DATA-DEPENDENT WEIGHTED AVERAGE FILTERING FOR IMAGE SEQUENCE ENHANCEMENT

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ABSTRACT

In this study, we consider a filtering method for image sequence degraded by additive Gaussian noise. In general, for the image sequence filtering, motion compensation (MC) method is required in order to obtain good filtering performance both in the still and moving regions of an image sequence. Nevertheless, a heavy computation load is imposed on MC method and MC tends to get mistaken motion vector owing to additive noise. To overcome above drawbacks of MC, we propose a Video-DDWA filter. The Video-DDWA filter is derived by the following 2 steps. In the first step, 2D-data-dependent weighted average (DDWA) filter, whose all weights are decided by local information is extend to 3D-DDWA filter. In the second step, a motion information as the motion detector with robustness for Gaussian noise is taken into the 3D-DDWA filter. In addition to less computational load than the 3D-DDWA filtering with MC, Video-DDWA filtering gives better image sequence restoration results.

1. INTRODUCTION

Restoring an image sequence degraded by additive noise is very efficient not only for improving image quality but also for a pre-processing of image coding or computer-vision, and so on[1],[2]. For image sequence restoration, motion-compensated spatio-temporal 3D filtering methods, which is the most popular image sequence restoration techniques, have been proposed[2]-[4]. In the still area of the image sequence, the correlation of the temporal direction signal is very high. Therefore, 3D filters whose support contains the temporal signal are efficient for removing an additive noise. Moreover, the correlation of the temporal signal in the moving area also can be high by using a motion-compensation. Consequently, the 3D filters with motion-compensation are popular for image sequence restoration.

Originally, motion-compensation method have been studied for image coding, the mean absolute difference (MAD) is used as the criterion of the motion estimation[5]. Nevertheless, MAD is not good motion estimator under the noisy image environment because the MAD tends to estimate the error motion vector affected by the noise. Add to this problem, the MC method is high computation load. In order to overcome these problems, we require a new filtering method which have a new motion information with robustness of the noise and is less computation than MC method.

By the way, we have proposed some data-dependent type filters, which are controlled by some local image information in each pixel, for restoring still (2D) images degraded by Gaussian and/or impulsive noise[7],[8]. These filters achieve good noise reduction at homogeneous area and preserve edges/ details in an image.

In this paper, we consider the restoration of the image sequence degraded by Gaussian noise. For eliminating above noise, weighted average filters are preferred[6],[10]. Therefore, we propose a novel data-dependent weighted average filter with motion information for image sequence restoration. We call this a Video-DDWA filter. The proposed filter is obtained to extend 2D-DDWA filter to 3D filter and to take motion information into the 3D-DDWA filters. For using the motion information as the motion detector, the filter weights of the neighboring frame in the still area can set large, on the other hand, the weights in the moving area can set small. Thus, the proposed filter can realize the high performance of noise suppression in the still area and the motion preserving in the moving area. Comparing to MC method, the proposed filter has good filtering results in spite of less computational time.

2. DATA-DEPENDENT WEIGHTED AVERAGE FILTERING FOR IMAGE SEQUENCE ENHANCEMENT

2.1 DDCWA filter and DDWA filter

In this section, we review the weighted average(WA) filters and two kinds of data-dependent WA filters, briefly. One of these is a data-dependent center WA(DDCWA) filter whose only the center weight is controlled by local image information[6]. Another is a data-dependent WA(DDWA) filter whose all weights are decided by using three local image information[7],[8].

Here, we consider the 2-dementional filtering of observed signals $x(i,j)$ given by

$$x(i, j) = s(i, j) + n(i, j) \tag{1}$$

where $s(i,j)$ is an original signal, $n(i,j)$ is zero mean Gaussian noise with variance σ_n^2. Weighted average (WA) filters are equivalent to FIR filters, whose each weight $W(p,q)$, $-P \leq p \leq P$, $-Q \leq q \leq Q$(i.e., $(2P+1)\times(2Q+1)$ window size) is assigned a real value. The output $y(i,j)$ of WA filters can be calculated as

$$y(i, j) = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} W(p,q) \cdot x(i+p, j+q) \Big/ \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} W(p,q) \tag{2}$$

where $x(i+p,j+q)$ is a signal within the window. If all weights $W(p,q)$ are equal values, WA filters are equivalent to simple mean filters.

At first, the weights of the DDCWA filters are defined as[6]

$$W(p,q) = \begin{cases} 2G \cdot K(i,j) + 1 & if\,(p,q) = (0,0) \\ 1 - K(i,j) & if\,(p,q) \neq (0,0) \end{cases} \tag{3}$$

where we set $2G+1=(2P+1)\times(2Q+1)$ and $K(i,j)$ is a local information which we call signal activity information. $K(i,j)$ is calculated by

$$K(i,j) = \sigma^2(i,j) / \{\sigma^2(i,j) + \sigma_n^2\} \tag{4}$$

where •$^2(i,j)$ is the estimated local variance of the original signal calculated as $\sigma^2(i,j) = \max[Var(i,j) - \sigma_n^2, 0]$. $Var(i,j)$ is the local variance of the input data and σ_n^2 is the variance of the additive noise. $K(i,j)$ lies between 0 and 1 when the local variance change. In homogeneous regions, $K(i,j)$ has a small number because•$^2(i,j)$<<•$_n^2$. On the other hand in edge/detail area, $K(i,j)$ has a large number. Therefore, we can find that local data is located at whether homogeneous region or edge/detail region by using $K(i,j)$.

From mentioned above, in homogeneous region where should be processed with the powerful noise reduction, the DDCWA filters are equivalent to mean filters that have the maximum noise reduction in the WA filters. On the other hand, in the edge/detail area where should be processed without signal degradation, the DDCWA filters are close to Identity filters that have the maximum signal preserving property. Thus, the DDCWA filters are effective for image restoration both in the homogeneous and in the edge/detail area.

Next, as the extension of the DDCWA filters, we show the DDWA filters. The weights of the DDWA filters are defined as[8],[10].

$$W(p,q) = W_T \cdot K(i,j) \cdot E_{p,q} \cdot D_{p,q} + 1. \quad \text{for all } (p,q) \tag{5}$$

Here, W_T is a positive valued parameter for controlling $W(p,q)$. $E_{p,q}$ and $D_{p,q}$ are local information which we call difference information and distance information, respectively. These information $E_{p,q}$ and $D_{p,q}$ are defined as follows.

[Difference information $E_{p,q}$]

$E_{p,q}$ is defined by a function of the difference between the value at the center point and it's surrounding points inside the window. We use the following step function

$$E_{p,q} = \begin{cases} 1 & if\ e(p,q) \leq \mu \\ 0 & otherwise \end{cases} \tag{6}$$

where,

$$e(p,q) = \left| x(i+p, j+q) - x(i,j) \right| / \sigma_n \tag{7}$$

and•$_n$ is the standard deviation of the additive noise. If $e(p,q)$ is smaller than some threshold value of μ, it is suspected that $x(i+p,j+q)$ belongs to a flat segment containing $x(i,j)$. To get good performance in noise suppression, and simultaneously for edge/detail preservations, threshold level μ is chosen between 2 and 3.

[Distance information $D_{p,q}$]

$D_{p,q}$ is determined by a function of the distance from the center point to it's corresponding sample. Since image signal is non-stationary, samples closer to the center sample are more important for filtering. Moreover, most of the practical and meaningful smoothing WA filters designed and used in practice are non-increasing symmetric weights. Thus, a symmetric function that can be used is

$$D_{p,q} = \{1 - d(p,q)\}^{\alpha} \tag{8}$$

where d(p,q) is given as

$$d(p,q) = \sqrt{p^2 + q^2} / \sqrt{P^2 + Q^2}. \tag{9}$$

•is a positive number which should be predetermined. $\sqrt{P^2+Q^2}$ is the largest distance from the center sample.

2.2 Video-DDWA filter

Here, we introduce a novel data-dependent WA filtering for image sequence restoration, which we call the Video-DDWA filters. The Video-DDWA filter is derived by the following two steps. In the first step, 2D-DDWA filter extends to 3D-DDWA filter. In the second steps, a motion information as the motion detector is taken into the 3D-DDWA filter.

In this section, the 3-dementional filtering of observed signals $x(i,j,k)$ given by

$$x(i,j,k) = s(i,j,k) + n(i,j,k) \tag{10}$$

where $s(i,j,k)$ is an original signal, $n(i,j,k)$ is zero mean Gaussian noise with variance σ_n^2.

The output $y(i,j,k)$ of Video-DDWA filters can be calculated as

$$y(i,j,k)=\sum_{p=-P}^{P}\sum_{q=-Q}^{Q}\sum_{l=-L}^{L}W(p,q,l)\cdot x(i+p,j+q,k+l) \Big/ \sum_{p=-P}^{P}\sum_{q=-Q}^{Q}\sum_{L=-l}^{L}W(p,q,l) \quad (11)$$

where $x(i+p,j+q,k+l)$ is a signal within the window. The 3D window size of the proposed filter is given (2P+1)×(2Q+1)×(2L+1) (P: horizontal Q: vertical L: time direction) and the weight $W(p,q,l)$ is a real value as follows.

$$W(p,q,l)=W_T\cdot K(i,j,k)\cdot R_{(T_R)l}\cdot E_{p,q,l}\cdot D_{p,q,l}+1 \quad \text{for all } (p,q,l) \quad (12)$$

$K(i,j,k)$, $E_{p,q,l}$, $D_{p,q,l}$ are extended version of the local information eq.(4),(6) and (8) to the 3D domain, respectively. Moreover, $W(p,q,l)$ uses new following local information R_l which we call motion information.

[Motion information R_l]

R_l is defined as the motion detector based on the Mean Absolute Difference(*MAD*)[5],[10]. *MAD* is well known as the criterion of the template matching for motion estimation. *MAD* between a center frame and l-th frame is determined as

$$MAD_l=\sum_{p=-P}^{P}\sum_{q=-Q}^{Q}\left|x(i+p,j+q,k+l)-x(i+p,j+q,k)\right|\cdot \quad (13)$$

If a neighborhood of (i,j) between a center frame and l-th frame has a motion, MAD_l is larger value than without a motion. Therefore, MAD_l can be estimated as the motion detector. Nevertheless, $x(i,j,k)$ has the additive Gaussian noise, MAD_l tends to larger value because of the affection of the noise.

To solve the problem, we introduce R_l as the noise robust motion detector. R_l is derived by the following steps. To eliminate the affection of the Gaussian noise from the MAD_l, we show the *MAD* value derived from only the Gaussian noise without a motion[10]. If the *MAD* value without motion is calculated from M data, Chebyshev's inequality can be shown as

$$\Pr ob.\{|MAD-E\{MAD\}|\geq\delta\}\leq\frac{Var\{MAD\}}{\delta^2} \quad (14)$$

where $E\{MAD\}$ and $Var\{MAD\}$are the expectation of *MAD* and the Variance of *MAD*, and δ is a certain value, respectively. From eq.(14), we can obtain the following equation for any γ[9],

$$\Pr ob.\left\{MAD\geq\frac{2M\sigma_n}{\sqrt{\pi}}+\gamma\sqrt{2M\sigma_n(1-\frac{2}{\pi})}\right\}\leq\frac{1}{\gamma^2}\cdot \quad (15)$$

From eq.(15), the minimum value of *MAD* , with a probability of $1/\bullet^2$, derived from the Gaussain noise can be obtain. We call this MAD_{noise} as follows.

$$MAD_{noise}=\frac{2M\sigma_n}{\sqrt{\pi}}+\gamma\sqrt{2M\sigma_n(1-\frac{2}{\pi})} \quad (16)$$

Finally, we show the R_l defined as

$$R_l=1-\max\left\{\frac{MAD_l-MAD_{noise}}{MAD_l},0\right\} \quad (17)$$

The range of R_l is [0.0, 1.0] according to the motion. In the still region, R_l has a large number because $MAD_l \bullet MAD_{noise.}$ On the other hand in the moving image region, R_l is smaller. Hence, the Video-DDWA filter with the motion information R_l can get the maximum noise suppression in the still area and the motion preserving property in the moving area.

3. EXPERIMENTAL RESULTS

In this chapter, we show the efficiency of the proposed filter through following simulations. The proposed filter, extends 2D-DDWA filters to 3D filters and takes motion information into 3D-DDWA filters as the motion detector. Therefore, to represent the performance of the proposed filters, we must clear the following two points.

(•) The effectiveness of the motion information R_l.

(•) How much degree of the performance of the proposed filters are superior than the motion-compensated (MC) 3D filters?

To show (•), we use 2D-DDWA and 3D-DDWA filters (without R_l in eq.(12)) . Comparing to 2D-DDWA and 3D-DDWA filters with the proposed filter, the Video-DDWA filters can be proven more efficient to suppress the noise and to preserve the motion in the image sequence.

To show (•), we use the 3D-DDWA filters with Full search MC(3D+MC(Full)) and Boyce's MC[9](3D+MC(Boyce)). The Boyce's MC has been proposed for improving the accuracy of the motion estimation under the Gaussan noisy images(see **appendix**). Through the simulations, the window size of the 2D and 3D filters are used 5×5 and 5×5×3, respectively. All DDWA filters set •=1, μ=3 and W_T =200. The search area of the two MC methods is used –10~+10 pixel with 8×8 square block and the two MC search for the motion vector in each pixel. Here, we suppose that the variance of the Gaussian noise is *a priori*.

In this simulation, we will show the practical effects on image sequence restoration of the proposed filters. Here, we prepare the sequential salesman from 0-th to 51-th frame degraded by Gaussian noise with $\bullet_n$=10. To control the degree of motion, we decimate y(=0,1,2,3,4) frames from the above sequential image and collect the remainder frames. Therefore, we have five sequential salesman which contain the different degree of the motion. Here, we judge the filtering performance by using a ratio of the compared filter to the Video-DDWA filter output MSE as follows.

$$\text{Ratio of MSE} = \frac{\text{MSE of the compared filtering}}{\text{MSE of the Video - DDWA filtering}} \quad (18)$$

Moreover, we should understand the performance of the filtering both in the still area and the moving area. We can see the performance of noise suppression in the still area and the motion preserving property in the moving area. To calculate these performance, we segment the (i,j,k) pixel into the still and the moving area by using a frame difference of the original images. If $|s(i,j,k)-s(i,j,k+1)|>30$ or $|s(i,j,k)-s(i,j,k-1)|>30$, (i,j,k) belongs to the moving area. To calculate eq.(18) in each area, we can obtain the performance both in the still and moving area.

The results of the simulation are presented in Fig.1(a)~(c). As can be seen from Fig.1(a), 3D filters are more efficient noise reduction in the still area than 2D filter. Moreover, we can see that 3D-DDWA filter with full search MC is not efficient under corrupted noise because of the error of estimated motion vector. From Fig.1(b), 2D-DDWA filter is the best performance of all filters in the moving area. In spite of the faster degree of the motion, the proposed filter(Ratio=1.0) and 3D-DDWA with Boyce's MC are efficient for filtering comparing to 3D-DDWA filters. Hence, 3D type of filtering method should be used with motion information or compensation for improving the performance of filters. From Fig.1(c), we can see that the proposed filters are the highest performance of all the filters in the total area of the image sequence. From Fig.1(a)~(c), we can recognize the proposed filters are powerful tools for real image sequence restoration.

Next, we will show the computation time of the filters for processing above 50 frames. In the simulation, we use the CPU Pentium-•450MHz, 128 Mb of main memory and program written by C language. From this, the computation time of Video-DDWA filters is 1/21 and half comparing to the 3D-DDWA filters with Full search MC and Boyce's MC method, respectively. The proposed filters are also effective in the point of computation time.

At the end, we show the restoration of the image sequence Salesman 9,12,15-th frame degraded by both Gaussian noise with $•_n$=20. The original image, noisy image and the restored image by the proposed filters compare with 3D-DDWA filter, 3D-DDWA filter with Boyce's MC in Fig 2(a)~(e). As can be seen by comparing restored images, the proposed filter gives much better performance both in the still and the moving area than the others.

4. CONCLUSIONS

The Video-DDWA filter, which adds the motion information to the 3D-DDWA filter, was proposed. Through the experimental results, the Video-DDWA filter is proven to be more effective both the restoration results and computation time than the 3D-DDWA filter and with Boyce's MC for restoring the image sequence degraded by the Gaussian noise.

5. ACKNOWLEDGEMENT

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6. REFERENCES

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APPENDIX

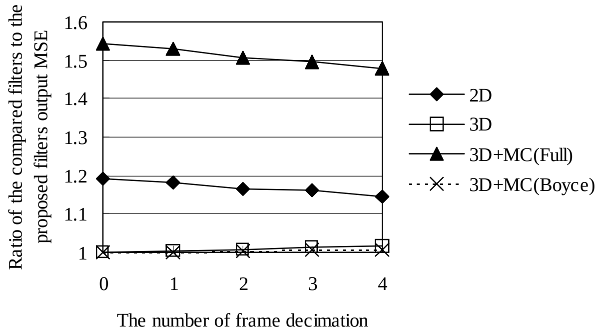
Here, we explain the Boyce's MC method[9]. By using the following Full search MC, we can obtain the estimated motion vector (Vec_i, Vec_j) and the minimum value of the MAD given by the estimated vector.

$$MAD_{\min} = \min_{Vec_i, Vec_j} \sum_{p \in W_{bm}} \sum_{q \in W_{BM}} | x(i+p+Vec_i, j+q+Vec_j, k+l) - x(i+p, j+q, k) | \quad (A{\cdot}1)$$

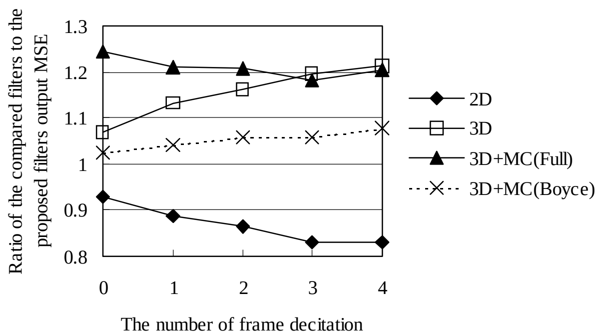
where W_{BM} is the support of the block-matching given by $M=N_i \times N_j$. To set (Vec_i,Vec_j)=(0,0) in eq.(A·1), we also get the value MAD_l. From these two MAD values (MAD_{min} and MAD_l) and the MAD value obtained by the noise effect (MAD_{noise})(eq.(16)), we can obtain the Boyce's motion vector (Vec_{bi},Vec_{bj}) given as

$$(Vec_{bi},Vec_{bj})=\begin{cases}(0,0)\ \ if\ \ MAD_l<\beta\cdot MAD_{\min} \\ \qquad\qquad\qquad or\ \ MAD_l<\rho\cdot MAD_{noise} \\ (Vec_i,Vec_j) \qquad\qquad\qquad otherwise\end{cases} \tag{A·2}$$

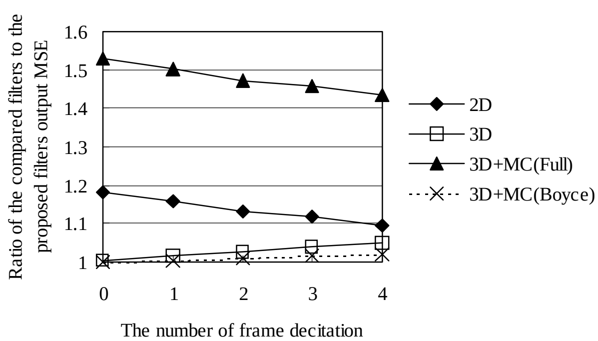
where β and ρ are real positive values and we set both 1.5.



(a) Still Area

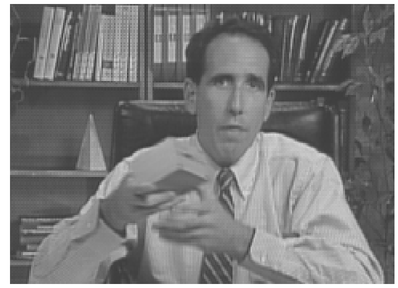


(b) Motion Area

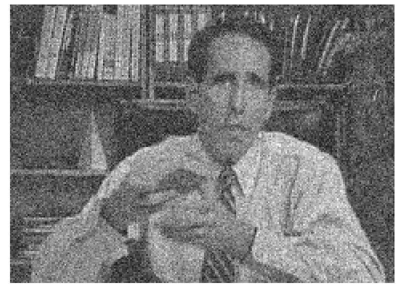


(c) Total Area

Fig.1 MSE of the various filters under various number of the frame decimation



(a) Original Image



(b) Noisy Image

(c) 3D-DDWA

(d) 3D-DDWA+MC(Boyce)

(e) Video-DDWA

Fig2. Output Image