Feature Extraction for License Plate Location Based on L_0-norm Smoothing

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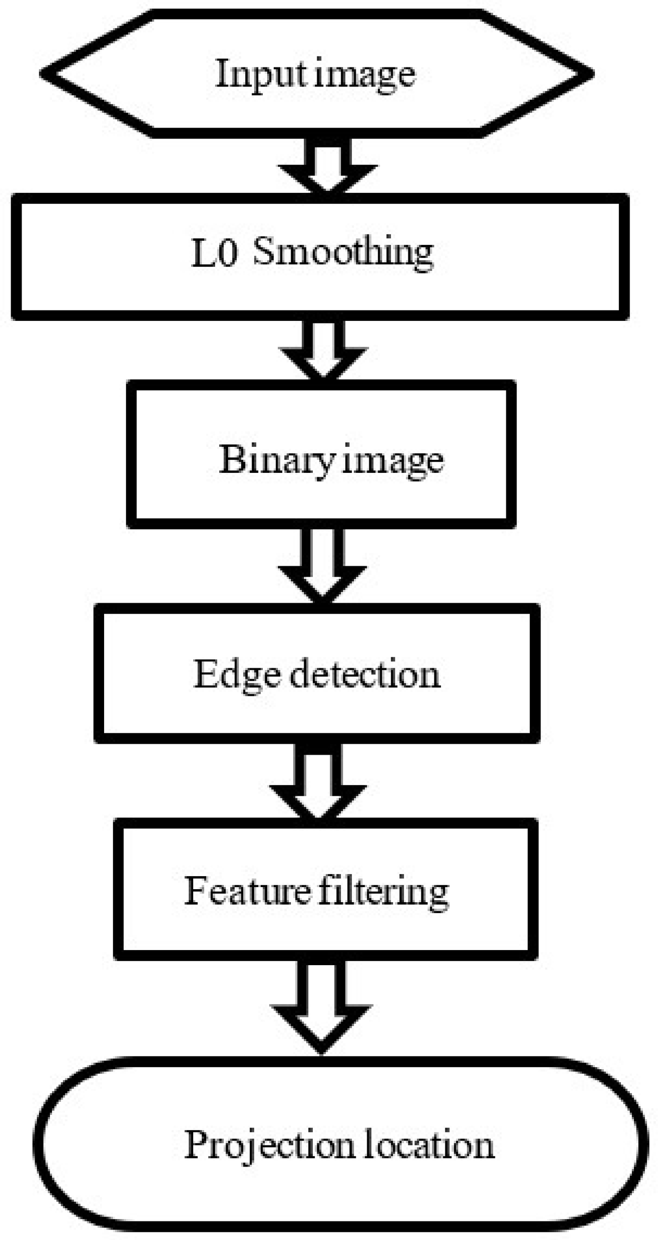
Overview

Abstract: The license plate location plays an important role in license plate recognition systems. As a premise of character recognition, the accuracy and robustness of license location directly determine the performance of the entire license plate recognition system. In many practical applications, license plate recognition systems mostly work outdoors, and the captured images inevitably suffer from different kinds of degradations caused by lighting, weather, and complex backgrounds, and so on. In general, it is a challenging problem under such a diverse, uncertain and complex environment and has also attracted considerable attention in both academic and industrial fields.

Main Idea: In regard to the complex background in license images, we first use an edge-aware filter, L^0-norm smoothing to remove the majority background textures but keep the license plate characters. Then, we take a series of feature filtering steps based on the geometrical textures and structures to furtherly to reduce the interference of pseudo-licenses. Finally, a simple projection location method is used to extract the position and size of the license plates. The whole location procedure is:



Contributions:

- Propose a practical license plate location system based on a series of feature extraction and filter steps.
- Use L_0 image smoothing algorithm to remove the background noise.
- Use a binarized image for fast multiscale resolution analysis.
- Take full use of textural information and projection location method to extract license plates.

Algorithm

L^0 Smoothing: In license plate images, license characters have high contrast textures, while the image background contains abundant low contrast details. We use the L_0-norm smoothing filters to suppress the details, which can be phased as,

$$\arg\min_f E(f) = \|f-g\|_2^2 + \lambda\|\nabla f\|_0, \quad (1)$$

where g and f are the source and target images in $\mathbb{R}^N$, ∇ is gradient operator, $\|\cdot\|_2$ is L^2-norm, and $\|\cdot\|_0$ is so-called L^0-norm, counting the number of non-zero elements of an vector, which leads to a sparse regularization, and λ is a weight scalar.

L^0-norm minimization: The Eq.(1) is NP-hard to solve, we instead introduce two auxiliary variables h_i and v_i for the 2D discrete image, and rewrite it as,

$$\min_{f,h,v} E(f) = \sum_i (f_i - g_i)^2 + \lambda C(h,v) + \beta((\partial_x f_i - h_i)^2 + (\partial_y f_i - v_i)^2), \quad (2)$$

where $C(h,v) = 1$ if $|h_i| + |v_i| \neq 0$, else 0. It is clear that the solution of Eq. (2) approximates that of Eq. (1) when $\beta \to +\infty$. We solve the Eq. (2) minimizing (h,v) and f alternatively.

1. Computing f: By fixing h_i and v_i and minimizing the function,

$$\min_f E(f) = \sum_i (f_i - g_i)^2 + \beta((\partial_x f_i - h_i)^2 + (\partial_y f_i - v_i)^2). \quad (3)$$

The above function is quadratic and thus has a global minimum. Here we use fast Fourier transform (FFT) to accelerate the solver,

$$f = \mathscr{F}^{-1}\{\frac{\mathscr{F}(g) + \beta(\mathscr{F}(\partial_x) * \mathscr{F}(h) + \mathscr{F}(\partial_y) * \mathscr{F}(v))}{\mathscr{F}(1) + \beta(\mathscr{F}(\partial_x) * \mathscr{F}(\partial_x) + \mathscr{F}(\partial_y) * \mathscr{F}(\partial_y))}\}, \quad (4)$$

where $*$ is a component-wise multiplication, $\mathscr{F}$ and $\mathscr{F}^{-1}$ denotes FFT and its inverse operators, and $\mathscr{F}(1)$ is the Fourier Transform of δ function.

2. computing (h,v): We solve (h,v) by minimizing

$$\min_{h,v} E(f) = \lambda C(h,v) + \beta((\partial_x f_i - h_i)^2 + (\partial_y f_i - v_i)^2), \quad (5)$$

where $C(h,v)$ returns the number of non-zero elements of $|\partial_x f_i| + |\partial_y f_i|$. Eq. (5) can be spatially decomposed and solved fastly, because each element h_p and v_p can be estimated individually. It reaches its minimum E^* under the condition,

$$h_i, v_i = \begin{cases} (0,0), & (\partial_y f_i + \partial_y f_i)^2 \leq \frac{\lambda}{\beta}, \\ 0, & \text{otherwise}. \end{cases} \quad (6)$$

Post-processing: To extract and locate the license more accurately, we also introduce the following post-processing steps:

Binarized image: Let I be an image, and I_s is resized from I with a scale s, where $s \in S = \{s_{m,n}\} = \{2^{-m}, 2^{-n}\}_{m,n\in Z}$ are row and column scales. If we rearrange the images $\{I_s\}_{s\in S}$ on a 2-D plane in descending scales, a new image $B = \{I_s\}_{s\in S}$, called binarized image, is obtained, which provides a multiscale analysis of license image.

Feature Filtering: By using the L^0-norm smoothing, a mass of local textures can be removed and an optimal scale of the license is also available with binarized image. We further propose a feature filtering, that is, edge extraction, removing long lines, structure analysis, and texture density analysis to further remove the pseudo-licenses.

Projection Location: After the above steps, the license is easy to locate, we use a very simple projection location method to extract the position and size information.

Experiments & Results

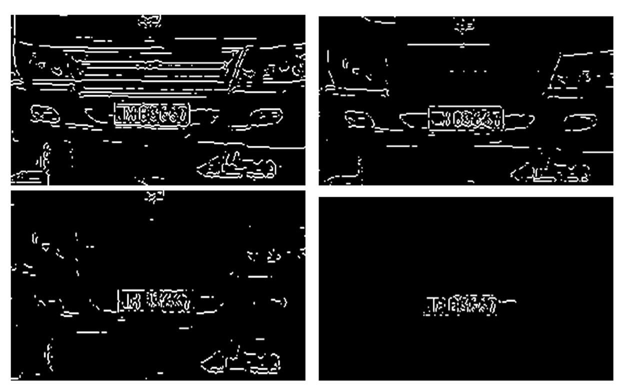
1. L^0-norm smoothing

- Left: input image, right: L^0-norm smoothing result. It is clear that the low-contrast details are significantly suppressed with L^0-norm smoothing.

2. Binarized image

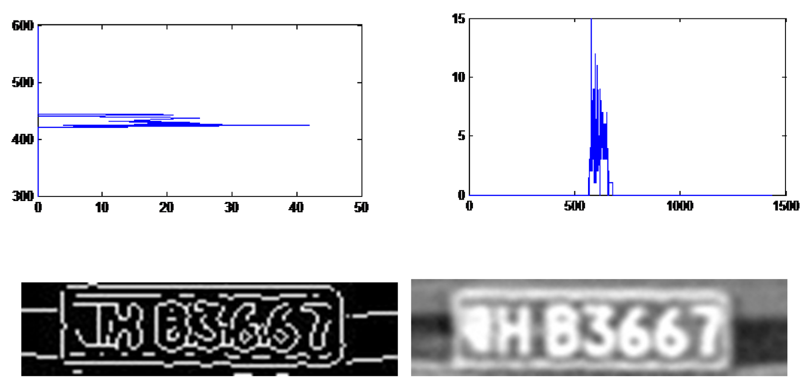
- The binarized image provides a multiscale analysis for licenses.

3. Feature filtering



- Edge extraction, removing lines, structural and textural analysis.

4. Projection results



- The horizontal and vertical projection histograms, and the output license plate.

Quantitative evaluation:

Method	Precision(%)	Recall (%)	F_1-score(%)
Top-hat	77.50	84.50	88.61
MSER&SIFT	83.73	90.47	86.97
Wavelet-based	90.30	94.03	95.00
CNN-based	97.80	95.30	96.01
Ours	96.10	95.40	95.30

- Quantitative evaluation on natural image datasets. We collected 1000 images with both simple and complex backgrounds.

References

Huang, J., Ruzhansky, M., Feng, H., Zheng, L., Huang, X. and Wang, H., 2019. Feature extraction for license plate location based on L0-norm smoothing. Open Computer Science, 9(1), pp.128-135.

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