Performance evaluation of filters VDF and VMF against impulsive noise in video sequences

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***Abstract*— In this paper, we present a study on VDF and VMF filters in terms of efficiency for filtering impulsive noise in video sequences. These nonlinear filters are used in improving the quality of image/video and especially the noise attenuation and detail preservation of the image/video. We evaluate the performance of the two filters by using three CIF (Common Intermediate Format) sequences (Akiyo, Foreman and Tb420). We used for the evaluation of filter performance three quality assessment criteria (PSNR, SSIM and DVQ). For all quality metrics (PSNR, SSIM, DVQ), we can conclude that the VDF filter gives poor quality scores compared same to the noise sequence. On the other hand, the VMF filter provides good performance against impulsive noise. We test the performance of two filters using our metric PSNR with CSF. For short viewing distance, the VMF filter is more efficient for the less eventful sequences. For long viewing distance, the VMF filter is more efficient for the most animated sequences.**

Keyword- VDF filter, VMF filter, PSNR, SSIM, DVQ, CSF "contrast sensitivity function", Impulsive noise, Video sequences

I. INTRODUCTION

The impulsive noise is a type of electromagnetic interference (EMI) that usually comes from the electric transmission, radio or television, electronic devices or even mobile phones. However, the noise emitters, in particular those corresponding to non-continuous sources, are very difficult to detect and to isolate due to its intermittent, very fast and different currents telecommunications signals. Impulse noise is common in images which arise at the time of image acquisition and or transmission of images. Images and video signals are often corrupted by additive noise and/or motion blur mostly during acquisition and transmission. Consequently, denoising these signals in order to remove the effect of noise is highly desired. Denoising of color images and video signals is highly desirable in order to enhance the overall perceptual quality, increase compression effectiveness, facilitate transmission bandwidth reduction, and facilitate accuracy in processes like feature extraction and pattern recognition that might be involved.

The vector method treats the color as a single entity and not as the sum of three independent components. The pixel is then considered as a vector (with three components in the case of color images) and the treatment carried out on these vectors. This approach, dealing jointly the different magnitudes attached to a pixel allows a better consideration of the nature of the multi-component image. However, it requires an adaptation of the processing techniques. The advantage of this approach is to use only scalar processing. All methods defined in monochrome imaging are then used directly, without any adaptation.

A large number of filtering techniques have been developed for removal of impulse noise from color images [1]-[2]. Most of these techniques use vector processing approach as it is broadly accepted that this approach is more suitable than the component-wise filtering approach, which can produce color distortions in the filtered image. The vector directional filter (VDF) [3], the directional distance filter (DDF) [4], the vector median filter (VMF) [5] and the fuzzy vector filter (FVF) [6]-[7] are the most commonly used filters for noise removal in color images.

In this paper, we are doing a study on VDF and VMF filters in terms of efficiency for filtering impulsive noise in video sequences.

So, this paper is structured as follows: Section 2 presents a brief overview of VDF and VMF filters. Section 3 dedicated to the description of three quality metrics used in our study (PSNR, SSIM and DVQ) and our metric PSNR with CSF. The experimental results in addition to associate discussion are given in section 4. Finally, conclusions are drawn in section 5.

II. OVERVIEW OF USED FILTERS

One of the important fields of application of the treatment of multivariate images and more precisely color image is filtering. It is well established now that the color image processing must be done taking into account the nature Vector data given the correlation between the color components. We emphasize, in this section, two types of filters from the families of the median filters (VDF and VMF).

A. Overview Of VMF Filter

It is easily to see impulsive noise in images which is independent and uncorrelated to the image pixels and is also randomly distributed over the image. Thus this paper utilizes a vector median filter (VMF) to remove impulsive noise in images. VMF is a vector processing operator that has been introduced as an extension of scalar median filter and preserves the image without getting blurred and no shifting of boundary [5][8]. It approaches the problem of noise reduction by searching the most robust vector in the processing window. VMF is a vector processing operator that has been introduced as an extension of scalar median filter. The Vector Median Filter (VMF) usually utilizes the L1 norm (City Block distance) to order vectors according to their relative magnitude differences. According to the original definition proposed in [5] the L2 norm (Euclidean distance) can also be used to order the input vectors inside the processing window. The VMF can be derived either as a maximum likelihood estimate when the underlying probability densities are double-exponential or by using vector order statistics techniques.

Noise reduction is an important step in many color image processing applications. The most popular nonlinear multichannel filters are based on the ordering of vectors in a predefined filter window. The output of these filters is defined as the lowest ranked vector according to a specific ordering technique [9]-[10].

B. Overview Of VDF Filter

Vector directional filters (VDF) are a class of multivariate filters that are based on polar coordinates and vector ordering principles considering the angle between the color image vectors as ordering criterion [3][11]. Similar to the median filter applied to the chromaticity the VDFs operate on the chromaticity components of a color. In other words, they are designed to detect chromaticity errors, but not intensity outliers. Vector directional filter (VDF) family operates on the direction of the image vectors, aiming to eliminate vectors with atypical directions in the vector space. To achieve its objective, the VDF utilizes the angle between the image vectors to order vector inputs inside a processing window. The VDF's are optimal directional estimators and consequently are very effective in preserving the chromaticity of the image vectors. The VDF family operates on the direction of the color vectors with the aim of eliminating vectors with atypical directions. The input vectors in a window are ordered according to their angular differences using the cosine distance function. These works are related with heuristic approach which makes homogeneity directed correlation among the color channels. However, the localization performance on ambiguous edges with weak variations is still unstable. Human visual system perceives small brightness variations using a knowledge-based analogy from color components. Perceptually motivated color spaces are used to evaluate mutual coherency and geometrical continuation.

III. THE USED METRICS

The quality metrics with full reference are criteria that evaluate the quality of a degraded image using the entire original image as a reference. These criteria are mainly used in systems introducing degradations, such as compression systems with the loss, to assess the quantity of distortions introduced by the compression and the quality of the resulting image. We explain in the following three quality assessment criteria of images / videos present in the literature. These metrics will be used for the evaluation of filter performance.

A. Peak signal-to-noise ratio (PSNR)

This metric, which is used often in practice, called peak signal-to-noise ratio — PSNR. The image and video processing community has long been using mean squared error (MSE) and peak signal-to-noise ratio (PSNR) as fidelity metrics (mathematically, PSNR is just a logarithmic representation of MSE) [12]. There are a number of reasons for the popularity of these two metrics. The formulas for computing them are as simple to understand and implement as they are easy and fast to compute. Minimizing MSE is also very well understood from a mathematical point of view. Over the years, video researchers have developed a familiarity with PSNR that allows them to interpret the values immediately. There is probably no other metric as widely recognized as PSNR, which is also due to the lack of alternative standards. Despite its popularity, PSNR only has an approximate relationship with the video quality perceived by human observers, simply because it is based on a byte-by-byte comparison of the data without considering what they actually represent.

$$MSE=\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{ori}(i,j)-I_{deg}(i,j)\right)^2 \tag{1}$$

$$\mathrm{PSNR} = 10\log_{10}\frac{255^2}{\mathrm{MSE}}(\mathrm{dB}) \tag{2}$$

Where, N and M are the dimensions of the images and Iori and Ideg are respectively the pixel values of the original and degraded image.

B. The Structural SIMilarity (SSIM) index

The SSIM similarity index uses the image quality index UIQI (Universal Image Quality Index) [13]. This index defines the luminance comparison measurements *l*(*x*, *y*), contrast *c*(*x*, *y*) and of structure *s*(*x*, *y*) between both x and y of luminance signal:

$$l(x,y) = \frac{2\mu_x\mu_y}{\mu_x^2 + \mu_y^2} \tag{3}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2} \tag{4}$$

$$s(x,y) = \frac{\mathrm{cov}_{xy}}{\sigma_x\sigma_y} \tag{5}$$

With, μ_x the average of *x*, μ_y the average of *y*, σ_x^2 the variance of *x*, σ_y^2 the variance of *y*, cov_{xy} the covariance between *x* and *y*, The *UQI* similarity index between x and y corresponds to:

$$\begin{aligned} UQI &= l(x,y)\times c(x,y)\times s(x,y) \\ &= \frac{4\mu_x\mu_y\,\mathrm{cov}_{xy}}{\left(\mu_x^2+\mu_y^2\right)\left(\sigma_x^2+\sigma_y^2\right)} \end{aligned} \tag{6}$$

The transition to SSIM [14] resulting from the consideration of the case where $\mu_x^2+\mu_y^2$ or $\sigma_x^2+\sigma_y^2$ may be close to zero. The formula is then transformed as follows:

$$SSIM = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\,\mathrm{cov}_{xy} + c_2\right)}{\left(\mu_x^2+\mu_y^2+c_1\right)\left(\sigma_x^2+\sigma_y^2+c_2\right)} \tag{7}$$

With, $c_1 = (K_1L)^2, c_2 = (K_2L)^2$, L is the dynamic of the pixels values, either 255 for images coded on 8 bits, $K_1 = 0.01$ and $K_2 = 0.03$ by default.

For the assessment of the quality of an image, the above formula is applied to the luminance only. Typically, quantities are calculated on the size of 8 × 8 windows. The current window can be moved pixel by pixel over the entire image. However, the authors propose to consider only a subset of these windows, such as reducing their number by a factor two in both dimensions. The SIM card measures obtained appear may leave undesirable block effects. To limit the effects, the authors use a weighting function $w = \{w_i \ with\ i = 1,2,3\ldots N_w\}$ Gaussian, circular, symmetry, size 11 × 11, standard deviation 1.5 and sum $\sum_{i=1}^{N_w} w_i = 1$. The previous values are then:

$$\mu_x = \sum_{i=1}^{N_w} w_i x_i \tag{8}$$

$$\mu_y = \sum_{i=1}^{N_w} w_i y_i \tag{9}$$

$$\sigma_{xy} = \sum_{i=1}^{N_w} w_i \left(x_i - \mu_x\right)\left(y_i - \mu_y\right) \tag{10}$$

$$\sigma_x = \left(\sum_{i=1}^{N_w} w_i \left(x_i - \mu_x\right)^2\right)^{\frac{1}{2}} \tag{11}$$

$$\sigma_y = \left(\sum_{i=1}^{N_w} w_i \left(y_i - \mu_y\right)^2\right)^{\frac{1}{2}} \tag{12}$$

Finally, the quality metric SSIM between the X and Y image is the average the SSIM measures on the N_f windows of the luminance of the image:

$$MSSIM = \frac{1}{N_f} \sum_{i=1}^{N_f} SSIM\left(x_i, y_i\right) \tag{13}$$

Two identical images have an SSIM equal to 1.

C. Modified Watson's Digital Video Quality (DVQ) Metric

This Modified Watson's Digital Video Quality (DVQ) Metric [15] is based on Watson's Digital Video Quality (DVQ) model [16]-[17] which uses the Discrete Cosine Transform (DCT). The DVQ metric computes the visibility of artifacts expressed in the DCT domain. The metric makes use of DCT coefficients to make it closer to human perception. The algorithm for this VQM is as follows: Both the processed and reference video sequences are converted to the YOZ color space, and undergo DCT transformation. The DCT coefficients are converted to units of local contrast, which is defined as the ratio of the AC amplitude to the temporally low-pass filter DC amplitude. The local contrasts are subjected to spatial contrast sensitivity functions for the static and dynamic frames, and the DCT coefficients are converted to just noticeable differences. The video sequences are subtracted to produce a difference sequence, and this is subjected to a contrast masking in a maximum operation and a weighted pooling mean distortion.

D. PSNR with CSF metric

The CSF "contrast sensitivity function" is one of the main ways to incorporate the HVS properties in an imaging system. This metric is based on the ability of the visual system to detect differences in luminance, thus it determines the existence of edges between homogeneous surfaces. It expresses the sensitivity variation of the human visual system to the contrast versus different spatial frequencies. Fig. 1 presented the model proposed in the work [18].

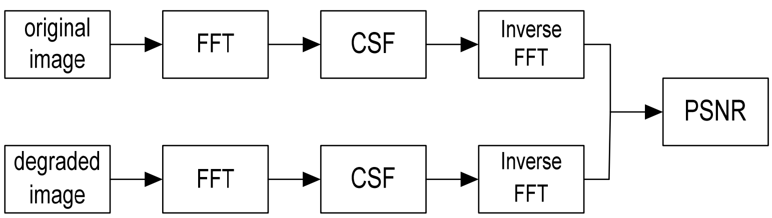

Fig. 1. The proposed model of CSF in the work [18]

For each image or frame, a two dimension DFT is applied (DFT 2D). Then each spatial frequency horizontal and vertical (f(u), f(v)) is converted to (cycle/degree) according to those expressions:

$$f(u)=(u-1)/(\Delta\ N) \tag{14}$$

$$f(v)=(v-1)/(\Delta\ N) \tag{15}$$

Where N is the number of frequencies and Δ = 0.25 mm (the dot pitch) and u, v =1, 2.3……………N.

$$f_s(\text{cycle/degree}) = f_i\ (\text{cycle/pixel}) \times f_n\ (\text{pixel/degree})$$
$$= \frac{\pi}{180 \times \arcsin\left(1 \Big/ \sqrt{1+\text{dis}^2} \right)} \times \sqrt{f(u)^2 + f(v)^2} \quad (16)$$

Where, "dis" is the viewing distance in millimetres.

The filtering operation is performed by multiplying each resulting value of the DFT (real part and imaginary part) by the coefficient of contrast sensitivity functions corresponding:

$$f_s(\text{filtré}) = f_s \times CSF(f_s) \quad (17)$$

Based on our previous works [19], we found that Nill filter [20] is best suited to our application and it gives better results in terms of correlation with the human visual system:

$$CSF_{Nill}\ (f) = (0.2+0.45f)\ e^{-0.18f} \quad (18)$$

To filter the image or the frame from CSF space, we [18] used the method based on the CSF normalization to the frequency peak. In which, the coefficient 1 is applied for frequencies below the peak value, to preserve the signal. They used a peak frequency equal to 5 cycles / degree.

After the filtering operation, the inverse DFT is applied to reconstruct the original and degraded images. Finally, the PSNR between two images is calculated. It is notified that for each viewing distance, we have a different PSNR for the same image. In fact, a distortion visible for a distance of 500 mm can be invisible for a distance of 3000 mm.

For video sequences, we used the Fast Fourier Transform (FFT). To have an image size of power of two for FFT algorithm, the authors used “image Mirrors” to increase the image size (512,512) instead of the traditional way “zero padding”. The method “image Mirrors” consists of copying the pixels from the image itself rather than completing nulls with pixels.

IV. Experimental results

A. Experimental conditions

We tested our algorithms on 300 frames common intermediate format (CIF) sequences (Akiyo, Foreman and Tb420) with a size of 352×288. The generation of a noisy signal, or the addition of noise in an image, can be useful to test the nonlinear filters to reduce noise. Impulsive noise affects only a few samples of the signal greatly modifying their value. Impulsive noise generated by example is transient electromagnetic disturbances.

Dusts or bites on photographic images are also an impulsive noise. We generated an impulsive noise on the video sequences for testing the performance of the filters. The video sequence is first converted into frames and consecutively frames into images. Then the proposed lone diagonal sorting algorithm is applied to the images which are separated from frames. After the filtering process, the frames are converted back to the original movie. To filter the noise, we have used two non-linear filters (VDF and VMF). We try to compare the performance of two filters on impulsive noise. In Figure 2, we present the first images of sequences (Akyio, Foreman and Tb420): originals, noised with impulse noise, filtered with a VDF filter and filtered with a VMF filter.

Fig. 2. The first images of: (a,e,j) Original sequences, (b,f,k) Noisy sequences, (c,g,l) Filtered sequences using VDF filter, (d,i,m) Filtered sequences using VMF filter

B. Results and discussion

To evaluate the performance of two filters (VDF and VMF), we used the three metrics (PSNR, SSIM and DVQ). The results are shown in Table 1.

TABLE I. PERFORMANCE OF TWO FILTERS VDF AND VMF

		Noisy sequences	**Filtered sequences using VDF filter**	**Filtered sequences using VMF filter**
Akyio	**PSNR**	27.8506	23.3005	35.5175
	SSIM	0.7087	0.8363	0.9685
	DVQ	3.3103	4.2859	1.0765
Foreman	**PSNR**	31.4748	21.9438	32.0779
	SSIM	0.8856	0.7415	0.9150
	DVQ	1.7171	5.1214	1.4712
Tb420	**PSNR**	26.7199	18.5182	28.1261
	SSIM	0.7511	0.6119	0.8720
	DVQ	4.4044	9.7373	2.6777

In terms of PSNR, VDF filter will result in bad quality values than the noisy sequences. For example, the VDF filter gives a decrease of 16.33% for Akyio, 30.28% for Foreman and 30.69% for Tb420. By cons, VMF filter will result better quality values than the noisy sequences. The VMF filter gives an improvement of 27.52% for Akyio, 1.91% for Foreman and 5.26% for Tb420 (see Fig.3).

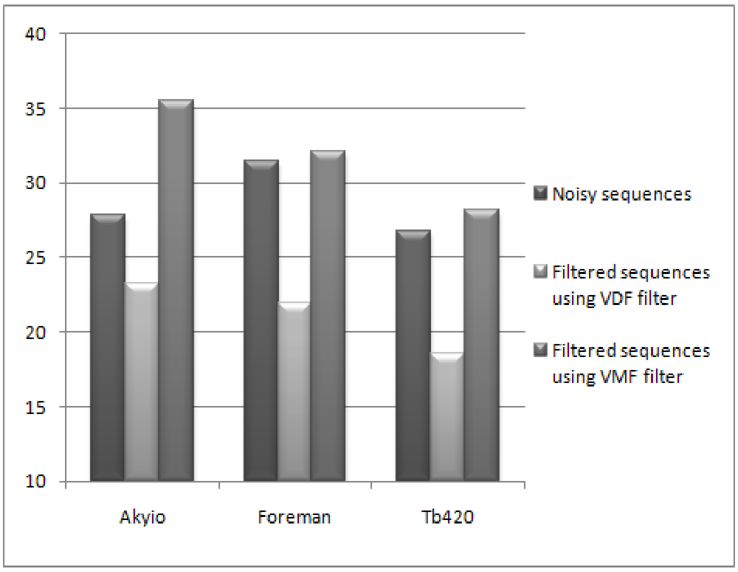

Fig. 3. Evolution of PSNR

Regarding the SSIM, for Akiyo sequence, VDF filter give an improvement of 18%. On the other side, VMF filter give an amelioration of 36.65%. By cost, the VDF filter gives a decrease 16.27% for Foreman and 18.53% for Tb420. But VMF filter gives an improvement of 3.32% for Foreman and 16.09% for Tb420 (see Fig.4).

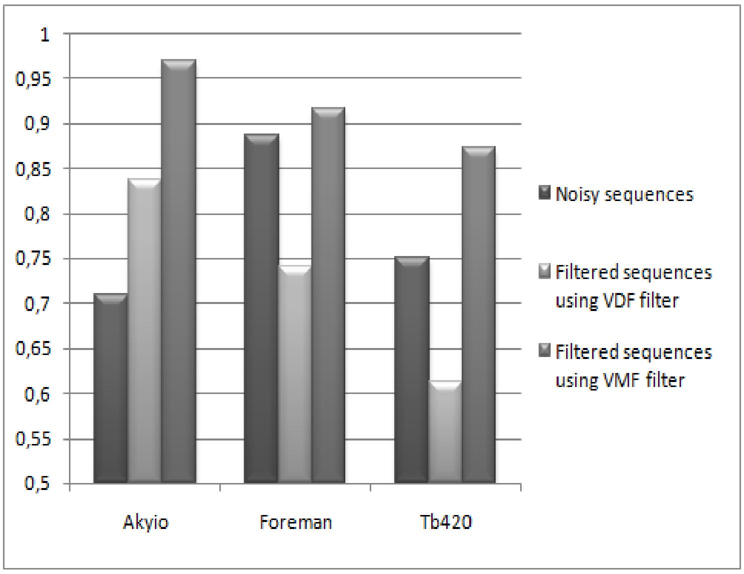

Fig. 4. Evolution of SSIM

For the metric DVQ, the quality is better for smaller ratings. So when the quality decreases the values of DVQ increases. VDF filter will result in bad quality values than the noisy sequences. For example, the VDF filter gives a decrease of 31.16% for Akyio, 290.54% for Foreman and 121.09% for Tb420. By cons, VMF filter will result better quality values than the noisy sequences. The VMF filter gives an improvement of 67.48% for Akyio, 14.32% for Foreman and 39.20% for Tb420 (see Fig.5).

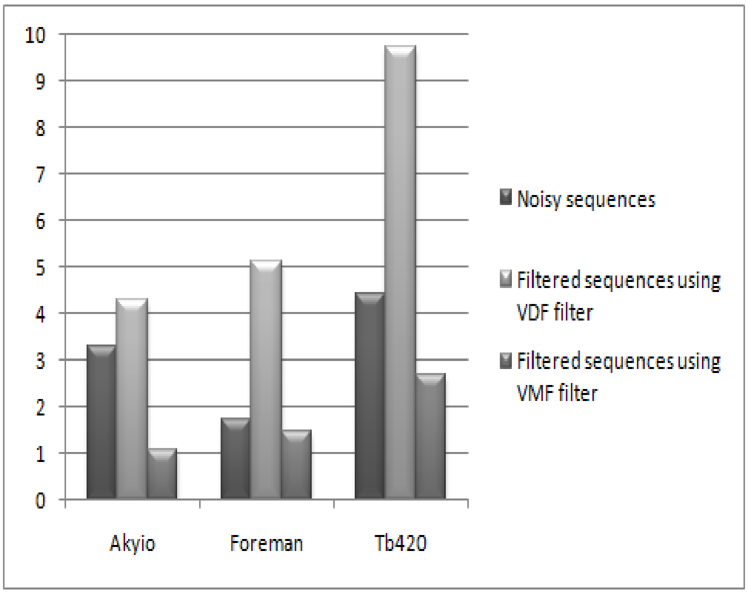

Fig. 5. Evolution of DVQ

For all quality metrics (PSNR, SSIM, DVQ), we can conclude that the VDF filter gives poor quality scores compared same to the noise sequence. All results show the weakness of VDF filter to eliminate impulsive noise from video sequences. During the filtering operation, the VDF filter causes errors which influence the filtered sequence.

On the other hand, the VMF filter provides good performance against impulsive noise. This filter is effective and gives filtered sequences of good quality compared to the noisy sequences. For all quality criteria used, we get similar results. VMF filter is most effective on impulsive noise in video sequences.

To evaluate the performance of two filters (VDF and VMF), we used our metric PSNR with a pretreatment CSF. The results are shown in Figure 6.

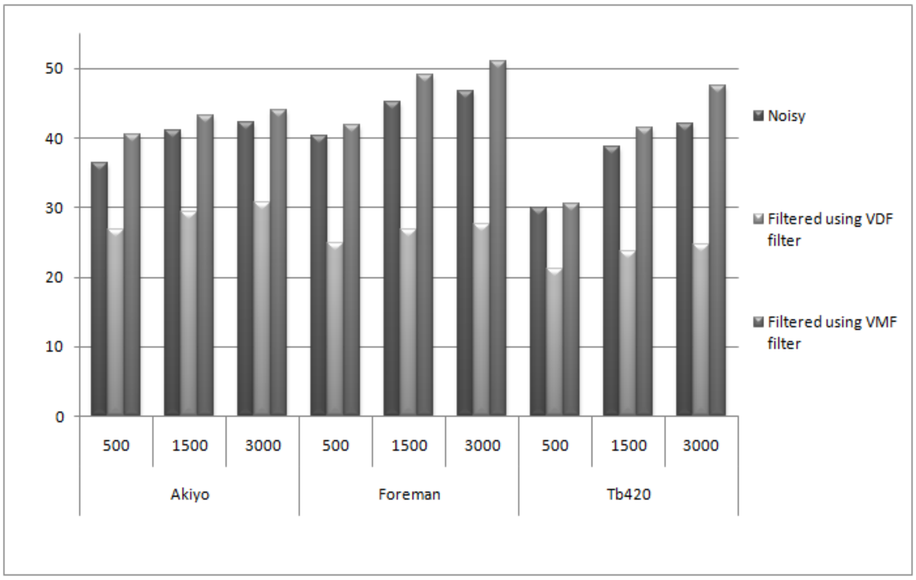

Fig. 6. PSNR of sequences at different viewing distances

Our method show that the VMF filter gives better performance than the VDF filter as indicated in previous metrics. Same if the viewing distance increases the difference between the two filters to increase. This shows that the VDF filter generates more degradation when it makes the filter operation of the impulse noise. For sequences where more movement as Foreman and Tb420, the performance difference between the two filter increases as the viewing distance increases. VMF filter is better performance for the most animated sequences. When the viewing distance increases we can see that the filter performance VMF nearly doubles compared to the VDF filter and the difference from the degraded sequence increases. But for the sequences where there is less movement as Akiyo, the performance difference between the two filters almost keeps for all distances observations and the difference from the degraded sequence decreases when the viewing distance increases. For short viewing distance, the VMF filter is more efficient for the less eventful sequences. For long distance observation, the VMF filter is more efficient for the most animated sequences.

V. CONCLUSION

Filtering is one of the most important elements of color image processing system. Its most important applications are noise removal, image enhancement, and image restoration. Many classes of nonlinear digital image filtering techniques have appeared in the literature. In this paper, we present a study on VDF and VMF filters in terms of efficiency for filtering impulsive noise in video sequences. We evaluate the performance of the two filters by using three CIF (Common Intermediate Format) sequences (Akiyo, Foreman and Tb420). We used for the evaluation of filter performance three quality assessment criteria (PSNR, SSIM and DVQ) and our metric PSNR with CSF. For all quality metrics, we can conclude that the VDF filter gives poor quality scores compared same to the noise sequence. All results show the weakness of VDF filter to eliminate impulsive noise from video sequences. The VMF filter provides good performance against impulsive noise. This filter is effective and gives filtered sequences of good quality compared to the noisy sequences. For short viewing distance, the VMF filter is more efficient for the less eventful sequences. For long viewing distance, the VMF filter is more efficient for the most animated sequences.

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