AN ADAPTIVE REAL-TIME DESCREENING METHOD BASED ON SVM AND IMPROVED SUSAN FILTER

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ABSTRACT

Scanned halftone images are degraded for the presence of screen patterns. It’s a challenge to automatically detect the halftone images and remove the noises on the fly. This paper proposes a novel adaptive real-time descreening method based on Support Vector Machine (SVM) and modified Smoothing over Univalence Segment Assimilating Nucleus (SUSAN) filter for imaging devices, including scanners and multifunction printers. The proposed algorithm contains two major steps: image classification and adaptive descreening. The image classification uses SVM methods to accurately classify the scanned images into three categories: continuous tone, amplitude modulation (AM) halftone or frequency modulation (FM) halftone. The halftone images are needed to descreen. The proposed descreening method is based on modified SUSAN filter. It considers screen cell size to choose the optimal filter parameters which can preserve more high frequency image detail. The experiment results show that the algorithm is effective and fully automation, and maintains higher image quality.

Index Terms—Descreening, halftone, Support Vector Machine, SUSAN Filter, adaptive

1. INTRODUCTION

Halftoning is a process of printing, which converts continuous tone images to binary forms suitable for printing. Most images in printed materials (such as books, magazines) are halftoned with two categories halftoning methods: amplitude modulation (AM) halftone and frequency modulation (FM) halftone [1]. When a halftone image is scanned, noise texture called screen pattern will appear on the scanned image as shown in Fig.2 (a). It seriously degrades the quality of the image, and it’s difficult to further processing the image such as image enhancement, facsimile, and compression. Therefore, descreening methods for detecting and removing the screen pattern are very important in the areas of image processing.

Current descreening methods can be classified into three categories: frequency domain approaches [2], wavelets based approaches [3], and spatial domain approaches [4-7].

Frequency domain descreening methods preserve image details well, such as median filtering in Fourier frequency domain [2]. However, they lead to a high complexity calculation.

Although wavelets based descreening methods can deal with both features of spatial and frequency domain, their computing complexity is very high. Furthermore, the reconstructed continuous tone image may suffer from some serious artifacts, such as ringing and blotchiness [3].

The above two approaches are not suitable for real-time processing for their complexity. Spatial domain algorithms are fast and easy to embed into hardware device. We hence consider spatial domain approaches in our work. Many descreening algorithms in spatial domain are proposed. Some methods take descreening as inverse halftoning [4, 5]. For example, inverse halftoning method is based on projection onto convex sets (POCS) [4] and based on lookup tables (LUT) [5]. These methods are designed for binary images. It is difficult to apply directly to scanned images. The other methods smooth the scanned images by a low-pass filter [6-8], such as resolution synthesis-based de-noising technology for imaging devices [6] and multi-resolution-based image segmentation and enhancement algorithm in copier application [7]. SUSAN filter [8] is a nonlinear filter. It can be used to reduce noises in smooth regions of the scanned image while preserving the edges and image details. However, the scanned halftone images are often in different resolutions. Most of these methods cannot adaptively choose parameters (such as window size) of the low-pass filter, so that they will lose some quality of the images with different resolution.

To descreen scanned images adaptively, we propose a novel adaptive real-time method based on SVM and modified SUSAN filter. This work contains two major steps or contributions as follow:

1) Automatic image classification based on SVM and useful features we selected. It will waste time and lose image quality if we descreening a scanned continuous tone image (such as photographic plate). Unfortunately, all exist descreening method are assume that the input image is halftoned. Our proposed method can detect accurately whether a scanned image is continuous tone, AM halftoned or FM halftoned, so that the continuous tone image can be skipped.

2) Adaptively determine the parameters of descreening filter. Screen pattern is determined by screen cell size, which is the consequence of printing and scanning resolution. Experiment results show that, it is not suitable to use a fixed smoothing filter for all of the scanned images. To address this issue and make the descreening process simultaneously with the scanning process, the proposed method represents an extension beyond all the methods described in literatures. For scanned AM halftone image, we calculate its screen cell size by a small piece of the scanned image at first, and then determine the filter’s parameters. With the coefficients determined, the final descreening procedure is applied on the original image by modified SUSAN filter.
The image classification and screen cell size calculation algorithms are designed to operate in only a small piece of input image. The descreening processing can be done within a window (a few rows stored in memory). As shown in Fig. 1, the window moves row by row vertically over the input. The algorithm is run on each movement. Therefore, our algorithm accomplishes the descreening task within a single pass, which rapidly scans an input page while simultaneously producing an output page.

Fig. 1 Processing is done on a few lows

The remainder of this paper is organized as follows: We explain in Section 2 the detail of the proposed scheme to detect halftone images. We depict in Section 3 the screen cell size calculation for a scanned AM halftone images, and modified SUSAN filter. The experimental results are shown in Section 4, and the conclusions are presented in Section 5.

2. HALFTONE IMAGE DETERMINATION

It is, obviously, wasting time and degrading image quality if we take the descreening processing on a scanned continuous tone image. Therefore, it is necessary to detect whether a scanned image is halftoned. In this section we present a SVM method to classify scanned image to continuous tone image, AM halftone image or FM halftone image. The features used and some aspects in SVM training are discussed as the following.

2.1 Features Extraction

In this work, we adopt holistic features to represent images. Our experiment results show that the histogram, edges and texture of an image can be used to distinguish continuous tone images from halftone images, and the Fourier spectrum will tell AM halftone from FM halftone image. The features used and some aspects in SVM training are discussed as the following.

Fig. 2 (a) Scanned halftone image, 600dpi, (b) continuous tone image, (c) histogram of image (a), (d) histogram of image (b)

(I) Histogram. Fig. 2 shows the histograms of halftone image and continuous tone image. We can find that there are absolute majority dark and lightness pixel in halftone image (Fig.2(c)). Histogram is hence chosen as an important feature for our method.

(II) Edges. As shown in Fig. 3, the edges between halftone image and its smoothed image are obvious difference, but the continuous images are not. Therefore, we extract the edge feature, and they are expressed as the difference between the original image and the smoothed one.

Fig. 3 (a) Continuous tone image, (b) low-pass filtered image of (a), (c) scanned halftone image, (d) low-pass filtered image of (c), (e) Sobel edge image of (a), (f) Sobel edge image of (b), (g) Sobel edge image of (c), (h) Sobel edge image of (d).

(III) Texture. The textures between continuous tone and halftone image are difference, because halftone image is maked up with dots. Thereby, texture is chosen and expressed by square deviation in our work.

(IV) Fourier spectrum. It introduces some strong peaks in its Fourier spectrum of AM halftone image (Fig. 3). Hence, the Fourier spectrum is a distinguished feature for classifying AM halftone image and FM halftone image. Our method uses the polar coordinates function (as Equation (1)) to express overall spectrum feature [9].

\[ S(r, \theta) = \sum_{\theta=0}^{\pi} S(r, \theta) \]  

Here \( S(r, \theta) \) is the image’s Fourier spectrum in polar coordinates.

2.2 Classification using SVM

For classification, we use SVM because of its good performance [10]. Each training example is represented by \((x_1, y_1)\), where \(x_1 \in \mathbb{R}^{58}\) is the image feature vector (16 histogram bins, 1 edge feature, 1 texture feature and 40 Fourier spectrum features \(S(r, r = 1, 2, \cdots, 40)\)), and \(y_1\) is the associated label, for three-class (FM halftone, AM halftone and continuous tone) case, \(y_1 \in \{-1, 0, 1\}\). The SVM classifier was first tested with various kernels in order to explore the performance. The RBF (radial basis function) kernel was found to perform the best. Given the promising features and the well trained SVM, the image classification method proposed is very efficient. The detailed experimental results are presented in Section 4.

3. DESCREENING WITH MODIFIED SUSAN FILTER

Once a scanned image is identified halftoned, a descreening procedure is followed. For AM halftone image, we calculate the screen cell size first, and then automatically determine the
parameters of SUSAN filter for descreening based on the result. We describe the details of these two steps in this section.

3.1. Screen Cell Size Calculation

In AM halftoning, the tone rendition is achieved by varying the dot size. The central distances of adjacent dots are identical, and they determine the resolution of printed image. When such a halftone image is being scanned, it introduces some strong peaks called halftone peak (Fig.4(b)) in its Fourier spectrum. Our method first calculate the screen cell size from the positions of halftone peaks, and then design the parameters of descreening filter according to the screen cell size.

![Fig.4 (a) Scanned AM halftone image, (b) Fourier spectrum of (a), one of halftone peaks is circled.](image)

We can locate the position of the halftone peak \((u,v)\) using local maximum, then the screen cell size \(T\) is figured out as Equation (2):

\[
T = \sqrt{M^2 \left(\frac{u}{N} - \frac{1}{2}\right)^2 + N^2 \left(\frac{v}{M} - \frac{1}{2}\right)^2}
\]

(2)

Here the image size is \(M \times N\).

3.2. Descreening Based on Modified SUSAN Filtering

In this section, we develop a modified SUSAN filter that will effectively remove screen patterns from scanned halftone image. The SUSAN filter was original proposed by Smith and Brady [8], which is denoted as Equation (3).

\[
J(x,y) = \sum_{i=0,\neq 0} I(x+i, y+j) e^{-\frac{r^2}{2\sigma^2}} \frac{(1+(x+i,y+j)-I(x,y))^2}{t^2}
\]

(3)

Where \(I(x,y)\) is the input image, \((i,j)\) is the coordinate of current pixel, \(r = \sqrt{i^2 + j^2}\), \(\sigma\) and \(t\) are two parameters of the SUSAN filter, which control the spatial extent and brightness range of pixels respectively. The main goal of the SUSAN filter is to compute a weighted average of local pixels. The weights are determined by both the spatial distance and lightness distance from the center pixel.

However, the SUSAN filter is not suitable to remove halftone noise, because pixels may have very different luminance after halftoning, though they should be similar in the underlying continuous-tone gray levels. Consequently, we develop the SUSAN filter as follow.

First, we determine the parameter \(\sigma = kT\) and filter mask size \((2\times T+1)\times(2\times T+1)\) automatically according to the screen cell size.

Second, we modify the SUSAN filter as follow.

\[
J(x,y) = \sum_{i=0,\neq 0} I(x+i, y+j) e^{-\frac{r^2}{2\sigma^2}} \frac{(1+(x+i,y+j)-I(x,y))^2}{t^2}
\]

\[
J(x,y) = \frac{\sum_{i=0,\neq 0} e^{-\frac{r^2}{2\sigma^2}} (1+(x+i,y+j)-I(x,y))^2}{t^2}
\]

(4)

Here \(I'(x,y)\) is the smoothed image of \(I(x,y)\) by Gaussian low-pass filter. The parameter \(t\) is not critical, and it is usually not varied.

4. EXPERIMENTAL RESULTS

The performance of our algorithm is evaluated on a total of 420 different images (100 scanned FM halftone images, 96 scanned AM halftone images and 224 continuous-tone images). They are scanned on a Vioneer OneTouch 9320 scanner at various resolutions (300dpi, 400dpi, 600dpi, etc.). The halftoned images are of different sources, such as various newspapers and magazines. All of them are representative of a variety of halftoning methods used in practice. The continuous tone images are from photographs.

In classification stage, we use tools from libsvm [11] in our implementations. The size of training set is 280 (80 FM halftone, 56 AM halftone and 144 continuous tone images) and the size of testing set is 140 (20 FM halftone, 40 AM halftone and 80 continuous halftone images). In order to speed up the classification procedure, we extract features from a small patch (with size 64×64 pixels) of the input image. The testing results show that our classification algorithm is very accurate (see Table 1).

<table>
<thead>
<tr>
<th>Image class</th>
<th>Number of test images</th>
<th>Right classification</th>
<th>Precision Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>FM halftone</td>
<td>20</td>
<td>19</td>
<td>95.0%</td>
</tr>
<tr>
<td>AM halftone</td>
<td>40</td>
<td>39</td>
<td>97.5%</td>
</tr>
<tr>
<td>Con-tone</td>
<td>80</td>
<td>77</td>
<td>96.3%</td>
</tr>
<tr>
<td>Total</td>
<td>140</td>
<td>134</td>
<td>96.4%</td>
</tr>
</tbody>
</table>

Table 1 Experiments result of classification

Then in descreening stage, we compare our algorithm with two methods: low pass Gaussian filtering and regular SUSAN filtering.

In general, the resolutions of printed materials are between 50 lpi and 200 lpi, so that the screen cell size is between \(R_s/200\) and \(R_s/50\) pixels, where \(R_s\) is the scan resolution. We limit the searching area within the range of screen cell size to find the halftone peak, and the maximum in this area is a halftone peak.

In our experiments, we set \(k = 0.36\), \(t = 100\), the filter mask size is \((2\times T+1)\times(2\times T+1)\), and the standard deviation \(\sigma = 0.36T\).

The experimental results for scanned AM halftone images are shown in Fig.5.

Fig.5 (a) is a scanned gray AM halftone image in 600 dpi. Its screen cell size \(T = 3.9\) pixels which is figured out by our algorithm, so the descreening filter mask size is \(7\times7\), \(\sigma = 1.41\); Fig.5 (e) is a scanned color AM halftone image in 300 dpi. We get its screen cell size \(T = 2.3\) pixels, hence the filter window size is
Fig. 5 (a) Scanned gray AM halftone image, 600 dpi, (b) descreened by Gaussian filter, (c) processed by SUSAN filter, (d) descreened image using the proposed method, (e) scanned color AM halftone image, 300 dpi, (f) descreened by Gaussian filter, (g) processed by SUSAN filter, (h) descreened image using the proposed method.

5 × 5, and σ = 0.83. Fig. 5 (b) and (f) show the results of processing the scanned halftone images with the Gaussian low-pass filter. We notice that, while the Gaussian kernel successfully suppresses the screen noise, the processed images are excessively blurred. Fig. 5 (c) and (g) are produced using regular SUSAN filter. We can see it cannot remove the halftone noise effectively. Fig. 5 (d) and (h) show the results of our proposed algorithm. The results show that our descreening method can remove the screen patterns effectively, and maintain significant high quality (preserving more high-frequency non-halftoned image detail).

5. CONCLUSIONS

To address scanned images descreening problems, we propose a novel adaptive real-time descreening method based on SVM and modified SUSAN filtering. The algorithm can accurately classify scanned image into continuous tone images, AM halftone images or FM halftone images. The subsequent descreening procedure can effectively removes screen patterns from the halftone image. The experiment results show that the proposed algorithm is robust and fast, and maintains the overall image quality in terms of edge and detail preservation. With a banded architecture, the algorithm provides significant functionality at a very low computational complexity. It can easily embed into hardware and descreen scanned images in real time.

7. REFERENCES


