New Robust Binarization Approach in Letters

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***Abstract*— We developed a local algorithm specialized in improving the images of letters. The goal is to extract the characters that have a lower gray level than the background. The new algorithm has an emphasis in the characthers edge. Using the gray level range in any pixel neighbourhood, we define the transition energy concept. Transition energy allows to include several models for the threshold function. These models can be statistical distributions or other mathemathic model. The experiments show that new algorithm is a fast and robust algorithm.**

INTRODUCTION

The binarization algorithm cluster the pixels in an image, into two classes: background Λ and foreground Ψ. We developed a not iterative algorithm. Several applications request fast binarization pre-process. Then, our new algorithm offer velocity and excelent segmentations for them. In fact, in small images we can use it in real time.

We divide the work into five parts: definitions, new proposed approach, complexity, test and results experiments and conclusions. In definitions, we present the transition energy concept and basic definitions. In the second section, we describe our algorithm and show three models: two linear and one statistical. In brief, we analyze the complexity in the third section. Results and experiments are showed in the fourth section. We establish standard parameters and runtime records in the conclusions.

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I. DEFINITIONS

We consider an image I, in grayscale, as matrix with $R(I) \times C(I) = k$ dimentions (rows by cols) and we denote a integer $I(i,j) \in [0,l)$ as the gray intensity for the pixel (i,j) in the image I.

Let $I \overset{\phi}{\mapsto} I^*$ be a transformation between a grayscale image into binary image. Define $p(i,j)$ the binary value of (i,j) in I^* as:

$$p(i,j) = \begin{cases} 0 & : \quad I(i,j) \leq t(i,j) \\ 1 & : \quad I(i,j) > t(i,j) \end{cases} \tag{1}$$

where the threshold $t(i,j)$ depends on the neighborhood $N(i,j)$ of the pixel (i,j).

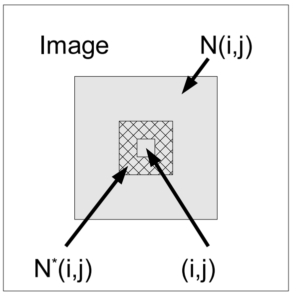

Fig. 1. Neighborhood $N(i,j)$ is in gray (including the pixel (i,j)) and the neighborhood $N^*(i,j)$ is marked with cross pattern.

A. Transition Energy

In [7] calculated the Laplacian, the discrete version for each pixel, for detect the edge pixels. Following the same idea, we define *transition energy* of a pixel (i,j) as:

$$\begin{aligned} e(i,j) \quad = \quad & \max_{(x,y)\in N^*(i,j)} (I(x,y)) - I(i,j) + \\ & \min_{(x,y)\in N^*(i,j)} (I(x,y)) - I(i,j) \end{aligned} \tag{2}$$

where $N^*(i,j) \subset N(i,j)$ is other neighborhood center in the pixel (i,j). In fact, $N^*(i,j)$ is usually a window between 3x3 and 7x7 pixels while $N(i,j)$ has a size about 31x31 or more pixels.

II. NEW PROPOSED APPROACH

On an ideal situation, there is a huge jump between a foreground pixel and a background pixel (when these are together). The edges pixels (in the letter), are easier to cluster than the others pixels because they have a higher jump than the average of pixels. Of course, a blurred images or with noise, there are pixels with false information. Then, we need a robust algorithm against false foreground. Our algorithm has three parts (see figure 2). we call this new algorithm as Mars algorithm.

A. Compute Energy

We compute transition energy (using eq. 2) for each pixel. Considering the transition energy, we have two sets: pixels with positive energy and pixels with negative energy.

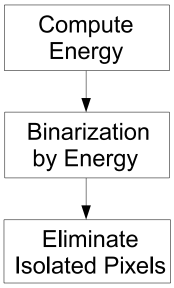

Fig. 2. Whole binarization process.

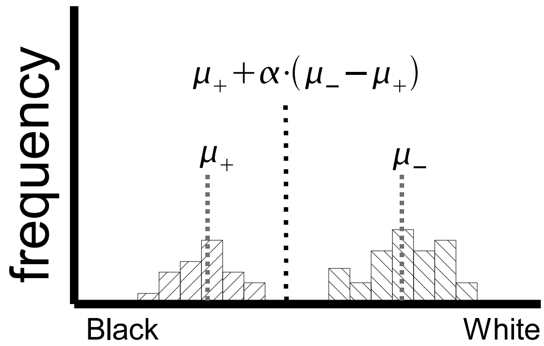

Fig. 3. Threshold computed by eq. 3 .

$$E^+(i,j) = \{(i,j)|e(i,j) \geq +\beta \in N(i,j)\}$$
$$E^-(i,j) = \{(i,j)|e(i,j) \leq -\beta \in N(i,j)\}$$

where β is a positive integer.

B. Binarization by Energy

After the energy was computed, we can use the mean and variance of E^+ and E^-. We propose two linears functions to fix the threshold. Fixing a pixel (i,j) compute t as:

$$t = \mu_+ + \alpha \cdot [\mu_- - \mu_+] \quad (3)$$
$$t = [\mu_+ + \alpha \cdot \sigma_+] + \omega \cdot \{[\mu_- - \alpha \cdot \sigma_-] - [\mu_+ + \alpha \cdot \sigma_+]\} \quad (4)$$

where:

μ_- is the average of E^-
σ_- is the variance of E^-
μ_+ is the average of E^+
σ_+ is the variance of E^+

Nevertheless, these functions have some disadvantages. Both functions depend on extra parameters considerability. Since α or ω can not be computed automatically, we have a new problem to find the right parameters for each image.

To avoid extra parameters, we use a statistical model. We can model E^- and E^+ with a gaussian distribution. Then, the threshold must be solution of equation 5. The solution

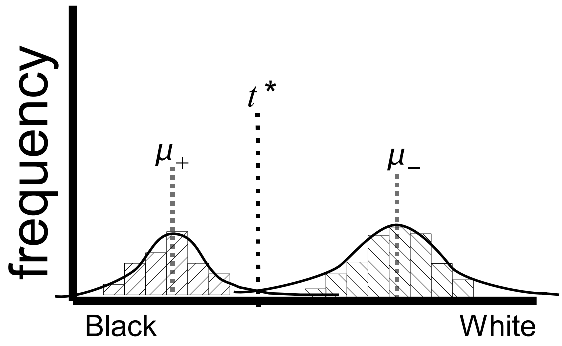

Fig. 4. Threshold computed by eq. 5 .

$\mu_+ \leq t^* \leq \mu_-$ is a root of quadratic equation with coefficients a, b and c given by eq. 6, eq. 7 and eq. 8 respectively.

$$\frac{1}{\sqrt{\sigma_+}} \cdot \exp(-\frac{(t-\mu_+)^2}{2 \cdot \sigma_+}) = \frac{1}{\sqrt{\sigma_-}} \cdot \exp(-\frac{(t-\mu_-)^2}{2 \cdot \sigma_-}) \quad (5)$$
$$a = \frac{1}{\sigma_+} - \frac{1}{\sigma_-} \quad (6)$$
$$b = \frac{2\mu_-}{\sigma_-} - \frac{2\mu_+}{\sigma_+} \quad (7)$$
$$c = \frac{\mu_+^2}{\sigma_+} - \frac{\mu_-^2}{\sigma_-} - \ln\frac{\sigma_-}{\sigma_+} \quad (8)$$

C. Eliminate isolated pixels

Sometimes, there are few isolated black pixels after the binarization. We use a morphological filter for eliminate the remaining pixels. If $p(i,j)$ is 0 then:

$$p(i,j) = \begin{cases} 1 & : \quad c \leq \sum_{x \in N^*(i,j)} p(x) \\ 0 & : \quad otherwise \end{cases} \quad (9)$$

where c is a positive integer. The pseudo-code is:

01.- inicialize: $E^+ \leftarrow \emptyset$, $E^- \leftarrow \emptyset$
02.- for $(i,j) \in I$
03.- compute $e(i,j)$ with equ. 2
04.- if $e(i,j) \geq +\beta$ then $E^+ \leftarrow E^+ \cup$(i,j)
05.- if $e(i,j) \leq -\beta$ then $E^- \leftarrow E^- \cup$(i,j)
06.- end for
07.- for $(i,j) \in I$
08.- compute μ_-, σ_-, μ_+, σ_+
09.- compute $t(i,j)$ as solution of eq. 5
10.- set p(i,j) as eq. 1
11.- end for
12.- for $(i,j) \in I^*$
13.- If $p(i,j)$ is 0 compute $p(i,j)$ with equ. 9
14.- end for

III. Complexity

We consider $|N^*(i,j)| = m$. Then, the complexity for compute the pixel energy is $O(m \cdot k)$.

Given (i,j), to compute μ_-, μ_+, σ_-, σ_+ has complexity $O(n)$ in the worst situacion. Where $|N(i,j)| = n$ is a rectangle with a rows and a cols. But, from the mean and variance of (i,j) we can compute the mean and variance of $(i, j \pm 1)$ or $(i \pm 1, j)$ with effort $2a$. Then, the Mars algorithm has complexity $O(a \cdot k)$ because usually $a > m$.

IV. Test and Results

We tested several images with ours algorithms (linear and gauss model). The first experiment was with images from [3], [4], [5], [6], [7] and compared theirs results against ours results. For the second experiment, we implemented Niblack (see [2] and [3]) and the algorithms from [6] and [7]. The resolution images were around 300x200, 600x300, 800x600, 1200x2000 and 2000x3000.

On the first experiment, we evaluate the quality segmentation of Mars algorithm against the others algorithms. For every image, we found the best parameter on linear and gauss model. All algorithms (see fig.6 to fig.8) had lower performance on test cases that Mars, except Yun Li algorithm. Both algorithm have a similar segmentation quality (see fig.9 and fig.10).

On figure 11- 14, we show some binarization results by ours methods. The Niblack algorithm is fastest algorithm because is no iterative and not need some extra calculation. However, our algorithm is almost as fast as Niblack. Kavallieratou has a regular runtime and Yun Li was the slowest. Into detail, Niblack and Mars algorithm could be run on real time for 300x200 and 600x300. On 800x600 cases the runtime is over 8 seg and on higher cases, the runtime rises over 20 seg or more.

The algorithm was been implemented in C++ in Pentium IV to 3.2 GHz with 2 GB in RAM.

V. Conclusion

The new algorithm is fast and robust with excellent segmentation quality. Although, when the images exceed 200,000 pixels, Mars algorithm is not suitable for applications on real time. We can use it when the applications needs quick and good binarization before to start other process. Since the algorithm is local, we reduce problems with shadows or irregular brightness. Normally, we can use a 31x31 windows for $N(i,j)$ and 5x5 windows for $N^*(i,j)$. The parameter β could be change between 10 and 90 (considering a scale between 0 to 255) but, in general, 10 or 15 are good parameters.

The transition energy concept permit us to use another mathemathic models for the threshold function. In fact, we can explore others models for β and get a better transition energy.

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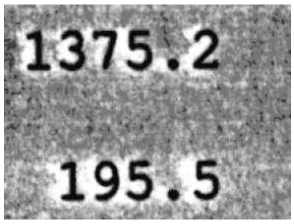

Fig. 5. Example extract from [7].

Fig. 6. First experiment, binarization by Kapurs entropy method.

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Fig. 7. First experiment, binarization by Tsais moment preservation.

Fig. 8. First experiment, binarization by Otsus method.

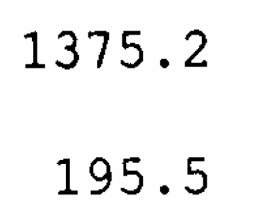

Fig. 9. First experiment, binarization by Yun Lis method.

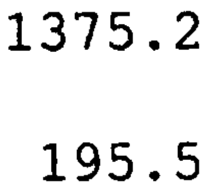

Fig. 10. First experiment, our gauss method.

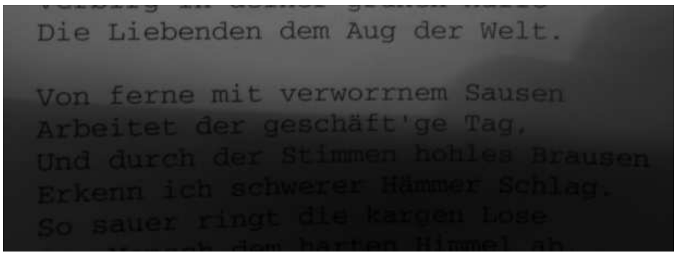

Fig. 11. Example from the second experiment.

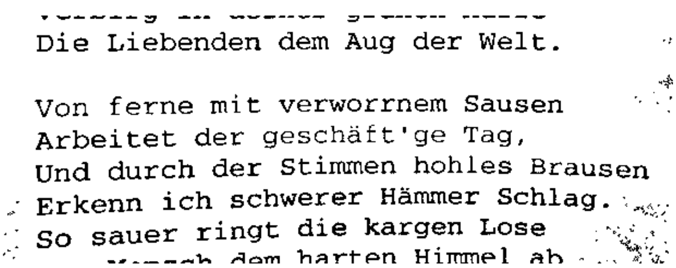

Fig. 12. Binarization by Niblack Algorithm, second experiment.

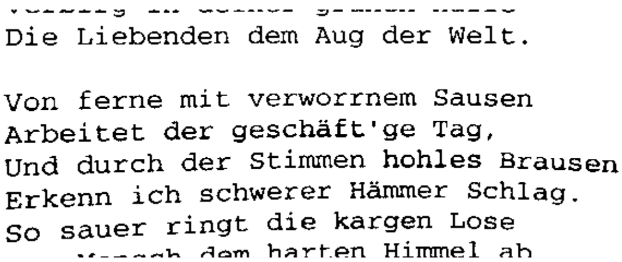

Fig. 13. Binarization by linear model, second experiment.

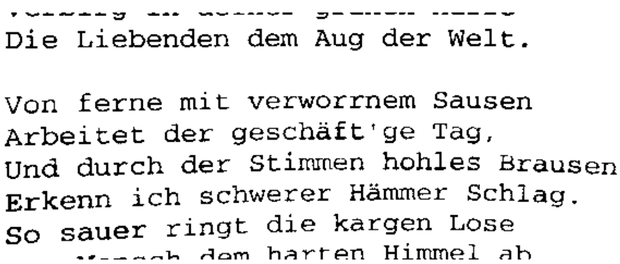

Fig. 14. Binarization by Gauss Model, second experiment.