A MUTUAL INFORMATION BASED AUTOMATIC REGISTRATION AND ANALYSIS ALGORITHM FOR DEFECT IDENTIFICATION IN PRINTED DOCUMENTS

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ABSTRACT

In this paper, we propose a defect analysis system, which automatically aligns a digitized copy of a printed output to a reference electronic original and subsequently illustrates potential image quality artifacts. We focus on image defects or artifacts caused by shortfalls in mechanical or electro-photographic processes. In this method, log-polar transform and mutual information techniques are used for image registration. A confidence map is then calculated by comparing the contrast and entropy of the neighborhood for each pixel in both images. This confidence map results in a qualitative difference between printed documents and electronic originals. The algorithm was demonstrated successfully on a database of 94 images with 95.7% accuracy.

Index Terms— Automation, Image Registration, Image Analysis, Printers, Quality Assurance.

1. INTRODUCTION

Current print environments utilize trained Quality Assurance Personnel (QAP) to visually inspect a subset of the output documents in order to ensure that customer hardcopies are free of defects. The QAPs are trained to spot defects like deletion, streaks, Debris-Centered Deletion (DCD), etc. and render an initial classification. This process is generally prone to errors, oversights and subjective judgments. To minimize these problems, an automated defect analysis system is essential. Such a system will help the QAP to quickly and objectively locate and classify the defects with the aid of a scanner and thereby select the proper diagnostic procedure in an automated fashion in order to render corrective action as swiftly as possible to minimize downtime and lost revenue. This system should not only be user friendly and compatible for commercial use but also be completely confident of its results.

Many automated image analysis systems were proposed in the past. These were designed either for specific printer types or restricted only to print labs and research facilities due to the requirement of special hardware. In [1], such a system was developed to analyze the quality produced by any print technology. However, it is limited to samples of different size for a specifically designed image known as "golden template" and requires additional hardware for analysis. Other systems [2] that were proposed to analyze the quality of printers in the perspective of dot size, dot location, optical density etc., are used only in development and research studies.

In this paper, we propose an automated defect detection algorithm to analyze and compare a printed output (digitized by an online scanner) to an electronic image irrespective of color, illumination, orientation and scale differences between them. The algorithm (see Fig. 1 for a block diagram) is designed to localize the defects and illustrate the region of interest. The outcome is utilized as input to the artifact classification algorithms developed in [3, 4], where the defect is classified and corrective measures are suggested. A test target is scanned and registered to an electronic image by the proposed registration algorithm. The input images are converted into L*a*b* color space and transformed into a single channel using principal component analysis [5]. Once the images have been aligned, we compute a contrast map using a Contrast Comparison Function (CCF) as explained in [6] and calculate the corresponding entropy. This provides a confidence level for each pixel.

The remainder of the paper is organized as follows: Section 2 outlines the image registration process. Section 3 introduces the defect analysis algorithm. Experimental results are presented and discussed in Section 4. Conclusions are drawn in Section 5.

2. PROPOSED REGISTRATION ALGORITHM

Image registration is a process where two images are aligned using optimal transformation parameters. Many unsupervised registration methods have been proposed and a survey can be found in [7]. In order to obtain high precision, it is important to use a technique that produces accurate transformation parameters. Results in [8] demonstrate that Maximization of Mutual Information (MMI) produces consistently sharper peaks of similarity measure at correct transformation values than correlation. Therefore, we consider an image registration algorithm by optimizing

Mutual Information (MI) using a stochastic gradient search strategy as discussed in [9]. However, the technique in [9] is effective only when the two images are misaligned by a marginal difference in affine parameters. To overcome this limitation, a log-polar registration technique [10] is first utilized to provide an initial estimate to marginally align the images followed by an MMI based approach. This proposed hybrid approach yields better results than the two approaches used independently. Hence, our proposed registration algorithm consists of two modules: log-polar registration followed by MMI registration algorithm. These are discussed in detail below.

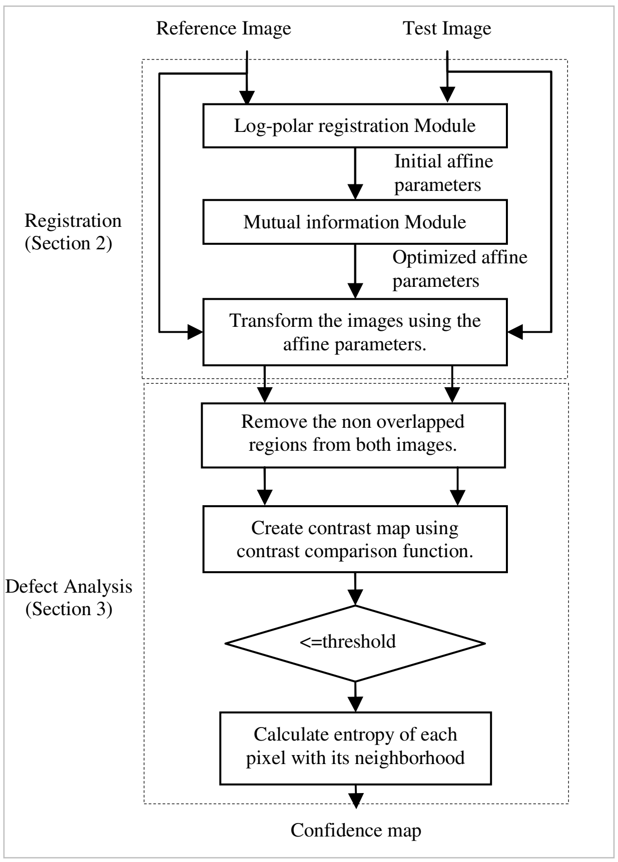

Fig. 1: Block Diagram of the proposed automatic defect detection algorithm.

2.1. Log-polar registration

Fig. 2 depicts the flow diagram of the log-polar registration module. This algorithm is based on the Fourier shift theorem. Let $I_1(m,n)$ and $I_2(m,n)$ represent, in this respect, the electronic image and test image which is a digitized print output, that differ by a shift (x_0,y_0). Their Fourier transforms F_1 and F_2 are related as:

$$F_2(u,v) = e^{-j2\pi(\mu x_0 + v y_0)} F_1(u,v) \tag{1}$$

A high pass filter is then applied to the magnitude of F_1 and F_2 to minimize the impact of the low frequency components. The resulting values are transformed from rectangular to log-polar coordinates, where the cross-power spectrum (R) of the two log-polar images with their Fourier transforms is computed as follows:

$$R = \frac{F(u,v) \bullet \hat{F}(u,v)}{\left|F(u,v)\right|\left|\hat{F}(u,v)\right|} \tag{2}$$

The Fourier shift theorem guarantees that the phase of the cross-power spectrum is equivalent to the phase difference between the images. Inverse Fourier transform of R, results in a function that is zero everywhere except for a small neighborhood around a single maximum value. The location of this maximum value $(\log(\rho),\theta)$ is used to calculate the angle and scale parameters as:

$$(Scale,\ Angle) = (10^{\log 10(\rho)}, (\theta) * 360 / C_L) \tag{3}$$

where, C_L is the number of columns in the log-polar space. Once, I_2 has been transformed using the resulting scale and angle parameters, we calculate the shift (dx,dy) in rectangular coordinates using the same Fourier shift theorem. This technique yields robust affine parameters that serve as an effective initial estimate for the subsequent registration module.

2.2. Registration using Mutual Information (MI)

In the context of image registration, the MI of two images is maximal when they are perfectly aligned. MI is calculated as follows:

$$MI(I_1, I_2) = H(I_1) + H(I_2) - H(I_1, I_2) \tag{4}$$

where $H(I_1)$, $H(I_2)$ are the entropy of images I_1, I_2 respectively and $H(I_1, I_2)$ is their joint entropy.

The optimization technique utilized in this work is based on the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm [11]. This algorithm uses only two measurements of a loss function and a random perturbation to estimate the corresponding gradient. As such, it does not rely on explicit calculations or measurements of gradient of the loss function. Let L be the objective or loss function to be optimized (i.e. the MI). The initial estimate for the iterative technique is obtained from the output values of the log-polar registration module. At any iteration k, the update law for the parameters is given by the steepest ascent estimate as:

$$\theta_{k+1} = \theta_k + a_k g_k \tag{5}$$

where the gradient vector $g_k = [g_k{}^1 g_k{}^2 .....g_k{}^m]$ for the m-dimensional parameter space is determined by:

$$g_k{}^i = \{L(\theta_k + c_k\Delta_k) - L(\theta_k - c_k\Delta_k)\} / \{2c_k\Delta_k{}^i\} \tag{6}$$

for $i=1,2,....m$. Each element in m-dimensional Δ_k is either +1 or -1, as generated by a Bernoulli distribution. The gain sequences a_k and c_k are:

$$a_k = \frac{a}{(k+A+1)^{\alpha}} \quad \& \quad c_k = \frac{c}{(k+1)^{\gamma}} \tag{7}$$

where, a, c and A are constants. The exponents α, γ control the speed of convergence.

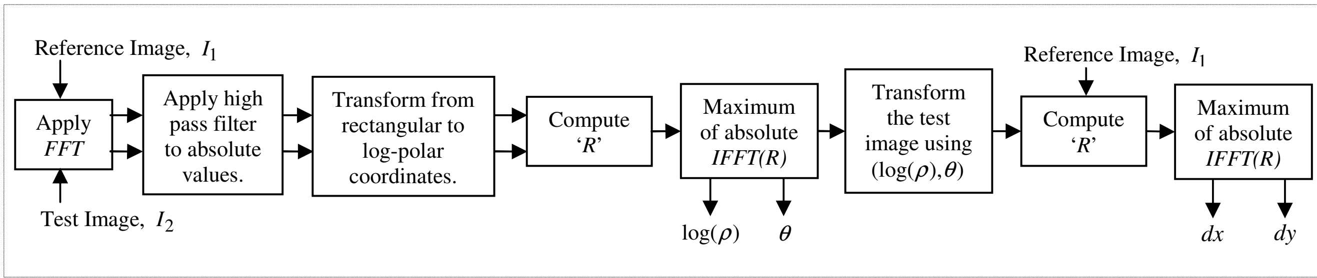

Fig. 2: Block Diagram of Log-polar registration module.

3. PROPOSED DEFECT ANALYSIS

Once the two images have been registered using our hybrid registration algorithm, we proceed to identify the spatial location of artifacts in the digitized hardcopy using a contract comparison metric. Our proposed approach provides an effective metric for automatic defect analysis between a reference image and its corresponding digitized output independent of luminance and color variations. This is done in a localized sense yielding a spatially varying quality map of the image that clearly highlights the location of potential artifacts. The contrast comparison function and the generation of the confidence map are discussed below.

Luminance of any surface being observed is a product of its illumination and reflectance. The major impact of illumination changes in the image is the variation of the average luminance and contrast. In our work, we compute the Contrast Comparison Function (CCF) in a localized sense on a block by block basis as follows:

$$CCF(x,y) = \frac{2\sigma_1\sigma_2 + \lambda}{\sigma_1^2 + \sigma_2^2 + \lambda} \qquad (8)$$

where, σ_1, σ_2 are the local standard deviation of the pixels in a specified neighborhood of (x, y) and λ is a non-negative constant included to avoid instability when $\sigma_1^2 + \sigma_2^2$ is very close to zero and is calculated as follows:

$$\lambda = (KM)^2 \qquad K << 1 \qquad (9)$$

where M is the dynamic range of the pixel values. The contrast map is calculated on the area where both images overlap. A CCF threshold image is then computed for those pixels that correspond to lesser than 10% of contrast map.

Entropy of a discrete random variable with a probability mass function $p(x)$ is defined as:

$$H(X) = -\sum_{x\in\Re} p(x)\log p(x) \qquad (10)$$

This entropy for each pixel within a specified neighborhood is calculated yielding a confidence level of the presence of the defect for each pixel. The confidence level assigned to each pixel in the confidence map is employed to select the region of interest(s).

The registration algorithm discussed in the previous section may result in one or two pixel error, but calculation of local entropy over the contrast image assigns a confidence level to each pixel irrespective of that error.

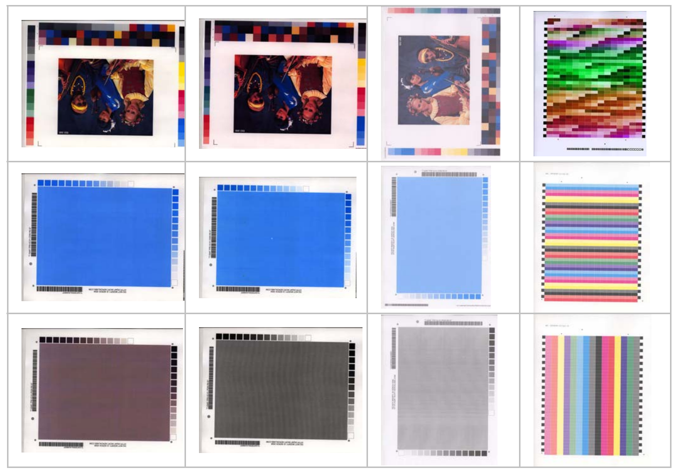

Fig. 3: Samples of digitized print outputs.

4. EXPERIMENTAL RESULTS

The proposed algorithm was tested on a database of 94 images provided by Xerox Corporation. In each test set, we have a reference image in L*a*b* color space which is free of defects and the corresponding halftone printed hardcopies with potential artifacts that are subsequently scanned at 600 dpi and converted to L*a*b* (see Fig. 3 for a subset of the images). The steps of the algorithm are illustrated in Fig. 4. In particular, we show: 1) the reference image (Fig. 4a), 2) the corresponding digitized printer output (Fig. 4b), 3) the transformed image after registration (Fig. 4c), 4) the contrast comparison image (Fig. 4d), 5) the CCF threshold image (Fig. 4e), 6) the confidence map (Fig. 4f), and 7) the defects in Fig. 4b (Fig. 4g-4j). Note the significant differences between Figs. 4a and 4b in terms of orientation and content. The defects in Fig. 4b are zoomed and shown in Figs. 4g-4j.

The size of rectangular grid used to transform the magnitude spectrum from rectangular to log-polar coordinates is 256x256. While optimizing the MI, 64 bins instead of 256 bins are used to compute the histogram in order to yield a smoother MI surface. The parameters used for the SPSA search algorithm are: $\alpha = 0.602$, $\gamma = 0.101$, A = 100, c = 0.5 and a = 12. The size of neighborhood window used for calculation of the contrast map and entropy is 3x3. Our algorithm accurately registered the images shown in Fig. 4 and provided a corresponding confidence map for the output where the differences are clearly highlighted in "false" coloring (see Fig. 4f similar results are also observed for all the images in the database, where all defects are clearly identified and labeled. The proposed algorithm yields 95.7% accuracy in aligning and detecting the defects among the test database. The failure modes include images that have been printed with a "low toner" condition resulting in a low contrast scenario.

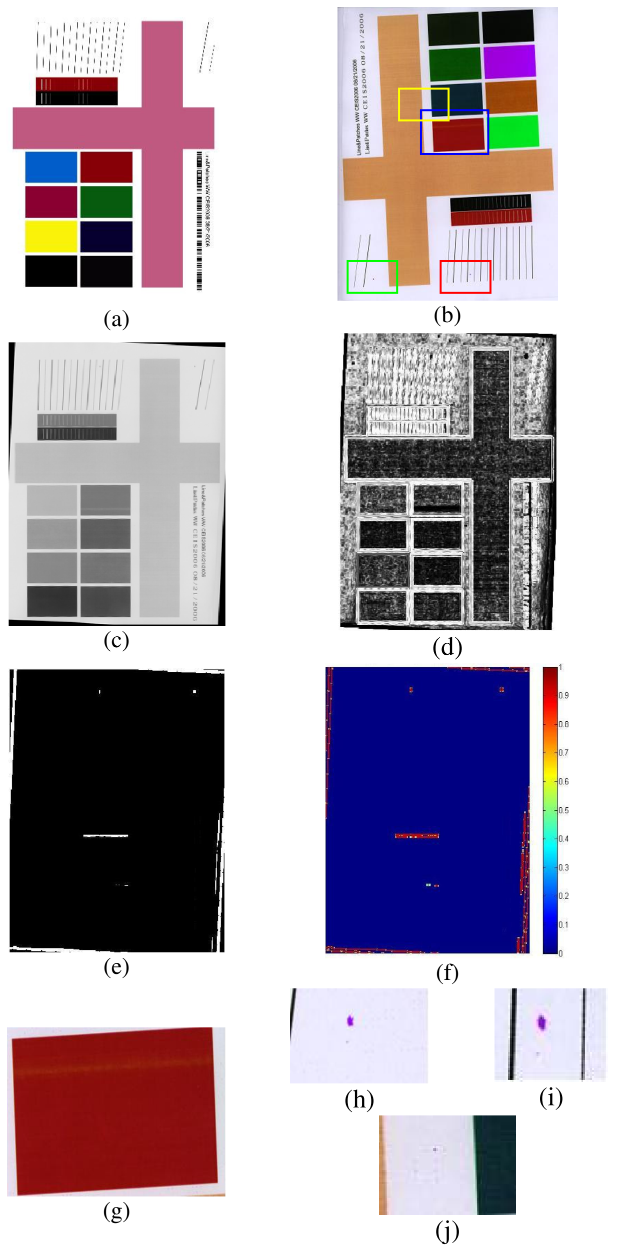

Fig. 4: Results for Line & patches (a) Reference Image, (b) Digitized printer output, (c) Transformed image after registration, (d) Contrast map, (e) CCF Threshold image, (f) Confidence map, (g) Defect in (b) with blue box, (h) Defect in (b) with green box, (i) Defect in (b) with red box, (j) Defect in (b) with yellow box.

5. CONCLUSIONS

This paper describes an automatic mutual information based defect localization algorithm capable of aligning reference electronic originals with their corresponding printed and subsequently digitized hardcopies. The proposed algorithm was demonstrated on a large database of images with pertinent results. It was shown to be very effective in registering electronic images with noisy halftone prints independent of translations, rotations, scale/zoom changes, color variations and illumination changes that may arise while printing in electrophotographic processes. Extreme and rare cases that contain significant image shear are not currently handled by our technique and stand beyond the scope of this work.

6. ACKNOWLEDGEMENT

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7. REFERENCES

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