Wavelet-Based Document Enhancement

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Abstract

We present in this paper a new system to segment and label document images by combining statistical and multiscale view of different image components. Texture of text, halftone and images are characterized by modeling the distribution of the wavelet detail coefficients using a mixture of k Gaussians. Model parameters are then estimated using the expectation maximization (EM) algorithm. Using the proposed alogrithm, halftone areas were succefully differentiated from text regions

1. Introduction

Digital copying, in which a digital image is obtained from a scanning device and then printed, involves a variety of inherent factors that compromise image quality. Ordered halftone patterns in the original document interact with the periodic sampling of the scanner, producing objectionable moiré patterns. These are exacerbated when the copy is reprinted with an ordered halftone pattern. In addition, limited scan resolution blurs edges, degrading the appearance of detail such as text. Fine detail also suffers from flare, caused by the reflection and scattering of light from the scanner's illumination source. Flare blends together nearby colors, blurring the high-frequency content of the document.

To suppress moiré, a filter may be constructed that is customized to the frequencies of interest. However, both the detection of the input halftone frequencies and the frequency-domain filtering itself can require significant computational effort. Although crude, a simple, small low-pass filter can correct the majority of moiré artifacts. Unfortunately, low-pass filtering affects detail as well, blurring it even further.

Sharpening improves the appearance of text and fine detail, countering the effects of limited scan resolution and flare. Edges become clear and distinct. Of course, other artifacts such as noise and moiré become sharper as well. The solution is simple in concept: determine the content of regions within the scanned image and then apply the appropriate filter to each region. Sharpening should be performed on fine detail, while moiré suppression should be applied to certain periodic artifacts.

From the above discussion, we can conclude that for an image enhancement system to work properly, a preprocessing step should include a segmentation of the document into text, halftone and background. If this step is successfully completed, the application of an appropriate filter should be straightforward.

Several approaches for document segmentation have been proposed [3]-[8]. These techniques can be broadly classified as bottom-up or top-down. Bottom-up methods start from the pixel level and merge regions together into larger and larger components. Top-down techniques apply a priori knowledge about the page to hypothesize and split the page into blocks which are subsequently identified and further subdivided. Top-down approaches work well with pre-specified layouts such as technical papers. However, the performance of these techniques degrades significantly when different components are touching or overlapping. Among bottom-up approaches, texture-based schemes have attracted much attention [6]-[8].

These methods treat different components of a document image as different textures. The scanned document images are convolved with a set of masks to generate feature vectors. Each feature vector is then classified into different classes using a pre-trained classifier. One problem associated with these approaches is the mask size for extracting local features. If the mask size is too small, it is difficult to detect large scale textures such as large fonts. On the contrary, if a large mask is chosen, the computational complexity will increase dramatically [8].

In this paper, we propose a simple document segmentation technique that involves extracting discriminating features and clustering them into different regions using the Expectation-Maximization (EM) algorithm.

2. The Wavelet Representation

The 2D discrete wavelet representation is computed by applying a seperable filter bank to the image $f(x, y)$

$$W_\phi(j_0, m, n) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\phi_{j_0,m,n}(x, y) \tag{1}$$

$$W_\psi^i(j, m, n) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\psi_{j,m,n}^i(x, y) \tag{2}$$

where j_0 is an arbitrary starting scale. ϕ and ψ are a low and bandpass filter respectively.

$$\phi(x, y) = \phi(x)\phi(y) \tag{3}$$

$$\psi^H(x, y) = \psi(x)\phi(y) \tag{4}$$

$$\psi^V(x, y) = \phi(x)\psi(y) \tag{5}$$

$$\psi^D(x, y) = \psi(x)\psi(y) \tag{6}$$

$W_\phi(j_0, m, n)$ coefficients define an approximation of $f(x, y)$ at scale j_0. The $W_\psi^i(j, m, n)$ coefficients add horizontal (H), vertical (V), and diagonal D details for scales $j \geq j_o$.

In this paper, the discriminating feature vector at every pixel was chosen to be the value of the detailed coefficient at different scales.

2.1. Image Segmentation

In order to segment the image, we model the joint feature distribution with a mixture of Gaussians. We use the Expectation-Maximization (EM) algorithm to estimate the parameters of this model. The EM algorithm is used for finding maximum likelihood parameter estimates when there is missing or incomplete data. In our case, the missing data is the gaussian cluster to which the points in the feature space belong [9].

Assuming that we use C clusters in the mixture model, then the joint distribution can be modeled as

$$p(y/\Theta) = \sum_{i=1}^{C} p(y, \theta_i) = \sum_{i=1}^{C} \pi_i p(y|\theta_i), \tag{7}$$

where y is the feature vector, π_i represents the weight of the i-th mixture, and

$$p(y|\theta_i) = \frac{1}{(2\pi)^{d/2} \, det \, \Sigma_i^{1/2}} exp[-\frac{1}{2}(y - \mu_i)^T \Sigma_i^{-1}(y - \mu_i)], \tag{8}$$

where μ_i and Σ_i are the mean and the covariance matrix for the i-th class.

2.2. Parameter Estimation

The EM algorithm to cluster N feature vectors iterates as follows:

1 **The E-step**: For every pixel at location t, $1 \leq t \leq N$, compute δ_{it} as

$$\delta_{it}^k = \frac{\pi_i^k p(y_t|\Theta_i^k, C_i)}{\sum_{l=1}^m \pi_l^k p(y_t|\Theta_l^k, C_l)} \tag{9}$$

where y_t is the feature vector at location t , $\pi_i^k$is the mixing proportion of the i-th mixture at step k, and Θ_i^k is estimated parameter for the i-th mixture at step k.

2 **The M-step**:we compute the new mean, the new variance and the new proportion from the following equation:

$$\pi_i^{k+1} = \frac{1}{N} \sum_{t=1}^{N} \delta_{it} \tag{10}$$

$$\mu_i^{k+1} = \frac{\sum_{t=1}^N \delta_{ti}^k y_t}{\sum_{l=1}^C \delta_{tl}^k} \tag{11}$$

$$\Sigma_i^{k+1} = \frac{\sum_{t=1}^N \delta_{tl}^k (y_t - \mu_i^k)(y_t - \mu_i^k)^T}{\sum_{l=1}^C \delta_{tl}^k} \tag{12}$$

3 Repeat steps 1 and 2 until the relative difference of the subsequent values of Eq. 10, Eq. 11, and Eq. 12 are sufficiently small.

3. Results

We tested our algorithm with several images scanned at 600 dpi. Each pixel was assigned a feature vector using a 5×5 window. As shown in Figures 1 and 2, the feature modeling step was performed using a mixture of 4 Gaussians. The parameters were estimated using the EM algorithm as described in section 2.2. Figures 1 and 2 show the original histogram of the features, their mixing components and the the final modeling. Once the modeling step is performed, document pixels are assigned to one of three classes: text, images, and background. Figures 3 and 4 illustrate such operation on two different scans. Figure 4 was further postprocessed to remove segmentation outliers.

4. Conclusions

In this paper, we presented a new technique to segment document images. With this technique, each pixel is assigned a feature pattern. The invariant feature pattern is then assigned to a specific region using the Expectation-Maximization algorithm. Once the segmentation step is performed, specific filters and interpolation functions can be applied to each document component.

Future work will seek the incorporation of an image modeling technique such as Markov random Field (MRF) to model spatial interactions between pixels. Such modeling should produce a segmentation that is more robut to noise.

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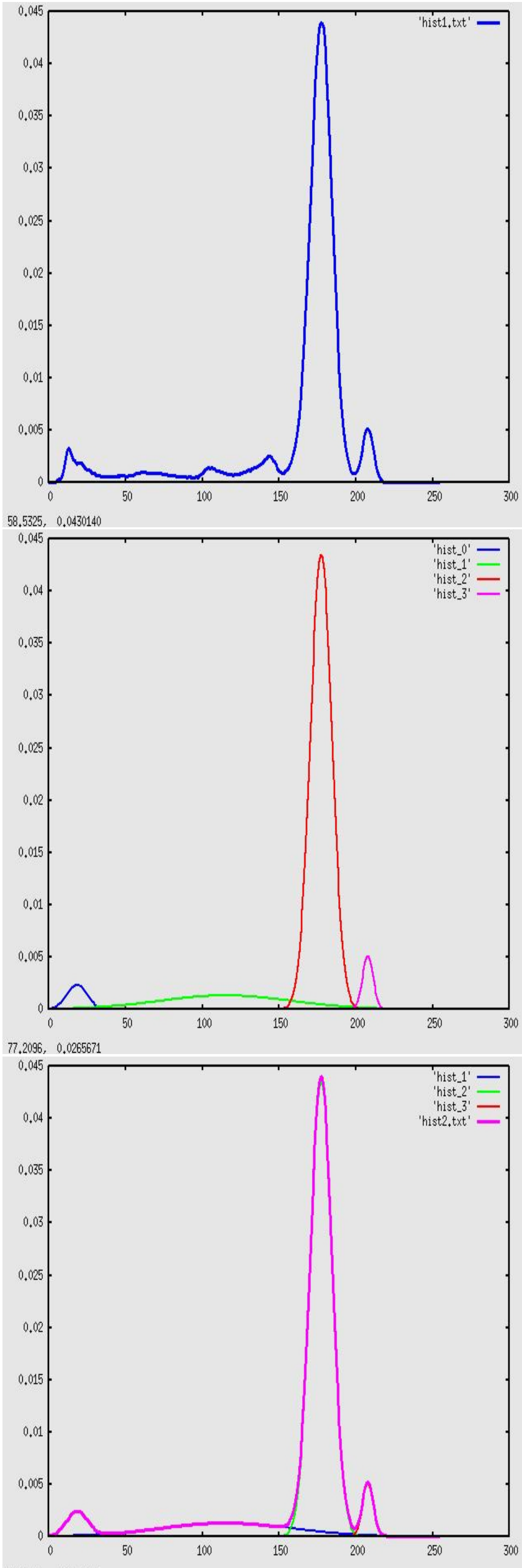

Figure 1: Example of the histogram of the detail feature at level 1 and its modeling using 4 gaussian mixtures. Middle figure shows the different components and Bottom figure shows their combination to model the histogram.

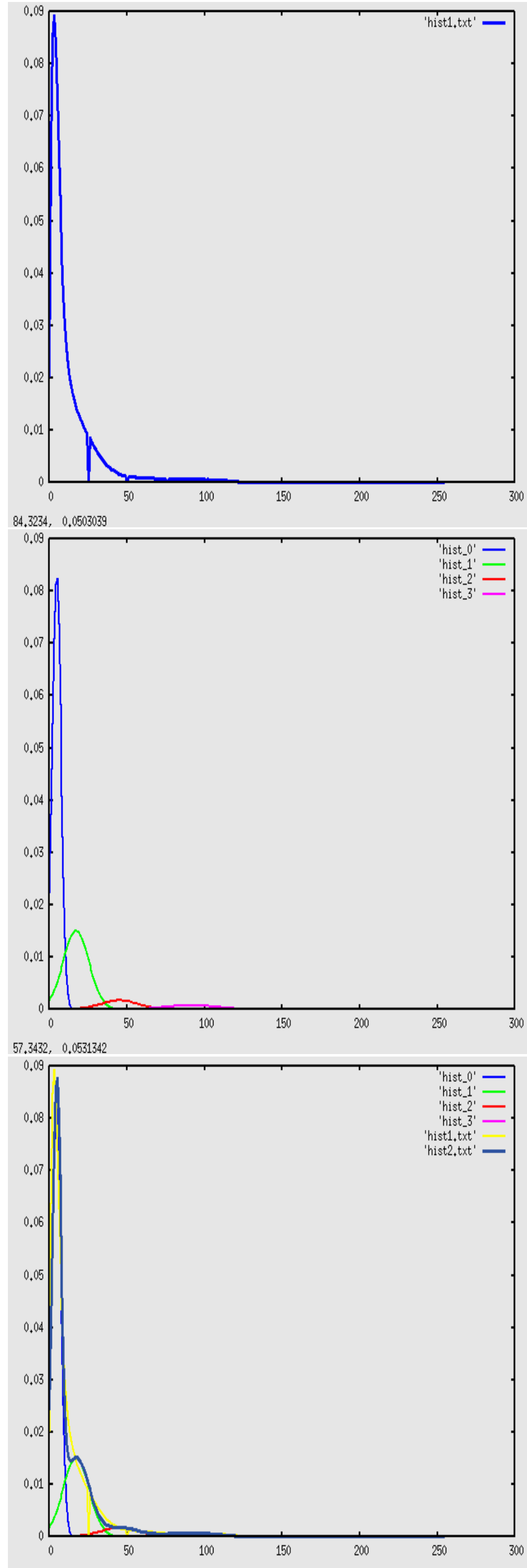

Figure 2: Example of the histogram of the detail feature at level 2 and its modeling using 4 gaussian mixtures. Middle figure shows the different components and Bottom figure shows their combination to model the histogram.

Figure 3: *Original and segmented document into text (back), image (gray), and background (gray)*

Figure 4: *Original and segmented document into text (black), image (gray), and background (gray)*