Video Denoising Quality Assessment for Different Noise Distributions

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***Abstract*—Denoising algorithms often presume a single noise model, for instance, Gaussian noise, but it has been observed that during acquisition, image and video sequences can be corrupted by different types of noise, which follow a distinct probability distribution model depending on the application. This paper aims to compare the performance of several denoising algorithms, among them Non-Local Means and Block-Matching 3D, and other classical techniques such as median, Gaussian, bilateral and anisotropic diffusion, by simulating different noise distributions in videos and comparing the methods efficiency in multiple scenarios. Objective evaluation uses structural similarity (SSIM) and provides video specific assessment scores with NTIA Video Quality Metric (VQM). Results show considerable differences between intraframe and interframe filtering quality, while variations in filtering responses to each type of noise contribute to more appropriate selection of techniques to noise reduction and provide insight to noise difficulty levels.**

I. Introduction

In recent years, technology has advanced to a point where acquisition, transmission and reproduction of digital videos have become quite practical and efficient. There is a range of applications that benefit from this evolution, such as video conferences, internet video sharing, digital television and medical procedures [1]. However, there are still many situations where recorded images and videos suffer significant degradations, such as poor ambient conditions, recording sensor and transmission device failures, signal interferences and distortions caused by compression algorithms [2]. Thus, restoration and enhancement of image and video have been an essential computer graphics field not only to improve visual quality but also to enable and increase the performance of later processing steps such as content segmentation, analysis and recognition.

Noise reduction is a critical phase in most graphic processing applications, since it seeks to isolate relevant information from external interferences [3]. Noise often originates due to natural conditions such as low illumination, which combined with cheap camera sensitivity results in noisy recording [4]. Videos tend to get even more noisy than images due to camera high frame rate [5], but on the other hand they have high temporal redundancy, that is, information present in each video frame is repeated by several adjacent frames, so interframe denoising algorithms can take advantage of this and improve quality more effectively [6]. Image filtering methods are also applicable, but this filtering approach termed intraframe take each frame as temporarily independent, and may obtain non-optimal results and also generate new temporal artifacts [1].

Denoising methods have been improved from linear functions such as Gaussian filter, which performs uniformly across image pixels [3], to nonlinear methods which are more selective and allow edge and detail preservation [7], such as median filtering, bilateral filter [8] and anisotropic or Perona-Malik diffusion [9]; and later from these local to nonlocal denoising methods such as Non-Local Means (NLM) [10], which considers an estimation of pixels weighted proportionally to the similarity with target pixel neighbors, and is constantly improved by search optimization of correct pixel groups or segments [11]. NLM also inspired the creation of Block-Matching and 3D Filtering (BM3D) [12] based on grouping and collaborative filtering, and by their nonlocal features subsequent interframe NLM and BM3D methods were presented [13], [14] where pixel grouping stages also include neighbor video frames and show better performance in relation to intraframe execution [15].

Denoising and enhancement methods are highly dependent on the processed content [16], so in most cases they tend to generate new artifacts and do not produce stable positive results, therefore, developing an universal approach to this problem remains a challenge [17]. Most denoising approaches consider a generalization of at most two types of noise, such as Gaussian and impulsive, which often does not occur in practice [5], [18]. Further common noises come from sources such as quantization, laser and radar systems [19], which can assume particular statistical distribution models such as uniform, poisson or gamma distributions [20], [21].

In this paper, we aim to compare the filtering efficiency for these different types of noise in addition to those commonly treated in other works, with quantitative evaluation using full-reference quality metrics, which measurement consists in comparing the original or reference video with the test version [22], including a specific metric for videos that takes into account temporal quality, contributing to adaptive approaches, noise difficulty levels and the relation of intraframe and interframe filtering. By relating different methods to improvement of video quality in multiple situations, this work allows the use of results in application of existing techniques as well as in the development and evaluation of new methods.

This paper is organized as follows: related work is reviewed in Section II; Section III presents the experimental methodology of video denoising tests; results are presented and discussed in Section IV; and finally Section V presents the main conclusions and future work possibilities.

II. Related Work

One of the works which concerns about modeling the noise structure present in videos points out that while most denoising algorithms development assume a generalization for the Gaussian distribution model, not only videos present more noise than images, but also that video noise often has different characteristics and denoising efficiency is directly related to the method's expected noise model. From this premise, Ji et al. [5] states that an effective algorithm for natural noise reduction should handle most different noise distributions that occur in video acquisition. To evaluate their proposed algorithm, they conducted tests which consisted on videos degraded by a mixture of Gaussian, poisson and impulsive noises, comparing against other denoising techniques such as BM3D through the peak signal-to-noise ratio (PSNR) metric, which defines the fidelity between two signals measured in decibel units (dB) [23], showing that algorithms designed for Gaussian noise removal are not as effective when other noise distributions are present.

Natural noise can usually be modeled or approximated by known probability density functions [21], which describe the relative probability of each value occurrence in the signal interval. Figure 1 shows various noise probability function models for the most common distributions. Gaussian noise is a regular model, caused by natural sources such as low illumination and high temperature [1]. Uniform noise is also called quantization noise since it occurs in the quantization process of image and video signal amplitude, defined by a continuous random variable [24]. Poisson noise is also termed shot or photon noise as it comes from measurement fluctuations caused by low photon count in optical devices [25]. Speckle or gamma noise follows the gamma probability distribution, and occurs in laser, radar or acoustic imaging systems. Impulse noise is also known as salt and pepper noise [26] because the corrupted pixels assume minimum or maximum value, and occurs during transmission with several causes, such as electromagnetic interference and conversion issues between analog and digital data [27].

Image denoising for Gaussian, impulse and gamma noise is evaluated in [28] by full-reference metrics, including PSNR and structural similarity (SSIM) metric [29] which measures quality by comparing luminance, contrast and structure features, and is employed in videos as an intraframe method [30]. Bilateral filter had better performance for gamma noise results, while for impulse noise the median filter was clearly superior. Most related work show that median filter and its variants are ideal for impulse noise removal, since its response to impulses is always zero [20], [31], while methods such as bilateral filter and anisotropic diffusion fail to remove it, as they treat it as edges [17]. In other work [32], image and video denoising with NLM variants and BM3D is also evaluated by SSIM quality metric. Sutour et al. also apply gamma and poisson noise besides Gaussian, but even their adaptive non-local means technique did not achieve better scores than BM3D due to over-smoothing.

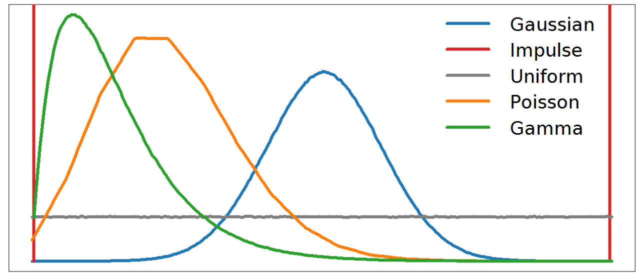

Fig. 1. Noise probability density function models: Gaussian ($\sigma = 30$), impulse, uniform, poisson ($\lambda = 4$) and gamma ($k = 2$) distributions.

Most work in noise reduction indicate a lack of filtering responses evaluation in more diversified and realistic scenarios, where other types of noise besides Gaussian prevail. Another matter is the frequent usage of relatively older quality metrics such as PSNR and SSIM [33] when compared to general filters improvement, with few application of metrics which have good correlation to human perception and also for video evaluation where temporal quality should also be taken into consideration. An example of such metric is *Video Quality Metric* (VQM) [34] from National Telecommunications and Information Administration (NTIA), a full-reference video specific metric which evaluates groups of frames in relation to various visual features such as color distortion, blurring, blocking, irregular motion and global noise. VQM has the highest complexity among objective quality metrics, but also presents better performance in relation to subjective metrics, having obtained a correlation coefficient of 0.95 in tests carried out by Wolf and Pinson [23].

III. Experimental Methodology

Our tests used a public digital video database[1] consisting of videos in H.264/SVC encoding without transmission errors. Seven video sequences with 640 x 480 pixels resolution and 249 frames each were selected, all reference versions identified with the zero condition number meaning "VGA reference" (no impairment). The samples identified by the following numbers were selected: 3, 5, 13, 24, 25, 29, 32. The selected sequences are of real scenarios, and contain a large variety of content including scene cuts or camera motion, therefore their spatial and temporal indicators vary on a large scale [35].

Most implementation for video processing tests was performed in C++ language using the OpenCV functions library[2], which has many useful tools for image and video manipulation. Figure 2 illustrates the quality assessment process

[1] ftp://ftp.ivc.polytech.univ-nantes.fr/IRCCyN_IVC_Influence_Content/Videos/

[2] http://opencv.org

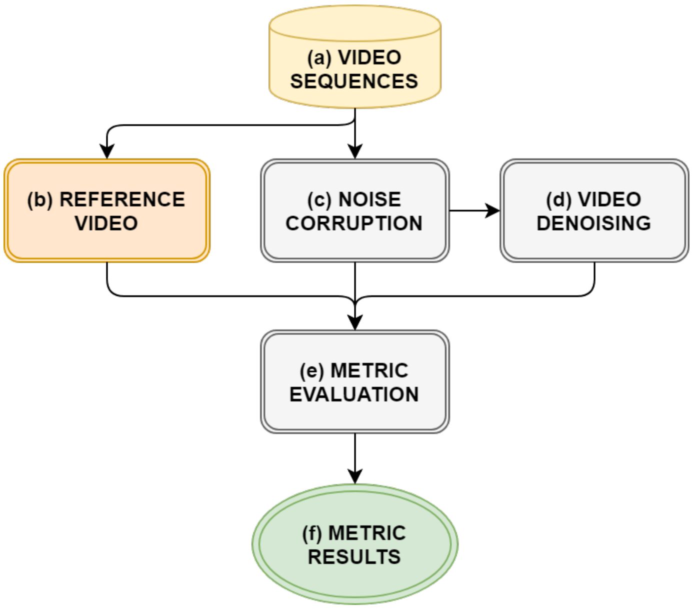

Fig. 2. Fluxogram for quality assessment of denoising algorithms.

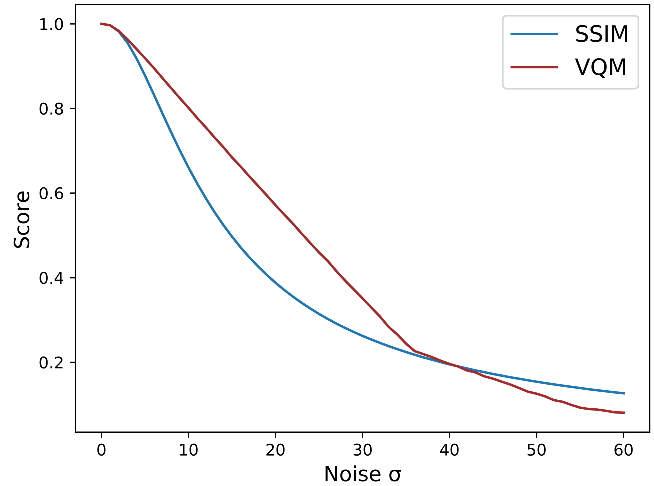

Fig. 3. Variation of quality metric scores according to noise level.

of denoising techniques. For (d) stage, six denoising algorithms were evaluated: Gaussian, median and bilateral filter, anisotropic diffusion, non-local means (NLM) and block-matching 3D (BM3D)[3], having employed the algorithms interframe version for a slightly better performance, where each frame was processed along with two neighboring frame pixels.

Noise models for (c) stage include Gaussian, impulsive, uniform, poisson and gamma distributions. As described in section II, each type of noise is characterized by different probability distributions, which generate values that can be applied on each video frame for simulation of noise. A noise defined by a random distribution function may vary in its intensity, usually indicated by the standard deviation (σ) [24], so tests were performed considering three levels of noise, with $\sigma = 10$, $\sigma = 20$ and $\sigma = 30$, representing scenarios simulation with weak, medium and strong noise, respectively. With exception of the Gaussian distribution that can be directly generated from a σ parameter, other models had a more indirect approach of adjusting their statistical parameters(for instance, λ or k), so that the standard deviation of the resulting distribution matches the desired value. Using the HSV color model, noise was applied to each frame hue and value channels of color video sequences.

Employed quality metrics for denoising evaluation of (e) stage were structural similarity (SSIM) and Video Quality Metric (VQM)[4], which are full reference, meaning they require the original video for comparison with the corrupted or further processed video version. Even though VQM evaluates the video in the temporal domain and is more closely aligned with human perception [23], SSIM is also considered mainly because of its usage in a large number of related works, and as it correlates better than PSNR, it serves to the intraframe evaluation and comparison with interframe results from VQM. Both SSIM and VQM scores can range from 0 to 1, where higher values indicate greater visual quality. To improve the comprehension of results, the graph in Figure 3 shows the relationship between the variation of Gaussian noise level in test samples given by the standard deviation on the x-axis and the measured quality scores on the y-axis. It can be observed that the VQM metric follows a similar trend of SSIM but with a more linear behavior until it becomes more sensitive to greater amounts of noise and its output score is reduced faster than SSIM's.

For the evaluation performance, each video is first artificially degraded with noise (c), then the filtering algorithm is applied (d) to the deteriorated video. The resulting processed video is objectively evaluated by SSIM and VQM - full reference metrics which require the non-degraded video as reference (b). The full processing cycle consists of evaluating with each metric the performance of each denoising algorithm, in relation to each type and amount of noise in the video.

Most of the denoising algorithms operate based on an estimation of the noise present in the image, and are able to adjust the strength of noise reduction according to the noise level. For tests accuracy the objective is to evaluate the capacity of each denoising technique, so the actual noise level for parameter selection was considered. For classic techniques that do not have the noise level as a direct input parameter, parameters were adjusted indirectly with an initial linear mapping followed by trial and error to obtain the highest score by evaluation metrics, so that it is obtained the best possible value for each specific denoising set. The most external cycle is the changing of content with different video sequences, which can result in distinct score intervals for each noise set. For a generalized result score, we consider the average score

[3]http://www.cs.tut.fi/~foi/GCF-BM3D/index.html\#ref_software
[4]https://www.its.bldrdoc.gov/resources/video-quality-research/software.aspx

TABLE I
ALGORITHMS RESULTS AND COMPARISON FOR GAUSSIAN NOISE REDUCTION.

Noise / Metric / Algorithm	$\sigma = 10$		$\sigma = 20$		$\sigma = 30$		
	SSIM	**VQM**	**SSIM**	**VQM**	**SSIM**	**VQM**	σ
—	0.63	0.74	0.38	0.48	0.26	0.23	0.022
Gaussian Filter	0.69	0.92	0.61	0.82	0.50	0.73	0.025
Median Filter	0.67	0.85	0.54	0.75	0.42	0.67	0.025
Bilateral Filter	0.81	0.87	0.49	0.62	0.34	0.36	0.033
Anisotropic Diffusion	0.75	**0.96**	0.72	**0.91**	0.67	**0.82**	0.042
Non-Local Means	0.72	0.85	0.73	0.82	**0.70**	0.76	0.038
Block-Matching 3D	**0.82**	0.95	**0.76**	0.87	0.59	0.67	0.035

TABLE II
ALGORITHMS RESULTS AND COMPARISON FOR IMPULSE NOISE REDUCTION.

Noise / Metric / Algorithm	$\sigma = 10$		$\sigma = 20$		$\sigma = 30$		
	SSIM	**VQM**	**SSIM**	**VQM**	**SSIM**	**VQM**	σ
-	0.26	0.90	0.13	0.80	0.08	0.52	0.005
Gaussian Filter	0.53	0.76	0.38	0.59	0.33	0.49	0.006
Median Filter	**0.82**	**0.98**	**0.78**	**0.94**	**0.74**	**0.93**	0.006
Bilateral Filter	0.26	0.94	0.17	0.87	0.13	0.58	0.007
Anisotropic Diffusion	0.29	0.95	0.19	0.78	0.15	0.49	0.011
Non-Local Means	0.42	0.93	0.20	0.84	0.13	0.57	0.011
Block-Matching 3D	0.29	0.96	0.17	0.85	0.14	0.56	0.008

value from different video sequences grouped by the same case, and the associated standard deviation for the $\sigma = 30$ case, which more clearly summarizes the oscillation trend of scores in relation to video content. Each table presents the results obtained for a specific noise distribution, where each table row corresponds to a denoising algorithm. Table columns are divided in relation to metrics on inner columns, and the amount of noise indicated by its standard deviation (σ) in external top columns. Numerical results are complemented by the processed video frames for each evaluated denoising algorithm.

IV. Results and Discussion

First results are for Gaussian and impulsive noise types which are most common in related work, followed by results for uniform, poisson and gamma noise distributions respectively. At the end some main points are synthesized and discussed.

Table I shows results obtained for Gaussian noise reduction with standard deviation (σ) of 10, 20 and 30. For $\sigma = 10$ and $\sigma = 20$, it can be observed that both anisotropic diffusion and BM3D obtained good results, whereas BM3D obtained a better score by structural similarity (SSIM), and anisotropic diffusion by VQM. For $\sigma = 30$ Gaussian noise, anisotropic diffusion also obtained the highest result in the VQM metric, but in this case the non-local means filter was more efficient by SSIM scores. From the scores standard deviation we can observe that linear and most simple nonlinear filters show less discrepancy between processed video content, while more complex algorithms which perform pixel grouping, such as NLM and BM3D, have greater variation for the same type and amount of noise in different videos. Anisotropic diffusion was the most unstable filter due to its edge enhancement, which highly depends on the video content.

Figure 4 shows the processing results of a video sample frame by the different techniques, deteriorated by Gaussian noise with $\sigma = 30$. It can be seen that NLM actually removed virtually all visible noise, but it also removed many details along with a blurring effect in similar areas of the frame, making its score somewhat lower by the VQM metric than anisotropic diffusion's.

As pointed out in related work, in Gaussian noise type it is expected superior performance of NLM and BM3D techniques, since these algorithms were specifically designed for this type of noise. However, bilateral filter displayed an equally high performance for tests with fewer noise, where more complex techniques could not perform less denoising independently of parameters settings, while anisotropic diffusion obtained the best evaluation by all VQM scores, indicating that it has less degradation of temporal quality. Fairly close metric values also show that in many applications that cannot rely on long local processing time for a small difference in the quality result, the usage of less complex filters such as anisotropic may be more advantageous than a technique such as BM3D.

Table II presents impulsive noise reduction results, which also compare to the ones seen in related work. It can be clearly verified that only the median filter was able to remove noise, with a reasonable decrease of result scores as noise intensity increases, while other algorithms did not have positive effect or even further reduced the video quality; as was said in section II, due to the sharp characteristic of this type of noise, filters such as the bilateral and anisotropic are not at all effective as they treat it as an edge.

The negative effect of impulsive noise is much more evident in SSIM metric scores, where values are already quite low for the fewer noise case; VQM scores manifests less sensitivity to this type of noise, producing higher scores while the noise does not reach the highest level. It can be observed that the stronger the impulsive noise, the greater the disparity of efficiency between median filter and other techniques. Standard deviation of metric scores indicate that video content had much less effect on scores than the persistent impulsive noise, in comparison to Gaussian noise results.

Figure 5 shows the algorithms visual effects on a frame deteriorated with the highest intensity of impulsive noise. As shown by Table II, only median filter was able to effectively remove it. It is difficult to identify a difference between other algorithms and the noisy frame results, except for Gaussian

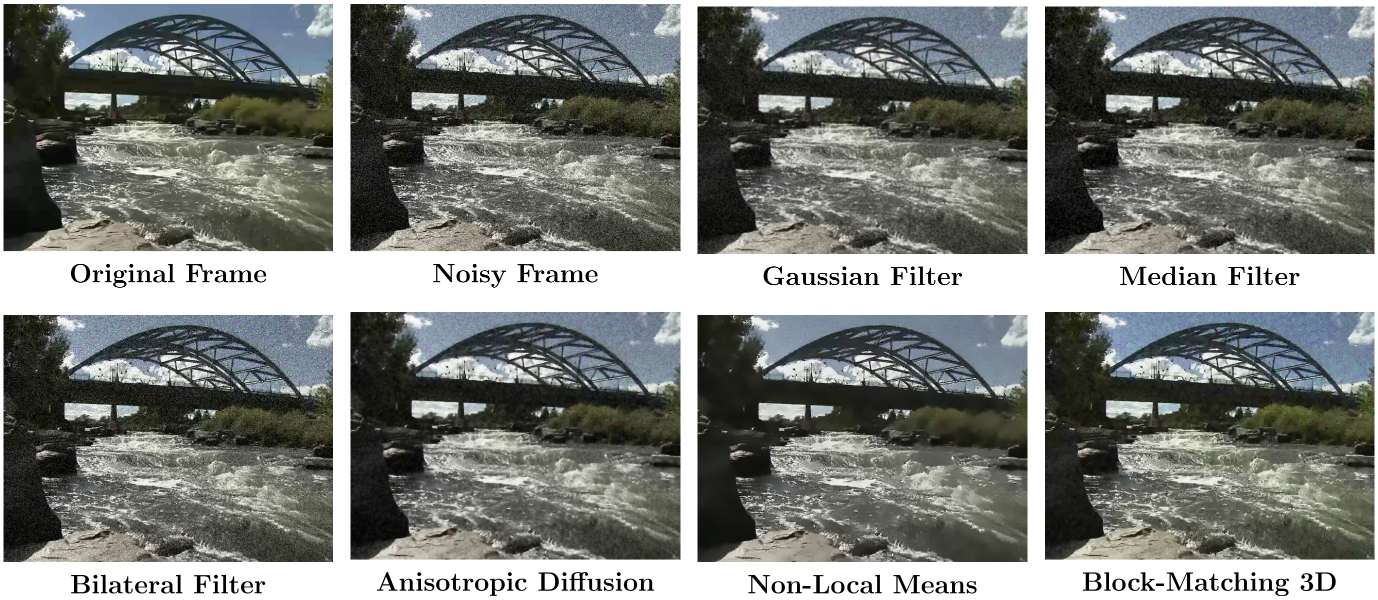

Fig. 4. Visual comparison of algorithms performance on Gaussian noise reduction with $\sigma = 30$ for a video sequence frame.

TABLE III
ALGORITHMS RESULTS AND COMPARISON FOR UNIFORM NOISE REDUCTION.

Noise	$\sigma = 10$		$\sigma = 20$		$\sigma = 30$		
Metric / Algorithm	**SSIM**	**VQM**	**SSIM**	**VQM**	**SSIM**	**VQM**	σ
—	0.67	0.67	0.38	0.26	0.25	0.05	0.017
Gaussian Filter	0.73	0.80	0.57	0.74	0.46	0.56	0.020
Median Filter	0.81	0.81	0.44	0.61	0.32	0.36	0.018
Bilateral Filter	**0.88**	**0.91**	0.70	**0.83**	0.60	0.63	0.022
Anisotropic Diffusion	0.85	0.87	0.56	0.80	0.58	0.61	0.031
Non-Local Means	0.78	0.83	0.68	0.81	**0.63**	**0.75**	0.026
Block-Matching 3D	0.87	0.87	**0.72**	0.77	0.46	0.37	0.024

TABLE IV
ALGORITHMS RESULTS AND COMPARISON FOR POISSON NOISE REDUCTION.

Noise	$\sigma = 10$		$\sigma = 20$		$\sigma = 30$		
Metric / Algorithm	**SSIM**	**VQM**	**SSIM**	**VQM**	**SSIM**	**VQM**	σ
—	0.64	0.73	0.39	0.45	0.27	0.13	0.018
Gaussian Filter	0.70	0.90	0.58	0.78	0.48	0.65	0.019
Median Filter	0.66	0.84	0.50	0.76	0.40	0.63	0.019
Bilateral Filter	0.78	0.89	0.48	0.56	0.33	0.22	0.024
Anisotropic Diffusion	0.76	0.95	0.71	**0.88**	0.64	0.77	0.037
Non-Local Means	0.70	0.85	0.70	0.83	**0.67**	**0.79**	0.035
Block-Matching 3D	**0.79**	**0.96**	**0.73**	0.85	0.51	0.63	0.028

filter, which, as a result of the generalized blurring effect, became more close to the reference video, which is also indicated by Table II.

Table III shows results obtained in uniform noise reduction. Bilateral filter was the most efficient for the first noise scenarios with $\sigma = 10$ and $\sigma = 20$, with the exception being the SSIM metric for $\sigma = 20$ where the BM3D algorithm obtained the highest result. NLM also produced good results, but only obtained the best values for all metric scores with $\sigma = 30$. Figure 6 shows a video frame decayed by $\sigma = 20$ uniform noise. As in Gaussian noise, it can be observed that the NLM filter virtually removes the noise content, but its best score performance comes at the expense of much frame quality, thus BM3D obtains higher results with fewer noise.

For poisson noise, table IV shows that unlike uniform distribution, scores were closer to Gaussian noise with some divergences. It is also possible to notice that values are slightly higher, although its proportion is maintained, showing that poisson denoising is more efficient than uniform. Figure 7 presents an instance of $\sigma = 20$ poisson noise reduction. Table V presents gamma noise results, which are similar to those obtained for poisson noise except for the first noise level. Magnitude of gamma noise results is also closer to poisson noise, being slightly lower as the amount of noise reduces and approaching uniform noise.

Figure 8 shows SSIM metric scores for each video frame denoised by NLM, which follows a similar trend for presented noise types (excluding impulsive), where oscillation depends on the video content. Score levels illustrate the denoising efficiency or yet each noise difficulty level in relation to the Gaussian noise distribution expected by the filtering technique. In comparison, Figure 9 shows results for frame-by-frame BM3D denoising, with slightly higher scores. The order sequence indicates a greater efficacy for Gaussian

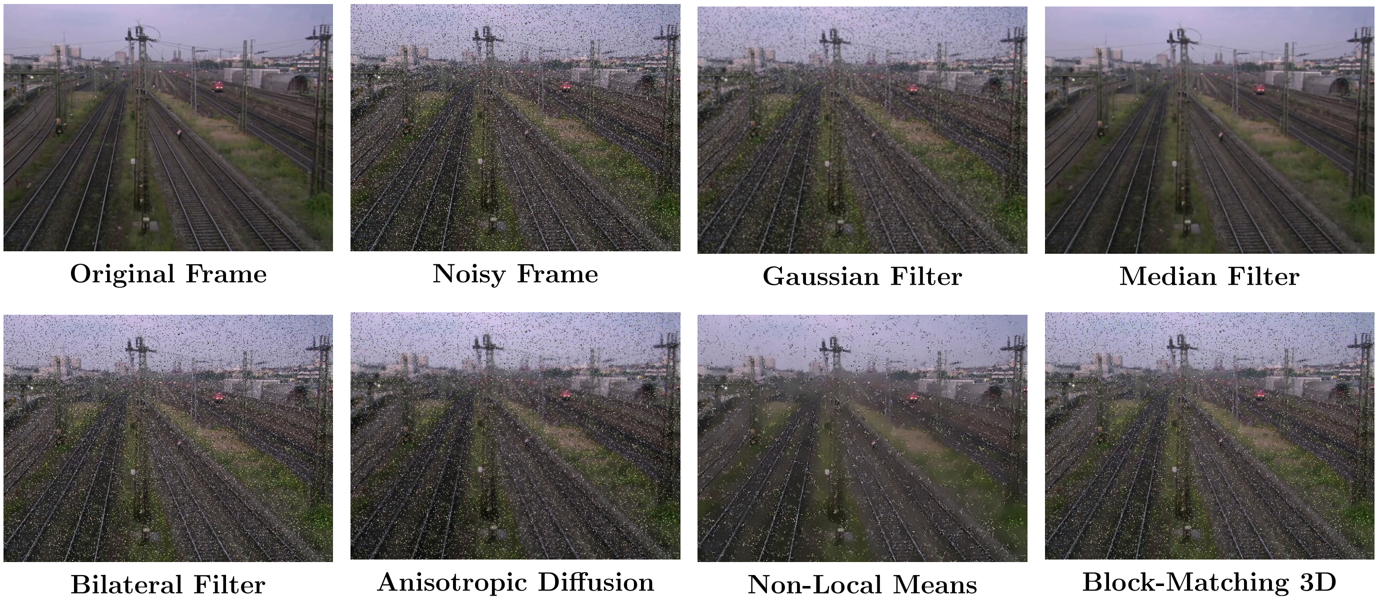

Fig. 5. Visual comparison of algorithms performance on impulse noise reduction for a video sequence frame.

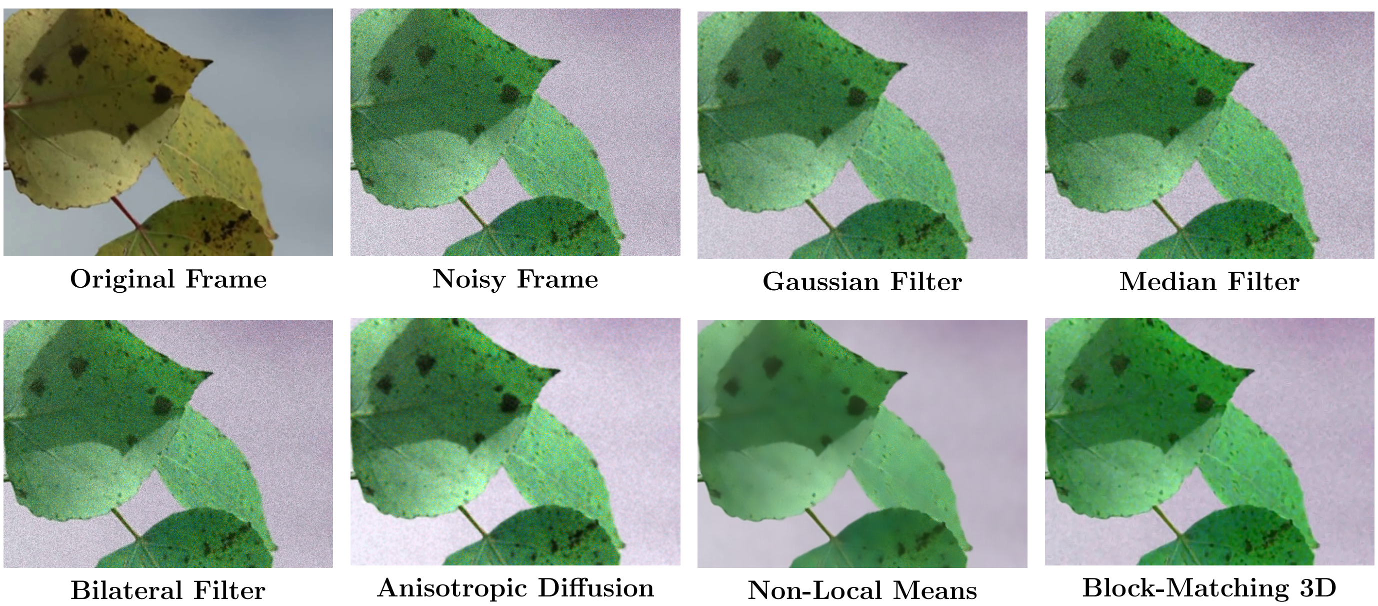

Fig. 6. Visual comparison of algorithms performance on uniform noise reduction with $\sigma = 20$ for a video sequence frame.

noise, followed by poisson, gamma and uniform noise with less difference between them. The discrepancy in filtering responses by quantitative evaluation revealed that although some distributions are closer to the Gaussian type, applying a denoising filter in a generalized manner is often not worth it, so that algorithm adaptation according to the present noise model is desirable and often required depending on the application.

It was verified that the best noise removal occurred for anisotropic, NLM and BM3D techniques, where NLM denoising suffers from over-smoothing, that is, noise tend to vanish but also impairs the sharpness of video frames, which also occurred in some of the works mentioned in section II. While for anisotropic diffusion and BM3D, noise is still visible but most detail quality remained. Metric results corroborate those found in the literature in relation to impulsive and Gaussian noise types, while other distributions provide complementary results. BM3D and NLM techniques are efficient in reducing Gaussian noise which is the common model presumed in their design, however it was verified that anisotropic diffusion overcame them for some video sequences degraded with reasonable amounts of noise, while non-local means was more suited for strong noise ($\sigma = 30$). For $\sigma = 10$ and uniform noise, bilateral filter efficiently removed noise mainly by being able to perform smoother attenuation when a heavy effect was

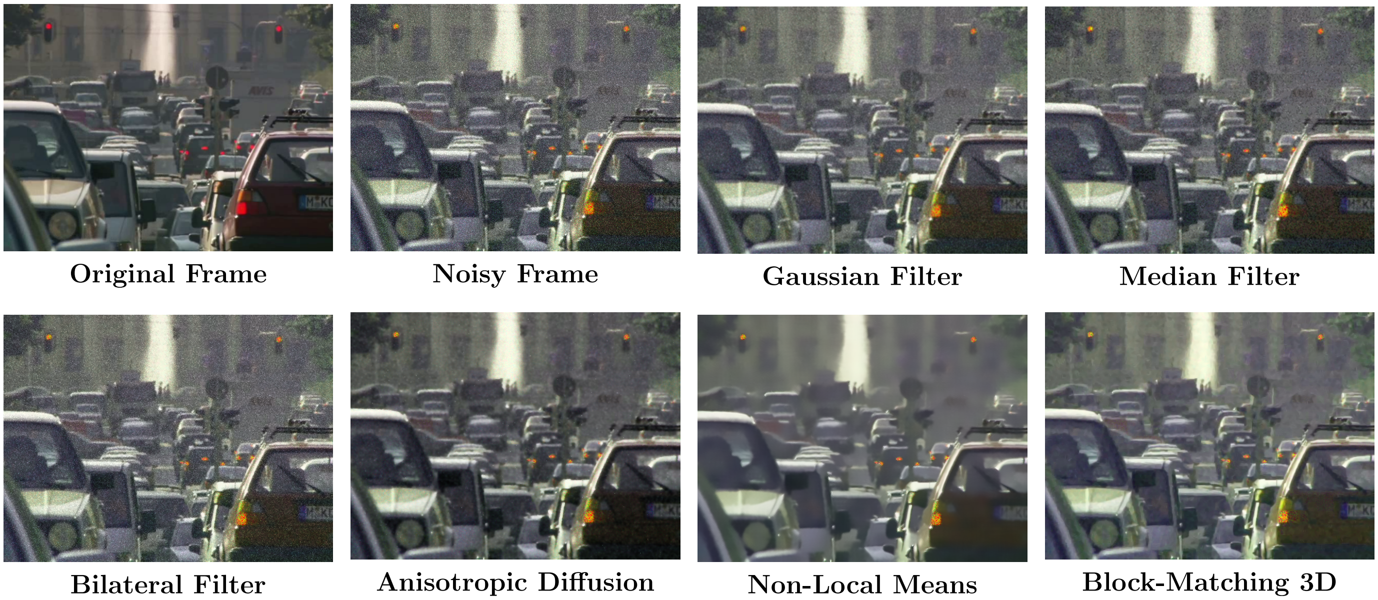

Fig. 7. Visual comparison of algorithms performance on poisson noise reduction with $\sigma = 20$ for a video sequence frame.

TABLE V
ALGORITHMS RESULTS AND COMPARISON FOR GAMMA NOISE REDUCTION.

Noise	$\sigma = 10$		$\sigma = 20$		$\sigma = 30$		
Algorithm \ Metric	SSIM	VQM	SSIM	VQM	SSIM	VQM	σ
—	0.64	0.74	0.40	0.43	0.27	0.09	0.014
Gaussian Filter	0.69	0.90	0.58	0.77	0.48	0.62	0.016
Median Filter	0.67	0.85	0.56	0.75	0.43	0.59	0.015
Bilateral Filter	0.77	0.89	0.48	0.58	0.35	0.19	0.019
Anisotropic Diffusion	0.73	**0.95**	0.70	**0.87**	0.62	0.76	0.028
Non-Local Means	0.70	0.84	0.69	0.83	**0.63**	**0.77**	0.024
Block-Matching 3D	**0.80**	0.94	**0.73**	0.84	0.54	0.66	0.021

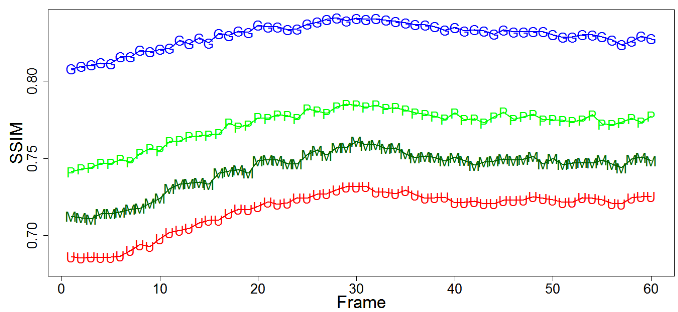

Fig. 9. Frame-by-frame SSIM output of sample sequence denoised by BM3D for Gaussian (G), uniform (U), poisson (P) and gamma (M) noise with average intensity.

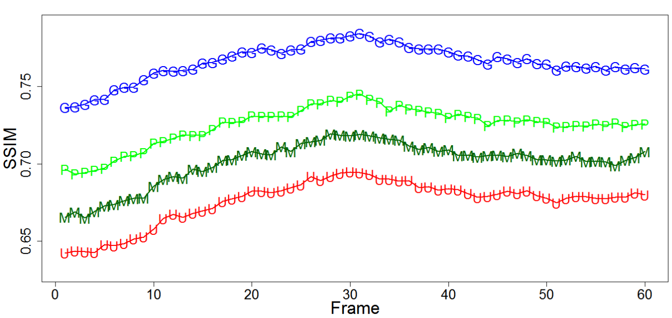

Fig. 8. Frame-by-frame SSIM output of sample sequence denoised by NLM for Gaussian (G), uniform (U), poisson (P) and gamma (M) noise with average intensity.

not necessary. Naturally the biggest exception is impulsive noise, where only median filter shows acceptable results.

Gaussian filter was not superior in any test due to linear operation and lack of edge preservation, but its results are useful for comparison purposes with other algorithms. Although simpler, Gaussian and median filters are able to process video sequences almost instantaneously, allowing its application in real time. Bilateral and anisotropic diffusion are a bit slower but did not take time greater than a minute, making them more satisfactory for various scenarios in which they perform as good as more complex techniques. NLM and BM3D processing have been very time consuming, in this way, their usage may be impracticable in several video applications.

It was evident that chosen metrics have great relevance in objective evaluation. Although they converge in the overall assessment, each metric has a different sensitivity level to a certain type of distortion, the smoothing effects caused by denoising algorithms and the temporal domain. Thus, results show that in addition to improving noise reduction methods, it is essential to apply metrics that are more aligned with human perception and that are able to reflect differences in interframe filtering, such as VQM.

V. Conclusion

This paper evaluated and compared the performance of some main denoising techniques. Results showed that the efficiency of noise reduction algorithms varies considerably according to the type and amount of noise present in video sequences, thus indicating the importance of noise analysis to apply adaptation of techniques as opposed to blind filtering with NLM or BM3D. From a general perspective of most denoising methods, it was verified a quality decrease from Gaussian noise results followed by poisson, gamma and the worst response from uniform and impulsive noise, although the latter can be exceptionally neutralized by median filtering. In addition to common quality metrics, VQM can be used to provide additional results to video denoising evaluation, as it takes into account the temporal differences by interframe filtering. In future work we can consider some arising issues, such as the automation of parameter selection for several of the denoising algorithms as well as the development of adaptive filtering according to detected noise features.

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