Adaptive Directional Filtering Techniques for Image Sequences

Sung-Jea Ko* *Regular Member*

동영상을 위한 적응 방향성 필터링 기술

正會員 高 聖 濟*

ABSTRACT

In this paper, statistical properties of the spatiotemporal center weighted median(CWM) filter for image sequences are investigated. It is statistically shown that the CWM filter preserves image structures under motion at the expense of noise suppression. To improve the CWM filter, a filter which can be effectively used in image sequence processing, the *adaptive directional center weighted median filter*(ADCWM), is proposed. This filter utilizes a multistage filtering structure based on adaptive symmetric order statistic(ASOS) operators which produce a pair of order statistics symmetric about the median. The ASOS's are selected by using adaptive parameters adjusted by local image statistics. It is shown experimentally that the proposed filter can preserve image structures while attenuating noise without the use of motion estimation.

요 약

본 논문에서는, 동영상 처리에 효과적으로 사용되고 있는 시공간 중간 가중 미디안(spatiotemporal center weighted median, CWM) 필터의 통계적 특성을 고찰한 결과, 중간 가중 미디안 필터는 잡음 감쇄 효과를 희생시킴으로써 동영상의 구조들을 보존할 수 있다는 것을 보였다. 또한 동영상에서, 보다 효과적으로 이용될 수 있는 적응 방향성 중간 가중 미디안(adaptive directional center weighted median, ADCWM) 필터를 제안하였다. 제안된 이 필터는 매 윈도우내에서 중심의 양쪽에 대칭인 한쌍의 oreder statistics를 국소 영상의 통계치에 의해 선택하는 적응 대칭성 order statistics(ASOS) 연산자에 기반을 두고 있으며 또한 다단 필터링 구조를 채택하고 있다. 적응 방향성 중간 가중 미디안 필터는 움직임 추정(motion estimation) 기술을 이용하지 않고 잡음을 줄이며 또한 동영상의 구조를 보존할 수 있다는 것을 실험을 통하여 입증하였다.

*高麗大學校 電子工學科
Dept. of Electronic Eng., Korea Univ.
論文番號 : 93-94

I. INTRODUCTION

The processing of image sequences involving motion has become increasingly important in a variety of areas including video signal coding, medical imaging, and robot vision[1]-[3]. Recently *high definition television*(HDTV) systems which make use of image sequence processing have received a great deal of attention. In many image sequence processing applications, the image sequences are often corrupted by noise. For example, noise may arise in the initial video signal generation, subsequent handling operations, or in the storage or transmission of the video signals. This noise degrades both the image quality and the performance of subsequent image coding operations. Thus, noise removal in image sequences in one of most important tasks in image sequence processing applications. Although many successful image restoration and enhancement techniques have been developed for two-dimensional(2-D) still images, a relative few techniques with limited success have been proposed for 3-D time-varying image sequences.

Some noise reduction techniques for image sequences use 3-D linear filters based on the assumption of spatiotemporal stationarity[4], [5]. Such linear filters, although reducing noise, smear edges and distort moving objects where the assumption of the stationarity is not justified. Since human visual perception is heavily based on edge information, the performance of these filters is unacceptable.

Various motion-compensated temporal filtering techniques have been proposed to overcome this problem[6]-[11]. Some of these techniques utilize a combined segmentation and motion detection algorithm to segment the images into moving and non-moving areas, applying a temporal filter only in the non-moving regions. These methods can preserve image structures under motion, but cannot reduce noise in moving regions. Although noise in moving areas is perceptually masked to some extent by the motion, it will be visible in slowly moving areas. Other techniques estimate the motion path of a pixel and the temporal filtering is performed over this trajectory so that the moving objects are not distorted. However, the amount of noise suppression which can be attained with the 1-D temporal flter is quite limited. It is possible to increase noise suppression by utilizing larger temporal windows. However, this leads to a computationally expensive motion estimation algorithm since a large number of possible motion trajectories need to be processed.

Spatial nonlinear filters such as median-type, order statistic, and morphological filters[12]-[20] have been recognized as useful alternatives to linear filtering for attenuating noise as well as preserving image details of still images. When applied to video processing, however, these spatial filters ignore the temporal correlations which inherently exist in image sequences, and thus do not perform as well as spatiotemporal filters which can utilize both spatial and temporal information.

The center weighted median(CWM) filter is an extension of the median filter which gives weight to the center sample in the window[21]-[22]. This fileter allows a degree of control of smoothing behavior of the filter via the central weight, and thus is a promising image enhancement technique. Recently, a spatiotemporal version of the CWM filter has been shown to be useful for the restoration of image sequences[21]. In this paper, statistical properties of the spatiotemporal CWM filter are investigated for image sequence processing. It is shown that the spatiotemporal CWM filter can preserve image structures under motion at the expense of noise suppression. To improve the performance of the CWM filter, an adaptive directional CWM(ADCWM) filter having spatiotemporally varying central weights is proposed for image sequence processing. This filter utilizes a multistage filtering structure having directional subwindows based on adaptive symmetric order statistic(ASOS) operators which produce a pair of order statistics symmetric about the median. The ASOS's are selected from each spatiotemporal window by using adaptive parameters adjusted by local image statistics. We will show that the ADCWM filter can preserve image structures while attenuating noise without the use of motion estimation.

The organization of this paper is as follows. In Section II, the CWM filter is reviewed and some of its statistical properties are analyzed. In Section III, the ADCWM filter is defined. Finally, in Section IV, CWM and ADCWM filters are applied to enhance noisy image sequences.

II. STATISTICAL PROPERTIES OF SPATIO TEMPORAL CWM FILTERS

In this section, we first review the CWM filter and analyze its statistical properties.

Let $\{X(.,.,.)\}$ and $\{Y(.,.,.)\}$ be the input and output, respectively, of a filter. Let $W=\{X(n_1-k_1, n_2-k_2, n_3-k_3) \mid -N \leq k_1, k_2, k_3 \leq N\}$ denote the set of samples inside a $(2N+1)$ x $(2N+1)$ x $(2N+1)$ cubic window centered at (n_1, n_2, n_3), with (n_1, n_2) and (n_3), respectively, representing the spatial coodinates and the time coodinate for a spatiotemporal signal. For simplicity, we will use the vector notation$(\mathrm{n})=(n_1, n_2, n_3)$. A CWM filter[21], [22] with window size $2L+1=(2N+1)^3$ and central weight $2K+1$ is denoted by CWM$(2L+1,2K+1)$, and is defined as follows :

Definition 1 : The output $Y(\mathrm{n})$ of the CWM$(2L+1,2K+1)$ filter is given by

$$Y(\mathrm{n})=median\{X(L+1-K;\mathrm{W}), X(L+1+K;\mathrm{W}), X(\mathrm{n})\} \quad (1)$$

where $X(r;W)$ is the r^{th} largest sample(order statistic) among $2L+1$ samples in the window W, and $X(\mathrm{n})$ is the central value of W.

Fig. 1 illustrates the two-stage structure of the CWM filter. In the first stage, a pair of SOS's, $X(L+1-K;\mathrm{W})$ and $X(L+1+K;\mathrm{W})$, which are symmetric about the median $X(L+1;\mathrm{W})$, are selected. The output of the two-stage CWM filter is equal to the three-point median of the SOS's (symmetric order statistics) and the central sample of the window. The process of generating the SOS's may be referred to as the SOS operator. If the central sample of the window is between the outputs of the SOS operator, the central sample becomes the output. If the central sample is outside this region, the output is equal to the boundary which is closer to the central sample in value. By varying the central weight of this filter, various filter responses can be obtained. For example, when $K=0$, the CWM filter becomes the median filter, and when $K=L$, it becomes an identity filter(no filtering).

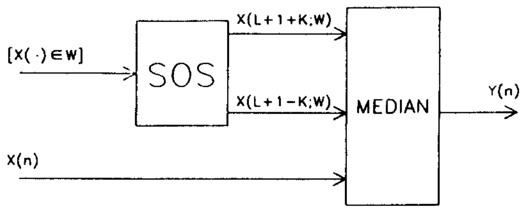


Fig 1. Structure of the CWM filter.

The motion preservation properties can be statistically examined by considering moving step edges which are corrupted by additive white noise.

The input sequence representing a noisy step edge which moves d pixels in n_2 direction at $n_3=j+1$ is expressed by

$$X(\mathrm{n})=X(n_1, n_2, n_3)=\begin{cases} V(\mathrm{n}), & n_2 \leq r \\ h+V(\mathrm{n}), & n_2 \geq r+1 \end{cases} \quad (2)$$

where

$$r=\begin{cases} 0, & n_3 \leq j \\ d, & n_3 \geq j+1 \end{cases}$$

where h is a constant repesenting edge height, V

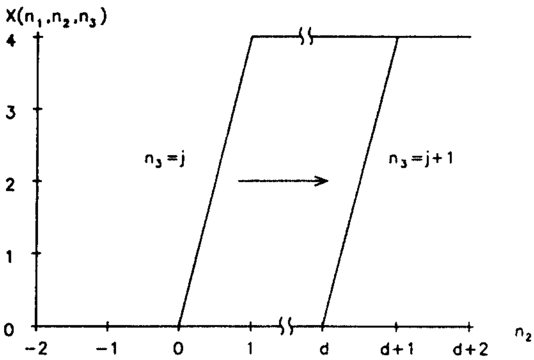


Fig 2. 1-D profile of the shifted step edge model.

(n) is i.i.d. noise with distribution $F_1(x)$. Let the distribution function of $h+V(\mathrm{n})$ be $F_2(x)$. Then, obviously, $F_2(x)=F_1(x-h)$. Fig. 2 illustrates the 1-D profile of the shifted step edge in (2).

The filter behavior near the noisy edge at $n_3=j$ can be examined by using the expected value of the output, $E[Y(\mathrm{n})]$, and the root mean squared error rmse(n), which is defined by rmse(n) $=\sqrt{E[Y(\mathrm{n})-S(\mathrm{n})]^2}$ with $S(\mathrm{n})$ as the noisefree input which is equal to 0 if $n_2 \le 0$, and is equal to h if $n_2 \ge 1$. In order to compute these quantities, we derive the distribution function $F_{Y(\mathrm{n})}(y)$ of the CWM filtered output $Y(\mathrm{n})$ which is taken from m_{n} samples with distribution $F_1(x)$ and $2L+1-m_{\mathrm{n}}$ samples with distribution $F_2(x)$ among $2L+1$ samples within the window centered at n. Note that the number of samples having $F_1(x)$ in the window, m_{n}, depends on the location of the window.

Property 1, [22]: For the moving noisy step edge input in (2), the output distribution function $F_{Y\mathrm{n}}(y)$ of the CWM(2L+1, 2K+1) filter is given by

$$F_{Y\mathrm{n}}(y)=\sum_{k=k_1-1}^{2L}\sum_{l=\max(0,\,k-(2L-m))}^{\min(k,\,m)}\binom{m}{l}\binom{2L-m}{k-l} F_1^{l}(y)\,(1-F_1(y))^{m-l}\, F_2^{k-l}(y)(1-F_2(y))^{2L-m-k+l}F_{\mathrm{n}}(y) \qquad (3)$$

$$+\sum_{k=k_2}^{2L}\sum_{l=\max(0,\,k-(2L-m))}^{\min(k,\,m)}\binom{m}{l}\binom{2L-m}{k-l} F_2^{k-l}(y)(1-F_2(y))^{2L-m-k+l}(1-F_{\mathrm{n}}(y)),$$

where $k_1=L+1-K$, $k_2=L+1+K$,

$$F_{\mathrm{n}}(y)=\begin{cases} F_1(y), & n_2\le 0 \\ F_2(y), & n_2\ge 1, \end{cases}$$

and

$$m=\begin{cases} m_{\mathrm{n}}-1, & n_2\le 0 \\ m_{\mathrm{n}}, & n_2\ge 1 \end{cases}$$

Using (3), along with the assumption that $F_1(x)$ is N(0, 1), we computed $E[Y(\mathrm{n})]$ and rmse(n) at $n_3=j$(the j^{th} image frame) through numerical integration. Fig. 3 shows plots of $E[Y(\mathrm{n})]$ and rmse(n), respectively, for CWM filters with the 3x3x3 cubic window, when the step edge ($h=4$) degraded by a Gaussian $N(0,\ 1)$ noise is shifted horizontally by $d=1$ and 2 at $n_3=j+1$. As expected, the edge preservation characteristics of CWM filters improve as the central weight increases. It is seen that the CWM filter $2K+1 \ge 15$ effects a greater degree of edge preservation under motion than median($2K+1=1$) filtering. Similar results can be obtained for vertically and diagonally shifted edges.

In Fig. 3(b), the results associated with rmse(n) for $n_2 \le -1$, where 3x3x3 window of the CWM filter contains only i.i.d Gaussian inputs with N(0, 1), illustrates the noise suppression characteristics of the CWM filter in non-moving regions. It is seen that the CWM filter provides a wide range of smoothing performance depending on the selection of the central weight. The noise suppression of the CWM filter decreases with increasing the central weight.

In summary, statistical analysis of the CWM filter indicates that it can preserve edges under

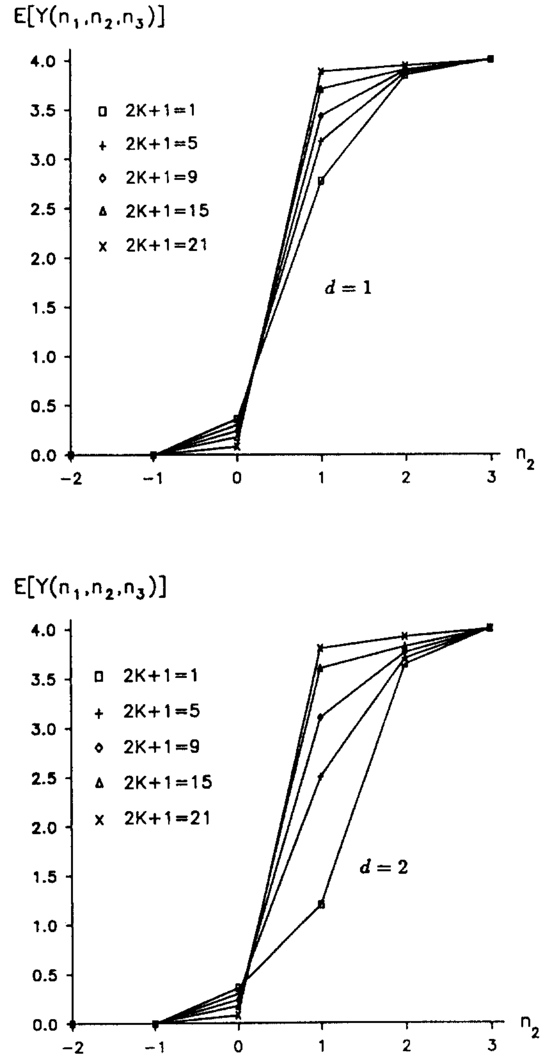


Fig 3. Results of median and CWM filters, with the 3x3x3 cubic window, when the noisy edge is shifted in n_2 direction by $d=1$ and 2 : (a) The output expected values,

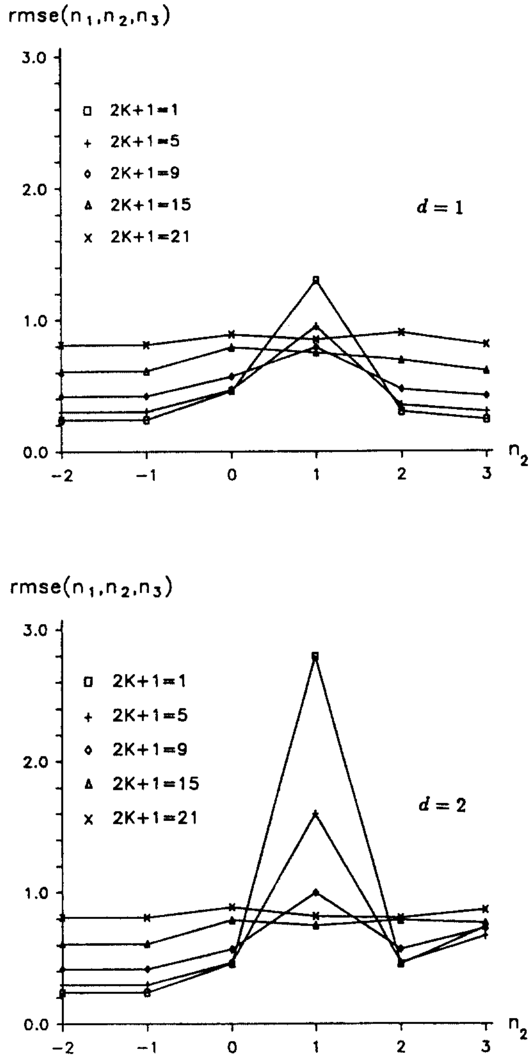


Fig 3. (Cont) (b) The root mean square errors.

motion at the expense of noise suppression, and thus exhibits a clear tradeoff between noise suppression and motion preservation.

Ⅲ. ADCWM FILTERS

The principal advantage of nonadptive filters is that they require neither *a priori* global statistical information such as noise variance nor the computation of local statistics such as sample variance. Therefore, the nonadaptive filters have lower computational complexity and should be easier to implement than adaptive filters. However, since these filters have fixed parameters, they may have varying levels of performance over different portions and frames of the image sequence. For example, if an object corrupted by noise moves abruptly, then it is expected that the CWM filter with a large central weight performs well around the moving object, but is ineffective in suppressing noise in slowly varying or nonmoving regions. This property leads to the design of adaptive filters which can take into account the spatiotemporal characteristics of the image sequence. It will be shown that the proposed adaptive filter can offer a desirable combination of motion preservation and noise suppression properties by using a spatiotemporally varying central weight adjusted by the local signal characteristics in the spatiotemporal neighborhood of each pixel.

An adaptive version of the CWM filter, the adaptive CWM (ACWM) filter, has been proposed in[22]. The output $Y(n)$ of an ACWM filter with a spatiotemporally varying central weight $2K_n+1$ can be expressed by

$$Y(n) = median\{X(L+1-K_n;W), X(L+1+K_n;W), X(n)\} \quad (4)$$

where

$$K_n = \begin{cases} \lceil (L-T)(1-\frac{\sigma_n^2}{\hat{\sigma}_W^2}) \rfloor, & \text{if } \hat{\sigma}_W^2 \geq \sigma_n^2 \\ 0, & \text{o.w.,} \end{cases} \quad (5)$$

where T is an integer, $0 \leq T \leq L$, and $\lceil x \rfloor$ represents rounding of x to the nearest integer, $\hat{\sigma}_W^2$ denotes the sample variance of data inside the window, and σ_n^2 represents the variance of the additive white noise which is assumed to be known.

The parameter T is used to preclude any value that would cause the ACWM filter to become an identity filter. Notice that the ACWM filter varies between the median filter and the CWM filter with $2K+1=2(L-T)+1$ depending on the estimated sample variance. Therefore, the ACWM filter performs like the CWM filter with a large central weight in regions with high variance, and thus may be somewhat ineffective in removing noise in both regions around edges and areas under motion.

The noise suppression characteristic of the ACWM filter in such regions can be improved by incorporating spatiotemporal directional subwindows covering points spatially shifted from frame to frame by the motion. The proposed filter, the adaptive directional center weighted median(ADCWM) filter, utilizes adaptive symmetric order statistic(ASOS) operators which produce a pair of order statistics symmetric about the median from each subwindow. The ASOS's are selected by using adaptive parameters adjusted by local image statistics. The ADCWM filter is defined as follows: Let W_i, $1 \leq M$, denote the directional subwindows of W, and $\hat{\sigma}_{W_i}^2$ represent the sample variance of W_i where M represents the number of directional windows. Let the window size of the directional subwindow be represented by $2L_1+1$. Define the two outputs of the ASOS operator for subwindow W_i as

$$Y_{U_i}(n) = X(L_1+1-K_{ni};W_i),$$

$$Y_{L_i}(n) = X(L_1+1-K_{ni};W_i), \quad (6)$$

where

$$K_{ni} = \begin{cases} \lceil L_1(1-\frac{\sigma_n^2}{\hat{\sigma}_W^2}) \rfloor, & \text{if } \hat{\sigma}_{W_i}^2 \geq \sigma_n^2 \\ 0, & \text{o.w.,} \end{cases} \quad (7)$$

At the first stage of the ADCWM filter, a pair of ASOS's $Y_{U_i}(n)$ and $Y_{L_i}(n)$, are selected from each subwindow W_i, $1 \leq i \leq M$, by using the adaptive parameter K_{n_i}. The output of the ADCWM filter is then given by

$$Y(n) = median\{Y_{U_i}(n), Y_{L_i}(n), X(n) \mid 1 \leq i \leq M\} \quad (8)$$

Fig. 4 shows the structure of the ADCWM filter. Using the ADCWM filter, a structure oriented in one direction can be preserved by a filter using a

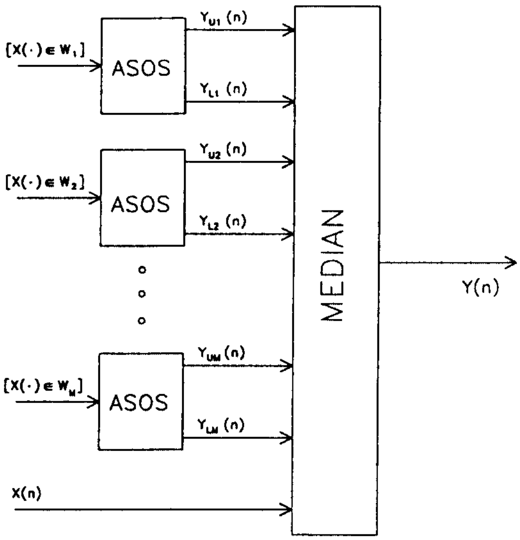


Fig 4. Structure of the ADCWM filter.

subwindow associated with that specific direction. By emplc ving a sufficient number of subwindows, motio·1 preservation can be achieved. This filter can utilize 1-D temporal subwindows representing the trajectory in time of a single point to preserve structures under motion. However, this may result in a reduction of noise suppression due to the small number of samples that the ASOS operators act upon. It is possible to increase the noise suppression by using directional spatiotemporal subwindows without the loss of feature preservation properties. As an example, Fig. 5 shows the spatiotemporal directional subwindows(with $M=9$ and $2L_1+1=9$) of a 3x3x3 cubic window. It is seen that the directional windows consist of the samples lying on linear planes including the central sample. In this paper, we will utilize these subwindows for implementing the ADCWM filters.

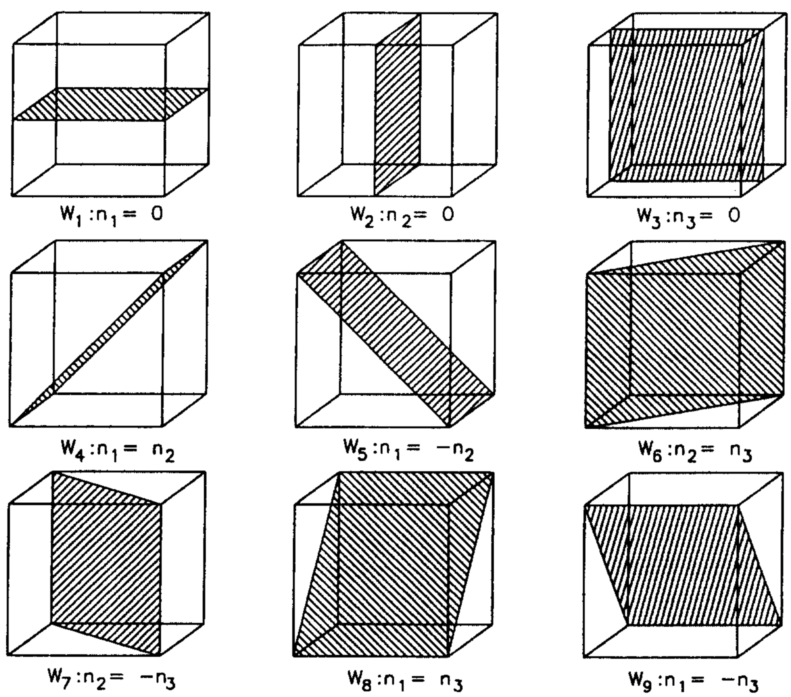


Fig 5. Subwindows of 3x3x3 Cubic Window.

IV. EXPERIMENTAL RESULTS

We evaluate the performance of the proposed filter using both real and synthetic image sequences, and compare the results both visually and quantitatively with those of the CWM and median filters as well as the motion-compensated temporal median(MCTM) filter[7].

Each frame of both the synthetic and real image sequences consists of 128x128 pixels with eight bits of quantization. In order to quantitatively compare the filter performance, the normalized mean square errors(NMSE's) between the original filtered images are evaluated. The NMSE is given by

$$NMSE=\frac{\sum_{n_1=0}^{M-1}\sum_{n_2=0}^{M-1}[Y(n_1,n_2,n_3)-S(n_1,n_2,n_3)]^2}{\sum_{n_1=0}^{M-1}\sum_{n_2=0}^{M-1}[X(n_1,n_2,n_3)-S(n_1,n_2,n_3)]^2} \quad (9)$$

where $S(n_1, n_2, n_3)$, $X(n_1, n_2, n_3)$, and $Y(n_1, n_2, n_3)$ are the orignal, noise corrupted, and filtered images, respectively, and $M=128$.

To quantify the error in human visual error criteria, the filter performance is evaluated visually through the use of the difference images. The pixel values of the difference images represent the absolute value of the difference between the original (noise-free) image frame and the processed image frame. The difference image provides information about both the motion/structure preservation and noise suppression characteristics of a filter.

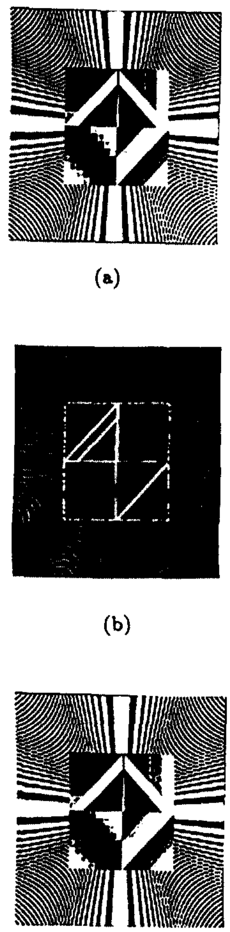
A. Experiments With Synthetic Image Sequences

The aforementioned filters were applied to the synthetic images in order to examine their motion/structure preservation and noise suppression characteristics. Each frame of these images consists of a square foreground image with four major directional patterns which is placed on top of a fixed spatial frequency sinusoidal background image. The background sinusoidal image is expressed in polar coordinates as

$$b(r)=(A/2)[1+cos(\frac{2\pi r}{p}+\phi)] \quad (10)$$

where r is the radius from the center and A, p, and ϕ represent the amplitude, spatial period, and phase of the sinusoid, respectively.

By varying the spatial shift of the square test pattern and the parameters of the sinusoid, several different types of motion can be simulated.



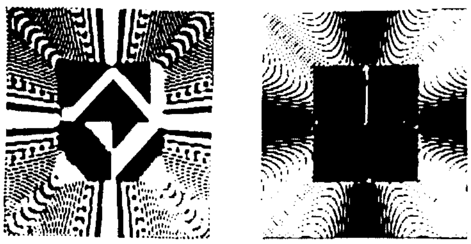
(a)

(b)

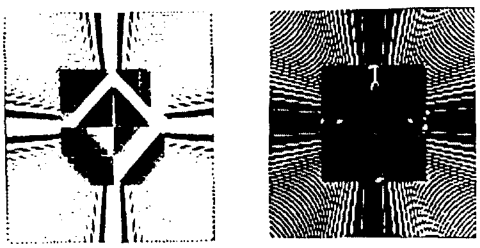
(c)

Fig 6. (a) An original frame of the synthetic image sequence, (b) the difference from the subsequent frame, and (c) noisy synthetic image(Gaussian noise $\sigma^2=64$).

(a)



(b)



(c)

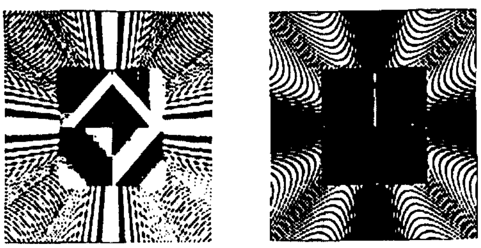
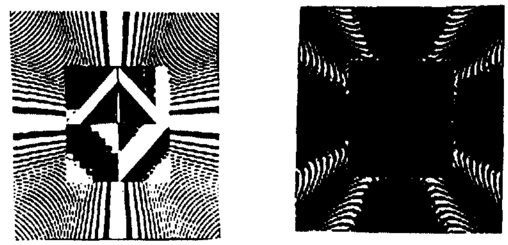


Fig 7. Filtered images and their differences from the original frame : (a) Median(CWM(27, 1)), (b) MCTM, (c) CWM(27, 7)

In order to simulate complex motions in our experiments, we generated subsequent image frames by uniformly varying the spatial shift of the square pattern by two pixels per frame and the phase of the sinusoid by 30 degrees per frame while fixing the period ($p=1$) and the amplitude ($A=255$). Fig. 6 (a) and (b) show a frame of the synthetic image sequece and its difference from the next subsequent frame. Three sets of noisy synthetic images were generated by adding zero mean i.i.d. Gaussian noise of variance 64, 100, and 400 and then were processed by the filters with a 3x3x3 cubic window. Fig. 6 (c) shows the noisy image with the noise variance 64. Table 1 shows the NMSE's of the CWM, median ($2K+1=1$),

(d)



(e)

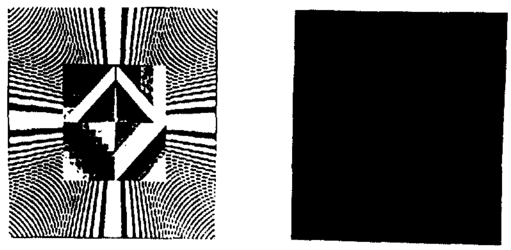


Fig 7. (d) CWM(27, 13), and (e) ADCWM.

MCTM, and ADCWM fiters. It is seen that the ADCWM filter outperforms the median, CWM, and MCTM filters. Fig. 7 shows some examples of the filtered images and the difference images from the original frame associated with variance 64. It is seen that the feature/motion preservation of the CWM filter improves with increasing the central weight. Note particularly that the ADCWM filter tracks the rapidly moving portions of the image while still suppressing noise.

Table 1. NMSE's of the CWM, median, MCTM, and ADCWM filters.

	NMSE		
Filter Type	$\sigma^2=64$	$\sigma^2=100$	$\sigma^2=225$
Median	106.55	68.14	30.27
MCTM	111.70	71.42	32.09
CWM(27, 7)	52.11	33.59	15.02
CWM(27, 13)	11.30	7.52	3.75
CWM(27, 19)	1.94	1.53	1.12
CWM(27, 21)	1.01	1.11	0.95
ADCWM	0.77	0.76	0.71

(a)

(b)

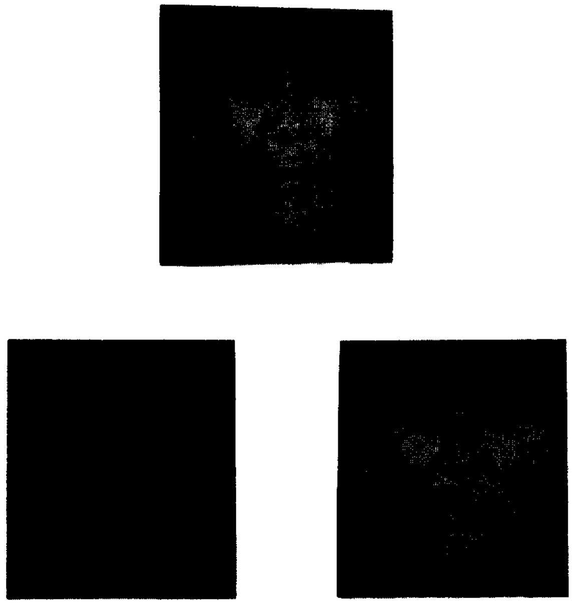


Fig 8. a) Original image frame ($n_3=6$), b) noisy image (Gaussian noise $\sigma^2=100$) and the difference between the original and noisy image.

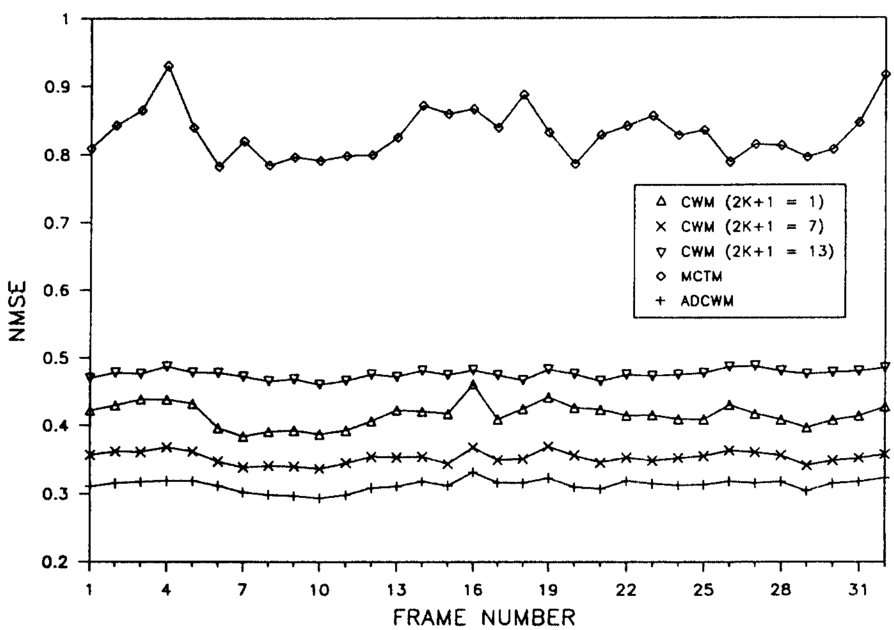


Fig 9. NMSE's for each of 34 frames.

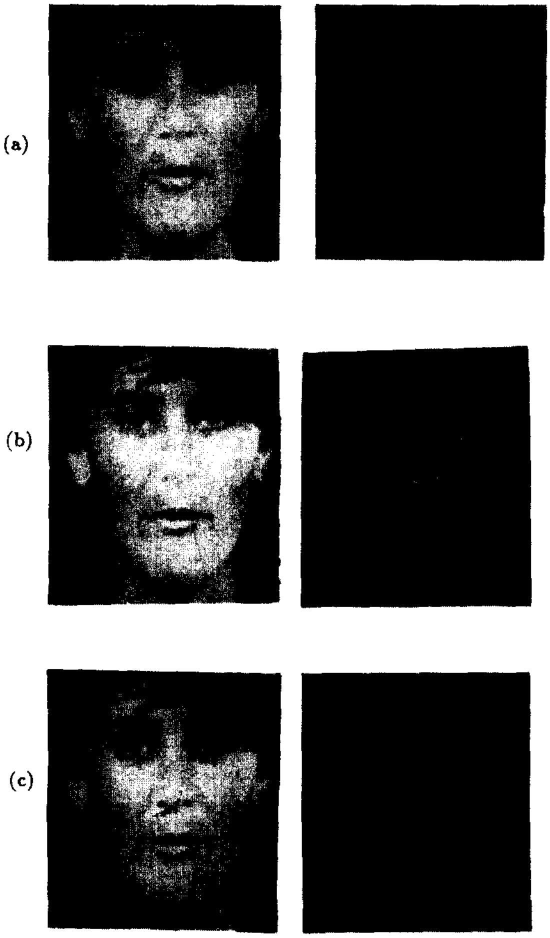


Fig 10. Filtered images and difference from the original frame : (a) Median (CWM(27, 1)), (b) MCTM, (c) CWM(27, 7).

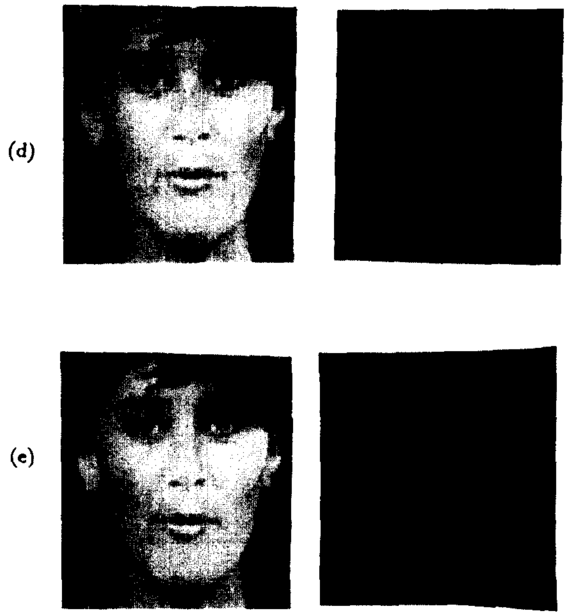


Fig 10. (Cont.), (d) CWM(27, 13), and (e) ADCWM.

B. Experiments With Actual Video Sequences

These filters were also applied to actual video sequences. The test sequence consists of a 34 frame segment of a televised video sequence. These frames were degraded by adding zero mean i.i.d. Gaussian noise of variance 100, and then were applied to the aforementioned filters. Fig. 8 shows the original image frame ($n_3=6$), noisy image, and the difference between the original frame and the noisy image. Fig. 9 shows the NMSE's of the various filters for each of 34 frames in the image sequence. The minimal NMSE of the CWM filters is smaller than the NMSE of the median filter ($2K+1=1$). The ADCWM filter yields the smallest NMSE, while the motion-compensated temporal median filter gives the largest NMSE.

Fig. 10 shows some examples of the filtered images and the difference between the original image and the filtered images. As expected, the median filter blurred the image, but performed well in suppressing noise in non-moving regions. It is seen that the CWM filter with a proper central weight ($2K+1=7$) preserved image structure under motion at the expense of noise suppression. The MCTM filter introduced artifacts in the area of eyes and noise where motion could not be tracked. The motion preserving characteristics of the ADCWM filter can be clearly seen.

The results in this section indicate that the ADCWM filter is an effective motion preserving filter that can suppress noise in image sequences.

CONCLUSION

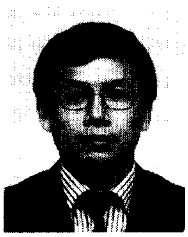
In this paper, statistical properties of spatiotemporal CWM filters for image sequences were analyzed. In order to improve the CWM filter, the ADCWM filter, which can be effectively used in image sequence processing, was proposed. It was shown that the proposed filter can preserve image structures while attenuating noise without the use of motion estimation.

본 논문은 과학재단 핵심전문연구비에 의해 연구되었음

REFERENCES

1. T. S. Huang, Ed., *Image Sequence Analysis*, Springer-Verlag, New York, 1981.
2. T. S. Huang, Ed., *Image Sequence Processing and Dynamic Scene Analysis*, Springer-Verlag, New York, 1983.
3. T. Young and K. S. Fu, Eds., *Handbook of Pattern Recognition and Image Processing*, Academic Press, New York, 1986.
4. U. Boes, "Linear filtering in image sequences," in *Image Sequence Processing and Dynamic Scene Analysis*, Springer-Verlag, New York, 1983.
5. D. Cano and M. Benard, "3D Kalman filtering of image sequences," in *Image Sequence Processing and Dynamic Scene Analysis*, Springer-Verlag, New York, 1983.
6. T. J Dennis, "Nonlinear temporal filter for television picture noise reduction," *IEE Proc.*, Part G, vol 127, pp. 52-56, Apr. 1980.
7. T. S. Huang and Y. P. Hsu, "Image sequence enhancement," *Image Sequence Analysis*, Springer-Verlag, New York, 1981.
8. E. Dubois and Sabri, "Noise Reduction in image sequences using motion compensated temporal filtering," *IEEE Trans. Communications*, vol. COM-32, pp. 826-831, July 1984.
9. D. Martinez and J. S. Lim, "Implicit motion compensated enhancement of noisy image sequences," *Proc. 1985 IEEE Int. Conf. Acoust., Speech, Signal Processing*, pp. 375-378, Tampa, FL, Ma 1985.
10. D. S. Kalivas and A. A. Sawchuk, "Motion compensated enhancement of noisy image sequences," *Proc. 1990 IEEE Int. Conf. Acoust., Speech, Signal Processing*, pp. 2121-2124, Albuquerque, NM, May 1990.
11. M. I. Sezan, M. K. Ozkan, S. V. Fogel, "Temporally adaptive filtering of noisy image sequences using a robust motion estimation algorithm," *Proc. 1991 IEEE Int. Conf. Acoust., Speech, Signal Processing*, pp. 2429-2431, Toronto, Canada, May 1990.
12. T. S. Huang, ed., *Two Dimensional Digital Signal Processing II: Transforms and Median filters*, Springer-Verlag, 1981.
13. A. Rosenfeld and A. C. Kak, *Digital Picture Processing*, vol. 1. 2nd ed., Academic Press, 1982.
14. J. Serra, *Image Analysis and Mathematical Morphology*, New York : Academic, 1982.
15. P. D. Wendt, E. J. Coyle, and N. C. Gallagher, Jr., "Stack filters," *IEEE Trans. Acoust., Speech, and Signal Proc.*, vol. ASSP-34, pp. 898-911, Aug. 1986.
16. G. R. Arce and M. P. Mcloughlin, "Theoretical analysis of max/median filters," *IEEE Trans. Acoust. Speech Signal Proc.*, vol ASSP-35, pp. 60-69, Jan. 1987.
17. A. Nieminen, P. Heinonen and Y. Neuvo, "A new class of detail-preserving filters for image processing," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-9, pp. 74-90, Jan. 1987.
18. P. Maragos and R. W. Schafer, "Morphological filters-Part I : Their set-theoretic analysis and relations to linear shift-invariant filters." *IEEE Trans. Acoust., Speech, and Signal Proc.*, vol. ASSP-35, Aug. 1987.
19. Y. H. Lee, S. -J. Ko, and A. T. Fam, "Efficient impulsive noise suppression via nonlinear recursive filtering," vol. ASSP-37, *IEEE Trans. Acoust. Speech Signal Proc.*, pp. 303-306, Feb. 1989.

20. G. R. Arce and R. E. Foster, "Detail-preserving ranked-order based filters for image processing," *IEEE Trans. Acoust. Speech Signal Proc.*, vol. ASSP-37, pp. 83-98, Jan. 1989.
21. G. R. Arce, "Multistage order statistic filters for image sequence processing," *IEEE Trans., Acoust., Speech, and Signal Proc.*, Vol-39, pp. 1146-1163, May. 1991.
22. S. -J. Ko, and Y. H. Lee, "Center weighted median filters and their applications to image enhancement," *IEEE Trans. Circuits and Systems*, vol. CAS-41, pp. 984-993, Sep. 1991.



高 聖 濟(Sung-Jea Ko) 正會員
1980년 : 고려대학교 전자공학과 졸업
1986년 : 미국 State University of New York at Buffalo, 전기 및 컴퓨터공학(공학석사)
1988년 : 미국 State University of New York at Buffalo, 전기 및 컴퓨터공학(공학박사)
1981년 8월~1983년 12월 : 대우통신 컴퓨터 사업부 연구원
1988년 8월~1992년 5월 : 미국 The University of Michigan-Dearborn, 전기 및 컴퓨터 공학과 조교수
1992년 3월~현재 : 고려대학교 전자공학과 조교수
※주관심분야 : 디지탈 신호 및 영상 처리, 패턴 인식 및 신경회로망, 전자제어 및 Car Electronics.