EDGE-PRESERVING PREFILTERING FOR DOCUMENT IMAGE BINARIZATION

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ABSTRACT

We propose a novel *coplanar filter*, which exploits the coplanarity of gray-level distribution of neighboring pixels, to pre-filter the document images. Experiments show that the proposed filter exhibits the following desired properties for document image binarization: (1) impulsive noise removal, (2) piecewise smoothing, and (3) sharp edge preservation.

1. INTRODUCTION

In many document processing systems, gray-level documents images are first binarized to form two-level (black/white) images. The binarization process involves the assignation of pixels to either foreground or background objects. The process is often achieved by global or local thresholding [8]. Both global and local thresholding schemes make use of the assumption that foreground and background pixels can be classified by comparing their intensity values to some prescribed or automatically selected thresholds. For document images corrupted by various kinds of noise, the assumption is violated wherever there is an outlier, and the binarized images may be severely blurred and degraded. It is, thus, a common treatment to preprocess the input image using certain noise suppressing filters. This paper proposes such a filter as preprocessing for document image binarization. Before we introduce the proposed filter, let us first investigate the desired properties of a noise suppressing prefilter.

First of all, an ideal filter should be able to completely remove the impulsive noise outliers, which could cause the misclassification of pixels by using direct thresholding methods. In addition, to make the selection of threshold more accurate and robust, it would also be a desired property that pixels belonging to the same object have the similar intensity values. This implies that intraregion intensity variations caused by Gaussian noise or lighting variation should be smoothed as much as possible. Finally, for document images, good preservation of edges and corners is crucial to the subsequent processing, e.g. optical character recognition [10].

There are numerous existing methods for image filtering. Among many others, Gaussian [1][3] and Median [2][11] filters are the two most commonly used filters. The former is capable of removing Gaussian noise, but smooth the sharp edges to various extents. The latter is good at removing impulsive noise, yet its output is ragged and not smooth for pixels in the same region. In this paper, we propose a novel *coplanar filter*, which exploits the coplanarity of gray-level distribution of neighboring pixels, to pre-filter the document images. The proposed filter exhibits the following desired properties for document image binarization: (1) impulsive noise removal, (2) piecewise smoothing, and (3) sharp edge preservation.

We note that Fontanot and Ramponi [4] proposed a quadratic filtering approach for preprocessing mail-address images. Mo and Mathews [6] later extended this work to adapt to the spatially varying statistics in the input images.

This paper is organized as follows: Section 2 introduces the coplanar matrices, followed by an illustration of the filter's properties. Experimental results and comparison of performances with other filters are presented in Section 3. Section 4 concludes the paper.

2. COPLANAR FILTER

We first briefly outline the algorithm of coplanar filtering, followed by an illustration of its properties with examples. Before introducing the filter, some notations are defined below. Let $\mathbf{x}_k, (k = 1,..., w * h)$ be the coordinates of pixels in a $w \times h$ image[1]; I_k the corresponding intensity values; and $\mathbf{p}_k = (\mathbf{x}_k, I_k)^T$ denotes a set of 3D vectors representing the coordinates and intensity values of the input image. The estimated filter output is denoted by $\hat{\mathbf{p}}_k = (\mathbf{x}_k, \hat{I}_k)^T$. Let $\mathbf{x}_i$, $i = 1,..., (u \cdot v - 1)$ denote the coordinates of N ($=u \cdot v-1$) neighboring pixels in a $u \times v$ local window centered at certain position in an

[1] Note that $\boldsymbol{x}$ = (x, y) is a 2D vector, for an image with rectangular grids. We choose this notation for simplicity.

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image. Correspondingly, $\mathbf{p}_i = (\mathbf{x}_i, I_i)^T$ denote the neighboring pixels' coordinates and intensity values.

2.1. Coplanar Filtering Algorithm

Given as input to the filter a set of pixels $\mathbf{p}_k = (\mathbf{x}_k, I_k)^T$, the objective is to estimate a set of new intensity values $\hat{\mathbf{p}}_k = (\mathbf{x}_k, \hat{I}_k)^T$ as the filter output. This can be achieved using the following two steps.

A. Estimation of Coplanar Matrix.

The first step involves the estimation of coplanar matrix as defined below. For each pixel vector $\mathbf{p}_k = (\mathbf{x}_k, I_k)^T$ and its N neighboring pixel vectors $\mathbf{p}_i = (\mathbf{x}_i, I_i)^T$, we compute a 3x3 pseudo-covariance matrix as below[2]:

$$\mathbf{C}_k = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{p}_k - \mathbf{p}_i)\cdot(\mathbf{p}_k - \mathbf{p}_i)^T \tag{1}$$

Note that the above matrix captures the ***directional*** distribution of neighboring pixel vectors with respect to $\mathbf{p}_k$. The flatter a cluster in which neighboring pixels scatter, the smaller the determinant of this matrix is. And vice versa. Moreover, the eigenvectors of the above matrix correspond to the principal directions of the neighboring pixel distribution. In this work, we use the matrix itself to quantify the 'coplanarity' around $\mathbf{p}_k$, and denote it as the *coplanar matrix*.

B. Energy Minimization for the Coplanar Filtering

The second step involves estimating the filter output $\hat{\mathbf{p}}_k = (\mathbf{x}_k, \hat{I}_k)^T$, for a given set of pixels and associated coplanar matrix $(\mathbf{p}_k, \mathbf{C}_k)$. The objective is to update all pixel intensities, such that the filter output exhibits high coplanarities among adjacent pixels. Since the coplanarity is a local measurement, we estimate each individual pixel intensity $\hat{I}_k$ within a local neighboring window. Therefore, we define below an energy function of N neighboring pixels $\mathbf{p}_i$ around the center pixel $\mathbf{p}_k = (\mathbf{x}_k, I_k)^T$, and minimize the energy function with respect to the estimated intensity value $\hat{I}_k$ at pixel $\mathbf{p}_k$:

$$E = -\sum_{i=1}^{N}\frac{1}{\sqrt{(2\pi)^3|\mathbf{C}_i|}}\exp[-\frac{1}{2}(\mathbf{p}_k - \mathbf{p}_i)^T\mathbf{C}_i^{-1}(\mathbf{p}_k - \mathbf{p}_i)] \tag{2}$$

[2] The matrix differs from a covariance matrix in that it uses $\mathbf{p}_k$, instead of the center of neighboring pixels.

in which $\mathbf{C}_i$ is the coplanar matrix and $\mathbf{C}_i^{-1} = \begin{bmatrix} \mathbf{v}_x^i & \mathbf{v}_{xI}^i \\ (\mathbf{v}_{xI}^i)^T & v_I^i \end{bmatrix}$ is its inverse. To find the minima of (2), we set $\partial E/\partial I_k = 0$, and iteratively estimate $\hat{I}_k$ using the following update equation:

$$\hat{I}_k^{(n+1)} = \frac{\sum_{i=1}^{N} w_i^{(n)}[v_I^i \hat{I}_i - (\mathbf{x}_k - \mathbf{x}_i)\cdot\mathbf{v}_{XI}^i]}{\sum_{i=1}^{N} w_i^{(n)} v_I^i} \tag{3}$$

in which *(n)* denotes the *n*th iteration, and $w_i^{(n)}$, is computed as:

$$w_i^{(n)} = \frac{1}{\sqrt{(2\pi)^3|\mathbf{C}_i|}}\exp[-\frac{1}{2}(\hat{\mathbf{p}}_k^{(n)} - \mathbf{p}_i)^T\mathbf{C}_i^{-1}(\hat{\mathbf{p}}_k^{(n)} - \mathbf{p}_i)] \tag{4}$$

The detailed derivation of (3) is given in [12]. From (3) and (4), it is shown that those neighboring pixels, whose coplanar matrix with smaller determinant, have dominant influences on estimating $\hat{I}_k$, while those pixels exhibiting lower local coplanarities, have relatively minor contributions. We note that this coplanarity-based weighting scheme is crucial to removing impulsive noise and preserving sharp edges.

C. The Algorithm Pseudo-Code.

We briefly outline the pseudo-code of the proposed coplanar filtering algorithm as follows:

Coplanar filter Algorithm pseudo-code:
Input: image pixels $\mathbf{p}_k = (\mathbf{x}_k, I_k)^T$,(*k=1, … w*h*)
For all p_k: **Coplanar Matrix Estimation**
  Compute $\boldsymbol{C_k}$ using (1);
End
For all p_k: **Energy Minimization**
  Iteratively compute $\hat{I}_k$ using (3);
End
Output: $\hat{\mathbf{p}}_k = (\mathbf{x}_k, \hat{I}_k)^T$

2.2. Properties of The Coplanar Filter

Let us illustrate the properties of the proposed coplanar filter with a 1D example (Figure 1) of signal filtering. The original signal consists of step and roof edges, and the input to the filter is corrupted by Gaussian noise (σ =1.0) and impulsive noise (p=0.02). There are three noticeable observations about the filter outputs. Firstly, it is shown that impulsive noises can be completely removed. As mentioned earlier, this is due to the fact we make use of the coplanarity assumption of gray-level distributions.

Secondly, in relatively smooth regions, the proposed coplanar filter is able to suppress small variations and result in piecewise smoothing. Note that this is a desired property for the document image binarization. Finally, step and roof edges are well preserved.

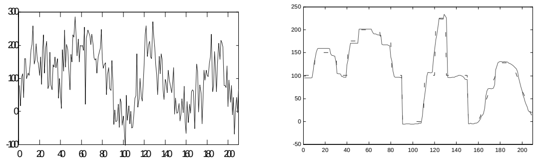

Figure 1 Left: Noise corrupted signal; Right: Filter output (solid line) vs. original signal (dotted line).

2.3. Computational Load

The update equation (3) normally converges to the local minima in a few iterations, so the computational speed is reasonably fast. In our experiments using a Pentium II 600MHz PC, it takes about 2 to 10 seconds to process images of size 256x256, depending on different local window sizes (3x3 to 7x7). In addition, the computation of update equation involves only pixels in a local region, therefore, the proposed algorithm is suitable for parallel processing to further speedup.

3. EXPERIMENTAL RESULTS

In this section, the results of two document image binarization experiments are presented. The noisy images are first filtered using the Gaussian, Median and coplanar filters respectively. The filter outputs are then binarized using three different thresholding schemes: (1) the prescribed thresholding; (2) the entropy thresholding [8]; and (3) the local thresholding proposed by Niblack [7]. Note that we aim to illustrate the applicability of prefiltering as a preprocessing procedure for document image binarization, rather than compare various thresholding schemes. Comparisons of different document thresholding methods can be found in [8][9][10]. In our experiment, unless stated otherwise, the neighboring window size for coplanar filter is set to 3×3.

3.1. Experiment 1: Synthetic Test image

The test image used in the first experiment is shown in Figure 2. We use this synthetic image because it makes the ground truth available for performance comparison. The test image is severely corrupted by Gaussian (σ =1.0) and impulsive (p=0.1) noise. The different filter outputs and the corresponding binarization results are shown in Figure 3. Visual inspections show that (1) using prefiltering can significantly improve the performance of document image binarization; (2) the coplanar filter output is sharper than those of Gaussian and Median filters. Corresponding binarization results demonstrate that the proposed coplanar filter outperforms in that it efficiently suppresses the noise and better preserves the edges and corners. We also quantitatively measure the Modified Hausdorff Distances (MHD) [5] between the different binarization results and the ideal binarization image, with results summarized in Table 1. Among three different filters, the coplanar filter produces the lowest MHD.

	No-filter	Gaussian	Median	Coplanar
Global	4.0003	1.6822	2.2808	0.7852
Entropy	3.5006	2.0635	1.7258	1.4648
Niblack	4.4354	4.2741	3.4688	2.1024

Table 1 Modified Hausdorff Distances (MHD) between the binarization images and the ground truth. Column 1 represents the results of three thresholding schemes without using any filters; Column 2 is the results using Gaussian filter; Column 3 and 4 are results using Median and Coplanar filters respectively. Row 1 is the binarization results using proscribed threshold (t=192); Row 2 using the entropy thresholding method; Row 3 using Niblack's local thresholding method.

3.2. Experiment 2: Real Images

Binarizations of two real document images are shown in Figures 4 (in Chinese) and 5 (in English). It is shown that for real document images severely corrupted with noise, using the proposed coplanar filter as a preprocessing stage to suppress noise also produce satisfactory results.

4. CONCLUSTION

We demonstrate that including prefiltering as a preprocessing procedure for document image binarization can significantly improve the performance. Among different filters, the proposed coplanar filter outperforms than Gaussian and Median filters, in that it allows piecewise smoothing and better preserves the edges and corners.

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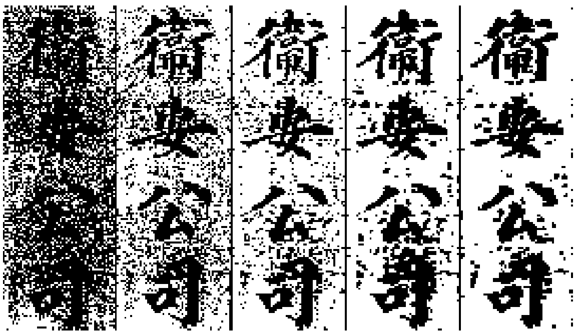

Figure 4 Left to right: Original document image; Direct binarization result using t=30; Binarization (t=30) with Gaussian filter; Binarization (t=30) with Median filter; Binarization (t=30) with Coplanar filter.

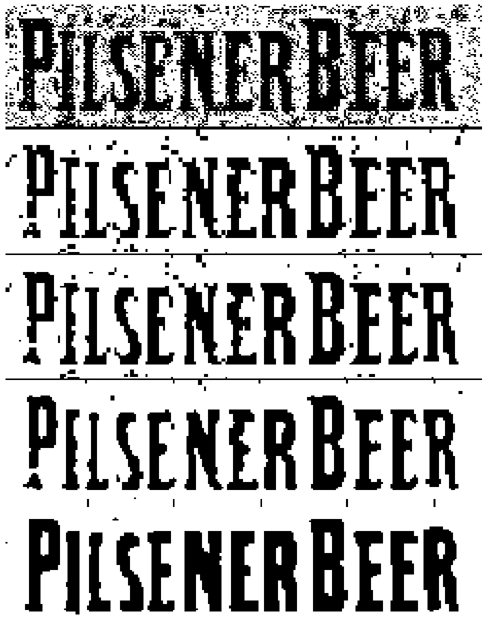

Figure 5 Row 1 to 5: Original document image; Direct binarization result using t=50; Binarization (t=50) with Gaussian filter; Binarization (t=50) with Median filter; Binarization (t=50) with Coplanar filter.

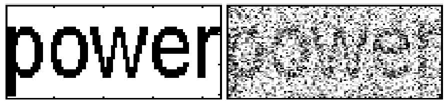

Figure 2 Left: Test image ideal binarization; Right: Original test image corrupted by Gaussian (σ =1.0) and impulsive (p=0.1) noise**.**

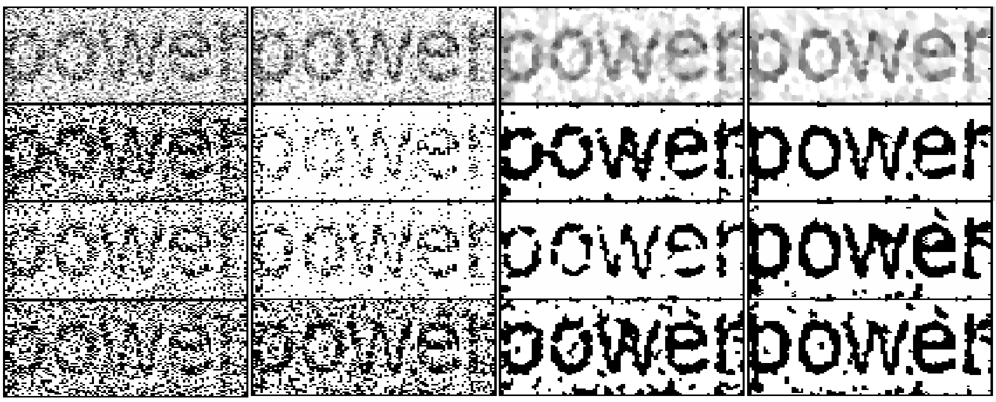

Figure 3 Row 1 (Left to right): Original test image; Gaussian filter output; Median filter output; Coplanar filter output; Row 2: Binarization of corresponding gray-level images in Row 1, using prescribed thresholding (t=192); Row 3: Binarization of corresponding gray-level images in Row 1, using the entropy thresholding method proposed by Sahoo *et. al* [8]; Row 4: Binarization of corresponding gray-level images in Row 1, using the local thresholding method proposed by Niblack [7] .