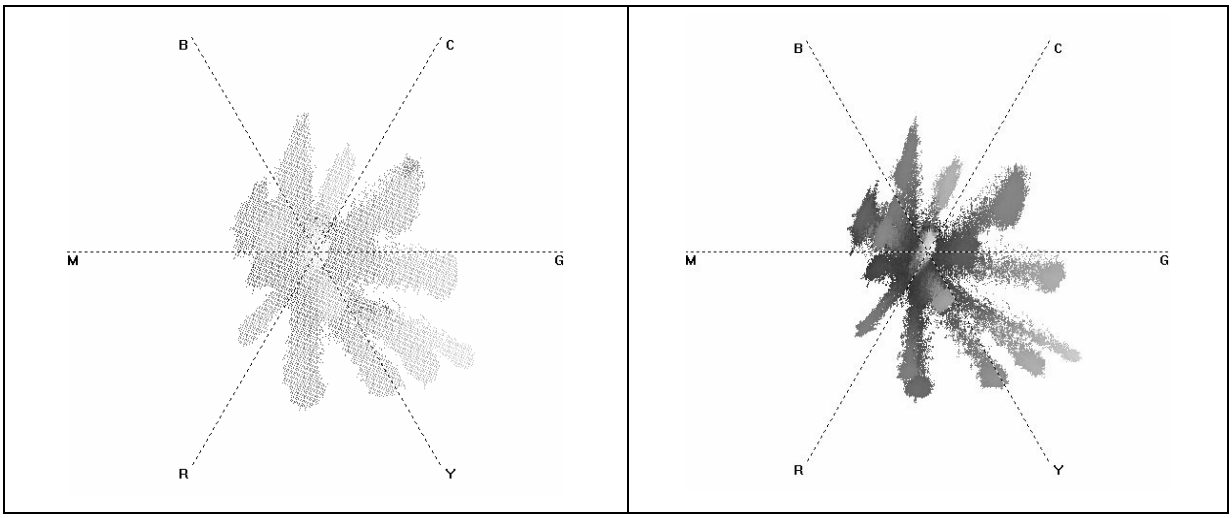


Figure 5: Chromaticity map for unfiltered Macbeth chart (left) and chroma filtered (right)

In addition we also compared our solution with NoiseNinja [18], a state of the art software solution. We present below the comparison in terms of real images (Cr and Cb channels from YCbCr space).



Figure 6a: YCbCr - Cr channel from left to right: input (100 lux, tungsten, 1.75um CMOS sensor), filtered with our solution, filtered with NoiseNinja (auto profiled, default settings)



Figure 6b: YCbCr - Cr channel from left to right: input (100 lux, tungsten, 1.75um CMOS sensor), filtered with our solution, filtered with NoiseNinja (auto profiled, default settings)

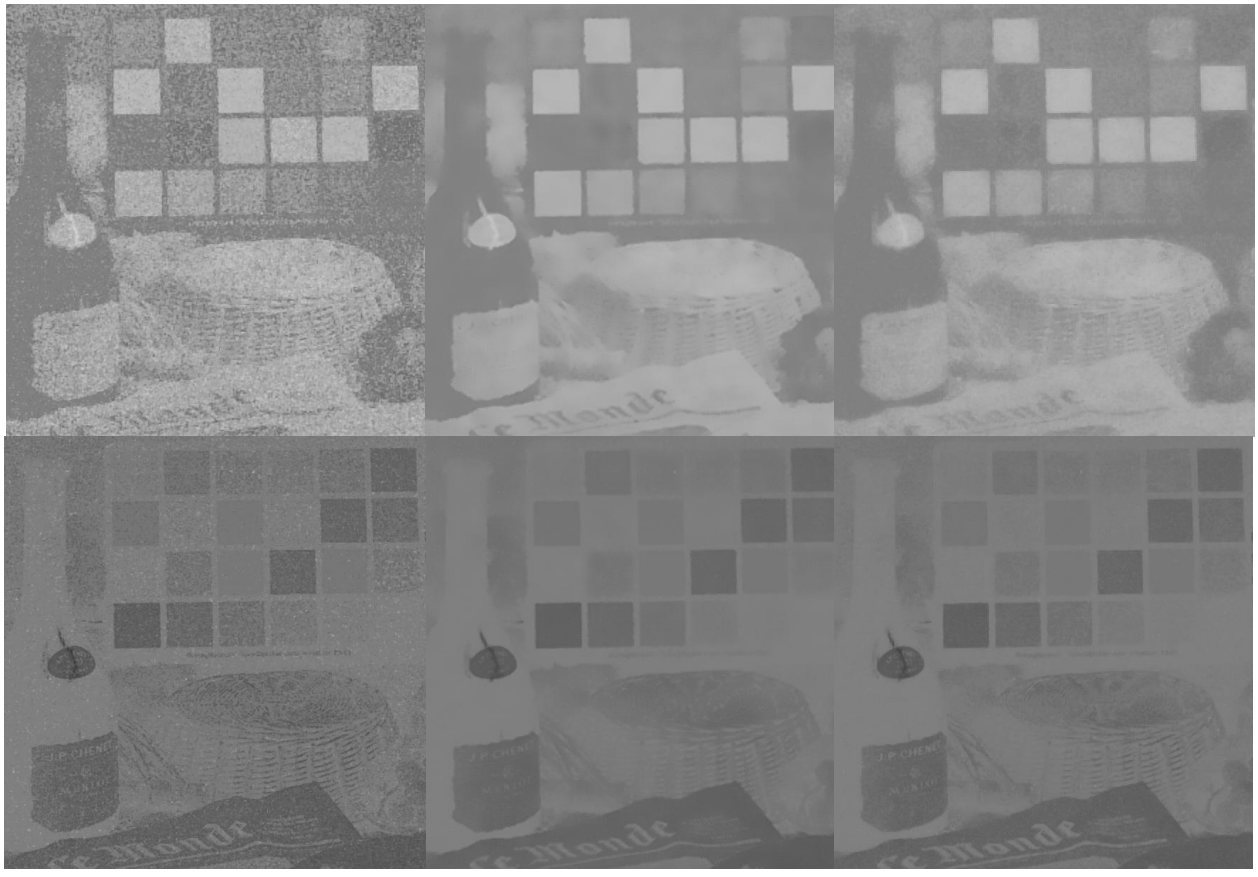


Figure 7: YCbCr – Cb (top row), Cr (bottom row) channel from left to right: input (10 lux, tungsten, 1.75um CMOS sensor), filtered with our solution, filtered with NoiseNinja (auto profiled, default settings)

Numerically, the results are presented in terms of the PSNR in the table below. It is worth mentioning that with respect to luminance, the software in [18] still presents some advantages.

Image	PSNR(Cb)	PSNR(Cb) NN	PSNR(Cr)	PSNR(Cr) NN
10 lux	31.16 dB	30.62 dB	27.22 dB	26.34 dB
100 lux	34.37 dB	34.01 dB	39.86 dB	39.35 dB

Figure 8: Peak signal to noise ratio for images in figures 6 and 7

4. CONCLUSION

In this paper we introduced a novel technique for denoising an image from a CMOS sensor with a 1.75um pixel. One of the problems associated with this type of sensor is the presence of a chrominance noise that is visually observable (relatively big ~15pixels color blotches), but appears absent in frequency domain. We used a bilateral filter based polyhedron classifier to extract the low frequency chrominance bands in the wavelet domain that we filtered using an edge aware averaging in a hue-saturation color space. Our approach differs from previous instances where the classic bilateral filter was used in a multi-scale framework. Within a dual tree wavelet decomposition structure, we have extended our low frequency polyhedron classifier filter to feed extracted edge information to a secondary filtering step acting upon the high frequency wavelet sub-bands. Using the edge information exchange step and an estimate of the local neighborhood variance, we built an adaptive wavelet coefficient thresholding mechanism. We presented results of our filtering process as compared with an existing state of the art solution.

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