Blotch Removal in Degraded Digital Video Using Independent Component Analysis

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Abstract—**Blotchy noise is one of the most common and visually annoying noises noticed in digitized motion picture films. This work investigates a three-stage blotchy noise reduction scheme combining efforts of temporal median filtering, ICA unsupervised learning and deflation after motion/compensation estimation. Implementation of each module of the scheme is discussed; finally performance of the scheme is tested and compared with other methods over real short sequences and results are discussed.**

I. Introduction

With the recent advent of digital technologies, and the ever increasing need for speed and storage, occluded or missing parts in images and video give arise to problems more and more widespread in several multimedia applications such as wireless communication and digital video restoration. For instance, current compression standards such as JPEG and MPEG divide the input signal in small (8x8 or 16x16) blocks which are first transform-coded and then transmitted. During wireless trasmissions packet loss can occur; some measurements report averages of about 3.6% of packet loss [27], [31]. Missing video data restoration is another issue, if we consider that many of the conventional media materials, like old black-and-white (B&W) motion picture films, are being digitized for a wide variety of purposes, from the protection of cultural heritage to the convenience of storage and manipulation. However, direct conversion of these films usually yields in very poor quality due to presence of noise and degradation of the original analog storage material over a long period of time, therefore it is desirable to process these converted sequences afterwards and provide some visual enhancement for them.

This work looks into noise reduction of motion pictures and mainly works on the removal of *blotchy noise*, since it is the most common and visually noticeable degradation of digitized videos. We consider blotchy noise reduction as a problem of detection and removal of missing part, i.e. we suppose to loose any information within the blotch. Typical techniques for dealing with such kind of problems are Forward Error Correction (FEC) and Automatic Retrasmission Query (ARQ), which require extra error correction packets to be transmitted [12], [28], [29], [31]. Recently, some authors are investigating the possibility of reconstruction of missing blocks by using the available information carried out by surrounding blocks [13], [27] or by nearby motion compensated frames [19]. Geometric surface evolution techniques or markov random field sampling are used.

Following these approaches, the detection of missing part for video signal is typically based on a temporal analysis of video in order to detect strong discontinuities in the motion fields between successive frames. A sufficiently general model of degraded video signal is the following for a pixel location $\mathbf{p} = (x, y)$:

$$I(\mathbf{p}, t) = (1 - b(\mathbf{p}, t))I^*(\mathbf{p}, t) + b(\mathbf{p}, t)c(\mathbf{p}, t) + \eta(\mathbf{p}, t) \quad (1)$$

where $I(\mathbf{p}, t)$ is the corrupted signal at spatial position $\mathbf{p}$ in frame t, $b(\mathbf{p}, t) \in \{0, 1\}$ is a binary mask indicating the points belonging to missing part of the degraded video, I^* is the ideal uncorrupted image. The (more or less constant) intensity values at the corrupted spatial locations are given by $c(\mathbf{p}, t)$. Although additive random noise is not considered to be the dominant degrading factor for our purposes, it is still included in (1) as the term $\eta(\mathbf{p}, t)$.

The removal of blotches is a two-step procedure. In the first most complicated step the blotches need to be detected, i.e., an estimate for the mask $b(\mathbf{p}, t)$ is made. There are various blotch detectors that exploit these characteristics. The first is a pixel-based blotch detector known as the spike-detector index (SDI). This method detects temporal discontinuities by comparing pixel intensities in the current frame with motion-compensated reference intensities in the previous and following frames, i.e.

$$SDI(\mathbf{p}, t) =$$
$$\min[(I(\mathbf{p}, t) - I(x - d_x(\mathbf{p}, t-1, t), y - d_y(\mathbf{p}, t-1, t), t-1))^2,$$
$$(I(\mathbf{p}, t) - I(x + d_x(\mathbf{p}, t, t+1), y + d_y(\mathbf{p}, t, t+1), t+1))^2]$$

where $(d_x(\mathbf{p}, t-1, t), d_y(\mathbf{p}, t-1, t))$, respectively $(d_x(\mathbf{p}, t, t+1), d_y(\mathbf{p}, t, t+1))$, is the motion between frames $t-1$ and t, respectively t and $t+1$.

Since blotch detectors are pixel-oriented, the motion field $\mathbf{d}()$ should have a motion vector per pixel, i.e., the motion field is *dense*[10]. Observe that any motion-compensation procedure must be robust against the presence of intensity spikes. A blotch pixel is detected if $SDI(\mathbf{p}, t)$ exceeds a threshold. More complicated blotch detectors explicitly incorporate a model for the uncorrupted frames, such as a two- or three-dimensional autoregressive model or a Markov random field to develop the maximum a posteriori detector for the blotch mask [14], [20], [24]. In the second step, the incorrect intensities $c(\mathbf{p}, t)$ at the corrupted locations are spatio-temporally interpolated [21], [22]. In case a motion-compensated interpolation is carried out, the second step also involves the local repair of motion vectors estimated from the blotched frames.

The new idea proposed here is to use ICA for both blotch detection and removal. There are not more two distinguished steps, but the result of the procedure we propose is the blotch removal, although, if it is of interest, the same procedure could produce the mask $b()$ too. We can assume that a degraded video frame consists of three additive components: first, the uncorrupted "ideal" image; second, images of blotches seen as dynamical events; and third, additive noise mainly due to the camera system or the digitalization process. The ICA based approach is motivated by the fact that for degraded video, the independence of these components is often theoretically guaranteed, and also the linear mixing model holds exactly. This is an almost ideal application for ICA. The ICA technique has been quite successful in artefact removal for biomedical signals [30], astronomical images [11]. Up to now, there have been few applications of ICA on the global analysis of video, with functional MRI imaging the most advanced one [26]. From a mathematical point of view, our problem has similarities with the fMRI analysis.

The contents of this paper are as follows: Section 2 outlines the proposed blotch removal scheme in details, while Section 3 describes the test for blotch removal. Some conclusions are drawn in Section 5.

II. The Proposed Blotch Removal Scheme

There are several challenges and constraints in trying to remove blotchy noise. First, it is noted that, while blotchy noise does not fit into any existing popular noise model for digital video, trying to find a new model for it may also be extremely difficult since it presents little mathematical tractability. Therefore model-based detection methods, which proved to be successful for line scratch removals cannot be adopted here (see as instance [7]). Secondly, presence of blotchy noise together with other artifacts like intensity instability might lead to inaccurate or spurious motion estimation results which are crucial if we want to incorporate motion-compensated filtering for noise reduction [2]. Thirdly, since the application fields have typically real-time requirements computational complexity should not be too huge. And lastly, there should not be obvious artifacts or blurring introduced after blotchy noise is removed. To overcome the above difficulties and constraints, the proposed scheme processes the sequence by the following steps: (a) motion estimation and compensation, (b) temporal median filtering, (c) IC estimation and projection.

A. Motion Estimation and Compensation

In video restoration literature, many attempts have been made to accurately estimate the dense motion field in the restoration of video sequences. Dense motion estimation is typically done by block-matching methods, which, in terms of the model efficiency, is much more computationally attractive. Many block-matching based methods have been developed using different searching to estimate the motion vector maximizing some similarity measure [9], [25]. We adopt here a method reported in [8] which combines the use of more features computed at each point along with the use of a multiresolution technique to efficiently perform the search of motion vectors. The idea consists in the minimization of differences of feature vectors between matched pixels in two consecutive images in terms of, among others, edgeness, positive and negative cornerness, etc. Two points $\mathbf{p}$ and $\mathbf{p} + d(\mathbf{p}, t, t + 1)$ may be matched according to their feature differences, minimized across different and varying vector field $d(\mathbf{p}, t, t + 1)$.

To cope with large displacements the matching is made on the Gaussian pyramids constructed over the frames at time t and $t + 1$ [6].

B. Temporal Filtering

We firstly apply a denoising process along the temporal dimension with some simple filter so that we might have a "cleaner" version of the original sequence to help in the later blotch removal.

In directional filtering different filter directions are considered corresponding to different spatio-temporal edge orientations. Effectively, this means that the filtering operation takes place along the spatio-temporal edges, avoiding the blurring of moving objects. The directional filtering approach may be superior to adaptive or switching filters since noise around spatio-temporal edges can effectively be eliminated by filtering along those edges, as opposed to turning off the filter in the proximity of edges. We apply the temporal median, belonging to the family of order-statistic (OS) filters, taken over three frames:

$$\begin{aligned}&\tilde{I}(\mathbf{p}, t) = \\ &\text{median}[I(x - d_x(\mathbf{p}, t-1, t), y - d_y(\mathbf{p}, t-1, t), t-1), \\ &I(\mathbf{p}, t), I(x + d_x(\mathbf{p}, t, t+1), y + d_y(\mathbf{p}, t, t+1), t+1)]\end{aligned}$$

Filters of this type are very suitable for removing shot noise. More elaborate OS-filters may be applied as the multi-stage median filter (MMF) [4].

C. ICA for Video Sequence

The basic ICA model assumes a set of observations which are mixtures of some underlying unknown sources. The only assumptions that are needed in ICA are [15]

1) the sources are statistically independent;
2) the probability densities of the sources are non-Gaussian (at most one of them is allowed to be Gaussian);
3) the mixing of the sources into the observations is linear;

▷ Input: A video sequence of N_f frames.
for $t = 0$ to $N_f - 1$ **do**
  Read frames related to $t - \lceil (m-1)/2 \rceil$, t and $t + \lfloor (m+1)/2 \rfloor$, m being the number of observations.
  Compute the motion estimation and compensation over m input frames.
  Organize data in a matrix $\mathbf{X}$ of dimension $(m \times N)$, N being the image size.
  Estimate the demixing matrix $\mathbf{W}$.
  Perform the decomposition of observations into independent components by $\mathbf{s}_n = \mathbf{W}\mathbf{x}_n$.
  Select the independent component corresponding to the largest kurtosis (or the smallest MSE).
  Eliminate all the components from the vector $\mathbf{s}_n$ except that selected and perform the back-projection $\tilde{\mathbf{x}}_n = \mathbf{W}^{+}\tilde{\mathbf{s}}_n$.
  Output $\tilde{\mathbf{x}}_n = \mathbf{W}^{+}\tilde{\mathbf{s}}_n$.
end for

Fig. 1. The proposed blotch removal scheme.

4) the number of observations is larger than or equal to the number of sources.

For artefacts in degraded video, all these assumptions seem to hold very accurately; artefacts such as noise, blotches, discrete dynamical events, etc. are theoretically guaranteed to be independent of each other. Except for impulsive noise, the overall probability density of such sources, corresponding to the intensity distribution over the whole image, is sparse and thus sharply non-Gaussian and the linear superposition holds for the artefacts (see eq. (1)). The number of available frames can be very high compared to the relatively few different artefacts present over the observation period. Thus, this is an almost ideal application for ICA. The ICA technique has earlier been quite successful in artefact removal from biomedical signals [30]. Other applications of ICA include speech separation, telecommunications, image and signal denoising, and financial time series analysis; for a review, see [17]. There have been relatively few applications of ICA to the global analysis of image data; one prominent application using images is functional magnetic resonance imaging (fMRI) [18]. Some works about blind image separation are given in [3], [23].

Let N be the number of pixels in an image and T be the number of video frames. Let $\mathbf{X} = [x_{in}]$ be the $(T \times N)$ data matrix whose rows are the individual frames, stacked row by row into vectors, and whose columns $\mathbf{x}_n$ are the single pixel luminance time series. In this case, formally similar to functional neuroimaging, we have two possibilities for performing ICA: spatial or temporal [26]. The spatial ICA model is

$$\mathbf{X} = \mathbf{A}\mathbf{S} \tag{2}$$

where $\mathbf{A}$ is an $(T \times M)$ mixing matrix and $\mathbf{S}$ is an $(M \times N)$ matrix whose rows are independent source images, with $M \leq T$. The temporal ICA model is

$$\mathbf{X}^T = \mathbf{A}'\mathbf{S}^T \tag{3}$$

where $\mathbf{A}'$ is another $(M \times T)$ mixing matrix and the rows of $\mathbf{S}^T$ are the individual frame pixels. For degraded video sequences, the temporal model is not feasible because the spatial dimension is very much larger than the temporal dimension and reliable estimation of matrix $\mathbf{A}'$ would be difficult in this case due to the need of computation of $\mathbf{X}^T\mathbf{X}$. Let us write the spatial ICA model (2) in the more conventional vector form as

$$\mathbf{x}_n = \mathbf{A}\mathbf{s}_n \tag{4}$$

Now $\mathbf{x}_n$ is the T dimensional vector representing the n-th luminance time series through all the T images, and $\mathbf{s}_n$ is the corresponding source vector with independent components though time related to the n-th pixel, $n = 1, \ldots, N$. Written as

$$\mathbf{x}_n = \sum_{m=1}^{M} \mathbf{a}_m s_{mn} \tag{5}$$

we see that the M columns of $\mathbf{A}$ or mixing vectors $\mathbf{a}_m$ can also be interpreted as "virtual luminance trajectories in time", whose linear combinations give the observed luminance values along time $\mathbf{x}_n$. The mixing vector characterizes the temporal behaviour of the m-th source, while the source image (s_{mn}), $n = 1, \ldots, N$ characterizes the spatial behaviour over the pixel field. Both of these can be used to interpret the physical meaning of a given term in the sum.

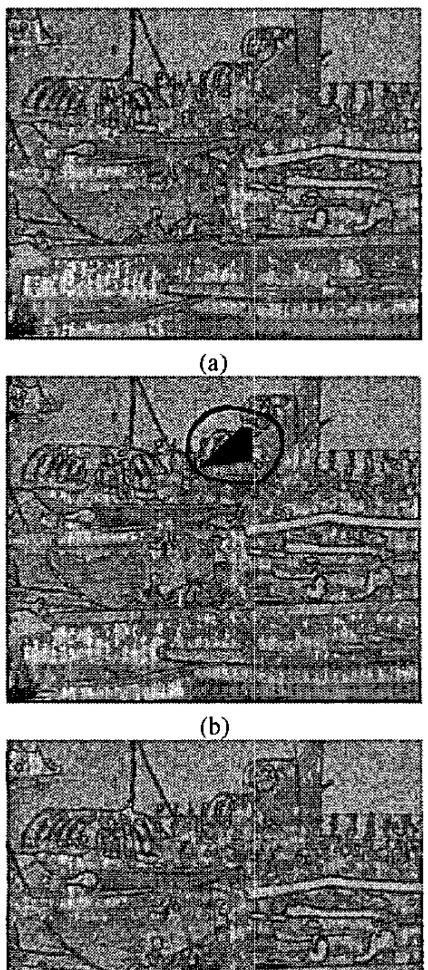
For ICA analysis, we have chosen to use the FastICA algorithm [16], [17] because of its appealing convergence properties. Preliminary sphering of the data is recommended to simplify the algorithm and to reduce noise. This means transforming the vectors $\mathbf{x}_n$ into $\mathbf{z}_n = \mathbf{V}\mathbf{x}_n$ such that the new vectors $\mathbf{z}_n$ have uncorrelated $(E\{\mathbf{z}_n\mathbf{z}_n^T\} = I)$, accomplished by setting $V = C^{-1/2}$ where $\mathbf{C} = E\{\mathbf{x}_n\mathbf{x}_n^T\}$ is the correlation matrix of data, and unit variance elements. One of the methods to accomplish this is the classical Principal Component Analysis (PCA). Computing the eigenvalues of the data covariance matrix gives indications about the number of sources to be used in the model. After whitening, the mixing model becomes

$$\mathbf{z}_n = \mathbf{V}\mathbf{x}_n = \mathbf{V}\mathbf{A}\mathbf{s}_n = \mathbf{W}\mathbf{s}_n \tag{6}$$

where the matrix $\mathbf{W}$ is orthogonal. To compute matrix $\mathbf{W}$ by the FastICA algorithm, its individual columns $\mathbf{w}_i$ are updated by the iteration

$$\mathbf{w}_i \leftarrow E\mathbf{z}_n g(\mathbf{w}_i^T\mathbf{z}_n) - Eg'(\mathbf{w}_i^T\mathbf{z}_n)\mathbf{w}_i \tag{7}$$

followed by orthonormalization of the matrix $\mathbf{W}$ after each updating step. Function $g(\cdot)$ in the update rule is an odd nonlinear function and $g'(\cdot)$ is its derivative. The choice of a suitable function is discussed in detail in [17]. In our case, the function was $g(u) = \tanh u$. This non linear, non-quadratic function has the effect of introducing higher order statistics of the data vectors $\mathbf{z}_n$ into the algorithm (7). When $\mathbf{W}$ has been estimated, the original mixing matrix is approximated by $\mathbf{A} = \mathbf{V}^{+}\mathbf{W}$, where $\mathbf{V}^{+}$ is the pseudo-inverse of V. The independent components are obtained from $\mathbf{s}_n = \mathbf{W}^T\mathbf{z}_n$, $n = 1, \ldots, N$.



(a)

(b)

(c)

Fig. 2. A large blotch in the central frame of a three frame sequence.

D. Deflation process

After extracting the independent components, the next step is to discard some of the components and then project the remaining components back to the luminance domain. The procedure, named deflation, allows to extract and remove one or more independent components characterizing the scene, the blotches, the noise, etc. To perform this operation, a measure should be adopted. Kurtosis, defined for a generic vecto valued random variable $\mathbf{x}$ as:

$$K(\mathbf{x}) = \frac{n * \sum_{i=1}^{n} (x_i - |\mathbf{x}|)^4}{\left(\sum_{i=1}^{n} (x_i - |\mathbf{x}|)^2\right)^2} - 3 \tag{8}$$

is a measure that is more sensitive to anomalies in an image than the standard deviation. Changing a few pixel values is usually enough to alter the kurtosis value. When the frame contains small objects and a large and homogenous background, the kurtosis value will be very high compared with a mostly noisy frame, while the kurtosis is smaller in the case when the frame contains a large class. The largest value computed over all the independent components lets to select the independent component to be keept in the deflation process. This means that the detection of blotches could be formulated as the following two steps:

1 Select the independent components corresponding to the largest kurtosis.
2 Eliminate the undesiderable components (i.e., by replacing them with zero) from the vector $\mathbf{s}_n$ except that selected and perform the back-projection $\tilde{\mathbf{x}} = \mathbf{W}^{+}\tilde{\mathbf{s}}_n$.

If we are interested in just the removal of blotches, the best measure is the Mean Squared Error (MSE), between a source image and the frame at time t that is under exam. The smallest value computed over all the independent components lets to select the independent component to be keept in the deflation process. The two-steps for the blotch removal becomes:

1 Select the independent component corresponding to the smallest MSE.
2 Eliminate the undesiderable components (i.e., by replacing them by zero) from the vector $\mathbf{s}_n$), except that selected and perform the back-projection $\tilde{\mathbf{x}} = \mathbf{W}^{+}\tilde{\mathbf{s}}_n$.

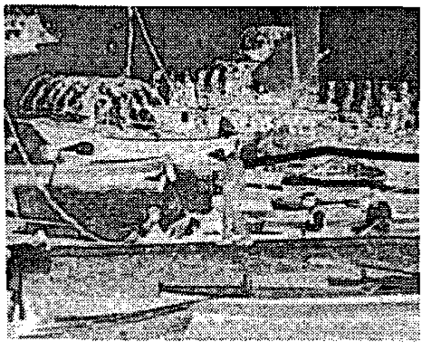
Summarizing, the blotch removal scheme could be sketched as depicted in Figure 1.

III. Results

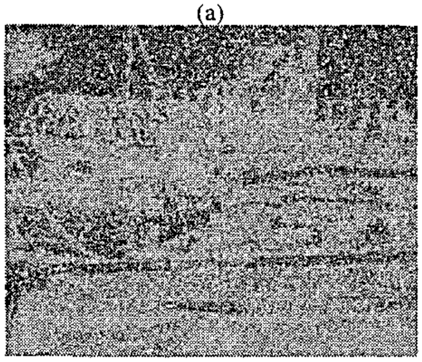
We compared the algorithm with two well known algorithms reported in literature for blotch removal, the technique involving interpolation (specifically a 3D autoregressive model), reported in [21], and that known as "image impainting" [5].

We tested the algorithm on artificially corrupted real frames of size 500×400. Specifically, we randomly created white or dark blotches in a frame, with a maximum radius of the circle containing it equal to $1/8$ of the frame size. (see as instance the central frame of Fig. 2). The extracted IC components are depicted in Fig. 3, while the result of the deflation process according to the blotch removal scheme reported above is depicted in Fig. 4.

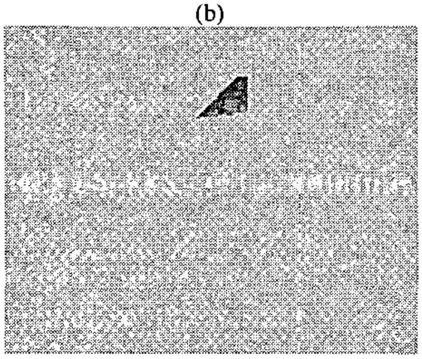
The qualitative results seem similar (see Fig. 5 over the same central frame of Fig. 2) and cannot be appreciated by just giving a look to the produced image. Anyway, the results could be more appreciated if we introduce quantitative results.



(a)



(b)



(c)

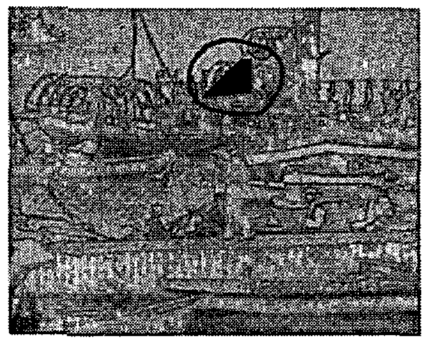
Fig. 3. Extracted independent components.

We thus measured the Mean Squared Error (averaged over number of pixels and number of frames) between the original uncorrupted frame and those produced by the three considered algorithms, obtaining values 13.13 (Kokaram [21]), 13.08 (Beltramio *et al.*[5]) and 12.44 (IC-based). From the qualitative results we can observe that, even though the removal algorithms taken into account perform quite well, their reconstruction accuracy can be enhanced. This is usually made by introducing texture synthesis models (see as instance [1]) that enhance the qualitative results, at the expense of a substantial increase of the computational complexity. The IC based approach, instead, tends to smooth the inaccuracies, still retaining the good performance of the considered algorithms, also without directly applying a texture synthesis method.

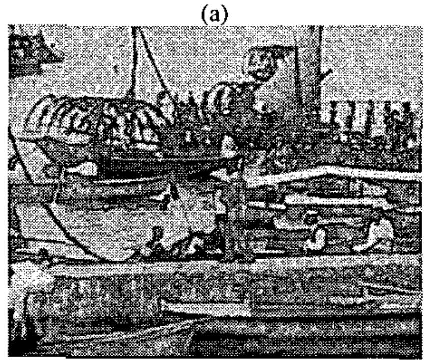
We also measured the approximate elapsed time spent in average by our procedure for just 1 frame over a Pentium IV 1,70Ghz against those produced by the considered algorithms for comparison: 156 seconds (Kokaram [21]), 360 seconds (Beltramio *et al.*[5]) and 28 seconds (IC-based). As it is clear the IC based procedure strongly outperform the others; the motivation resides in the fact that the considered algorithms are iterative ones, like the ICA, but the iteration number needed to reach convergence (and consequently satisfactory results) are usually high (of the order of 100 for the Beltramio procedure).

IV. Concluding Remarks

We have reported an algorithm that performs unsupervised detection and removal of portions of missing data, i.e. blotch, in video. To the best of our knowledge, this is the first application of ICA on this specific problem. Our model satisfies assumptions for the applicability of ICA quite well. At the end of the ICA iterative process, we adopt a very simple but efficient measure, kurtosis, to select the IC base frame with the largest value for the deflation step in the case of the blotch detection, but more significantly the smallest MSE IC base frame is that should be retained in the deflation step in the case of blotch removal. The iterative step converges fast and to corroborate our claim about the robustness of the ICA-based method, we compared the results obtained with those produced by the autoregressive model [21] and multi-scale analysis of movies [13]; the results indicate that ICA provides an efficient way to separate features present in a scene.



(a)



(b)

Fig. 4. The original blotched frame (a) and the restored frame by the ICA-based scheme (b).

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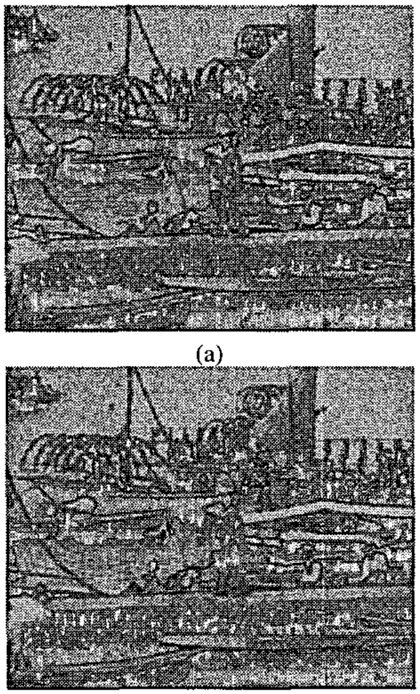

(a)

(b)

Fig. 5. Multi-scale removal (a) and interpolation (b) over the central frame of 2.