TWO STAGE ADAPTIVE MOTION-COMPENSATED FILTER FOR NOISY IMAGE SEQUENCES

Abstract

In this paper, we propose a new technique for motion compensated filtering of noisy image sequences which aims to achieve an efficient noise reduction without introducing blurring artefacts. The technique consists in a cascade of the versions of the temporal and the spatiotemporal Adaptive Weighted Averaging (AWA) filter proposed in [11]. We referred the technique as *a Two-Stage AWA filter (*TS-AWA) [1][2]. The process consists in: first, the noisy observation is filtered temporally using the temporal AWA filter (AWA 1-D) along a large motion compensated temporal support. Second, the resulting image sequence is then processed by the spatiotemporal AWA filter (AWA 3-D) along a smaller support which the motion trajectories are estimated after the first stage. In each stage, motion trajectories are estimated with a modified block matching motion estimation algorithm [3]. Simulation results show that the proposed TS-AWA filter outperforms the AWA 3-D filter in both terms of visual quality and Signal to Noise Ratio improvement.

Keywords: *Image sequence processing, motion estimation, motion compensation, adaptive filtering.*

Résumé

Dans cet article, nous proposons une nouvelle technique de filtrage de mouvement compensé de séquences d'images, qui vise à réaliser une réduction efficace du bruit sans introduire des artefacts à la séquence filtrée. La technique consiste à mettre en cascade les versions temporelles et spatio-temporelles du filtre de moyennage pondéré adaptatif AWA proposé dans [11]. Le processus consiste d'abord à filtrer temporellement l'observation bruitée utilisant le filtre AWA temporel (AWA 1-D) à travers un large support temporel de mouvement compensé. Ensuite, la séquence d'images résultante est traitée par le filtre AWA spatiotemporel (AWA 3-D) à travers un support temporel moins large, dont les trajectoires de mouvements sont estimées après le premier étage du filtrage. L'estimation de mouvement est opérée en utilisant l'algorithme de l'appariement des pixels (PMA) [3]. Les résultats de la simulation montrent que le filtre TS-AWA proposé surpasse le filtre AWA 3-D en terme des deux critères : qualité visuelle et amélioration du SNR.

Mots clés: *Traitement de séquences d'images, estimation du mouvement, compensation du mouvement, filtrage adaptatif.*

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ملخص

في هذه المقالة نقترح تقنية جديدة في الترشيح ذو الحركة المعوضة لسلسلة صور متردية بالضجيج و ذلك بهدف تحقيق تخفيض فعال للضجيج دون حدوث أي تدهور للصورة. تشمل التقنية على التوالي الصيغتين الزمنية والمستوية للمرشح المتكيف AWA المقترح في [11]. أطلقنا على التقنية تسمية المرشح ذو الطابقين TS-AWA[1,2].

تبـــدا العملية أولا بترشيح سلسلة الصور باستعمال المرشح الزمني AWA 1-D على مدى زمني كبير ثانيا سلسلة الصور الناتجة تعالج باستعمال المرشح المستوي الزمني AWA 3-D على مدى زمني أصغر يتم حساب مساره بعد المرحلة الأولى من الترشيح. حساب الحركة يتم باستعمال طريقة PMA[3]. النتائج التجريبية تدل على أن المرشح TS-AWA يفوق المرشح AWA في كل من الناحيتين النوعية المرئية للصورة وتحسن نسبة SNR.

الكلمات المفتاحية: معالجة سلسلة صور، حساب الحركة، الترشيح المتكيف.

During the last few years great efforts have been made in the design of new methods for noisy image sequences filtering. This can be used in several applications such as: image surveillance, digital video broadcasting, digital film restoration, medical image processing, etc. The challenge in image sequence filtering process consists in the possibility of removing noise while preserving both temporal and spatial image sequence sharpness. Variety of techniques has been proposed in order to achieve this goal; unfortunately, most of them [4,10] introduce spatial and / or temporal blurring to the filtered sequence. One of the most successful techniques is the adaptive weighted averaging filter (AWA) proposed in [11]. Under several conditions constraints (existing of occlusion regions in the scene, severe noise corruption and sudden scene change) the AWA filter is able to establish a good balance between noise suppression and preserving of image sharpness. However, for low SNR levels, its temporal version (AWA 1-D), gives insufficient noise reduction although it doesn't introduce any spatial blurring to the filtered sequence. Wherever, the spatiotemporal AWA, despite its efficient adaptativity and noise reduction capacity, it introduces necessarily an oversmoothing to the filtered image sequence. The ideal would be the possibility to achieve a higher noise reduction without evidently affecting image sharpness. This necessitates a filtering technique of same performance that the AWA filters (1-D and 3-D) in terms of image sharpness preservation, but of noise suppression capacity better. In order to achieve this goal, we have developed a *Two-Stage Adaptive weighted averaging filter* (TS-AWA*)* [1,2]. Constituted of

the AWA 1-D and the AWA 3D filters in series, the TS-AWA filters benefits from their performances together providing a higher noise reduction while preserving image sequence sharpness.

This paper is organised as follows: In section 1, we present some background information's on the general principles of motion compensated filtering, where the motion estimation algorithm used in this work is briefly described. It is a modified version of the Block-Matching Algorithm (BMA) in order to accelerate the search process [3].

In section 2, the principle of the AWA filter is first summarised, then we derive the Two-Stage AWA filter.

The implementation description and the experimental evaluation of the proposed filter are performed in section 3. The conclusion is given in section 4.

1- BACKGROUND

It is well known that in image sequence filtering, in order to take full advantage from the spatiotemporal correlation's between frames in the sequence, filters must be performed temporally and spatiotemporally along motion trajectories of the image sequence. This can not evidently be achieved without a prior efficient motion estimation in the scene. Figure 1 presents a block diagram describing these operations. Filters so built are refereed as *motion-compensated filters*.
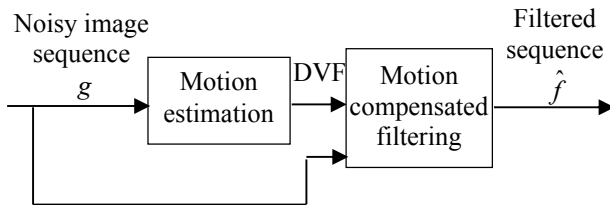

Figure 1: Block diagram of the motion compensated filtering process DVF denote the displacement vector field.

The two-stage AWA filter which we propose in this paper is a motion compensated one, since it is composed by two AWA filters (AWA 1-D and AWA 3-D) which are motion compensated in their nature [11]. We are so necessarily confronted here to the problem of motion estimation from the image sequence prior to filtering.

A. Motion estimation

For applications such as image sequences filtering, the block matching algorithm BMA [5,6] is one of the most used technique for motion estimation purpose. However, it suffers from several drawbacks: unreliable motion field in the sense of the true motion in the scene, block artefacts and poor motion compensated prediction along moving edges. Furthermore, convergence toward the global minimum is only guaranteed by performing an exhaustive search, the full search method [8]. In order to avoid these drawbacks, motion trajectories are estimated during the two stages of our filter using a modified version of the block-matching algorithm.

The classical BMA estimates the motion vectors between two frames by subdividing one frame into blocks of size $N \times N$ and by assuming that all pixels within each nonoverlapping block have the same displacement vector. For each block, the displacement vector is evaluated by searching through a larger block (search window) centred at the same location on the previous frame, for a spatial location which minimise a matching criterion. The must used matching criterion for its ease implementation, is *the Mean Absolute Difference MAD* [7] described as follows:

$$MAD(i,j) = \frac{1}{N \times N} \sum_p \sum_q |f(p,q,l) - f(p+i,q+j,l-1)| \qquad (1)$$

where $f(p,q,l)$ is the pixel of location (p,q) situated in the lth frame in the sequence and $f(p+i,q+j,l\text{-}1)$ is the pixel of location (p,q) situated in the previous frame shifted by i lines and j columns. In this measure, the smallest $MAD(i,j)$ within the search area $-x \leq i \leq x$ and $-y \leq j \leq y$ represent the best match, where x and y are respectively the horizontal and the vertical directions of the search.

An absolute minimum for the matching criterion can be guaranteed only by performing an exhaustive search (*the full search method*)[4] of a series of discrete candidate displacements within a search area, which is very pricey in terms of computation complexity. Although the several fast search techniques proposed achieve a good time computation reduction, they risk to converge toward local minimum during the search process if the matching criterion is not a monotonic function of the displacement $\vec{d}$ [9] contrarily to the full search method. For this reason we have chosen to use the full search method, in which, the only way to decrease the computation load is to decrease the search area size. To achieve this goal, we have slightly modified the block-matching algorithm into a *Pixel Matching Algorithm* PMA [3]. Instead of operating the search block per block, we search for each pixel its matching one in the previous frame. This reduces greatly the amount of computation, since first the block size reduction do not have a considerable impact in the computation process [5] and second, a smaller search area size will be sufficient to find the best match [8]. It is clear that the algorithm so built is not suitable for coding applications because of the considerable amount of information to transmission (motion vector field is dense). Furthermore it seems to be more sensitive to noise than the BMA. In our work, motion compensated filtering, we are not concerned by the former inconvenient since we have no obligation to transmit the motion vector field. However to avoid the latter drawback, we perform a simple spatial smoothing to the noisy sequence prior to perform the motion estimation.

B. Motion compensated filtering

In motion compensated filtering, we first determine the motion trajectory $\tau_{i,j,k}$ for each pixel (i,j) in the kth frame using a motion estimation algorithm. The motion trajectory $\tau_{i,j,k}$ is defined by the set of pixel locations, in the N neighbouring frames, that correspond to pixel (i,j) of the kth frame. The success of motion compensated filtering strongly depends on the accuracy of the motion estimation,

especially at low SNR as well as in the presence of occlusion and varying scene content.

The motion compensated filter can have either a spatiotemporel or a temporal support. In motion compensated spatiotemporal filtering; the filter support $SMC_{i,j,k}$ is defined as the union of predetermined spatial neighbourhoods (3×3 square regions) centred about the pixel locations on the motion trajectory.

In motion compensated temporal filtering, the filtered value of the pixel (i,j) of the kth frame is determined by applying a 1-D filter along the motion trajectory $\tau_{i,j,k}$. In other words, the filter support $S_{i,j,k}$ coincides with the motion trajectory $\tau_{i,j,k}$.

In noise filtering, it is well known that there is a trade-off between the amount of noise removal and blurring. At high SNR levels, motion compensated adaptive filters can provide effective noise reduction without introducing spatial blurring if the estimated motion trajectories are sufficiently accurate. At low SNR levels, however, the number of image points within the temporal support may not be large enough to achieve sufficient noise reduction. The number of image points within the filter support can be increased by either using temporal filters with a larger number of frames or using spatiotemporal filters and hence including spatial neighbourhoods in the filter support. The problem with the former option is that as the number of frames in the filter support increases, the accuracy of motion estimation at distant frames may decrease. The latter option does not bring additional burden on the motion estimation, but it may cause blurring when the spatiotemporal neighbourhood is not uniform enough [11].

The AWA filter proposed in [11] aims at weighting down the effect of the pixels that create the nonuniformity and achieving effective filtering by concentrating on the remaining image values within the filter support. Unfortunately, its performances decrease for severe noise levels: the temporal AWA (AWA 1-D) although it does not introduce any spatial blurring, it gives insufficient noise reduction. Wherever its spatiotemporal counterpart (AWA 3-D), despite its efficient adaptativity and noise reduction capacity, introduce inevitably an oversmoothing to the filtered sequence [1]. In this paper, we will propose a two-stage adaptive weighted averaging filtering (TS-AWA) which combines both the AWA 1-D and AWA 3-D filters in a cascade filtering structure in order to avoid their drawbacks and take full advantage from their performances to achieve better results.

2- NOISE FILTERING

2.1- The adaptive weighted averaging filtering (AWA)

The adaptive motion compensated weighted averaging AWA [11] is based on the premise that spatiotemporal motion compensated averaging is an effective means of suppressing noise while preserving image sharpness, provided that the spatiotemporal filter support is uniform. The AWA filter assigns a weight to each pixel within the motion compensated spatiotemporal support *SMC*, which the value is, function of the difference between that image

value and the noisy pixel $g(i,j,k)$. In cases when the spatiotemporal support is nonuniform because of very detailed image structure and /or inaccurate motion estimation and / or abrupt scene change from one frame to another, the AWA filter simply weights down the effect of those pixels that are decidedly different from $g(i,j,k)$, hence avoiding excessive blur or inefficient filtering. On the other hand, when the spatiotemporal support is sufficiently uniform, AWA approaches direct averaging.

The AWA estimate at the pixel location (i,j) in the kth frame is defined as:

$$\hat{f}(i,j,k) = \sum_{p,q,l \in SMC_{i,j,k}} w(p,q,l)g_i(p,q,l) \qquad (2)$$

with

$$w(p,q,l) = \frac{K(i,j,k)}{1 + a\left(\max\left[\varepsilon^2, (g(i,j,k) - g(p,q,l))^2\right]\right)} \qquad (3)$$

where $g(p,q,l)$ is the noisy observation which can be modelled by:

$$g = f + n$$

with f is the original sequence and n denotes the noise sequence which is supposed additive and Gaussian.

$w(p,q,l)$ are the weights assigned to the image sequence pixels within the motion compensated support of the filter $SMC_{i,j,k}$.

$SMC_{i,j,k}$ is defined as the union of predetermined spatial neighbourhoods (e.g., 3×3 square regions) centred around the pixel locations on the motion trajectory.

K is a normalisation constant given by:

$$K(i,j,k) = \left(\sum_{p,q,l \in SMC_{i,j,k}} \frac{1}{1 + a\left(\max\left[\varepsilon, (g(i,j,k) - g(p,q,l))^2\right]\right)} \right)^{-1} \qquad (4)$$

and ε is a parameter of the filter given by:

$$\varepsilon^2 = 2\sigma^2$$

with σ^2 being the noise variance.

The parameter a is a penalty parameter which controls how the weights should decrease as a function of the squared difference $(g(i,j,k) - g(p,q,l))^2$ between $g(i,j,k)$ and its neighbours in the motion compensated support (Later, we will describe how it affect the AWA estimate).

AWA filter properties

The AWA filter has the following properties:

1/ When $(g(i,j,k) - g(p,q,l))^2 < \varepsilon^2 \Rightarrow$

$$w(p,q,l) = \frac{K}{1 + a\varepsilon^2} = \frac{1}{L}, \quad \forall (p,q,l) \in SMC_{i,j,k}$$

where L is the total number of the image sequence values in $SMC_{i,j,k}$.

These happen when image sequence values differ only by noise, then all the weights attain the same value $\frac{1}{L}$.

In this case, $\hat{f}(i,j,k)$ reduces to spatiotemporel direct averaging. This averaging will reduce the noise variance by factor equal to the number of the image sequence pixels within the support in the case of signal independent noise [11].

2/When $(g(i,j,k)-g(p,q,l))^2 > \varepsilon^2 \Rightarrow w(p,q,l) < \frac{K}{1+a\varepsilon^2}$

This happens when the neighbour $g(p,q,l)$ is different from $g(i,j,k)$ in the sense of the image structure.

In this case the contribution of $g(p,q,l)$ to the weighted average is weighted down by $w(p,q,l)$ less than $\frac{1}{L}$ to avoid spatial blurring.

3/ The effects of the penalty parameter on the performance of the AWA filter can be visualised clearly with the following example.

$N = 2M + 1$ frames are used to filter the frame k, and filtering is performed temporally along the motion trajectory $\tau_{i,j,k}$. The last frame in the sequence is supposed completely different from the other $2M$ frames because it is recorded at a different camera view, and all the $2M$ matching frames differ to noise only.

Here we have:

$(g(i,j,k)-g(p,q,l))^2 < \varepsilon^2$

for $\qquad l = k-M,...,k-1,k,k+1,...,k+M-1$

and $(g(i,j,k)-g(p,q,l))^2 = \Delta^2 > \varepsilon^2$ for $l = k+M$

where $(p,q,l) \in \tau_{i,j,k}$.

In this case, the weights of the matching frames are the same. Using (3) we can define them as follows:

$$w_1 = \frac{\left(1+a\Delta^2\right)}{\left(1+a\varepsilon^2\right)+2M\left(1+a\Delta^2\right)}$$

Whereas the weight of the non-matching frame is given by:

$$w_2 = \frac{\left(1+a\varepsilon^2\right)}{\left(1+a\varepsilon^2\right)+2M\left(1+a\Delta^2\right)}$$

We can see that for very small values of a $w_1 \approx w_2 = \frac{1}{(2M+1)}$. In other words, there is no penalty parameter for the mismatch case and the AWA filter performs direct averaging.

Let us now consider the extreme case where the parameter a can have sufficiently larger values, especially when:

$$1+a\varepsilon^2 = a\varepsilon^2 \text{ and } 1+a\Delta^2 = a\Delta^2$$

This results in:

$$w_1 = \frac{\Delta^2}{\varepsilon^2+2M\Delta^2} \text{ and } w_2 = \frac{\varepsilon^2}{\varepsilon^2+2M\Delta^2}$$

In this case, if $\Delta^2 >> \varepsilon^2$ due to an important mismatch,

the weights of the matching frames w_1 approach $\frac{1}{2M}$ and the weight of the mismatching one w_2 approaches 0. This says that the AWA filter performs direct averaging over only the $2M$ matching frames and eliminates the nonmatching frame. Unfortunately, despite this great adaptativity capacity, the AWA filter performances decrease at severe noise levels, where it gives either filtered image sequences which are blurred spatially or in which noise persists [1]. The TS-AWA filter that we propose here aims for instance to overcome this drawbacks by combining both the temporal and the spatiotemporal versions of the AWA filter in a filtering cascade structure.

2.2- Two-stage AWA filtering

The two-stage AWA filtering process can be described by the following block diagram (Fig.2):
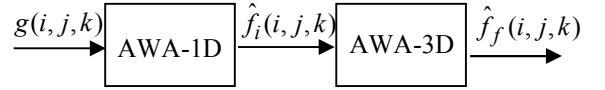

Figure 2: Two-stage AWA filtering.

The idea behind performing first the AWA 1-D filtering is the need to remove a part of noise from the degraded image sequence without affecting its sharpness, which risk to occur if an AWA 3-D is performed in first on a severely corrupted image sequence. Thereafter, in order to remove effectively the remainder noise, a spatiotemporel filtering is so more suitable than its temporal counterpart.

At the first stage the noisy image sequence is filtered temporally using the temporal version of AWA filter along the motion trajectories estimated using the pixel-matching algorithm described in section A. The resulting filtered sequence is then (second stage) filtered using the AWA 3-D filter.

Stage1:

We define the initial filtered sequence $\hat{f}_i(i,j,k)$ as:

$$\hat{f}_i(i,j,k) = \sum_{p,q,l \in \tau_{i,j,k}} w_i(p,q,l)g(p,q,l) \qquad (5)$$

where

$$w_i(p,q,l) = \frac{K_i(i,j,k)}{1+a\left(\max\left[\varepsilon_1^2,\left(g(i,j,k)-g(p,q,l)\right)^2\right]\right)} \qquad (6)$$

and

$$K_i(i,j,k) = \left(\sum_{p,q,l \in \tau_{i,j,k}} \frac{1}{1+a\left(\max\left[\varepsilon_1^2,\left(g(i,j,k)-g(p,q,l)\right)^2\right]\right)}\right)^{-1} \qquad (7)$$

$\tau_{i,j,k}$ is the motion trajectory of the pixel of co-ordinates (i,j,k) presented in figure 3.

ε_1^2 is set equal to two times the noise variance :

$$\varepsilon_1^2 = 2\sigma_1^2$$

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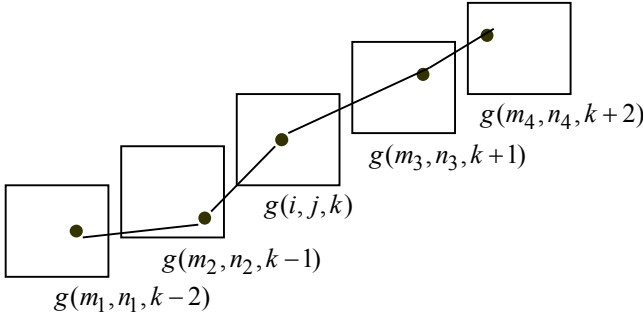σ_1^2 is the initial noise variance.

Figure 3: TS-AWA temporal support $\tau_{i,j,k}$ illustration (case of 5 frames).

Stage2:

The final filtered sequence $\hat{f}_f(i,j,k)$ is given by:

$$\hat{f}_f(i,j,k) = \sum_{p,q,l \in SMC_{i,j,k}} w_f(p,q,l)\hat{f}_i(p,q,l) \qquad (8)$$

Except the support change, which becomes spatiotemporel in this case *SMC* (Fig.4), the weights and the normalisation constant are obtained by the same manner as in the first stage by (6) and (7).
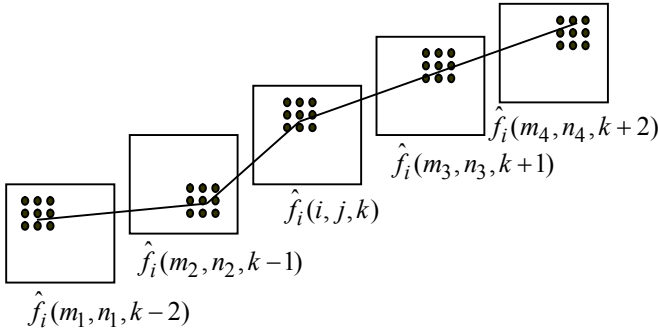

Figure 4: TS-AWA spatiotemporal $SMC_{i,j,k}$ support illustration (case of 5 frames).

ε_1^2 however is replaced in this stage by ε_2^2 which is equal to two times the new noise variance σ_2^2 estimated from the initial filtered sequence $\hat{f}_i$, since we consider it as a noisy sequence.

In the study reported in [11] concerning the sensitivity of the performance of the AWA filter to the value of the penalty parameter *a* it was shown that there is a threshold for *a* which as *a* is increased beyond it, the performance filter does not change. The optimal value of *a* is equal or smaller than the threshold value in the mean square error (MSE) sense. As in the case of the AWA filter of [11], the parameter *a* is set here also arbitrarily equal to unity to demonstrate the fact that the performance of the two-stage AWA filter may be quite good for various different cases even when the penalty parameter is not necessarily set to its optimum value.

Discussion:

During the first stage of filtering, due to the large support of the temporal AWA filter, a part of the noise is removed from the image sequence without affecting image sharpness (this is the major advantage of the AWA 1-D). The resulting sequence is less degraded than the initial one.

In the second filtering stage, the spatiotemporel AWA filter with a smaller temporal extend than that of the AWA 1-D one is sufficient to remove the remainder noise in the sequence. As the amount of noise has been reduced in the first stage, the 3-D AWA filter doesn't risk introducing any spatial blurring to filtered sequence.

The temporal and the spatiotemporel AWA filters are so combined in a manner that the filtered sequence benefits from their performances together: a higher noise suppression capacity with image sharpness preservation.

3- EXPERIMENTS

Let us evaluate the performance of the proposed TS-AWA filter and compare it with that of the spatiotemporal AWA filter proposed in [11] (since this latter is more preferment than its temporal counterpart).

To achieve this, we have used different dynamic image sequences: "Scène routière", "Caltrain" and "Carphone", under several severe noise levels (Gaussian noise). The sequence "Scène routière" (100 frames) contains moving objects on a stationary background and contains also some occlusion regions. Each frame is 120×160 pixels. The motion in the sequence is relatively fast. The well-known "Caltrain" and "Carphone" test sequences include respectively moderate and low amount of motion.

Figure 5 shows the 9th, 10th and the 11th frames of the sequence « Scène routière », where the 3 black cars move locally on a stationary background and the white one causes an occlusion phenomena (it disappears in the 11th frame from the camera vision field).

Figures 6 and 7 present respectively the 4th, 5th and the 6th frames of the sequences "Caltrain" and "Carphone".

The white Gaussian noise at different Signal to Noise Ratios (10, 6 and 3 dB) has been simulated and added to the sequences. The SNR expression used is the following:

$$SNR = 10\log_{10}\left\{\frac{\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M} f(i,j,k)^2}{\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(f(i,j,k)-g(i,j,k)\right)^2}\right\} \text{ (dB)}$$

where $f(i,j,k)$ and $g(i,j,k)$ denote the kth frame intensities at the spatial position (i,j) in the original and the noisy image sequences respectively.

K denotes the frames number used in filtering.

N and M are respectively the lines and columns numbers in each frame in the sequence.

3.1- Motion estimation

The noisy observation is first smoothed spatially with a simple low-pass filter D defined as:

(a)   **(b)**   **(c)**

Figure 5: **(a)** 9th, **(b)** 10th and **(c)** 11th frames of the original sequence "Scène routière".

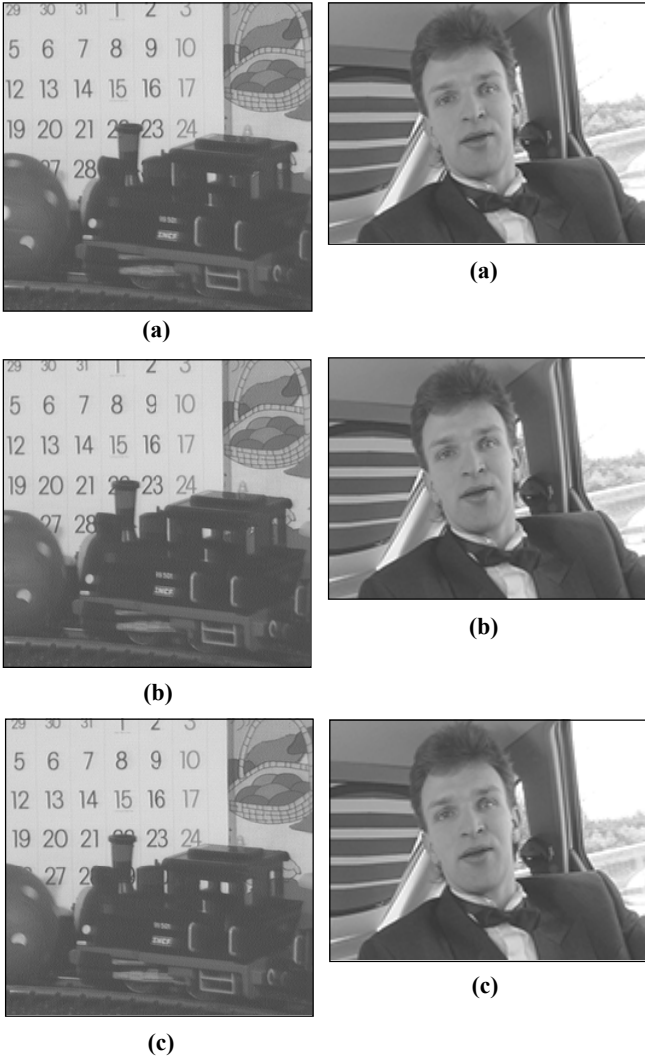**(a)**

(b)

(c)

Figure 6: **(a)** 4th, **(b)** 5th and **(c)** 6th frames of the original sequence "Caltrain".

Figure 7: **(a)** 4th, **(b)** 5th and **(c)** 6th frames of the original sequence "Carphone".

$$D = \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Motion trajectories have then been estimated (at the first stage of the TS-AWA filter) using the pixel matching

algorithm [3] with the Mean Absolute Difference *MAD* Search Criterion [7]. The maximum displacement allowed in the search is $dm = 8$ for one pixel resolution. In determining motion trajectories, we estimate the displacement vectors from the frame of interest to those contributing to the filter support.

At the second stage, motion trajectories are estimated directly from the initial filtered sequence from the first stage f_i.

3.2- TS-AWA filter implementation

Once motion trajectories are estimated, we use the TS-AWA filter to remove the noise affecting the image sequence.

During the AWA 1-D filtering, frames are processed with seven frames $T=7$ (the current frame, the 3 frames before and the 3 frames after) in order to reduce maximum possible amount of noise.

This choice is based on our experiments reported in [1], where we have tested the temporal AWA filter with different support sizes and we have found that $T=7$ is the best trade-off between the filter capacity of noise reduction and computation load required.

At the second stage (AWA 3-D filtering), frames are filtered spatiotemporally along a smaller temporal support: three frames $T=3$ (the current frame, one frame before and one frame after) and a 3x3 spatial window. In this case, we have chosen to use a smaller temporal support ($T=3$) because, The AWA 3-D filter has also been tested experimentally in [1] where it has been proved that the spatial neighbourhood improve significantly its capacity of noise reduction. That's why, a smaller temporal support is sufficient in this case.

The criterion used to evaluate the performance of the filters is *the improvement in SNR* at each frame, expressed in *decibels* (dB), according to:

$$\overline{SNR} = 10\log_{10} \frac{\displaystyle\sum_{i=1}^{120}\sum_{j=1}^{160}[f(i,j,k) - g(i,j,k)]^2}{\displaystyle\sum_{i=1}^{120}\sum_{j=1}^{160}\left[\hat{f}(i,j,k) - f(i,j,k)\right]^2} \qquad (9)$$
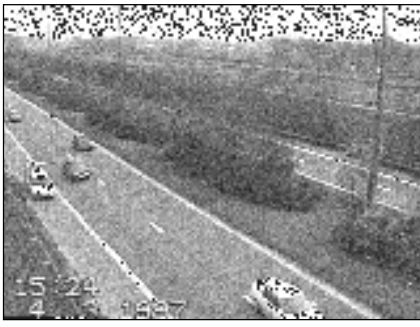
The noisy and the filtered frames of the sequence "Scène Routière" provided by the TS-AWA filter are shown in details in figure 8. However, for simplification reasons,

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corresponding results to the remainders sequences are given in figure 9 at only 10 dB SNR level.
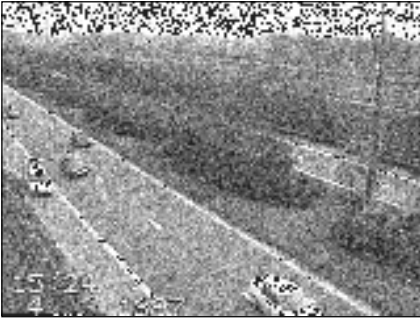
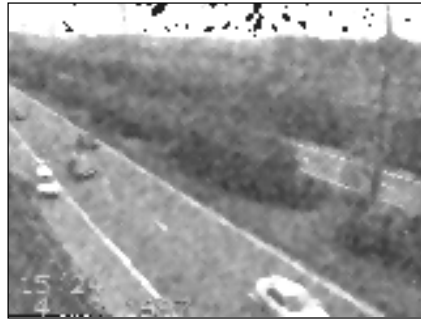The SNR improvement values achieved over the three

Image sequence	Filter	SNR = 10 dB	SNR = 6 dB	SNR = 3 dB
Scène Routière	AWA-3-D	3.4235	4.9335	5.9689
	TS- AWA	3.6905	5.0122	6.3057
Caltrain	AWA-3-D	6.3964	7.2274	7.7557
	TS-AWA	7.1072	8.1495	8.8249
Carphone	AWA-3-D	5.60	6.6725	7.3588
	TS-AWA	6.0737	7.3991	8.2616

Table 1: SNR improvement values.

(a) Original frame 10 of "Scène routière".

(b) Noisy frame 10 of "Scène routière" (SNR = 10 dB)
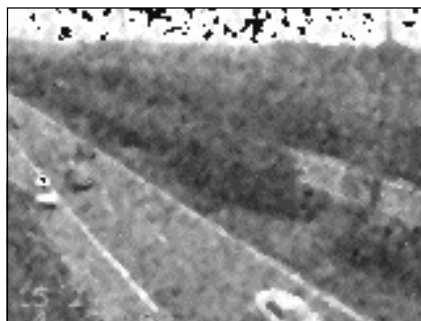

(c) TS-AWA

(d) Noisy frame 10 of "Scène routière" (SNR = 6 dB)

(e) TS-AWA

(f) Noisy frame 10 of "Scène routière" (SNR = 3 dB)

(g) TS-AWA

Figure 8: Frame 10 of "Scène routière" filtered using the TS-AWA filter at 10, 6 and 3 dB SNR levels.

sequences by both the TS-AWA and the AWA-3-D filters are summarised in table 1.

From these results, we have made the following observations:

It is clear from figure 8 that the TS-AWA filter provide interesting results in terms of noise reduction and image sharpness preservation. At 10 SNR dB, noise is eliminated correctly, providing a filtered image sequence of pleasant quality without affecting its sharpness.

This is due to the two-stage filtering process of the TS-AWA: during the first stage, a part of noise has been eliminated with image sharpness preservation grace to the AWA 1-D filter with its enlarged support which is compensated correctly using the PMA algorithm. The remaining noise after the first filtering step being reduced (compared to the initial one), the AWA spatiotemporal filter with a smaller temporal support (than the AWA-1D) success to eliminate it without introducing any temporal or spatial blurring to the image sequence.

At 6 and 3 dB SNR, the TS-AWA filter achieves also a considerable noise reduction. We can see by comparing figures (d), (e), (f) and (g), that although noise persists in the filtered sequences, it has been considerably reduced: the filtered images present better visual quality than the noisy ones without introduction of any temporal or spatiotemporal artefacts. This is also due to the pixel matching motion estimation algorithm PMA, which has correctly compensated the motion during filtering.

(a) Original frame 6 of "Caltrain".
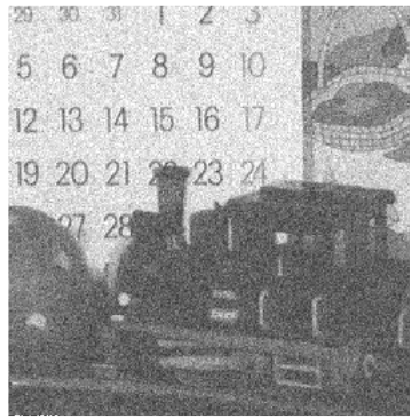
(b) Noisy frame 6 of "Caltrain" (SNR = 10 dB)
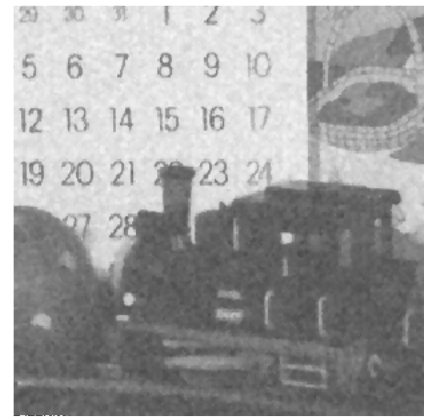
(c) TS-AWA

(d) Original frame 6 of "Carphone".

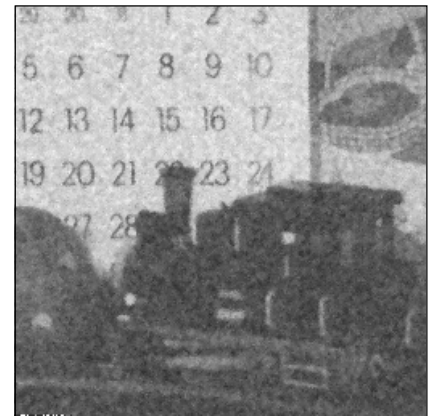**(e)** Noisy frame 6 of "Carphone" (SNR = 10 dB)

(f) TS-AWA

Figure 9: Frames 6 of "Caltrain" and "Carphone" sequences filtered using the TS-AWA filter at 10dB SNR level.

(a) AWA 3-D

(c) AWA 3-D

(e) AWA 3-D

(b) TS-AWA

(d) TS-AWA

(f) TS-AWA

Figure 10: AWA 3-D and TS-AWA performances comparison at 10 dB SNR.

All these results have been well confirmed on the other sequences "Caltrain" and "Carphone" (Fig.9).

The comparison (Fig.10) of the TS-AWA and the AWA 3-D filter shows explicitly that at 10 dB SNR, (noise level at which both filters give their best performances in the context of severely noisy image sequences filtering), the TS-AWA achieves a higher noise reduction than that achieved by the spatiotemporal AWA filter, which gives a filtered image where noise still persists.

Concerning the numerical results from table 1, we have reached the following conclusions:

- The $\overline{SNR}$ increases as the *SNR* decreases (for the three SNR levels we have tested), this is due to the increase in the values of the numerator in the $\overline{SNR}$ formula.

- The TS-AWA filter outperforms the AWA 3-D for the three SNR levels which is consistent with the visual quality results.

4- CONCLUSIONS

In this paper we have presented a new technique for adaptive motion compensated filtering for noisy image sequences: the two-stage AWA filter (TS-AWA). The filtering process consist in two stages: first a temporal AWA filtering with a large support is applied to the noisy image sequence, then a spatiotemporal AWA one, with a smallest support is performed on the resulting sequence. During filtering, the TS-AWA filter combines the performances of both temporal and spatiotemporal AWA filters providing a higher noise reduction with image sharpness preservation. The visual quality provided by this filter is more pleasant than that of its spatiotemporal counterpart: noise is more removed without introducing blurring artefacts.

Prior to filtering, motion is estimated from the sequence and compensated for. To achieve this goal we have used the pixel matching algorithm with the Mean Absolute Difference (*MAD)* search criterion which aims to reduce the computation burden required by the full search technique in the classical BMA. The motion compensated filtered image sequences resulting have a good visual quality, in which block and temporal artefacts are avoided. The computation complexity of the algorithm resides in the motion estimation phase, which is the case of the most motion compensated filters.

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