A NEW AUTO-REGRESSIVE (AR) MODEL-BASED ALGORITHM FOR MOTION PICTURE RESTORATION

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ABSTRACT

This paper proposes a new AR model-based restoration algorithm which is able to suppress mixed noise processes and recover lost signals in an image sequence. A drawback of an AR model is the limiting size of the block (of pixels) that can be adequately modeled. Using a single set of AR coefficients to restore large region of missing data will result in a homogenized texture region. In order to overcome this inherent limitation of the AR model, a block-based divide-and-conquer approach is proposed. In addition, a new Gaussian weighting scheme is used to better estimate the AR coefficients for the interpolation process.

1. INTRODUCTION

The existing motion picture restoration algorithms are based on either spatio-temporal filters[1,2], statistical approaches[3] or auto-regressive (AR) models[4]. Spatio-temporal filters are applied along the estimated motion trajectory of the image region under consideration. Two such filters are the spatio-temporal low-pass filter and the spatio-temporal median filter. The former tends to blur sharp edges while the latter tends to homogenize highly textured regions in the image. Statistical approaches[3] have produced better results but at a much higher computational cost.

In this paper, a new AR model based algorithm is proposed. Motion compensation in the proposed model is carried out using a *bi-directional motion estimator*[6] and a *Gaussian Weighting Function* (GWF) is used during the recalculation of the video model for restoration. GWF is shown to provide better Signal-to-Noise Ratio (SNR) results due to the enhancement of the spatial support for the AR model.

Unlike in the existing AR-based algorithms[5], the new restoration algorithm is formulated using a block based *divide-and-conquer* methodology, that is able to remove blotch and scratch artifacts. It also retains the sharpness of the original image and does not introduces new artifacts into the uncorrupted regions of the image. This has resulted in the development of a more complete motion picture restoration algorithm, one that can handle most types of common noise processes.

2. BI-DIRECTIONAL 3D-AR MODEL

The *Bi-directional 3D Auto-Regressive* (B3D-AR) model [6] is described by the following equation (1):

$$\hat{I}(i,j,n)=\sum_{k=1}^{N}a_k I([i+q_{xk}+\alpha_{n,n+q_{tk}}(i,j)],[j+q_{yk}+\beta_{n,n+q_{tk}}(i,j)],[n+q_{tk}]) \qquad (1)$$

where, $\hat{I}(i,j,n)$ is the predicted pixel intensity at the location *(i,j)* in the *n*th frame, a_k are the model coefficients, N are the total number of Auto-Regressive model coefficients, $[q_{xk}, q_{yk}, q_{tk}]$ are the support vectors that point to each pixel neighborhood used for the AR model. The component of the offset vector which determines the temporal direction of the supporting pixel is q_{tk} and its value is determined by $t(i,j,n)$ [6]. Therefore $I(i+q_{xk}, j+q_{yk}, n+q_{tk})$ is the gray level of the pixel at the *k*th support position for the pixel at *(i,j,n)*. $[\alpha_{n,m}(i,j), \beta_{n,m}(i,j)]$ is the displacement vector between the *n*th and *m*th frames.

For parameter estimation, the task is to choose parameters so as to minimize some function of the prediction error $\varepsilon(i,j,n)$, as shown in the following equation (2) :

$$\varepsilon(i,j,n) = I(i,j,n) - \hat{I}(i,j,n) \qquad (2)$$

There are two sets of parameters to be estimated: the displacement vectors and the model coefficients. The displacement vectors are to be computed first using a bi-directional motion estimation algorithm. Subsequently

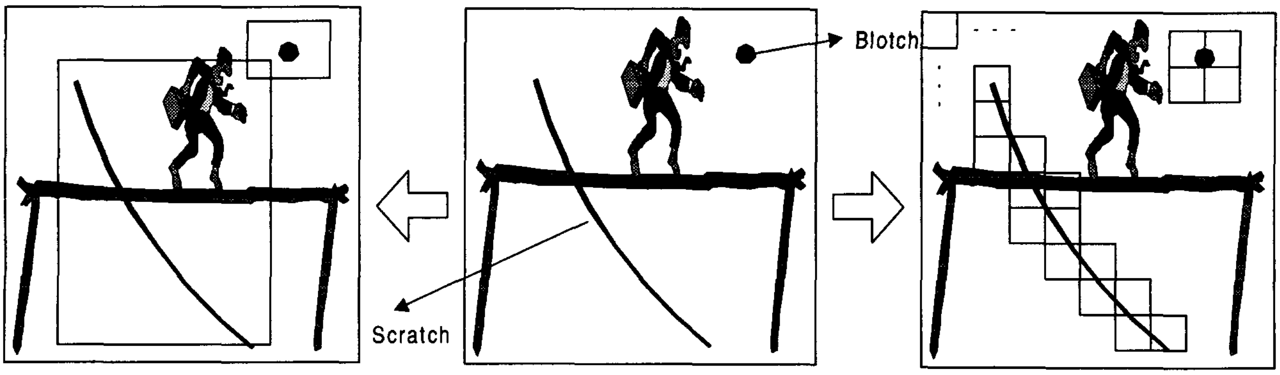

Figure 1. Comparison of Kokaram's Algorithm [4, 5] to the New Algorithm's

the Least Mean Square (LMS) approach is used to compute the model coefficients.

The coefficients chosen to minimize the square of the error in equation (2) leads to the normal equations :

$$\mathbf{Ra} = -\mathbf{r} \quad (3)$$

Where **R** is an $N \times N$ matrix of correlation coefficients, **a** is the vector of model coefficients and **r** is an $N \times 1$ vector of correlation coefficients. The solution [6] to equation (3) yields the model coefficients.

3. THE NEW VIDEO MODEL

Scratches are one of the common artifacts that cannot be adequately removed by the existing AR model-based algorithms[5]. An AR model attempts to account for intensity variation in an image. We attempt to use the AR-based model to predict the missing data such that the interpolated regions blend smoothly with the rest of the image regions while preserving the texture details. An important aspect in using an AR model is that the size of the block (of pixels) being modeled should be such that one set of model coefficients can adequately describe the block of pixels. When the block-size of the missing data in images sequences is too large, using a single set of AR coefficients to restore missing data in this region[5] may not be adequate.

In order to overcome the inherent limitation of the AR model in restoring large regions of missing data such as large blotches and scratches, a block-based divide-and-conquer approach is proposed.

Figure 1 depicts how the model is computed compared to previous approaches [4, 5] where the region of computation of the model is centered around the whole artifact. In the new model, the divide-and-conquer method ensures that the number of non-corrupted pixels for modeling a block (of pixels) provides adequate support for the computation of accurate model coefficients while limiting the size of the block to be modeled. The new method thus allows the restoration of long scratches and blotches of varying sizes.

4. DETECTING AND REMOVING DISTORTIONS

The position of local distortion can be detected by applying some threshold to $\varepsilon_d(i, j, n)$, the square of the error between the actual and predicted intensity of the pixel at location (i, j, n) which is given by (4):

$$\varepsilon_d(i,j,n) = (I(i,j,n) - \hat{I}(i,j,n))^2 \quad (4)$$

where $\hat{I}(i,j,n)$, given in equation (1) is calculated from AR coefficients $\{a_1, a_2, \ldots\ldots\ldots\ldots a_N\}$ as in [6].

The new restoration process can be seen as a threefold process. First, the pixels which are detected as distorted pixels are weighted according to a GWF instead of using a binary weighting scheme, as shown in figure 2. Second, a new set of Gaussian Weighted AR coefficients is re-computed using Equation (5). Finally, the distorted pixels identified by using equation (4)

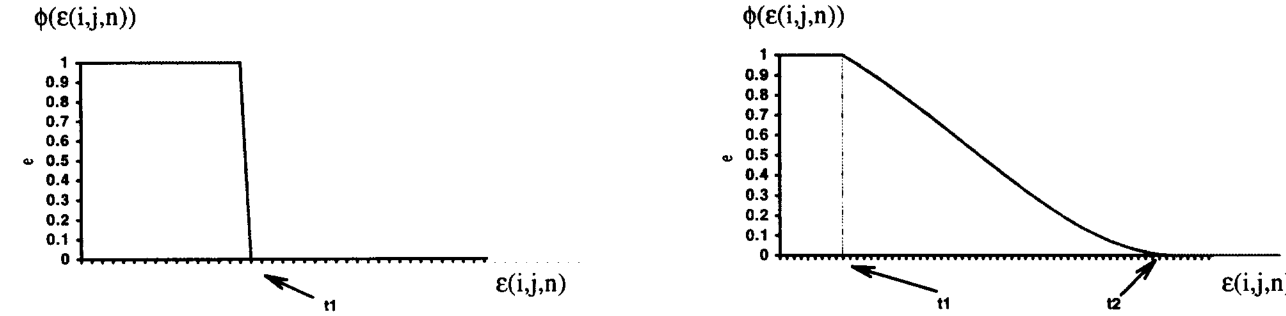

Figure 2. Binary Weighting and Gaussian Weighting Functions

are replaced using the predicted pixels $\hat{I}(i,j,n)$ from the newly computed AR model.

The new Gaussian Weighted error equation is written as:

$$\varepsilon_w(i,j,n) = \phi(\varepsilon(i,j,n))\sum_{k=0}^{N} a_k I([i + q_{xk} + \alpha_{n,n+q_{nk}}(i,j)] \quad (5)$$
$$,[j + q_{yk} + \beta_{n,n+q_{nk}}(i,j)],[n + q_{tk}])$$

The GWF employed is described in equation (6).

$$\phi(\varepsilon(i,j,n)) = \exp[-(\frac{\varepsilon(i,j,n) - t_1}{t_2 - t_1})\pi] \quad \text{for} \quad t_1 < \left|I - \hat{I}\right| < t_2$$
$$\phi(\varepsilon(i,j,n)) = 0 \quad \text{for} \quad \left|I - \hat{I}\right| \geq t_2$$
$$\phi(\varepsilon(i,j,n)) = 1 \quad \text{for} \quad \left|I - \hat{I}\right| \leq t_1 \quad (6)$$

The parameters t_1 and t_2 are set to 10 and 45 respectively in our experiments. Minimizing the squared error $[\varepsilon_w(i,j,n)]^2$ with respect to the coefficients, yields a set of $N+1$ normal equations similar to equation (3).

5. RESULTS AND PERFORMANCE ANALYSIS

Using the GWF in the re-computation of the AR-based model is shown to improve the restoration capability of the algorithm. The results are shown in Table 1 for the "Corridor" and "Salesman" sequences. The GWF leads to an improvement in the PSNR results because a better spatial support is provided for the AR model.

Figures 3a and 3b show the restoration results of the new algorithm on the "Salesman" sequence, on which temporally isolated artificial distortions have been added to the image sequence. It can be seen that the distortions have been successfully removed while the sharpness of the image is retained. Figures 4a and 4b show the restoration results on a naturally degraded image sequence where a scratch is present. The divide-and-conquer approach has successfully alleviated the presence of artifacts in the old video archives tested.

Frame	BAR-3D PSNR (dB)		GWB3D-AR PSNR (dB)	
No.	Salesman	Corridor	Salesman	Corridor
1	44.26	35.70	45.40	36.45
2	43.35	35.84	44.55	36.63
3	40.60	35.68	42.31	36.32
4	39.06	36.1	40.41	36.5
5	40.1	35.2	41.5	36.2

Table 1. Performance comparisons between Gaussian Weighted B3D-AR and Binary Weighted B3D-AR.

6. CONCLUSIONS

In this paper, we have presented a new AR model-based algorithm for motion picture restoration. It has been shown that a more complete restoration algorithm is obtained by using the divide-and-conquer approach as most common noise processes can now be tackled In addition, the GWF provides a better spatial support for the AR model leading to improvement in the interpolation performance.

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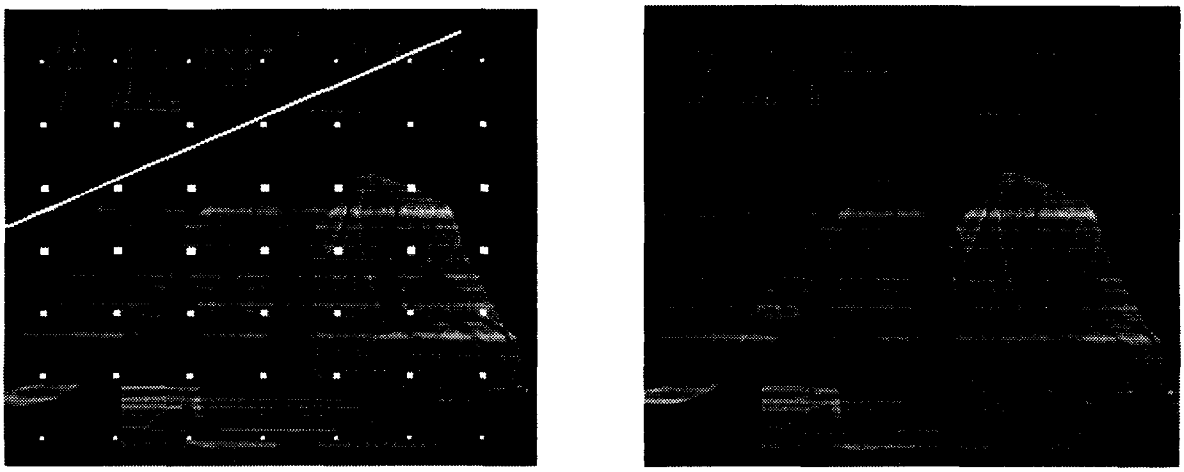
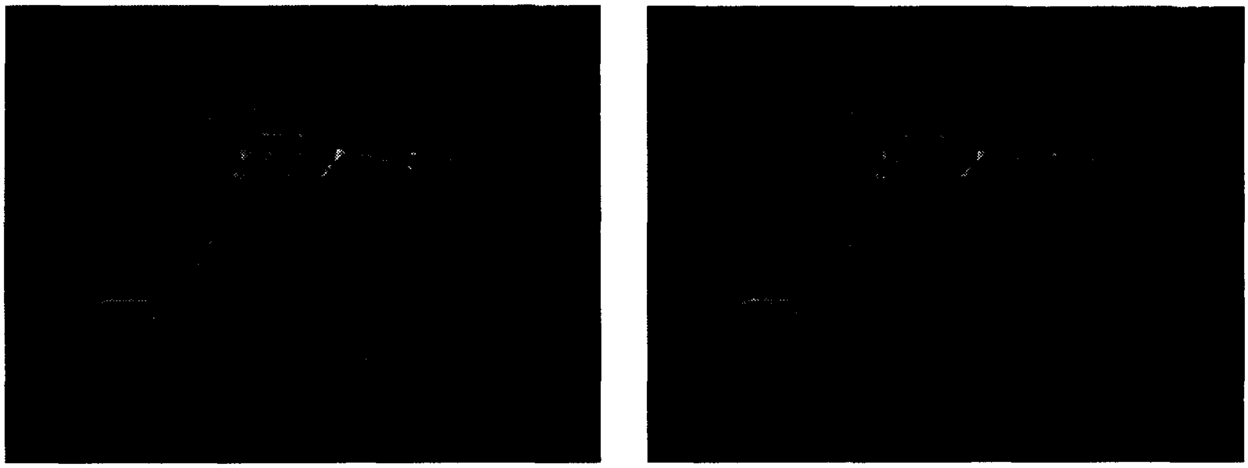


(a) (b)

Figure 3a. A noise-corrupted frame with blotches of size 2×2 to 4×4 and a scratch of width 2 pixels.
Figure 3b. Restored frame using the GWB3D-AR algorithm.



(a) (b)

Figure 4a. A frame from a real noise-corrupted image sequence
Figure 4b. The corresponding restored frame using GWB3D-AR model.

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