Learning Print Artifact Detectors

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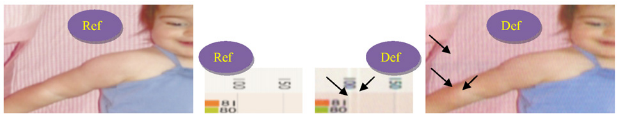
Abstract

An important aspect of image and print quality is the existence of artifacts, such as compression or print artifacts. A general perceptual masking model, that describes the perceptual severity of artifacts on general background, could have been used to extract specific artifact detectors. However, currently general models are not mature enough to provide print artifact detectors for commercial print quality control application. Consequently we propose to employ machine learning techniques to learn a specific model for each print artifact based on a relevant set of features. We used the approach to develop two print artifact detectors. While the proposed approach was developed for print quality purpose, the method is general and can be used for learning automatic evaluators for image defects and quality degradation as well.

Introduction

Artifact Specific Severity Evaluation Tools (ASSETs) compare a defected version of an image with it's perfect reference and evaluate the perceptual severity of specific artifacts in the defected image. In the print quality context, the defected images are the scans of printed jobs, and we are interested in whether or not it contains a specific print artifact. ASSETs are the building blocks of many print quality control applications, both off line and inline: (a) Off line press health analysis identifies artifacts on scans of specifically designed test jobs[10, 13]. (b) Perception guided automatic press diagnosis automatically prints test jobs, scans them using an inline scanner and analyze the scans to diagnose the problem [14], and (c) Inline Inspection continuously compares the digital job sent to print with the inline scan of the actual print, alerting the operator when significant print artifact occur [1, 16]. All of those applications relay of correct identifications of print artifacts on scans.

Figure 2 shows some of the print artifacts, which constitute gross differences between the intended image (the digital original) and the actual image (the scan of the print). However, in some of the cases, the differences are minute and they are objectionable only due to large scale or Gestalt type aggregations in the human visual system. Figure 1 demonstrates such a challenge. The figure shows a close up of two sets of two images. In each set, one image (left) is the digital image sent to print, and the other is the scanned print. The images in each pair are registered, so that their colors, dimensions, and position are as similar as possible. The spacial and color registration are beyond the scope of this paper. After registration, there still exist spatial, color and texture differences between the digital reference (Ref, left) and the scanned image (Def, right), mostly due to negligible inaccuracies in the printing and scanning processes. The unobjectionable differences, e.g. contrast and detail deterioration, are more prominent than the defect present in the scanned image: a scratch artifact whose faint impression is marked by arrows, however, is visually aggregated to an objectionable artifact on the actual print. An automatic detection tool should detect the artifact, and ignore the non-artifact differences.



— (a) (b) (c) (d)

Figure 1. *Close up on originals (a: Ref, left) and scans (d:Def, right) of two images after color and position registration. Arrows point to faint scratch artifacts on Def images. The most prominent local differences are contrast and detail loss in Def. This type of scratch artifacts is so faint that you may need to look on an enlarged digital version to see the artifacts.*

The visibility of different artifacts in natural images was studied in many articles, both in the image fidelity and masking fields of research. Many fidelity approaches, e.g. [12] and [4], are based on the human visual models in the frequency domain (MTF), originally extracted for harmonic bands. Other works use similar models, were the sinusoidal basis of the frequency domain is replaced by Gabor basis [15, 20, 21] or alternative basis [2, 5, 7, 9, 11], where the weights of the different basis are determined according to an MTF function, or extracted from small scope tests. Another approach, called SSIM, is based on correlation between the image and it's distorted version [19]. An extension of those, called SPSSIM [1], identify general significant image differences between a scan and the digital reference of the scanned image. However, such a general purpose algorithm can not detect all print defects while maintaining low false alarm rate. SPSSIM detects well localized defects with high contrast, but other specific defects, e.g., bands and streaks, may appear as low contrast luminance variations that are hardly detectable with SPSSIM though significant to the human eye, see Fig. 2 for examples of printed documents that contain bands and streaks.

We propose a new defect specific detection framework, that utilizes prior knowledge on a specific defect to achieve high detection vs. false alarm rate. In the proposed framework, described in the next section, We learn models for specific print artifacts from examples. Human perception and background texture masking models define the feature layer of our approach. ASSETs are built applying machine learning modules on sets of tagged artifacts. We used the proposed framework to develop ASSETs for two print defects: First artifact is an especially faint type of a vertical scratch and the other is a specific type of a horizontal band.

Algorithm

Overview

The framework receives a training set of digital jobs that were printed, scanned and registered to align the scans to the digital reference in both color and position. We refer to the digital reference of each image as *Ref*, and to the scanned image as *Def*. The Ref and Def of each of the images in the training set are registered, to align the scans to the digital reference in both color and position. The registration process is beyond the scope of this

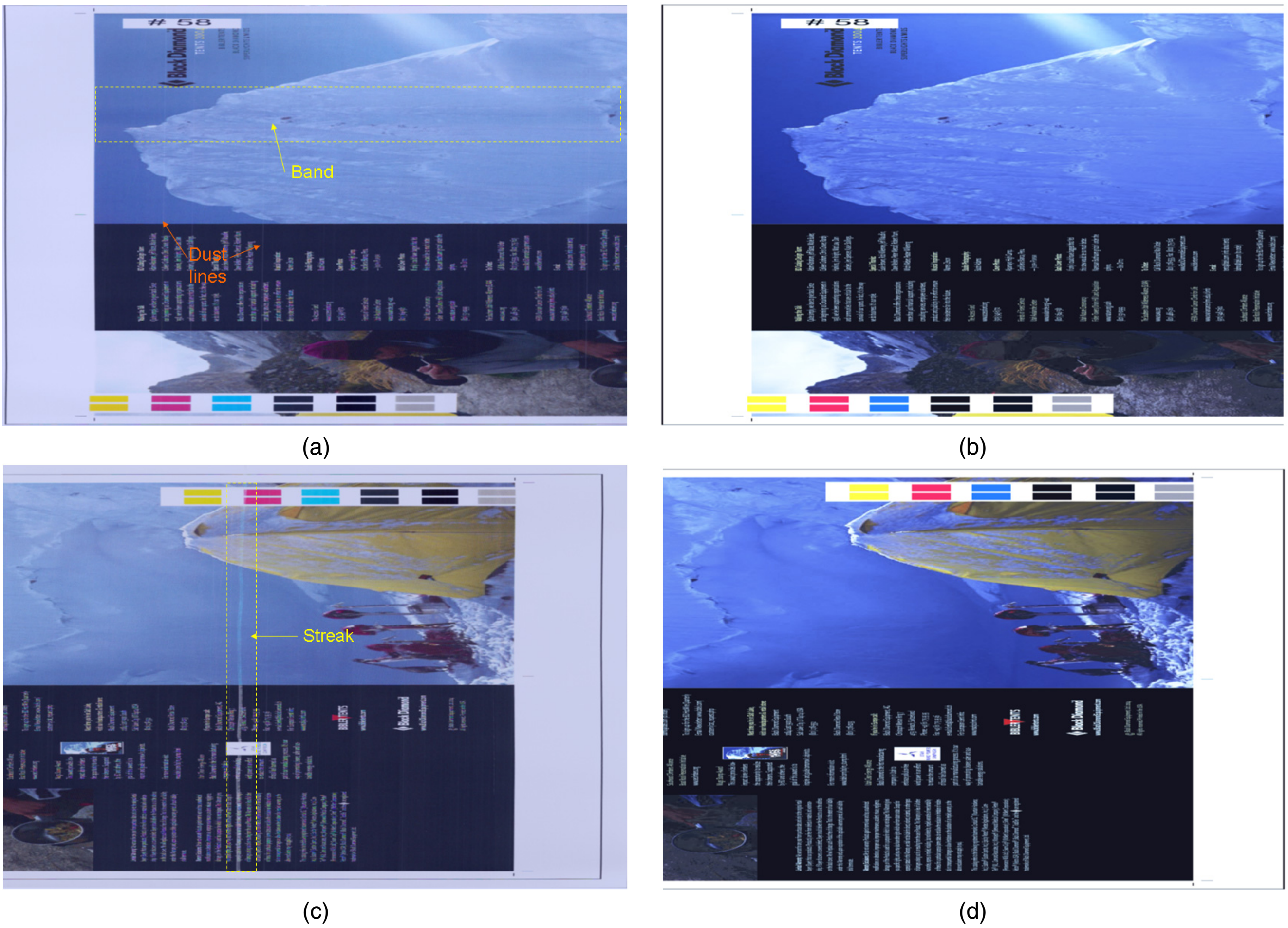


Figure 2. (a) shows a scanned document after registration which contains a band. In addition, the scanned image contains some vertical dust lines that come from the scanning process. (b) shows a digital reference of (a). (c) shows a scanned document which contains a streak and (d) shows the corresponding digital reference.

framework as the images go through several registration steps before reaching the actual defect detection stage.

The user marks the artifact of interest on the Def image, thereby separates the image into artifact regions and clear regions. Next, the training images are tiled into non-overlapping small regions, tagged as either artifact or clear. For each region, the system calculates a set of features described below, and relates them to the tagging marked by the user in the previous stage. Consequently, the system samples a small subset of regions from the training image set, and use it to learn the ASSET. The ASSET is then tested on a bigger test set of new images.

Features

The features integrate accumulative knowledge on defect detection and defect masking by the image into the proposed system. Fourteen features are calculated for each of regions. Nine of the features are basic features. Most basic features come in pairs. In each pair, one feature is calculated on the region of interest in the Ref image, denoted by r, and the other on the corresponding region in the Def image, denoted by s. The remaining features are non linear combinations of the basic features.

Basic features

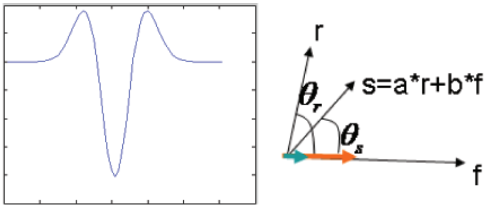
Mean gray level. Artifact is expressed via change in gray levels. Many artifacts have typical deviation towards either lighter or darker colors.

Standard deviation. Defects exist in the Def image only, hence influence the standard deviation in the Def region and differentiate it from the standard deviation in the Ref region. In addition, Standard deviation in the Ref image serves as activity measure, and high activity in the image have a significant masking effect.

Proximity to edges. Artifacts are easier to see in smooth regions, away from edges. This features is calculated on the Ref image only.

Projection. The projection of the Ref or Def region on filter f, which describes the structure of the artifact. Bands, for example, have a typical vertical cross section that looks like the second derivative of a gaussian (Fig. 3 left) [13]. We assume that f is normalized such that $\|f\| = 1$. We take the maximal value of filter response in the region, $f_s = \langle s, f\rangle$ for the Def region, and $f_r = \langle r, f\rangle$ for the Ref region, to represent structure similarity to the artifact. The Ref image contains no defects, hence artifact-like structures in the Ref image are to be expected in the non-artifact Def image, and may even reduce the visibility of an actual artifact in these regions.

Angle. The angles θ_s, θ_r, defined as in Fig. 3 right, are the normalized projection features, and reflect the correlations between r or s and f.



— (a) (b)

Figure 3. Left (a): The filter we use, which shape is a typical shape of a band. Right(b):A geometrical illustration of the specific defect detection principle.

Similarity measures

The similarity between a pair of Ref and Def features is computed by

$$\frac{2 \cdot f_r \cdot f_s}{{f_r}^2 + {f_s}^2 + C_1} \quad (1)$$

for the projection pair of features defined above, where C_1 is a small non zero constant to prevent singularity. The similarity of the angle and standard deviation pairs of features is defined in the same manner. Mean similarity in the region represents the similarity measure in the region.

Artifact detectors

If the printed page contains an artifact in the specific location of s, then s is a linear combination of r and f: $s = \alpha r + \beta f$ where $\alpha, \beta > 0$. In this case, the vectors triplet s, r and f will hold a geometric relation as illustrated in Fig. 3 right. We want to identify this situation by using a mathematical operation that gets high values only if s, r, f hold this geometrical relation. Let us define the next two terms:

projection ratio. Defined by

$$d_1 = \frac{min(f_s, kC_2)}{f_r + C_3} \quad (2)$$

where C_2,C_3 and k are predefined constants that limit the values range: $0 < d_1 < k$.

Closeness. Define as

$$d_2 = \max(|cos\theta_s| - |cos\theta_r|, 0) \quad (3)$$

where θ_s, θ_r are the angle features in the Def and Ref images.

Note that both d_1 and d_2 get higher values as s is more directed towards f then r is, which is exactly the case of an artifact that is added to the original image.

Learning method

We propose to use the Regularized Least Squares (RLS) [8] learning method, described next, to learn the ASSETs.

Each region j in the sampled learning set is represented by a feature vector $\vec{x}_j$ and a scalar tag-value y_j. We assume that the ASSET function $f(\vec{x})$ is a smooth function, and denote it's smoothness norm in a Reproducing Kernel Hilbert Space (*RKHS*) H by $\|f\|_K$. In addition we demand that the value of $f(\vec{x}_j)$ is close to the tag of this region, y_j. Eq. 4 expresses those demands.

$$\min_{f \in H} \frac{1}{l} \sum_{j=1}^{l} \left(y_j - f\left(\vec{x}_j\right)\right)^2 + \lambda \|f\|_K \quad (4)$$

were l is the number of regions in the sampled learning set. Let us consider the case were the norm $\|f\|_K^2$ is induced by a symmetric, positive definite function $K(\vec{x}, \vec{y})$. In such cases it is possible to show that the function that minimizes the functional 4 has the form:

$$f(\vec{x}) = \sum_{j=1}^{l} c_j K(\vec{x}, \vec{x}_j), \quad (5)$$

where the coefficients c_j depend on the data and satisfy the following linear system of equations:

$$(K + \lambda I)\, c = y$$

where I is the identity matrix, and we have defined

$$(y)_i = y_i, \;\; (c)_j = c_j, \;\; (K)_{ij} = K(\vec{x}_i, \vec{x}_j).$$

Filters

We use the presented approach to develop two ASSETs, listed below. Both ASSETs seek one dimensional artifacts, one is a streak artifact and the other is a band artifact.

Faint scratch

We learn a detector for faint scratches. Those scratches appear as very thin streak artifacts in the process direction: from top to bottom on figures 1 and 5. We use the approach described in this paper to learn the filter. Looking for a one dimensional artifact, we average ASSET response along the scratch direction, obtaining artifact likelihood evaluation across the print, as shown in black in Figure 5. Black line in Figure 5 demonstrate the success of the ASSET in predicting high artifact likelihood in scratch location, vs. lower scratch likelihood in non-scratch locations. We compare the results obtained using the suggested framework to the results obtained when replacing the RLS learning method with widely known Support Vector Machine (SVM) [3, 17] or Fisher Linear Discriminant(FLD) [6]. Figure 4 shows false vs. missed detections for eight test pages in all three methods. We need to identify at least one scratch on scratched regions, with no false alarms on non scratched regions. Therefore, To put all filters on equal ground, we represent each page by two values for each filter: the clear regions in the page are represented by the detector's highest response in the clear regions and the scratches in the page are represented by the detector's highest response in the artifact-tagged regions. Blue line shows the proposed ASSET. Using the best threshold the propose ASSET has two missed detections, hence it detects scratches in 6 out of 8 pages with no false alarms. The green line in Figure 4 demonstrates the results of a filter learned using SVM. This filter detects scratches in 5 out of 8 pages with no false alarms. The red line shows the results obtained using Fisher Linear Discriminant (FLD).

Paper Marks

We use the approach described in this paper to provide a real time ASSET for a band type artifact called Paper Marks. To accelerate the detector we take a subset of the features: Mean gray level and standard deviation for Ref and Def images, two projections, two similarity measures, one for the projections and one for the angles, and the two Artifact detectors. Filter tests includes 360 prints, that contained 37 strong paper mark artifacts. The Paper Marks filter detected 36 out of the 37 paper marks, with no false alarms.

Conclusions

In this paper we present a new framework for developing specific print artifact detectors and learning perceptual masking

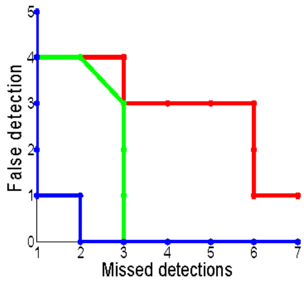


Figure 4. False detection vs. missed detections for three wiper scratches detectors: The tool developed with the proposed approach (blue), a tool learned on the same feature set using SVM(green) and using FLD(red). Both axes run from zero to eight, with no more than one false alarm and one true detection considered in each page.

models for specific print quality problem in an image. The approach combines machine learning with a set of perceptual features. The features are based on accumulative understanding of visual masking as studied in the fields of perceptual descriptors and masking. We use the RLS learning method to learn to combine the relevant features into a model that describes the visibility of the specific artifact on different image backgrounds. We use this approach to develop detectors to identify two print defects on customer jobs. Successful tests of the detectors obtained by the framework on a new set of samples implies that the underling model describes the way people perceive this artifact on different backgrounds. Those successful tests supports the hope that gaining understanding of the perceptual masking models of several artifacts can lead to generalization of those models to a general perceptual masking model.

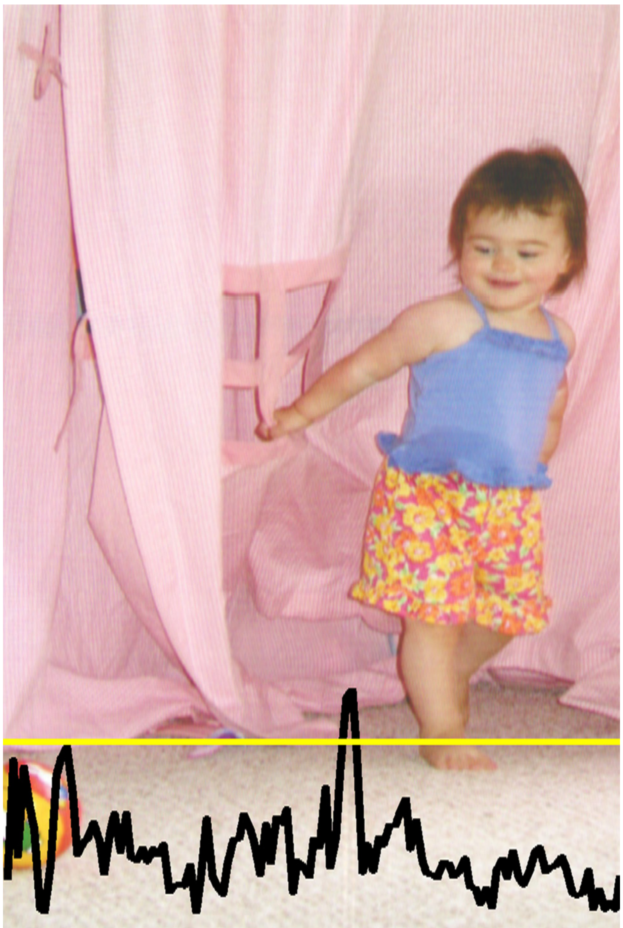


Figure 5. Black line on top of the Def image is wiper scratch likelihood according to the proposed ASSET. The proposed ASSET finds the wiper scratches, which are brought in close up in Figure 1, despite of the similar misleading structures in the image.

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