heart sequence, impulse noise,
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ADAPTIVE IMPULSE DETECTION BASED APPROACHES FOR THE NOISE REDUCTION IN HEART IMAGE SEQUENCES

This paper focuses on three-dimensional (3-D) adaptive median filters based on the impulse detection approach designed to effectively remove the impulse noise from cardiographic image sequences. Impulse noise affects the useful information in the form of bit errors and it introduces to the image high frequency changes that prohibit to process and to evaluate the heart dynamics correctly. Therefore biomedical imaging such as vascular imaging and quantification of heart dynamics is closely related to digital filtering. In order to suppress impulse noise effectively, well-known non-linear filters based on the robust order-statistic theory provide interesting results. Although median filters have excellent impulse noise attenuation characteristics, their performance is often accompanied by undesired processing of noise-free samples resulting in edge blurring. The reason is that median filters do not satisfy the superposition property and thus the optimal filtering situation where only noisy samples are affected can never be fully obtained. The presented adaptive impulse detection based median filters, can achieve the excellent balance between the noise suppression and the signal-detail preservation. In this paper, the performance of the proposed approaches is successfully tested for the heart image sequence of 38 frames and the wide range of noise corruption intensity. The results are evaluated in terms of mean absolute error, mean square error and cross correlation.

1. INTRODUCTION

Many authors [4],[11],[12],[17] have analysed the cardiographic image sequences affected by strong noise that makes immediate and accurate tracking of the heart motion difficult. Besides automatic detection of the heart contours, in order to precise the tracking of the heart motion, some digital filtering algorithms for the impulse noise reduction were developed.

In case of the impulse noise corruption, the aim of the optimal filtering is to design the filtering algorithm so that it will affect only corrupted samples, whereas the desired (noise-free) samples will be invariant to a filtering operation. This is accomplished by adaptive impulse-detection based median filters [1],[10],[14] which replace the noisy samples by the median of the input set spanned by a filter window and perform the identity operation related to noise-free

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samples. The measure of the output distortion depends on the capability to detect atypical image artefacts such as impulses and outliers that can be very similar to edge samples [18].

2. IMAGE SEQUENCE FILTERING

In terms of signal dimensionality and considered correlation present in the input set, the filtering techniques for noisy image sequences or generally said image sequences can be divided into three classes [2],[7],[9], such as temporal filters, spatial filters and spatiotemporal filters. This partition is based on the fact that image sequences represent time sequences of 2-D images, i.e. the spatiotemporal data.

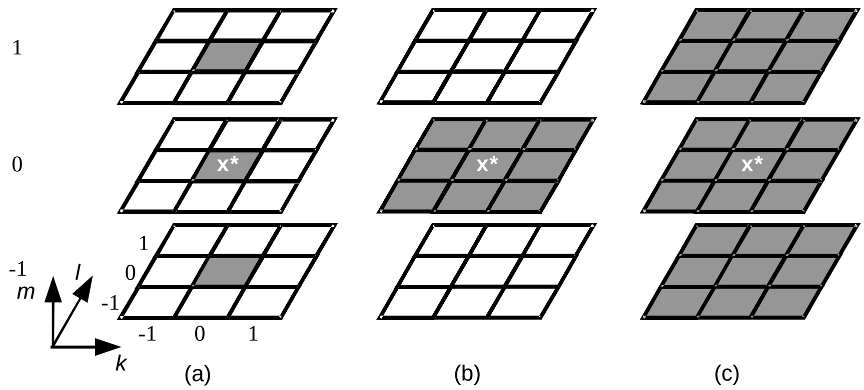

Fig.1. Filtering methods for the image sequences divided according to a filter window dimensionality.
(a) Temporal filters, (b) Spatial filters, (c) Spatiotemporal filters

The class of temporal filters (Fig.1a) is referred to the temporal correlation of frames. These one-dimensional (1-D) filters remove noise without impairing the spatial resolution in stationary areas. In order to improve a filter performance, the temporal filtering is usually connected with a motion compensation method [2] to filter objects along their motion trajectory. However, this way is computationally very complex and it often does not work well on the ground of the spatial warping and the scene changes.

In general, 2-D filters [3],[16] are probably the most frequently used image filtering techniques in the image processing. In case of image sequences, these filters process each frame independently (Fig.1b) so that the excluded information about the motion trajectory can result in a large motion blurring.

It can be easily seen, that 3-D filters [2],[6],[7],[9],[13],[19] also called spatiotemporal filters, (Fig.1c) utilise both temporal correlation and spatial correlation present in image sequences. For that reason, spatiotemporal filters represent a natural filter class for noisy image sequences and it is possible to observe the significant reduction of the spatial and motion blurring in the dependence on the chosen filtering algorithm.

Since the degree of noise corruption significantly influences the motion estimation precision, the image sequence filtering algorithms are usually referred with no motion estimation. Thus, a $3\times3\times3$ cube spatiotemporal filter window represents the most frequently used window shape because it respects all kinds of the correlation present in image sequences.

3. IMPULSE DETECTORS

In case of heavy tailed noise, e.g. impulse noise with uniform distribution of random values, the popular class of linear filters exhibits worse noise attenuation characteristics. In order to suppress the impulse noise effectively, a wide class of non-linear order-statistic filters [3],[9],[15], based on the ordering of the input samples spanned by a filter window is preferred. The ordering operation removes the atypical image samples, often the noise, to the borders of the ordered set and the mid-positioned samples, e.g. median value, in ordered sequence represent the robust estimates.

Probably the most popular non-linear filter is the well-known median [16] characterised by the excellent robustness against the impulse noise. However it often introduces to an image too much smoothing resulting in a blurring that can be more objectionable than the original noise. Since the non-linear filters do not satisfy the superposition property [3], the optimal filtering situation, where only noisy samples are filtered whereas the desired image features will be invariant to a filtering operation, can never be fully obtained. For that reason there were developed several adaptive impulse detection-based median filters (Fig.2) taking the advantage of the optimal filtering situation.

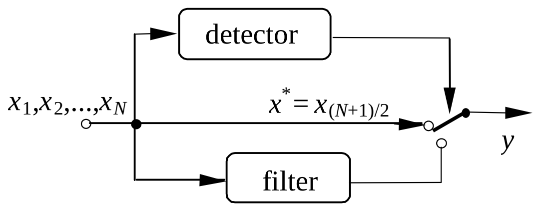

Fig.2. Impulse detector based filtering.

In general, the detection-filtering algorithm can be stated [10] as follows

$$\begin{aligned} \text{IF} \quad Val \geq Tol \quad \text{THEN} \quad & y = y_{MF} \\ \text{ELSE} \quad & y = x_{(N+1)/2} \end{aligned} \tag{1}$$

where Val is the detector operation value that is compared with the threshold value Tol. If the condition $Val \geq Tol$ is satisfied, the central sample $x_{(N+1)/2}$ of the filter window represents the impulse and it is estimated by median filter, i.e. the filter output $y = y_{MF}$. Otherwise, the adaptive median filter performs no smoothing or identity operation, where the central sample $x_{(N+1)/2}$ remains unchanged, i.e. $y = x_{(N+1)/2}$.

3.1. MEDIAN DETECTOR (MD)

Let $x_1, x_2, ..., x_N$ be a discrete-time continuos-valued input set determined by a filter window and $x_{(1)}, x_{(2)}, ..., x_{(N)}$ an ordered set so that

$$x_{(1)} \leq x_{(2)} \leq ... \leq x_{(N)} \tag{2}$$

$$x_{(i)} \in \{x_1, x_2, ..., x_N\} \;\; for \;\; i = 1, 2, ..., N \tag{3}$$

The median filter output [3],[16] is given by

$$y_{MF} = x_{((N+1)/2)} \tag{4}$$

where $x_{((N+1)/2)}$ is the middle positioned order-statistic, i.e. the median.

The advantage of the median operator lies in the robust estimation in the environments corrupted by impulse noise because the median value taken over the filtering window has the highest probability to be the noise-free sample. For that reason, the median value can be used successfully in the equation (1) so that the operation value Val is given by

$$Val = \left| y_{MF} - x_{(N+1)/2} \right| \tag{5}$$

i.e. the operation value Val is equal to the absolute difference between the median output y_{MF} and the central sample $x_{(N+1)/2}$. Note that the threshold value Tol is experimentally set to $Tol = 20$.

3.2. SIGMA CONCEPT BASED DETECTOR (SD)

The sigma filtering concept [8], i.e. the filtering based on the simple statistical measures such as the mean value and standard deviation is given by the operation value defined as

$$Val = \left| \mu - x_{(N+1)/2} \right| \tag{6}$$

where μ is the sample mean of observed data $x_1, x_2, ..., x_N$ and the adaptive threshold value Tol is given by

$$Tol = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{7}$$

If the detection value is greater than or equal to the standard deviation or the adaptive threshold Tol, the central sample is probably distorted because it is more different from other input samples.

3.3. ORDER-STATISTIC DETECTOR (OD)

Now, consider the set of n mid-positioned ordered samples $x_{((n+1)/2)}, x_{(1+(n+1)/2)}, ..., x_{(N-(n+1)/2)}$ and the simple trimmed mean defined as

$$\mu_n = \frac{1}{n}\sum_{i=(n+1)/2}^{N-(n+1)/2} x_{(i)} \tag{8}$$

Since, the extreme order-statistics (usually outliers) are excluded and the trimmed mean μ_n is determined by probably no corrupted samples, it will provide the precise value necessary to be compared with the central sample $x_{(N+1)/2}$. Thus, the detector value [14] can be stated as follows

$$Val = \left|\mu_n - x_{(N+1)/2}\right| \tag{9}$$

In case of cube filter window, the OD optimally works for the threshold value $Tol = 15$ and the number of considered mid-positioned samples $n = 13$.

3.4. LOCAL CONTRAST PROBABILITY BASED DETECTOR (LCP)

The idea of the LCP detector [1] is based on fixed threshold $Tol = 1/N$ computed from the window size N and the operation value given by

$$Val = \frac{\left|x_{(N+1)/2} - \mu\right|}{\sum_{i=1}^{N}\left|x_i - \mu\right|} \tag{10}$$

where μ is the sample mean of observed data $x_1, x_2, ..., x_N$. If the equation (10) results in the value greater than or equal to the threshold value $Tol = 1/N$, the central sample is considered as the impulse and the output value is determined by the median.

4. EXPERIMENTAL RESULTS

The original heart image sequence of 38 frames of the size 256×256 image samples and 8 bit per sample representation was used (Fig.3a,b). The original signal was corrupted by 5% and 10% (Fig.3c) random-valued impulse noise [3],[5],[9] defined as

$$x_{i,j} = \begin{cases} o_{i,j} & \text{with probability } 1 - p_\upsilon \\ \upsilon & \text{with probability } p_\upsilon \end{cases} \tag{11}$$

where $x_{i,j}$ is the noisy image sample, $o_{i,j}$ describes the sample original image, i, j are indices of the sample location, υ is the random value from <0,255> and p_υ is the impulse probability. Note that impulse noise frequently occurs as bit errors [3]

$$^{*}k_{i,j}^{m} = \begin{cases} k_{i,j}^{m} & \text{with probability } 1 - p_\upsilon \\ 1 - k_{i,j}^{m} & \text{with probability } p_\upsilon \end{cases} \tag{12}$$

where p_υ is the bit change probability, $k_{i,j}^{m}$ and $^{*}k_{i,j}^{m}$ are binary values {0,1} of B-bit original sample $o_{i,j}$ and noisy sample $x_{i,j}$ given by

$$o_{i,j} = k_{i,j}^{1} 2^{B-1} + k_{i,j}^{2} 2^{B-2} + ... + k_{i,j}^{B-1} 2 + k_{i,j}^{B} \tag{13}$$

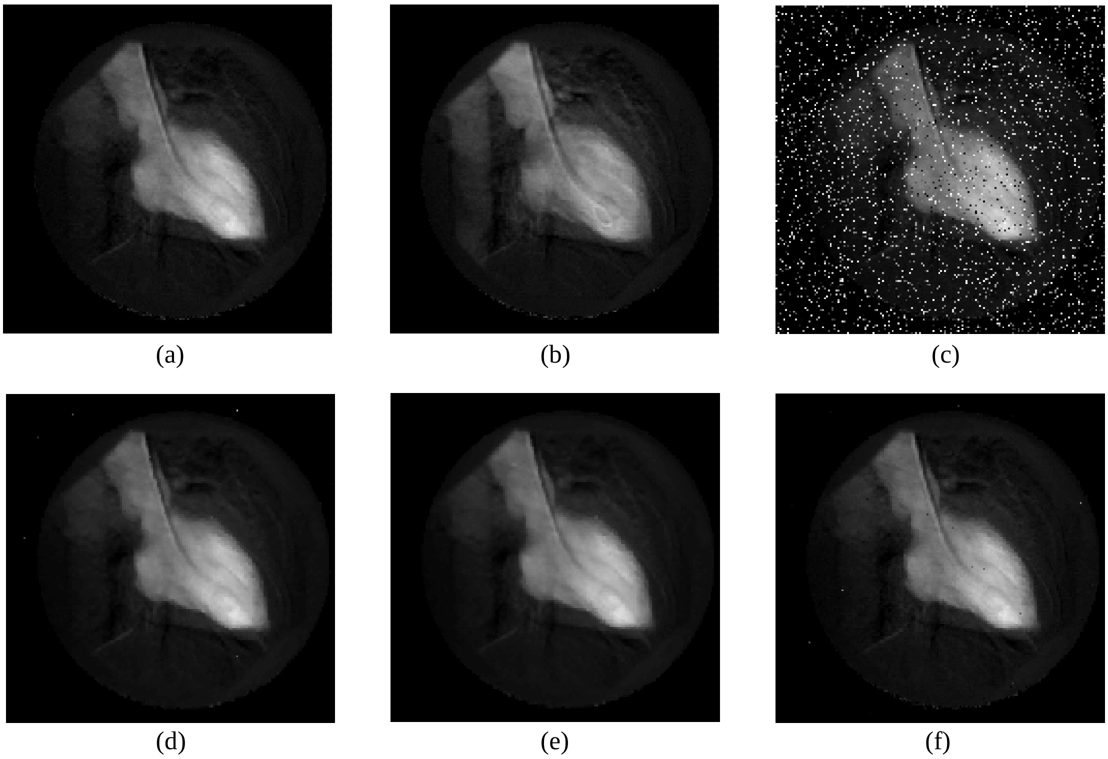

Fig.3. Achieved results
(a) Original 5th frame, (b) Original 35th frame, (c) Noisy (10% impulse noise) 5th frame,
(d) Filtered by 2-D median, (e) Filtered by 3-D median, (f) Filtered by 3-D OD + 2-D median

$$x_{i,j} = {}^{*}k_{i,j}^{1} 2^{B-1} + {}^{*}k_{i,j}^{2} 2^{B-2} + ... + {}^{*}k_{i,j}^{B-1} 2 + {}^{*}k_{i,j}^{B} \tag{14}$$

The objective measure of the filter performance, the experimental results were evaluated according to three error criteria [9] such as the mean absolute error (MAE), mean square error (MSE) and cross correlation ΔR . Mathematically, the MAE and MSE are defined as

$$MAE = \frac{1}{NMK} \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{t=1}^{K} \left| o_{i,j,t} - x_{i,j,t} \right| \tag{15}$$

$$MSE = \frac{1}{NMK} \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{t=1}^{K} \left(o_{i,j,t} - x_{i,j,t} \right)^2 \tag{16}$$

where $\{o_{i,j}\}$ is the original image, $\{x_{i,j}\}$ is the filtered (noisy) image, i, j, t are indices of the sample position and N, M, K characterise the sequence size. The cross correlation ΔR is given by

$$R^t = \frac{\left| \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} x_{i,j}^t x_{i,j}^{t+1} - E^t E^{t+1} \right|}{\sigma^t \quad \sigma^{t+1}} \tag{17}$$

where E^t is the mean value and σ^t is the standard deviation of the *t*th frame and E^{t+1} is the mean value and σ^{t+1} is the standard deviation of the $(t+1)$th frame.

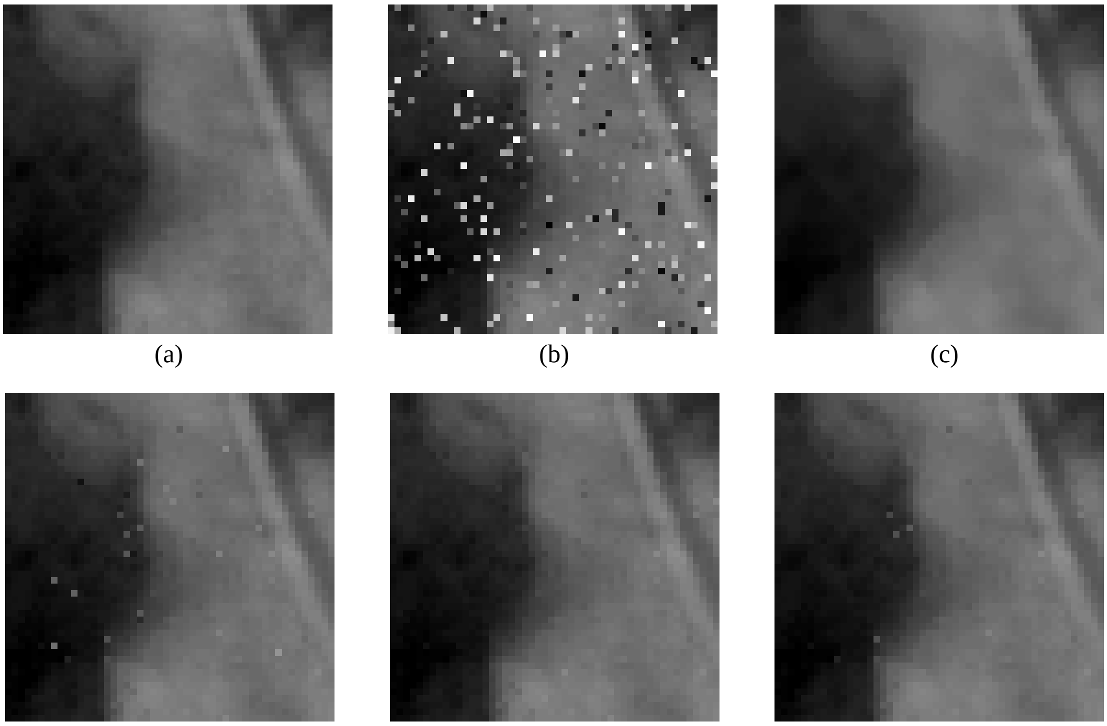

Fig.4. Detailed view
(a) Original, (b) 10% Impulse noise, (c) 2-D median, (d) SD, (e) OD, (f) LCP

Noise	0% (original signal)			5% impulse noise			10% impulse noise		
Criteria	MAE	MSE	ΔR	MAE	MSE	ΔR	MAE	MSE	ΔR
Identity	-	-	-	5.105	572.3	0.345	9.940	1506.8	0.504
2-D Median	1.136	5.3	0.001	1.219	5.9	0.001	1.342	8.2	0.001
Median	1.432	6.9	0.003	1.473	7.3	0.003	1.531	7.7	0.003
MD	0.023	0.9	0.001	0.311	4.1	0.002	0.375	4.7	0.001
SD	0.520	3.0	0.001	0.386	6.6	0.003	0.757	25.9	0.015
OD	0.268	2.4	0.001	0.379	2.7	0.001	0.489	4.1	0.001
LCP	0.652	3.5	0.001	0.418	3.7	0.001	0.564	12.0	0.006

Tab.1. Evaluation of achieved results

In general, MAE is a mirror of the signal-details preservation, MSE well evaluates the noise suppression and ΔR expresses the preservation of the motion trajectory in an image sequence. Thus, the quality of the filtered cardiographic image sequences is quantified with a high accuracy.

The achieved results are evaluated in Table 1 and shown in Fig.3d-f and Fig.4. It can be seen that the median (Fig.3d,e and Fig.4c) allows to suppress noise (the noisy image is shown in Fig.4b) effectively, however it results in significant blurring of fine edges. Some adaptive impulse detector-based median filters such as MD and OD can achieve the excellent signal-detail preservation with the simultaneous noise suppression (Fig.3f and Fig.4e), however other approaches (Fig.4d,f) provide insufficient noise attenuation capability because these approaches are more appropriate for standard video applications.

5. CONCLUSION

The reconstruction of the heart image sequences corrupted by bit errors or impulse noise was provided. Since standard robust non-linear filtering approaches, e.g. well-known median filters, blur important heart edges and affect the heart dynamics details, in order to allow immediate and accurate tracking of the heart motion, we have tested four adaptive median filters that proposed significantly better balance between the noise suppression and signal detail preservation than that of the standard median filtering.

BIBLIOGRAPHY

[1] ABREU, E., LIGHSTONE, M., MITRA, S.K., ARAKAWA, K., A New Efficient Approach for the Removal of Impulse Noise from Highly Corrupted Images. IEEE Transactions on Image Processing, Vol. 5, No. 6, pp. 1012-1025, June 1996.

[2] ARCE, G.R., Multistage Order Statistic Filters for Image Sequence Processing. IEEE Transactions on Signal Processing, Vol. 39, No. 5, pp. 1146-1163, May 1991.

[3] ASTOLA, J., KUOSMANEN, P., Fundamentals of Nonlinear Digital Filtering. CRC Press, 1997.

[4] BOSNJAK, A., TORREALBA, V., MONTILLA, G., VILLEGAS, H., BURDIN, V., SOLAIMAN, B., ROUX, C., Segmentation, Reconstruction, Modeling and 3D Visualization of the Ventricles in Echocardiographics Images. Proc. IEEE - EURASIP ISPA'01, Pula, Croatia, pp. 260-265, 2001.

[5] BONCELET, C., Image Noise Models, in Handbook of Image & Video Processing (ed. A. Bovik), Academic Press, pp. 325-336, 2000.

[6] KLEIHORST, R.P., LAGENDIJK, R.L., BIEMOND, J., Noise Reduction of Image Sequences Using Motion Compensation and Signal Decomposition. IEEE Transactions on Image Processing, Vol. 4, No. 3, pp. 274-284, - March 1995.

[7] KOKARAM, A. Motion Picture Restoration. Springer-Verlag, London, 1998.

[8] LEE, J.S., Digital Image Smoothing and the Sigma Filter. Computer Vision, Graphics, and Image Processing, Vol. 24, No. 2, pp. 255-269, November 1983.

[9] LUKAC, R., MARCHEVSKY, S., LUM Smoother with Smooth Control for Noisy Image Sequences. EURASIP Journal on Applied Signal Processing, Vol. 2001, No. 2, pp. 110-120, June 2001.

[10] LUKAC, R., Impulse Detectors for Noised Sequences. Radioengineering, Vol. 10, No. 2, pp. 24-31, July 2001.

[11] LUKAC, R., Reconstruction of Noisy Hearth Dynamics by Optimised Permutation Filters. 16th Biennial International EURASIP Conference BIOSIGNAL 2002 in Brno, Czech Republic, 2002, pp.289-291.

[12] LUKAC, R., SMOLKA, B., Hearth Dynamics Filtered by Optimised Adaptive Median. Proc. of the 2nd European Medical & Biological Engineering Conference EMBEC’02 in Vienna, Austria, 2002, (accepted for publication).

[13] NIKOLAIDIS, N., PITAS, I., 3-D Image Processing Algorithms. Wiley, 2000.

[14] PARK, J., KURZ, L., Image Enhancement Using the Modified ICM Method. IEEE Transactions on Image Processing, Vol. 5, No. 5, pp.765-771, May 1996.

[15] PELTONEN, S., GABBOUJ, M., ASTOLA, J., Nonlinear Filter Design: Methodologies and Challenges. Proc. IEEE Region 8-EURASIP Symposium ISPA'01 in Pula, Croatia, pp. 102-103, 2001.
[16] PITAS, I. VENETSANOPOULOS, A.N., Order Statistics in Digital Image Processing. Proceedings of the IEEE, Vol. 80, No. 12, pp. 1892-1919, December 1992.
[17] PLEBE, A., GALLO, G., Filtering Echocardiographic Image Sequences in Frequency Domain. Proc. IEEE Region 8-EURASIP ISPA'01, Pula, Croatia, pp. 238-243, 2001.
[18] SMOLKA, B., WOJCIECHOWSKI, K., Random Walk Approach to Image Enhancement. Signal Processing, Vol. 81, No. 3, pp. 465-482, 2001.
[19] VIERO, T., OISTAMO, K., AND NEUVO, Y., Three-Dimensional Median Related Filters for Color Image Sequence Filtering. IEEE Transactions on Circuits and Systems for Video Technology, Vol. 4, No. 2, pp. 129-142, April 1994.