

# HMM based Archive Film Defect Detection with Spatial and Temporal Constraints

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Image analysis can be applied for automated archive film defect detection and restoration, as well as quality assessment. In this paper, unlike previous methods, we examine longer temporal information at each pixel location and its neighbouring space to help us pinpoint defects. We assume the appearance of a defective pixel as a stochastic pixel-change event and use HMM and MRF to model the temporal and spatial information respectively to obtain better results with fewer false detections. First, an HMM based Archive Film Defect detection method (HAFID) is presented. We train an HMM on normal observation sequences and then apply it within a framework to detect defective pixels by examining each new observation sequence and its subformations via a leave-one-out process. The resulting defect map from HAFID encapsulates the defects very well, but suffers from many false alarms. We therefore extend HAFID to add a two-stage false alarm elimination process and refer to the entire method as HAFID-STC (Spatial and Temporal Continuity analysis). First, the defect map from HAFID is modeled with a MRF to enforce spatial continuity constraints and then the pyramidal Lucas-Kanade feature tracker is applied to impose temporal correlation constraints. We shall outline a comparison of HAFID-STC (and HAFID) against four commonly used and/or state-of-the-art techniques [1, 2, 3, 4] to demonstrate its superior detection rate.

## 1 HMM based defect detection

To begin with, we train a single HMM,  $\theta$ , for normal image pixel sequences, which is then applied in the testing stage to compute the likelihood of a new sequence being normal. In total, 207,561 observation sequences were used for training the HMM  $\theta$ . The estimation of the parameters for our HMM was optimized by maximizing  $P(\{o(k)\}_x^t | \lambda_\theta)$  through an iterative procedure until convergence, using Baum-Welch's method.

A leave-one-out process is then used to create subformations of the target observation sequence  $\{o(k)\}_x^t$  centred at candidate pixel  $\mathbf{x}$  with observation  $o(c)$  for each image pixel location. This will result in  $K$  observation sequences of length  $K - 1$ . We can then obtain (for each of these  $K$  observation sequences) the likelihood of the observation sequence  $\{o(h), h \neq k\}_x^t$  arising from normal data,

$$V_x^t(k) = P(\{o(h), h \neq k\}_x^t | \lambda_\theta) = \sum_m P(\{o(h), h \neq k\}_x^t, s_m(k') = s_m | \lambda_\theta) = \sum_m \alpha_{k'}(m) \beta_{k'}(m) \quad (1)$$

where  $k = 1, \dots, K$ ,  $k' = k - 1$ , and  $\alpha_y(m), \beta_y(m), y \in \{k, k'\}$  are defined using the Forward-Backward procedure. After computing  $u_x^t$  for every pixel  $\mathbf{x}$  in frame  $t$ , we obtain the likelihood map  $U^t = \{u_x^t\}$  for all  $\mathbf{x}$  in frame  $t$ .

$$u_x^t = \frac{V_x^t(c)}{\frac{1}{K} \sum_{k=1}^K V_x^t(k)} \quad (2)$$

Finally, any pixel  $\mathbf{x}$  is marked as a defect in a global frame binary defect map  $D^f = \{d_x^t, d_x^t \in \{0, 1\}\}$  if  $u_x^t > \tau_\theta$  where  $\tau_\theta$  is a threshold.

## 2 Elimination of false alarms

The HMM model performs extremely well in locating true defects, however it is rather sensitive to scene motion leading to false positives. This over-detection followed by false positive elimination is preferred to under-detection and its consequences. In order to identify and remove the false alarms, we apply a two-stage process enforcing (a) spatial continuity and (b) temporal correlation constraints.

For those false alarms that locate around the edges, such as the red pixels around the TV presenter's head in the top row example, strong spatial correlation with their neighbors may be found. In such cases local smoothness can be exploited by modeling the defect map  $D^f$  and the likelihood map  $U^t$  with MRFs to encourage grouping defects into connected

regions while removing false positives by propagating neighbouring non-degraded pixel locations.

For those false alarms that make up an entire moving region, for example, the shadows in the curtain folds in the bottom row example in Fig. 1 which leave the scene as the camera pans and zooms in towards the girl, no relationship with other pixels may be found unless we trace forwards and backwards on the temporal axis. The pyramidal Lucas-Kanade feature tracker is adopted here in order to impose temporal constraints.



Figure 1: Example results: (left) original images (middle) HAFID results before false alarm elimination, and (right) after false alarm elimination.

## 3 Experiments and results

The specificity and sensitivity of the proposed method HAFID-STC is measured with reference to handlabeled groundtruth produced from 30 film sequences totalling 580 frames. The ROC graph in Figure 2 shows a comparison of HAFID-STC against those of four commonly used and/or state-of-the-art techniques. The results from using only our HMM based detector HAFID for different window sizes  $K$  are also shown.

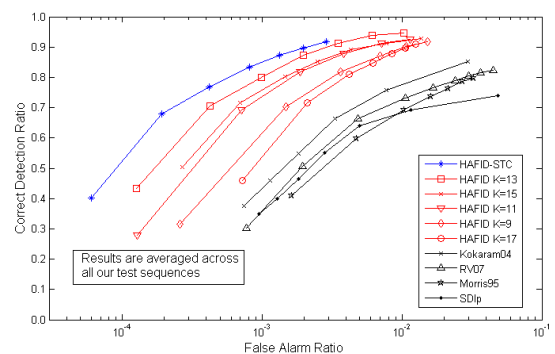


Figure 2: ROC graph shows a comparison of HAFID-STC against four well known or current state-of-the-art techniques [1, 2, 3, 4], averaged across our entire test data set.

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