Efficient, robust license plate detection

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Abstract. The contributions of this paper are twofold: We present our approach to license plate detection based on Niblack's binarization scheme and we propose a theoretically more founded selection of the tuning parameter the scheme relies on.

Any automatic number plate recognition (ANPR) or automatic license plate recognition (ALPR) system always begins with the detection of license plate candidates. We focus on a family of detection approaches that looks for components in a binarized image. In a first step, the image is binarized or segmented. Next, the pixels are grouped into potential letter candidates. Finally, the letter candidates are grouped into license plate candidates. The approach makes only few assumptions about the shape of the letters and only relies on the fact that there is good contrast between letters and background. Key to success is a good binarization method.

Niblack [3] proposed a binarization method that uses the local standard deviation as follows:

$$T(x,y) = m(x,y) \pm \mathrm{k} * \mathrm{s}(\mathrm{x},\mathrm{y}) \tag{1}$$

where k is set to -0.2. This approach is still the basis for many document binarization methods (e.g., [1, 2]). Unfortunately, the proper choice of k is non-obvious. Furthermore, computation of the local standard deviation is costly as it requires a square root and at least 16 bit accuracy.

The threshold we propose is computed as follows:

$$T(x,y) = m(x,y) \pm 0.5 * \overline{|\mathrm{d}|}(\mathrm{x},\mathrm{y}) \tag{2}$$

where $\overline{|\mathrm{d}|}(\mathrm{x},y)$ is the local mean of the absolute differences to the local mean. In Niblack's equation (1) the standard deviation is the root of the average squared difference to the local mean. Our formula uses the average absolute difference to the local mean. Most importantly, the parameter k is replaced by the fixed constant 0.5.

To compare the two approaches, we will investigate the optimal case where all foreground pixels are black and all background pixels are white. Without loss of generality we will assume that pixel values vary between 0 (black) and 1 (white). Suppose the local window contains n pixels of which n_1 are white and n_2 are black such that $n_1 + n_2 = n$. We define $\nu = n_1/n$ to be the fraction of white pixels with value 1. It is then easy to show that

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$$m(x, y) = \mathrm{v} \tag{3}$$
$$s(x, y) = \sqrt{\mathrm{v}(1 - \mathrm{v})} \tag{4}$$
$$0.5 * \overline{|\mathrm{d}|}(\mathrm{x}, \mathrm{y}) = \mathrm{v}(1 - \mathrm{v}) \tag{5}$$

Fig. 1 shows how these values compare as a function of v. Niblack subtracts *s(x,y)* from *m(x,y)* only after multiplication with *k*. Without *k*, the threshold would be negative for any $v < 0.5$ and regions with a large percentage of black pixels would be classified as white. To avoid this *k* must be chosen much smaller than 1 with the result that the standard deviation does not have much effect. With $k = 0.2$ the threshold is at most 0.1 away from the local mean. In contrast, our approach guarantees a threshold between 0 and 1 while it can differ up to 0.25 from the local mean. This makes it more robust to dirt and noise in the white parts of the plate as the threshold is closer to the black pixels.

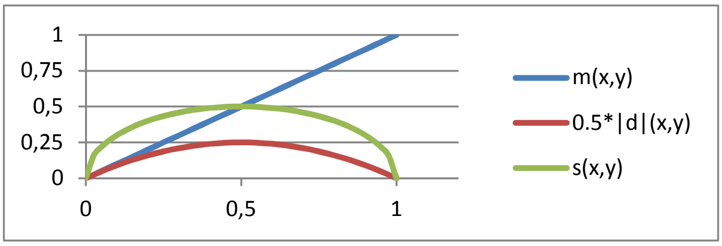

Fig. 1. Comparison of equations (3) – (5)

For our experiments we selected a set of images where the license plate detector exhibits a fairly high error rate so as to test the limits. The images were recorded at a resolution of 752x480 pixels in an outdoor setting in South Africa with 1054 images of which 1009 actually contain a license plate. The images were taken during the night and sunny day and include plates in varying states from almost new and clean to very dirty and damaged.

Table 1 compares Niblack binarization with our modification. The table shows both the absolute number of errors as well as the relative numbers in percent. The non-detections show how much of the overall system error rate is due to the license plate detector. The false detections show how much of the system load is overhead.

	Not detected		False detections		Time
Niblack	32	3.17%	2187	69.12%	6.0ms
Niblack modified	26	2.58%	1194	54.85%	4.6ms

Table 1. Experimental results on South Africa data

1. Kim, M.-K.: Adaptive Thresholding Technique for Binarization of License Plate Images. In: Journal of the Optical Society of Korea, vol. 14, no. 4, pp. 368-375. (2010)
2. Khurshid, K., Siddiqi, I., Faure, C., Vincent, N.: Comparison of Niblack inspired Binarization methods for ancient documents. In: Document Recognition and Retrieval XVI, Proceedings of SPIE-IS&T Electronic Imaging, vol. 7247, 72470U, pp. 1-10 (2009)
3. Niblack, W.: An Introduction to Image Processing pp. 115-116. Prentice-Hall, Englewood Cliffs, NJ (1986)