Kybernetika

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Kybernetika, Vol. 34 (1998), No. 4, [423]--428

Persistent URL: http://dml.cz/dmlcz/135226

KYBERNETIKA — VOLUME 34 (1998), NUMBER 4, PAGES 423-428

A SCRATCH REMOVAL METHOD

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We present a new type of scratch removal algorithm based on a causal adaptive multidimensional prediction. The predictor use available information from the failed pixel surrounding due to spectral and spatial correlation of multispectral data but not any information from failed pixel itself. Predictor parameters cannot be directly identified so a special approximation is introduced.

1. INTRODUCTION

In copying machines or desktop scanners the glass panel often gets scratched after extensive usage. Similar problem occurs when copying film negatives. The problem how to recover lost or damaged image data is old – since the dawn of photography to the digital images obtained directly using CCD cameras, radiotelescopes, scanners on board of satellites, etc. Methods used to reconstruct image scratches are mostly very simple and the reconstruction quality is seldom satisfactory. In our paper we called these methods "classical" and were used for comparison under the defined test criteria.

The simplest method (A) replaces missing pixels by the local mean values from the corresponding neighbourhood windows. This scheme can cause very observable distortions especially in images of high contrast features. A variant (B) of mentioned method [5] replaces missing values by the average of their known neighbours in 3×3 window starting with pixels with four known neighbours, and then switching to the ones with three known neighbours. Another method (C) linearly interpolates missing data using neighbours from both sides of unknown data section. These methods produce visible distortions mainly on colour images. Even interpolation with higher order curves, such as quadratic fit, is of no help [1]. More sophisticated template-like methods suggested in [1] cannot be used for reconstruction of multi-spectral pixels with all spectral components missing what is the case of scratch reconstruction.

An optimal reconstruction resulting in visual disappearance of the scratch is difficult to achieve, however a much more precise replacement beyond the scope the current methods is needed. From this originated an idea to reconstruct missing data from attainable information due to large correlation between single image elements. We have proposed a regression model prediction based line reconstruction method [3], which clearly outperforms the previously used reconstruction methods.

The method was further improved in [4] to select a locally optimal predictor from two mutually competing symmetrical adaptive predictors for each pixel to be reconstructed. In this paper we generalize this method for reconstruction of multi-line scratches with all spectral components missing (D).

2. SCRATCH MODEL

We assume that a scratch was already located within a bounding box of a minimal width ν. Let the scratch band to be modelled as:

$$Y_t = P^T Z_t + E_t \ , \tag{1}$$

where

$$P^T = [A_1, \ldots, A_\beta] \tag{2}$$

is the $\nu \times \beta^*$ unknown parameter vector,

$$\beta = card\, I_t$$

$$\beta^* = \nu\beta.$$

I_t is some neighbour index shift set excluding unknown data (i,j,k), $(m^a - m^f + i, j, k) \notin I_t$, where $i \in \langle 0; \nu \rangle$, $k \in \langle 0; d \rangle$ m^a is the leading approximation line (see (8)) and m^f is the leading reconstructed line, respectively. The leading lines are the top-most lines in their corresponding objects. We denote the $\nu\beta \times 1$ data vector

$$Z_t = [Y_{t-i} : \forall\, i \in I_t]^T \ . \tag{3}$$

Data arrangement in (3) corresponds to the arrangement of parameters in (2). $t = (m,n,d)$ is a multi-index; Y_t are $\nu \times 1$ reconstructed mono-spectral pixel band values, m is the row number, n the column number, d ($d \geq 1$) denotes the number of spectral bands and also the spectral band with the scratch to be reconstructed (the arrangement of spectral bands can be chosen at will), A_i are $\nu \times \nu$ unknown model parameter matrices, E_t is the white noise component vector with zero mean and constant but unknown dispersion.

Note that although the model reconstructs a mono-spectral corrupted scratch band, the model can use information from all other spectral bands of an image ($d \geq 1$) as well. For mono-spectral images (e.g. Sun spot data) $d = 1$.

Let us choose a direction of movement on the image plane to track the scratch band $t-1 = (m, n-1, d)$, $t-2 = (m, n-2, d), \ldots$ We assume that the probability density of E_t has a normal distribution independent of previous data and is the same for every time t. Let us formally assume the knowledge of the bad data, then the task consists in finding the conditional prediction density $p(Y_t | Y^{(t-1)})$ given the known process history

$$Y^{(t-1)} = \{Y_{t-1}, Y_{t-2}, \ldots, Y_1, Z_t, Z_{t-1}, \ldots, Z_1\}$$

where Z is defined by (3) and taking its conditional mean estimation $\tilde{Y}$ for the reconstructed data. We have chosen the conditional mean estimator for data reconstruction, because of its optimal properties [2]:

$$\tilde{Y}_t = E[Y_t | Y^{(t-1)}]. \tag{4}$$

Assuming normality of the white noise component E_t, conditional independence between pixels, an a priori probability density for the unknown model parameters chosen in the normal form [3] we have shown [3] that the conditional mean value is:

$$\tilde{Y}_t = \hat{P}^T_{t-1} Z_t \ . \tag{5}$$

The following notation is used in (5):

$$\hat{P}_{t-1} = V^{-1}_{zz(t-1)} V_{zy(t-1)} \ , \tag{6}$$

$$\tilde{V}_{xw(t-1)} = \sum_{k=1}^{t-1} X_k W_k^T \tag{7}$$

and

$$V_{xw(t-1)} = \tilde{V}_{xw(t-1)} + V_{xw(0)}$$

(see [3] for details).

To evaluate predictor (5) we need to compute the parameter estimator (6), but we do not know the past necessary data Y_t, because they are those to be reconstructed. On the other hand the data from Z_t in (5) are known: we can select a contextual support of the model I_t in such a way to exclude unknown data. This problem is solved using the approximation based on spatial correlation between close leading lines

$$\tilde{Y}_t \doteq \tilde{P}^T_{t-1} Z_t \ , \tag{8}$$

where $\tilde{P}_{t-1}$ is the corresponding parameter estimator (6) for the nearest known leading line (including known contextual neighbours (3)) to our reconstructed one in the spectral band d. Note the different Z (3) in (8) and $\tilde{V}_{zy(t-1)}, \tilde{V}_{zz(t-1)}$. This approximation assumes similar directional correlations on both lines, but not necessarily a mutual correlation of these leading lines themselves.

3. OPTIMAL MODEL SELECTION

Let us assume two regression models (1) M_1 and M_2 with the same number of unknown parameters ($\beta_1^* = \beta_2^* = \beta^*$) and mutually symmetrical neighbour index shift sets $I_{1,t}, I_{2,t}$ with the missing leading line being their symmetry axis. The optimal decision rule for minimizing the average probability of decision error chooses the maximum a posteriori probability model, i.e. a model whose conditional probability given the past data is the highest one. The presented algorithm can be therefore completed [4] as:

$$\tilde{Y}_t \doteq \begin{cases} \tilde{P}^T_{1,t-1} Z_{1,t} & \text{if} \quad p(M_1|Y^{(t-1)}) > p(M_2|Y^{(t-1)}) \\ \tilde{P}^T_{2,t-1} Z_{2,t} & \text{otherwise} \end{cases} \tag{9}$$

where $Z_{i,t}$ are data vectors corresponding to $I_{i,t}$. Following the Bayesian framework used in our paper, choosing uniform a priori model in the absence of contrary information, $p(M_i|Y^{(t-1)}) \sim p(Y^{(t-1)}|M_i)$, and assuming conditional pixel independence, the analytical solution has the form [4]

$$p(M_i|Y^{(t-1)}) = k\ |V_{i,zz(t-1)}|^{-\frac{1}{2}}\ \lambda_{i,t-1}^{-\frac{\gamma(t-1)-\beta+2}{2}} , \qquad (10)$$

where k is a common constant. To evaluate $p(M_i|Y^{(t-1)})$, we have to use a similar approximation in (10) as for the predictor (5). All statistics related to a model M_1 $\tilde{V}_{zy(t-1)}, \tilde{V}_{zz(t-1)}$, (10) are computed from data on one side of the reconstructed scratch band while symmetrical statistics of the model M_2 are computed from the opposite side. The solution of (10) uses the following notations:

$$\gamma(t-1) = \gamma(0) + t - 1 , \qquad (11)$$

$$\gamma(0) > \beta^* - 2$$

$$\lambda_{t-1} = V_{yy(t-1)} - V_{zy(t-1)}^T V_{zz(t-1)}^{-1} V_{zy(t-1)} . \qquad (12)$$

The determinant $|V_{zz(t)}|$ as well as λ_t can be evaluated recursively see [3]. If $A_i = diag[a_{1,i}, \ldots, a_{\nu,i}]$ $\forall i$ then the multi-dimensional model reconstruction is identical with separately applied single-dimensional model reconstruction on every scratch line component.

4. RESULTS AND CONCLUSIONS

In this section we present simulation results of the proposed reconstruction method and compare them with methods briefly surveyed in the introductory section. The performance of the methods is compared on artificially created scratches (removed from the unspoiled parts of the images so that the original data are known) using the criterion of mean absolute difference between original and replaced pixel values

$$MAD = \frac{1}{n\nu} \sum_{j=1}^{\nu} \sum_{i=1}^{n} |Y_{i(j)} - \tilde{Y}_{i(j)}|$$

where $\nu = 1$ is for the single-line scratch model.

The first example is the defective Sun spot image shown in Figure 1. The second tested example (Figure 2, Figure 3) is a waterfall image.

Table 1 contains mono-spectral scratch reconstruction results. The Sun example demonstrates significant reconstruction improvement over the classical methods and similar results were obtained also for the other experimental image data. The regression model was superior over the classical methods not only using the MAD criterion but also visually. Both methods A and B suffer with clearly visible blurring tendency, while the method C produces discernible columns in the reconstructed scratch.

The results of our test are encouraging. The proposed method was the best one in our experiments. Our method can be used for colour or any other multispectral

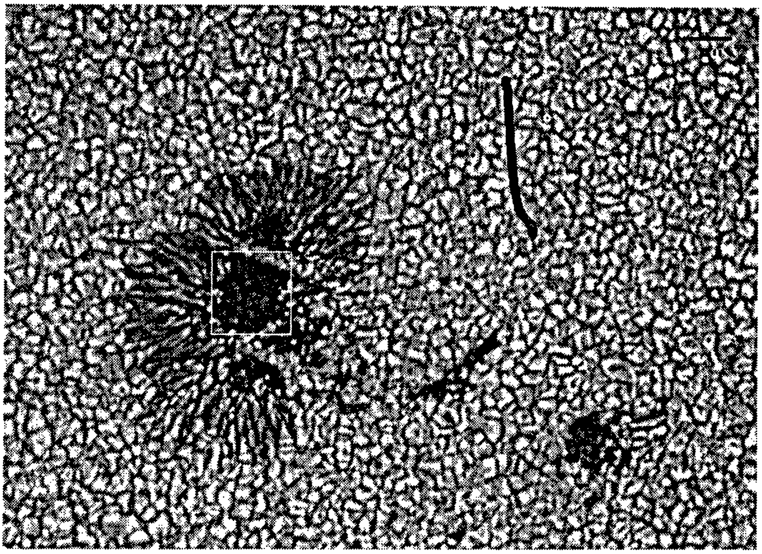

Fig. 1. The defective Sun spot image.

Table 1. Scratch reconstruction.

method	mono-spectral reconstruction	
	Sun spot MAD	waterfall MAD
A	0.75	2.36
B	0.75	2.76
C	0.91	2.94
D	0.64	2.25
D*	0.58	2.05

scratch reconstruction, too. In this case the multi-dimensional mono-spectral model is applied repeatedly to all missing monospectral scratch bands after the multispectral data space decorrelation using the Karhunen-Loeve transformation.

Scratches with high curvatures can be reconstructed in a piece-wise linearised parts to minimize the predictor dimensionality ν.

Finally if the method is used for isolated image pixels (or short lines perpendicular to the model movement) reconstruction then the predictor and similarly the model probability expression do not need any data approximation and the regression method performs better (D*) than for scratch reconstruction and much better than any of the classical methods. The proposed method is fully adaptive, numerically robust and still with moderate computation complexity so it can be used in an on-line image acquisition system.

(Received December 18, 1997.)

Fig. 2. The defective waterfall image (←).
Fig. 3. The reconstructed waterfall image using the method D (→).

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