ESTIMATION OF MORPHOLOGICAL DEGRADATION MODEL PARAMETERS

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ABSTRACT

Noise models are crucial for designing image restoration algorithms, generating synthetic training data, and predicting algorithm performance. However, to accomplish any of these tasks, an estimate of the degradation model parameters is essential. In this paper we describe a parameter estimation algorithm for a morphological, binary image degradation model. Inputs to the estimation algorithm are the ideal and degraded images. We search for the optimal parameter by looking for a parameter value for which the corresponding noise pattern distribution in the simulated image and the given degraded image are most similar. The parameter space is searched using the downhill simplex algorithm of Nelder and Mead. We use the p-value of the Kolmogorov-Smirnov test of difference between the two pattern distributions as the objective function value. We show results of applying our algorithm on document images.

Keywords: *document degradation models, model validation, parameter estimation, Nelder-Mead, simplex, optimization, Kolmogorov-Smirnov, mathematical morphology.*

1. INTRODUCTION

There are numerous document image degradation models that have been proposed in the literature [7, 8, 1]. However, prior to using these models, it is important to i) validate the models — that is verify that the simulations generated by these models are similar to real world examples, and ii) provide algorithms for estimating the model parameters from real samples. The issue of validation was address by Kanungo *et al.* [6, 5] by converting the validation problem into a hypothesis testing problem and then using a permutation test to test the null hypothesis that a synthetic sample of degraded characters and another sample of real sample of degraded characters come from the same underlying distribution. Lopresti *et al.* [9] instead proposed to study the differences in the error characteristics of the OCR output for the real and synthetic samples. This method, however, considers the degradation coupled with the OCR system and not just the degradation process.

The issue of model parameter estimation has been studied to a lesser extent. Kanungo and Haralick [4] reported results of some preliminary experiments that they conducted to estimate the degradation model parameters using an objective function based on the power function. They assumed that that an ideal document image and the corresponding degraded image were given. Baird [2] used the same power function approach to estimate the parameters of another physics-based degradation model and Sural and Das [12] estimated the parameters of a two-state Markov chain document degradation model using the power function approach. The drawback of all the above estimation approaches is that they assume that the degraded image and the ideal image are perfectly aligned and that the character level geometric groundtruth (bounding boxes) is available. This, however, is a not easy to achieve since pixel-level alignment of documents with arbitrary warping present due to changes in printer and scanner speeds, is difficult.

In this paper we propose a parameter estimation algorithm that does not require the degraded and ideal images to be aligned and does not require character-level geometric groundtruth either. The algorithm is based on computing differences between distribution of local patterns in the degraded and synthetic images. In Section 2 we describe our document degradation model. We outline the estimation algorithm in Section 3 and provide simulation results in Section 4.

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2. THE MORPHOLOGICAL DOCUMENT DEGRADATION MODEL

In this section we briefly describe a document degradation model for the local degradation that are introduced when documents are printed, scanned and digitized[7, 8, 5].

The model accounts for (i) the pixel inversion (from foreground to background and vice-versa) that occurs independently at each pixel due to light intensity fluctuations, pixel sensitivity, and thresholding level, and (ii) the blurring that occurs due to the point-spread function of the optical system of the scanner. We model the probability of a background pixel flipping as an exponential function of its distance from the nearest boundary pixel. The parameter α_0 is the initial value for the exponential and the decay speed of the exponential is controlled by the parameter α. The foreground and background 4-neighbor distance are computed using a standard distance transform algorithm [3] . The flipping probabilities of the foreground pixels are similarly controlled by β_0 and β. The parameter η is the constant probability of flipping for all pixels. Finally, the last parameter k, which is the size of the disk used in the morphological closing operation [3], accounts for the correlation introduced by the point-spread function of the optical system.

The degradation model thus has six parameters: $\Theta = (\eta, \alpha_0, \alpha, \beta_0, \beta, k)$. These parameters are used to degrade an ideal binary image as follows:

1. Compute the distance d of each pixel from the character boundary.
2. Flip each foreground pixel with probability $p(0|1, d, \alpha_0, \alpha) = \alpha_0 e^{-\alpha d^2} + \eta$.
3. Flip each background pixel with probability $p(1|0, d, \beta_0, \beta) = \beta_0 e^{-\beta d^2} + \eta$.
4. Perform a morphological closing operation with a disk structuring element of diameter k.

The application of the various steps of the model is illustrated in Figure 1. The procedure described above works on bit-mapped images. Since there is no restriction on the size of the image that can be degraded, or the language of the written text, an entire document page image can be degraded using this model.

3. THE ESTIMATION ALGORITHM

Our estimation algorithm is based on the assumption that if the degradation parameters are estimated correctly, the local degradations in simulated image generated using the estimated parameters will look similar to that of the real image. The way we capture this fact

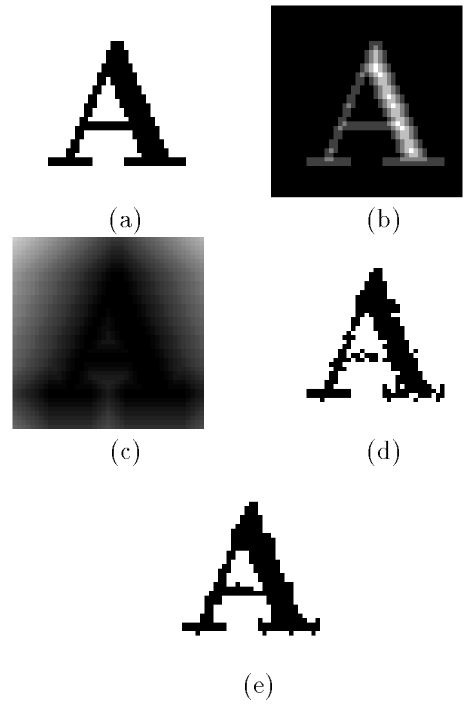

Fig. 1. Local document degradation model: (a) Ideal noise-free character; (b) Distance transform of the foreground; (c) Distance transform of the background; (d) Result of the random pixel-flipping process (the probability of a pixel flipping is $p(0|d, \beta, f) = p(1|d, \alpha, b) = \alpha_0 e^{-\alpha d^2}$; here $\alpha = \beta = 2$, $\alpha_0 = \beta_0 = 1$); (e) Morphological closing of the result in (d) by a 2×2 binary structuring element.

is by looking at the distribution of the neighborhood patterns.

Let P be a set of neighborhood bit patterns and p be an arbitrary element in the set P. For example, p could be a 3×3 neighborhood with all 1s, or it could be a 5×5 neighborhood with a 1 in the middle and 0s everywhere else. Now we define pattern distribution of an image R. Let H_R denote a pattern distribution so that $H_R(p)$ where $p \in P$ is the number of times the pattern p occurs in the binary image R. Using mathematical morphology [3] we can define $H_R(p)$ quantity more precisely: $H_R(p) = \#\{R \ominus p\}$.

Now let I be the ideal image and R be the given degraded image. The problem is to estimate the model parameter θ such that if we degrade I with the model with parameter fixed at θ, we will get an image S_θ that looks similar to R. For our purposes, we say that two images R and S are similar if the corresponding pattern distributions H_R and H_{S_θ} are similar. We use Kolmogorov-Smirnov test [10] to test the similarity of the two pattern distributions. Finally, let $KS(H_R, H_{S_\theta})$ denote the KS test p-value for the null hypothesis that the two distributions are same. We will use this p-value as the objective function that the estimation process tries to maximize. That is,

$$\hat{\theta} = \max_{\theta} KS(H_R, H_{S_\theta}). \quad (1)$$

Notice that S_θ is computed by simulation. Thus derivatives of the objective function cannot be computed in closed form. Hence, standard derivative approaches to maximizing KS are not possible. Thus we use the Nelder-Mead derivative-free optimization algorithm [11] to maximizing KS. Furthermore, there is no reason to believe that KS is unimodal over the model parameter space and so the Nelder-Mead algorithm provides us with a local maximum. To circumvent this problem we do multiple random starts and then pick the optimal solution corresponding to the highest optimal value.

4. PROTOCOL AND RESULTS

We start with a 400×400 ideal binary image I shown in Figure 2(a). The given degraded image R, shown in Figure 2(b) was created using the model parameter $\theta = (0.0, 0.6, 1.5, 0.8, 2.0, 3)$. The pattern set P was chosen to be all the possible binary patterns in a 3×3 window. Thus P has 512 patterns. The pattern histogram corresponding to Figure 2(a)-(c) is shown in Figure 3(a)-(c). Notice that some patterns occur more frequently than others, and that the distributions of the ideal and degraded images are different. The search was done for $\alpha_0, \alpha, \beta_0, \beta$; and η and k were assumed known. The Nelder-Mead algorithm was started 10 times with random start locations. The objective function value (1 - pvalue) is plotted as a function of iterations in Figure 4. The best optimal solution is found to be $\hat{\theta} = (0.0, 0.64, 1.57, 0.96, 2.02, 3)$, in Figure 2(c) we show the image $R_{\hat{\theta}}$ generated using the optimal solution $\hat{\theta}$. Notice that the pattern histogram corresponding to the estimated image, which shown in Figure 3(c), is quite similar to histogram of the original degraded image shown in Figure 3(b).

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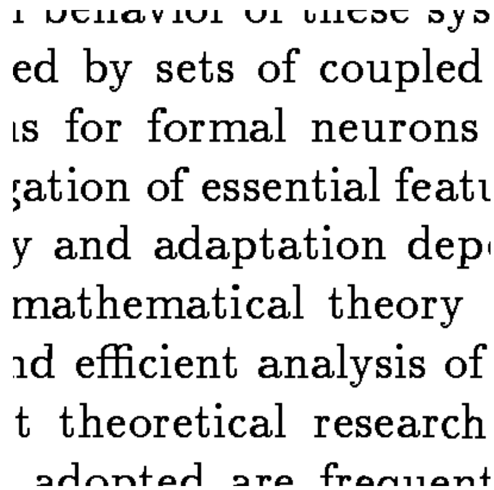
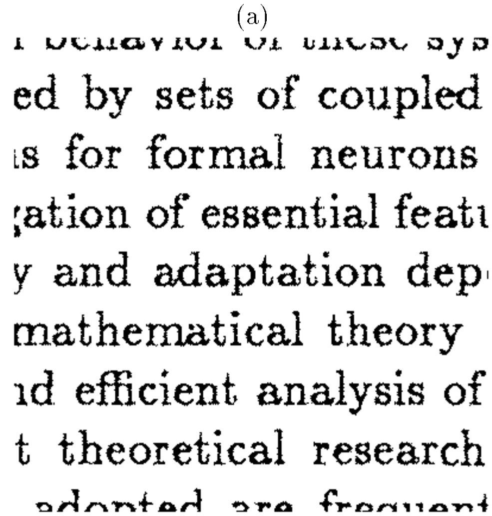
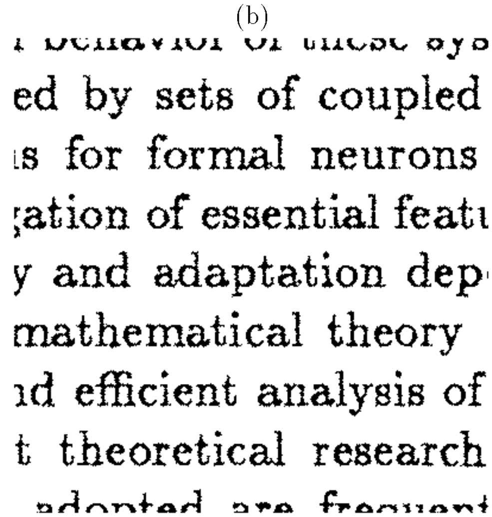


(a)

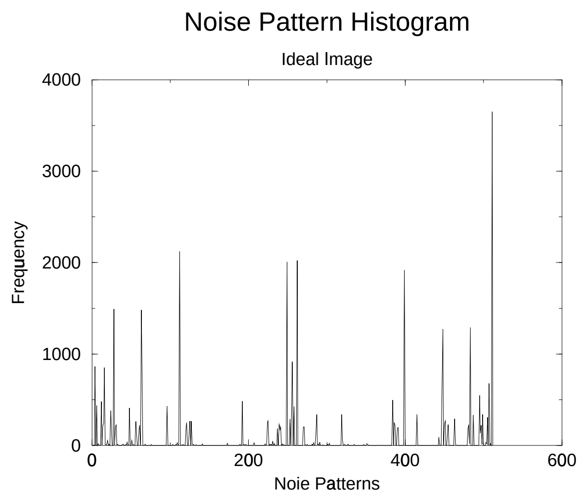


(b)

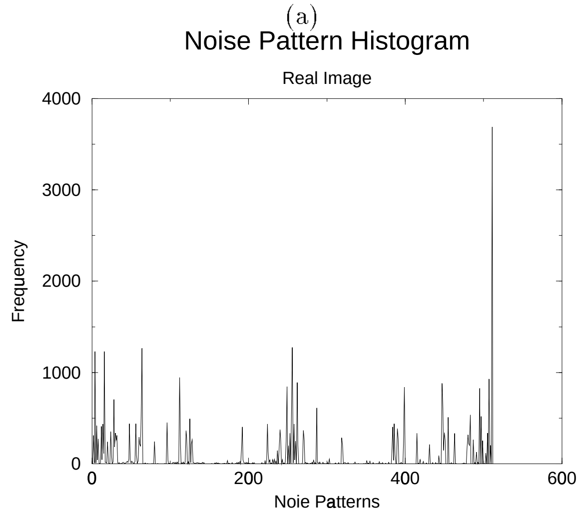


(c)

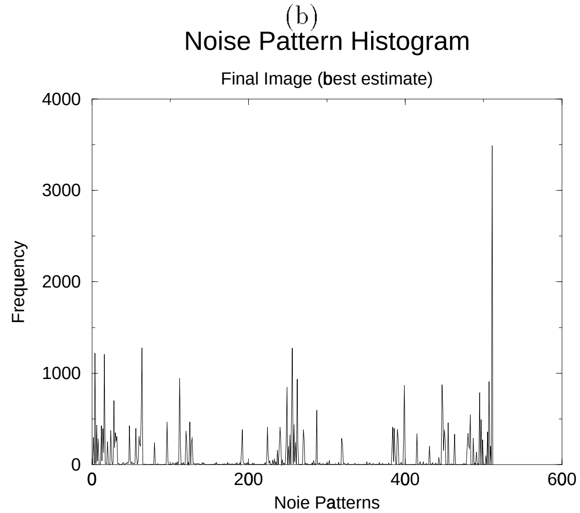
Fig. 2. (a) An typical ideal image; (b) A degraded image with parameters $(0.0, 0.6, 1.5, 0.8, 2.0, 3)$; (c) Image generated using the estimated parameter $(0.00.64, 1.57, 0.96, 2.02, 3)$.



(a)



(b)



(c)

Fig. 3. Noise pattern distributions corresponding to Figure 2(a)-(c). Each bin along the x-axis corresponds to a different 3×3 point pattern.

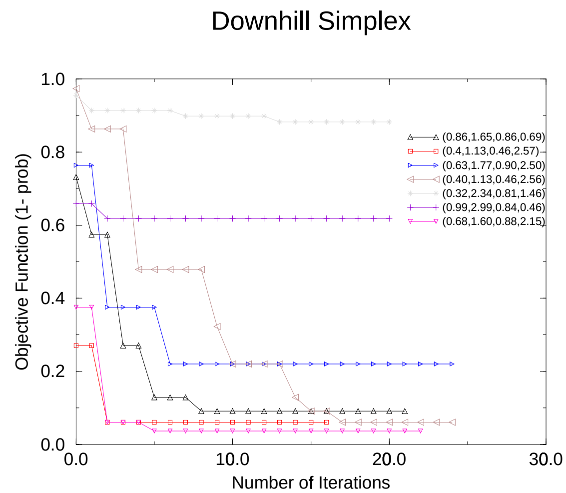


Fig. 4. Downhill simplex convergence for different (random) starting locations.

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