Adaptive, Quadratic Preprocessing of Document Images for Binarization

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***Abstract*—This paper presents an adaptive algorithm for preprocessing document images prior to binarization in character recognition problems. Our method is similar in its approach to the blind adaptive equalization of binary communication channels. The adaptive filter utilizes a quadratic system model to provide edge enhancement for input images that have been corrupted by noise and other types of distortions during the scanning process. Experimental results demonstrating significant improvement in the quality of the binarized images over both direct binarization and a previously available preprocessing technique are also included in the paper.**

***Index Terms*—Blind equalization, character recognition, image preprocessing, nonlinear filtering.**

I. Introduction

IN MANY applications involving character recognition from digitized document images such as mail addresses, the input images are first binarized to form two-level images. However, direct binarization of such images often results in unsatisfactory performance because of the poor quality of the input images. Consequently, it is usual to preprocess such images in order to enhance the edges in the presence of noise and other types of distortions that occur during the scanning process. Edge enhancement and noise reduction are conflicting requirements for linear, space-invariant filters. Therefore, it is necessary to employ nonlinear and/or adaptive techniques for processing document images prior to binarization. This paper introduces an adaptive nonlinear method for preprocessing and binarizing document images.

There are several methods available for thresholding images to produce binary images. An experimental performance evaluation of several such techniques may be found in [11]. These methods include global and local thresholding algorithms. In global thresholding methods, a single threshold value is found based on the histogram of the input image and then the two-level output image is created by mapping the pixels above and below the threshold value to one or the other of the two output levels. In local thresholding techniques, the threshold is spatially varying, and selected based on the local statistics of the the input image. To demonstrate the inadequacy of direct thresholding methods without preprocessing, we consider the two digitized mail addresses shown in Figs. 1 and 2. These images contain 256 $\times$ 256 pixels with 8 b per pixel gray-scale resolution. The binarized version of these images obtained using the direct global thresholding scheme of [12] are shown in Figs. 3 and 4, respectively. The two levels in the output images were selected to be zero and 255. It is not difficult to argue, based on the results in Figs. 3 and 4, that the binarization process has distorted and often eliminated the boundaries between characters, and that an automatic character recognition system may find it difficult to identify and recognize the alphabets and numbers in these images.

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Fig. 1. Digitized image of a typewritten mail address.

It is clear from the above results that edge enhancement and noise reduction in the input images are desirable *before* binarization and character recognition. Edge enhancement can be achieved by using linear highpass filters, but such filters tend to amplify noise and other types of distortions present in the images. On the other hand, lowpass filters reduce wideband noise present in input images, but tend to smooth the edge details. Consequently, it is necessary to employ a nonlinear system to achieve both of the desired objectives of the preprocessor.

Ramponi and Fontanot [1], [7] recently proposed a simple quadratic filtering approach for preprocessing mail-address images. They used empirically selected filters with fixed coef-

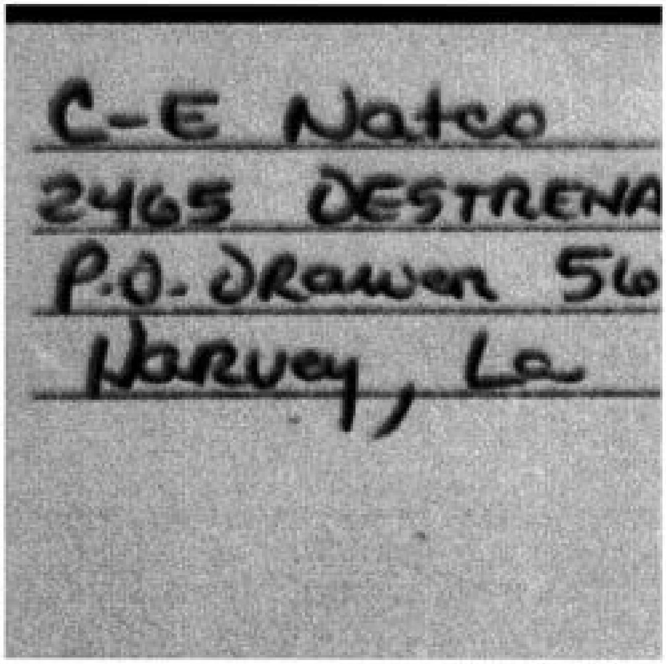

Fig. 2. Digitized image of a hand-written mail address.

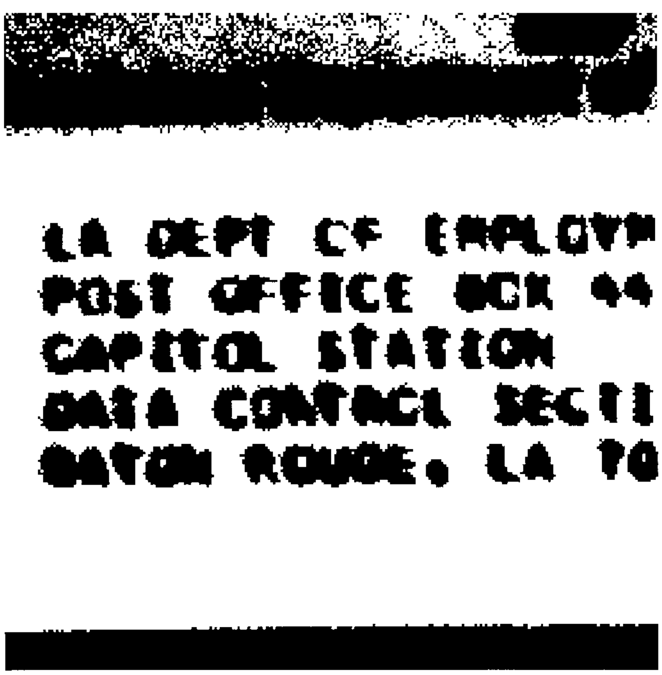

Fig. 3. Binarized version of Fig. 1 obtained without preprocessing.

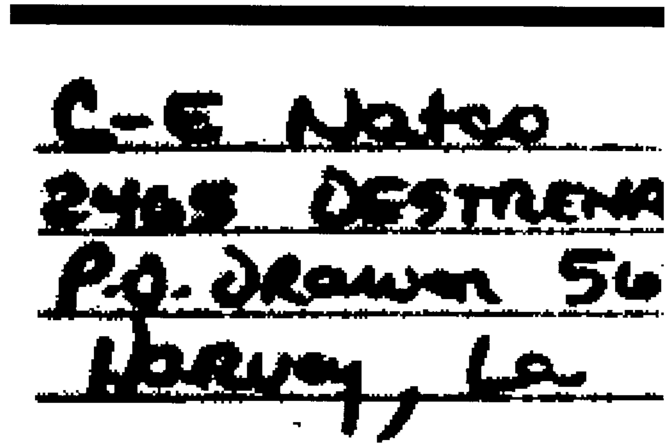

Fig. 4. Binarized version of Fig. 2 obtained without preprocessing.

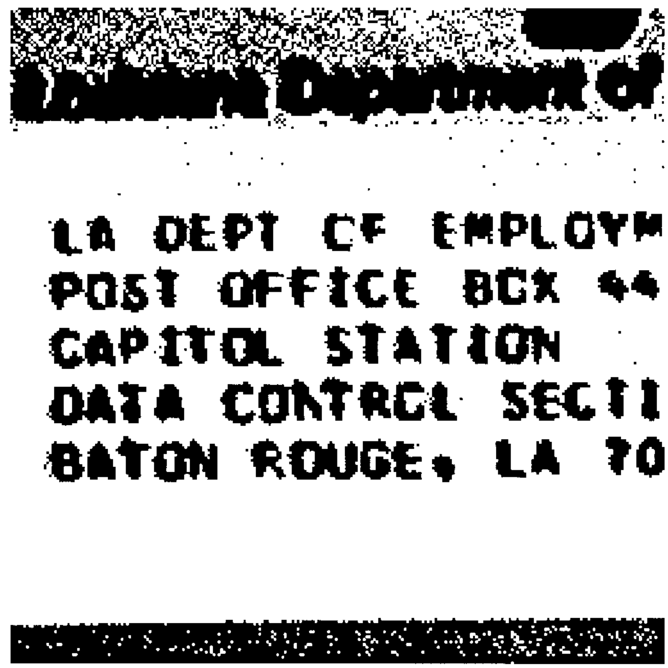

Fig. 5. Binarized version of Fig. 1 obtained after preprocessing as suggested in [1] and [7].

ficients in their work. The binarized images after preprocessing as suggested in [1] and [7] are shown in Figs. 5 and 6. The improvement in the quality of the binarized images can be clearly seen in these figures. In particular, the edges of most characters are much better defined in these figures and most characters are separated from each other when compared with the results in Figs. 3 and 4. Consequently, we infer that many character recognition algorithms should perform better with the binarized image obtained after the preprocessing. However, we note that the preprocessing did not significantly improve the recognizability of the characters on the top portion of Fig. 5. Recall that this portion of the input image is much more noisy than the other parts. The above result is a consequence of the fact that the preprocessing was performed with a spatially invariant filter that is incapable of adapting to the spatially varying statistics in the input images. Obviously, such a filter cannot be guaranteed to work well for preprocessing all types of document images, or even for a single image having different characteristics in different locations.

This paper presents an adaptive algorithm for preprocessing document images before binarization. We show that the problem addressed here is similar to the problem of adaptively equalizing binary communication channels. Therefore, many blind equalization algorithms can be adapted to fit our situation. Our method employs a quadratic system model for preprocessing the input images. The rest of the paper

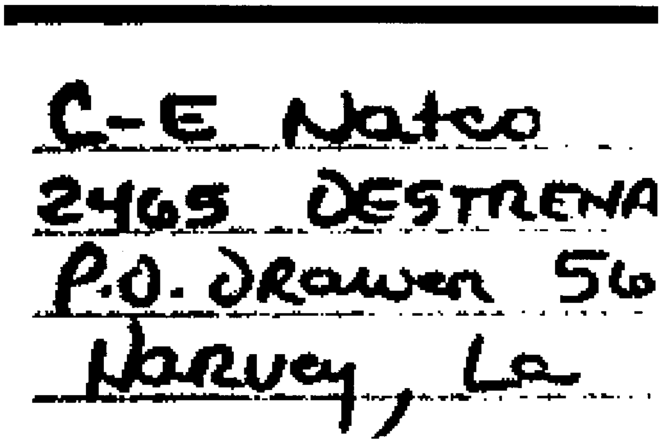

Fig. 6. Binarized version of Fig. 2 obtained after preprocessing as suggested in [1] and [7].

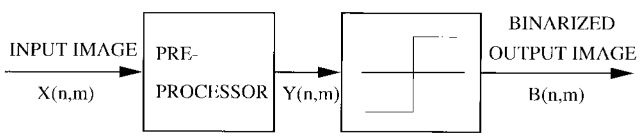

Fig. 7. Block diagram of the image binarization system.

Fig. 8. Model for generation of input image.

is organized as follows. Section II describes the derivation of the adaptive binarization algorithm. Experimental results comparing our technique with direct binarization algorithms and the preprocessing technique in [1] and [7] are presented in Section III. Finally, Section IV contains the concluding remarks.

II. The Adaptive, Quadratic Preprocessor

Consider the block diagram of the binarization system shown in Fig. 7. The preprocessor attempts to force each sample of its output signal $y(n,m)$ to take one of the two values of the binarized signal. We can consider the "error-free" or "ideal" binarized image for the problem as the desired response signal of the preprocessor and model the input image as a distorted and noisy version of this desired response signal as shown in Fig. 8. This characterization is similar to that of a binary communication system in which the received signal is a distorted and noisy version of a binary signal that is transmitted through the channel. Just like the equalizer is designed to offset the effects of the channel, the preprocessor should be designed to compensate for the distortions in the original document. Because of the similarity in the two problems described above, the design of an adaptive binarization system can be performed in a similar manner as the design of an adaptive blind equalizer for a binary communication system.

As described in the introduction, the dual requirements of edge enhancement and noise reduction necessitate the use of a nonlinear filter for preprocessing document images. In this work, we use a quadratic filter to perform this task because of their relative simplicity and effectiveness. However, the ideas described here can be easily extended to other types of nonlinear preprocessors. The output $y(n,m)$ of a two-dimensional (2-D) quadratic filter considered in this paper satisfies the input-output relationship

$$\begin{aligned} y(n,m) = {} & \sum_{k_1=N_1}^{N_2} \sum_{k_2=N_3}^{N_4} h_1(k_1,k_2;n,m)x(n-k_1,m-k_2) \\ & + \sum_{k_1=N_5}^{N_6} \sum_{k_2=N_7}^{N_8} \sum_{k_3=N_5}^{N_6} \sum_{k_4=N_7}^{N_8} \\ & h_2(k_1,k_2,k_3,k_4;n,m)x(n-k_1,m-k_2) \\ & \cdot x(n-k_3,m-k_4), \end{aligned} \tag{1}$$

where $h_1(k_1,k_2;n,m)$ represents a coefficient of the linear component and $h_2(k_1,k_2,k_3,k_4;n,m)$ denotes a coefficient of the homogeneous quadratic component of the filter. It is common practice to employ a symmetric kernel for the homogeneous quadratic component such that $h_2(k_1,k_2,k_3,k_4;n,m) = h_2(k_3,k_4,k_1,k_2;n,m)$.

Let $\boldsymbol{X}(n,m)$ represent an input data vector that contains all the elements of the form $x(n-k_1,m-k_2)$ and those of the form $x(n-k_1,m-k_2)x(n-k_3,m-k_4)$ employed in the input-output relationship in (1). Also, let $\boldsymbol{H}(n,m)$ denote a coefficient vector in which the coefficients are arranged such that the ith entry of $\boldsymbol{H}(n,m)$ scales the ith entry of $\boldsymbol{X}(n,m)$ in (1). Then, the input-output relationship in (1) can be compactly written as

$$y(n,m) = \boldsymbol{H}^T(n,m)\boldsymbol{X}(n,m). \tag{2}$$

The dimensionality of the vectors in the above equation may be reduced by utilizing several constraints imposed on the coefficients. For example, the symmetry conditions may be employed so that only one of $x(n-k_1,m-k_2)x(n-k_3,m-k_4)$ and $x(n-k_3,m-k_4)x(n-k_1,m-k_2)$ appears in $\boldsymbol{X}(n,m)$ whenever $(k_1,k_2) \neq (k_3,k_4)$. In such situations, the coefficient $h_2(k_1,k_2,k_3,k_4;n,m)$ may be replaced by $h_2(k_1,k_2,k_3,k_4;n,m) + h_2(k_3,k_4,k_1,k_2;n,m)$ in $\boldsymbol{H}(n,m)$ and the coefficient $h_2(k_3,k_4,k_1,k_2;n,m)$ may be eliminated altogether from the coefficient vector.

The objective of the adaptive preprocessor is to update the coefficient vector $\boldsymbol{H}(n,m)$ at each spatial location such that the output signal $y(n,m)$ is as close to its binarized version $y_b(n,m)$ as possible. The binarized signal $y_b(n,m)$ is obtained as

$$y_b(n,m) = \begin{cases} \alpha, & \text{if } y(n,m) > \tau \\ \beta, & \text{otherwise.} \end{cases} \tag{3}$$

Here, α and β are two constants, representing the two levels in the binarized image, and τ is a preselected threshold value. To derive an adaptation algorithm, we define an "error" signal $e(n,m)$ as

$$e(n,m) = y_b(n,m) - y(n,m) \tag{4}$$

and then define an instantaneous cost function $J(n,m)$ as

$$J(n,m) = e^2(n,m). \tag{5}$$

TABLE I
ADAPTIVE BINARIZATION ALGORITHM

Initialization	
$\mathbf{H}(n,m)$ may	be initialized arbitrarily.
Main Iteration	
$y(n,m) =$	$\mathbf{H}^T(n,m)\mathbf{X}(n,m)$
$y_b(n,m) =$	$\begin{cases} \alpha; & \text{if } y(n,m) > \tau \\ \beta; & \text{otherwise} \end{cases}$
$e(n,m) =$	$y_b(n,m) - y(n,m)$
$\mathbf{H}(n,m+1) =$	$\mathbf{H}(n,m) + \mu e(n,m)\mathbf{X}(n,m)$

We can now derive a stochastic gradient adaptation algorithm that attempts to reduce $J(n,m)$ at each location. The coefficients are updated in the stochastic gradient adaptive filters as

$$\begin{aligned} \boldsymbol{H}(n,m+1) &= \boldsymbol{H}(n,m) - \frac{\mu}{2}\frac{\partial}{\partial \boldsymbol{H}(n,m)} J(n,m) \\ &= \boldsymbol{H}(n,m) + \mu e(n,m)\boldsymbol{X}(n,m), \end{aligned} \tag{6}$$

where μ is a small, positive step size parameter that controls the convergence, tracking and steady-state characteristics of the adaptive filter. In the above derivation, we assumed that the adaptation is performed along the rows of the image. In the experiments described later, the possible sudden changes in the input signal statistics while moving from one row to the next was avoided by changing the direction along which the pixels were scanned during the adaptation process, i.e., if the adaptation occurs along the west-east direction for one row, the system adapts along the east-west direction for the next row, and so on.

The complete algorithm for adaptive preprocessing and binarization is given in Table I. We note that the structure of the adaptive filter is identical to that of the LMS adaptive filter, except for the definition of the error signal $e(n,m)$.

A. Some Design and Implementation Issues

We now discuss several implementation and design issues for the algorithm of Table I. These issues include normalization of the input data, selection of the step size parameters μ, selective adaptation for providing robustness against noise in the input signals, and the binarization procedure.

1) Normalization of Input Images: It is well known that the performance of stochastic gradient adaptive filters depend critically on the input signal power [2]. In order to provide the adaptive filter with a certain amount of robustness against the variations in the signal powers in the input images, it is useful to normalize the image in such a manner that the character pixels are mapped to values close to one and the background pixels are mapped to values closed to zero. One approach for making an initial determination of whether a particular pixel is a background pixel or a character pixel is as follows: Given an input image, we first find a global threshold level for binarizing this image without any preprocessing. Many algorithms for threshold selection are available [3], [8], and any one of them could be used for this purpose. In all the experiments described in this paper, we used the method presented in [12]. The pixels whose values lie above and below the threshold level are characterized as *background* and *character* pixels, respectively.

To normalize the pixels, we calculate the average gray-level values for the character pixels and the background pixels separately. Denote these averages by m_0 and m_1, respectively. The input image is then normalized to obtain

$$x_n(n,m) = (x(n,m) - m_1)/(m_0 - m_1). \tag{7}$$

The normalized image represented by $x_n(n,m)$ is the input to the adaptive preprocessor. The above normalization procedure is similar to that employed in [1] and [7].

2) Selection of the Step Size Parameter: Selection of the step size parameter μ is a key issue in the design of the adaptive preprocessor. Because of the nonlinear nature of the coefficient update equation, the derivation of the bound for the step size that would ensure stable operation of the adaptive filter is a difficult problem. However, the similarity of the update equation (6) to the corresponding update equation for the least mean square (LMS) adaptive filter enables us to derive a heuristic bound for μ using analyses performed on LMS adaptive filters. For the LMS adaptive filter, it is shown under a variety of simplifying assumptions that choosing μ such that

$$0 < \mu < \frac{2}{3\,\mathrm{tr}\{\boldsymbol{R_{XX}}\}} \tag{8}$$

where $\mathrm{tr}\{\cdot\}$ denotes the trace of the matrix within the brackets and $\boldsymbol{R_{XX}}$ is the statistical autocorrelation matrix of the input vector $\boldsymbol{X}(n,m)$, ensures that the mean-square behavior of the coefficients of the adaptive filters is stable [2]. The above result assumes stationarity of the input signals. If we assume that the binarization process is independent of the adaptation process, we can use the same bound for the blind adaptation algorithm derived in this paper. Obviously, the assumption that the binarization process and the adaptation process are independent is incorrect in practice, and therefore, the above derivation is a heuristic one. We have conducted a large number of experiments using a wide range of step sizes within the range suggested above, and the algorithm operated in a stable manner in all our experiments.

3) Selective Adaptation: Recall from the description of the normalization process that the background pixels are mapped to values that are close to zero. In the absence of distortion, all these pixels would have taken zero values. This implies that the coefficient updates in the background areas depend primarily on the distortions present in the image. Since this is not a desirable characteristic for the adaptive filter, the system is constrained to update only in locations in which the pixels are characterized as character pixels during the normalization step. This selective adaptation process provides the system with more robustness against the noise present in the input image.

4) Binarization: Since the adaptive preprocessor attempts to map the character pixels to values close to α and the background pixels to values close to β, an easy approach to binarization is to simply map all the output samples of the preprocessor with values larger than a threshold τ to α and all the output samples with values smaller than τ to β. In our work, we chose α to be equal to or slightly larger than twice the maximum values of the normalized pixels. β may be chosen to be zero, since the normalization procedure attempts to bring the background pixels close to zero. Selection of α and β as above provides adequate separation for the character and background pixels, and therefore it enables the binarization to be performed satisfactorily. The normalized value of the global threshold selected as described earlier may be chosen as the threshold value for binarization of the output of the preprocessor.

III. Experimental Results

In this section, we present the results of several experiments that demonstrate the superior performance capabilities of the adaptive preprocessor described in the previous section. The objectives of this section are to demonstrate the properties of our algorithm and to compare its capabilities with that of direct binarization and the space-invariant preprocessing technique described in [1] and [7]. In order to make the comparisons as fair as possible, we employ the same structure employed in [1] and [7] for the quadratic filter.

A. System Model

The generic quadratic filter employed in the experiments processed nine input samples at each time to find its output as

$$\begin{aligned} y(n,m) = & \sum_{k_1=-1}^{1}\sum_{k_2=-1}^{1} h_1(k_1,k_2)x(n-dk_1,m-dk_2) \\ & + \sum_{k_1=-1}^{1}\sum_{k_2=-1}^{1}\sum_{k_3=-1}^{1}\sum_{k_4=-1}^{1} \\ & h_2(k_1,k_2,k_3,k_4) \\ & x(n-dk_1,m-dk_2)x(n-dk_3,m-dk_4), \end{aligned} \tag{9}$$

where d is a positive integer number. By choosing d to be 1, 2, or 3, the plane of support of the filter becomes 3×3, 5×5, or 7×7 pixels, respectively, without increasing the complexity of the filter. The choice of d is made based on the thickness of the characters present in the input image. For character sizes similar to those in Figs. 1 and 2, we have found $d = 3$ to be a good choice. For thinner characters, a smaller value of d should be selected.

The work in [1] and [7] employed the symmetry and isometry conditions [5] as well as additional simplifications in the design of the filter to obtain an easy to realize system with input-output relationship

$$y(n,m) = x_0(n,m) + \boldsymbol{H}_{\boldsymbol{S}}^T(n,m)\boldsymbol{X}_{\boldsymbol{S}}(n,m), \tag{10}$$

where

$$\begin{aligned} x_0(n,m) = & {x_n}^2(n,m) + \frac{1}{8}\sum_{k_1=-1,}^{1}\sum_{\substack{k_2=-1 \\ (k_1,k_2)\neq(0,0)}}^{1} \\ & [x_n(n-dk_1,m-dk_2) \\ & - x_n^2(n-dk_1,m-dk_2)] \end{aligned} \tag{11}$$

and $\boldsymbol{X}_{\boldsymbol{S}}(n,m)$ is a two-element input vector given by

$$\boldsymbol{X}_{\boldsymbol{S}}(n,m) = [x_1(n,m) \quad x_2(n,m)]^T \tag{12}$$

with $x_1(n,m)$ and $x_2(n,m)$ defined as

$$\begin{aligned} x_1(n,m) = & x_n(n,m) - x_n^2(n,m) - \tfrac{1}{8}\sum_{k_1=-1,}^{1}\sum_{\substack{k_2=-1 \\ (k_1,k_2)\neq(0,0)}}^{1} \\ & [x_n(n-dk_1,m-dk_2) \\ & - x_n^2(n-dk_1,m-dk_2)] \end{aligned} \tag{13}$$

and

$$\begin{aligned} x_2(n,m) = & \Bigg[x_n(n,m)\sum_{k_1=-1,}^{1} \\ & \sum_{\substack{k_2=-1 \\ (k_1,k_2)\neq(0,0)}}^{1} x_n(n-dk_1,m-dk_2)\Bigg] \\ & - [x_n(n-d,m) + x_n(n+d,m)] \\ & \cdot [x_n(n,m-d) + x_n(n,m+d)] \\ & - \tfrac{1}{2}x_n(n-d,m-d)[x_n(n-d,m) \\ & + x_n(n,m-d)] \\ & - \tfrac{1}{2}x_n(n-d,m+d)[x_n(n-d,m) \\ & + x_n(n,m+d)] \\ & - \tfrac{1}{2}x_n(n+d,m+d)[x_n(n+d,m) \\ & + x_n(n,m+d)] \\ & - \tfrac{1}{2}x_n(n+d,m-d)[x_n(n+d,m) \\ & + x_n(n,m-d)], \end{aligned} \tag{14}$$

respectively. The coefficient vector $\boldsymbol{H}_{\boldsymbol{S}}(n,m)$ also contains two elements denoted by $h_{s,1}(n,m)$ and $h_{s,2}(n,m)$ so that

$$\boldsymbol{H}_{\boldsymbol{S}}(n,m) = [h_{s,1}(n,m) \quad h_{s,2}(n,m)]^T. \tag{15}$$

It is shown in [1] and [7] that the above filter contains a component with lowpass characteristics that reduces the noise present in the input images and another component that serves to enhance the edges in the input images. The design technique for the system model as well as the rationale for the approximations and constraints employed in the design are also described in [1] and [7]. Additional details on the selection of the particular system model described above is not provided here, since our objective in selecting this structure was to provide a basis for fair performance comparisons with the binarization method described in [1] and [7].

Based on the quadratic filter structure described above, the adaptive filter has only two free parameters given by $h_{s,1}(n,m)$ and $h_{s,2}(n,m)$. These coefficients are updated in the same manner as the coefficient update structure given in Table I. The relevant equation is

$$\boldsymbol{H}_{\boldsymbol{S}}(n,m+1) = \boldsymbol{H}_{\boldsymbol{S}}(n,m) + \mu e(n,m)\boldsymbol{X}_{\boldsymbol{S}}(n,m), \tag{16}$$

where

$$e(n,m) = y_b(n,m) - y(n,m) \tag{17}$$

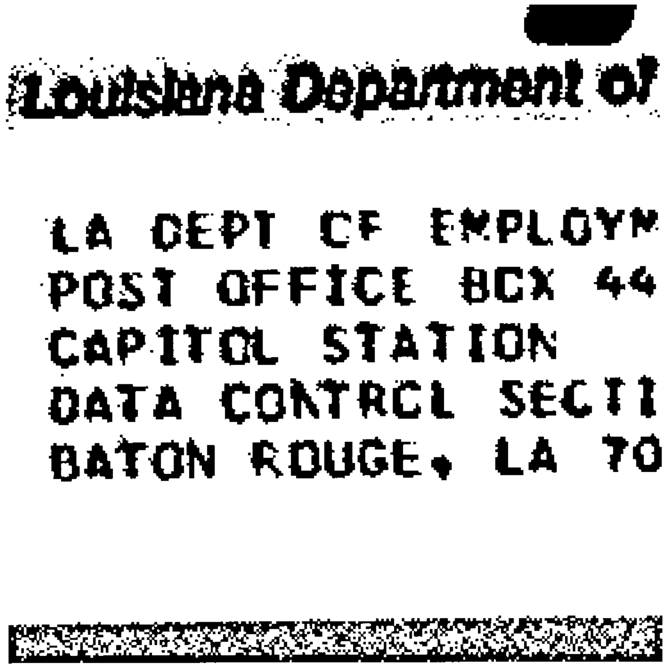

Fig. 9. Binarized version of Fig. 1 obtained using the adaptive technique.

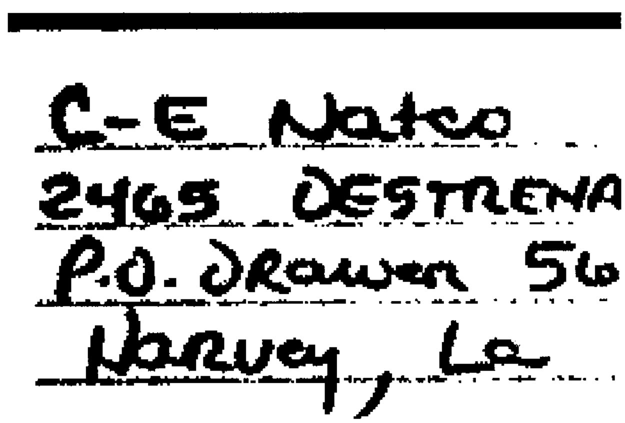

Fig. 10. Binarized version of Fig. 2 obtained using the adaptive technique.

and $y(n,m)$ is computed as in (10). A large number of experiments using a variety of document images and a number of step size values were conducted. All the step size values used in these experiments fall in the range suggested by (8). On the basis of visual inspection of the binarized images, it was determined that the values of μ in the range of $[10^{-4}, 10^{-3}]$ provided satisfactory results for a wide range of documents. Consequently, the experiments presented in this paper used a step size value of $\mu = 0.0003$.

B. Experimental Results on the Images in Section I

The results of binarizing the input images in Figs. 1 and 2 using the adaptive system of this paper are shown in Figs. 9 and 10. The coefficients of the adaptive filter were initialized to zero values. The distance d in the plane of support was set to be equal to three. The results of adaptive preprocessing appears to be perceptually superior to binarization without preprocessing as well as binarization with the space-invariant quadratic preprocessing. In particular, our technique was able to provide binarization of the top portion of Fig. 1 with sufficient clarity. The space-invariant preprocessing technique was not able to provide adequate clarity to the binarized image in this portion, justifying the need for adaptive techniques in this application. Fig. 11 displays the evolution of the two adaptive filter coefficients for the typewritten mail address image. The input image has nonstationary statistics, and therefore one should not expect the coefficients to converge to any particular values. Instead, these curves simply demonstrate the ability of the system to change its coefficients at a reasonable speed. The curve depicting the evolution of coefficient $h_{s,2}$ may be divided into three components. The first part, where the coefficient changes very fast, corresponds to the top, noisy portion of the image. The second part, in which the coefficient varies more slowly corresponds to the portion of the image containing the address. Finally, in the bottom portion of the image which is noisy, there is another significant change in the behavior of the coefficient.

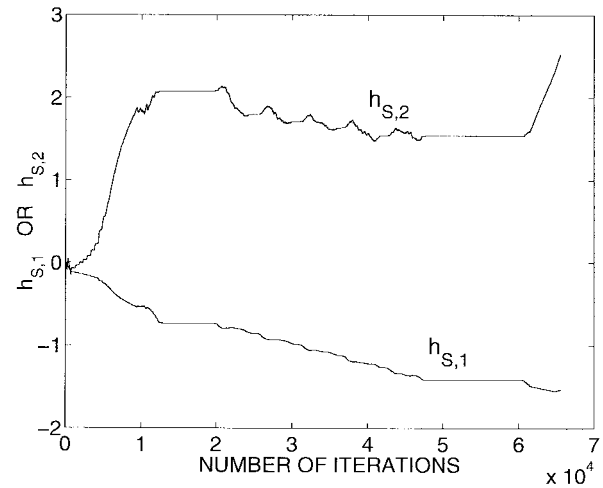

Fig. 11. Evolution of the coefficients $h_{s,1}$ and $h_{s,2}$ on the input image Fig. 1.

C. Experiments on a Receipt Image

Another set of experiments were performed using the receipt image shown in Fig. 12. This image contains 399 $\times$ 400 pixels with 8 b per pixel gray-scale resolution. The binarization results without the preprocessing technique, with the space-invariant preprocessing system suggested in [1] and [7] and with the proposed adaptive preprocessing system are displayed in Figs. 13–15, respectively. The adaptive system used the same parameters as those employed in the experiments on Figs. 1 and 2 with the exception that the distance parameter d was set to be equal to one because of the relative thinness of the characters in the image. We can make similar observation as in the previous experiments for this set of results also. Experiments involving a variety of other document images provided results comparable to those presented here.

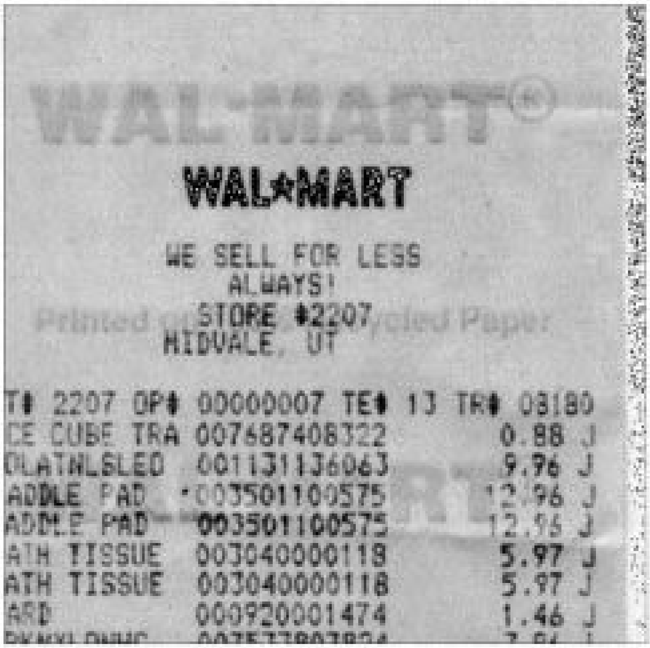

Fig. 12. Receipt image.

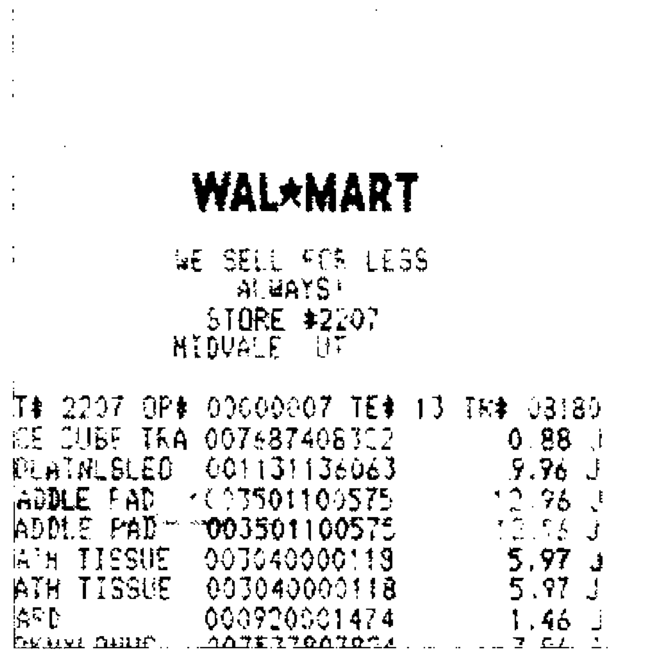

Fig. 14. Binarized version of Fig. 12 obtained using the space-invariant preprocessing technique.

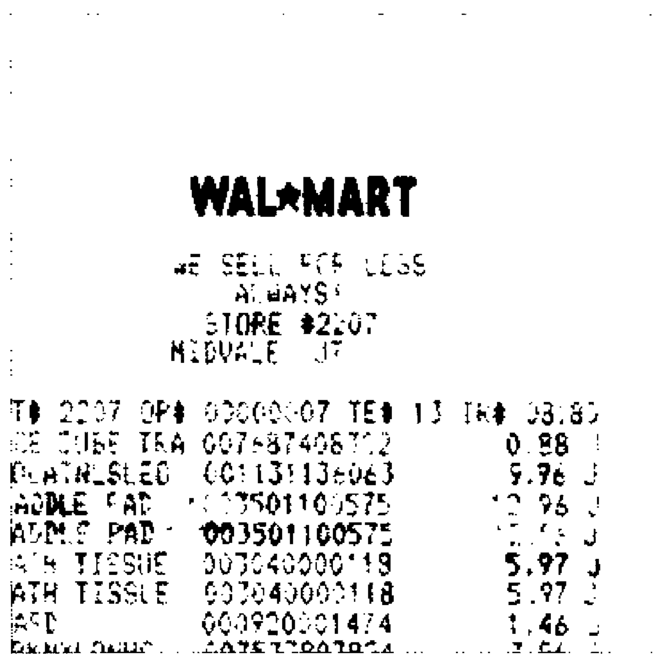

Fig. 13. Binarized version of Fig. 12 obtained without preprocessing.

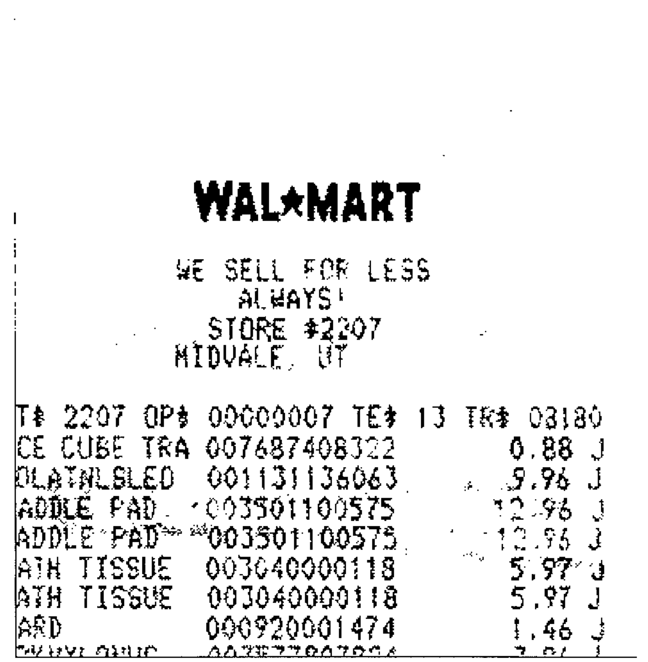

Fig. 15. Binarized version of Fig. 12 obtained using the adaptive preprocessing technique.

D. Character Recognition

Omnipage Pro 6.0, a character recognition software that runs on Macintosh computers, was used to recognize characters in the binarized images. This software is capable of recognizing only typewritten characters, and the experiments were conducted on the images derived from Figs. 1 and 12. Only six out of 94 characters were recognized in Fig. 3, which is a binarized version of Fig. 1 obtained without any preprocessing. After preprocessing the input image using space-invariant preprocessing system suggested in [1] and [7], 38 characters were recognized. The software recognized 61 characters when the adaptive preprocessor was employed. Similar improvement was also found on the receipt image, as documented in Table II. Even though the improvement obtained by using the adaptive preprocessing technique is significant, the percentage of characters correctly recognized is relatively low for these images. The primary reason for this is the extremely poor quality of the images employed in these experiments. Our objective in these experiments was to demonstrate the superiority of the adaptive preprocessing system over previously

TABLE II
PERCENTAGE OF CHARACTER RECOGNITION WITH VARIOUS PREPROCESSING TECHNIQUES

Algorithms	Type-written Mail Address	Receipt
Direct Binarization	6.4%	15.8%
Space-invariant Binarization	40.4%	52.9%
Adaptive Binarization	64.9%	62.1%

available methods, and we believe that the results met this objective. More advanced character recognition systems may provide better overall results than the system employed in our experiments.

IV. CONCLUDING REMARKS

This paper presented a blind adaptive binarization algorithm for document images. Experimental results presented in the paper indicate that the algorithm provides good results even in situations where the input images are highly distorted. As a result, we believe that our technique is an attractive alternative to currently available methods for preprocessing and binarizing document images. Results of adaptive preprocessing on several other images can be found in [9]. Several other blind adaptation algorithms available for channel equalization [4] may be adapted to our application. However, such a study was not part of this paper.

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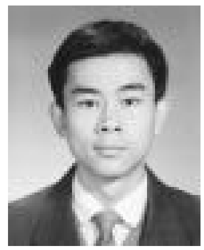

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