License Plate Detection Using Morphological Transformations and Filters

Burak EVREN[1]

Department of Computer Engineering
{burakevren.26@gmail.com}

Abstract

Automatic License Plate Recognition (ALPR) is crucial for Intelligent Transportation Systems. A key initial step is accurate license plate detection (LPD). This report outlines a MATLAB-based LPD system using image processing techniques. The process involves preprocessing (resizing, grayscale conversion), Sobel edge detection, and morphological operations (closing, dilation, filling, erosion, area opening) to enhance plate regions and reduce noise. An intermediate filter prunes unlikely candidates early. Final candidates are identified using region-props to measure geometric features (Area, Aspect Ratio, Extent, Solidity, Eccentricity, Orientation). Hard thresholds filter non-plate shapes, and a weighted geometric score ranks remaining candidates. The top-scoring region's bounding box is returned. This method leverages distinct edge and shape characteristics for detection.

Keywords: *License Plate Detection, Morphological Transformations, MATLAB, Region/Prop Analysis*

1. Introduction

Automatic License Plate Recognition (ALPR) is fundamental to Intelligent Transportation Systems (ITS). It automates reading license plates for applications like electronic tolling, traffic surveillance, law enforcement, parking management, and access control. The typical ALPR pipeline includes image acquisition, license plate detection (LPD), character segmentation, and character recognition (OCR). Accurate LPD is the critical first step; failure here leads to overall system failure.

1.1. Problem Statement: Challenges in LPD

Real-world LPD faces challenges from varying conditions:

- **Environmental:** Variable illumination (glare, shadows, low light, night), adverse weather (rain, fog, snow), dirt.
- **Plate:** Differences in size, aspect ratio, color, font, layout; damage, occlusion. Multiple plates in one image.
- **Imaging:** Varying angle and distance (skew, scale), motion blur, image quality (resolution, focus, noise). These factors challenge traditional LPD algorithms relying on specific heuristics.

1.2. Proposed Approach Overview

This report details a license plate detection system developed and implemented using MATLAB. The primary objective is to accurately localize the rectangular region corresponding to a vehicle's license plate within an input image. The system employs a sequential image processing pipeline that leverages fundamental computer vision techniques. The core methodology involves:

1. **Preprocessing:** Resize image, convert to grayscale.
2. **Edge Detection:** Use Sobel operator for edge mapping.
3. **Morphological Processing:** Apply closing, dilation, filling, intermediate filtering, erosion, area opening to enhance plate structure.
4. **Region Analysis & Filtering:** Measure geometric properties (Area, Aspect Ratio, Extent, Solidity, Eccentricity, Orientation) using region-props filter using thresholds.
5. **Scoring & Selection:** Rank candidates with a weighted geometric score; select highest score.
6. **Output:** Return bounding box scaled to original image size.
7. **User Interface:** An application where user can select input image to detect plate.

1.3. Related Work

Numerous approaches have been proposed in the literature for license plate detection and localization. Many classical methods rely on extracting specific features characteristic of license plates.

Edge-Based Methods: Edge detection is a fundamental technique, as license plates typically exhibit strong edges due to the contrast between characters and the background, as well as the plate's boundary. Operators like Sobel or Canny are frequently used as an initial step to obtain an edge map. Subsequent steps often involve analyzing the density or connectivity of these edges to identify rectangular regions. [1] [2]

Morphology-Based Methods: Mathematical morphology plays a significant role in many LPD systems, often used in conjunction with edge detection. Morphological operations like dilation and erosion, using carefully selected structuring elements (SEs), can connect broken character strokes or plate boundaries, remove noise (e.g., small spurious edges), separate characters from the plate background, or enhance the overall plate structure. Operations like opening (erosion followed by dilation) and closing (dilation followed by erosion) are commonly used to remove small objects or fill small holes, respectively. Top-hat and black-hat transforms can be used to enhance bright or dark features against the background. [3] [4] [5]

Feature-Based Methods: These methods often analyze candidate regions based on expected features. Geometric features are widely used for filtering, leveraging the typically rectangular shape and specific aspect ratio of license plates. Properties like area, aspect ratio (width/height), extent (ratio of region area to bounding box area), and solidity (ratio of region area to convex hull area) are calculated for candidate regions, and those falling outside predefined ranges are discarded. Texture-based features and color-based features have also been explored, although they can be less robust to variations in plate design and illumination. [6]

Hybrid Methods: Recognizing the limitations of relying on a single feature type, many successful systems employ hybrid approaches, combining techniques like edge detection, morphological processing, and geometric or textural feature analysis in a multi-stage pipeline to improve robustness and accuracy. [7]

Learning-Based Methods: In recent years, machine learning and deep learning techniques, particularly Convolutional Neural Networks (CNNs) and object detection frameworks like YOLO (You Only Look Once) or Faster R-CNN, have achieved state-of-the-art performance in LPD. These methods learn features directly from data, often providing superior robustness in complex and unconstrained scenarios compared to traditional methods. [8]

After detailed research, we decided to use a hybrid approach. Especially, this article [7] gave us a basic understanding about the inter-dynamics of LPR algorithms.

2. Material and Method

This section provides a detailed description of the license plate detection algorithm implemented in the MATLAB. The algorithm operates as a sequential pipeline, processing the input image through several distinct stages to isolate and identify the license plate region.

2.1. Image Preprocessing

The initial stage focuses on preparing the input image for subsequent analysis, ensuring consistency and simplifying processing.

- **Input Image:** The application accepts either a color (RGB) or a grayscale image as input.
- **Resizing:** The input image is resized to have a fixed height of 480 pixels while the width is adjusted automatically to maintain the original aspect ratio. This standardization is crucial for ensuring that the parameters used in later stages, such as structuring element sizes and area thresholds, have a consistent effect regardless of the original image resolution.
- **Grayscale Conversion:** If the resized image is in color, it is converted to a grayscale intensity image using the rgb2gray. If the input is already grayscale, it is used directly. Most subsequent operations, particularly edge detection and morphological processing, are typically performed on single-channel grayscale images, simplifying the analysis by focusing on intensity variations.
- **Data Type Conversion:** The grayscale image is explicitly converted to an 8-bit unsigned integer format (uint8) if it is not already in that format.

2.2. Edge Detection

The next stage aims to identify potential boundaries of objects within the image, leveraging the fact that license plates typically have high contrast edges.

- **Sobel Operator Theory:** The Sobel operator is a gradient-based edge detection method that uses two 3x3 convolution kernels (masks) to approximate the first derivative of the image intensity function in the horizontal (Gx) and vertical (Gy) directions. These kernels emphasize changes in intensity. The gradient magnitude, often approximated as $|Gx|+|Gy|$, is calculated at each pixel. Pixels with a gradient magnitude exceeding a certain threshold are classified as edge pixels, while others are classified as background. The Sobel operator incorporates some inherent smoothing due to its kernel structure, making it slightly less sensitive to noise than simpler gradient operators, but generally more sensitive than the Canny operator.
- **Output:** The result is a binary image where white pixels represent detected edges, and black pixels represent the background. These edges correspond to regions of high spatial frequency or rapid intensity change in the grayscale image.

2.3. Morphological Processing Pipeline

Following edge detection, a series of morphological operations are applied to the binary edge map to refine the detected structures, enhance potential license plate regions, and remove noise. Morphological operations process image shapes using a structuring element (SE). SEs are small, predefined shapes (e.g., disk, line, square) that probe the image, modifying pixels based on the SE's fit or hit with local neighborhoods.

2.3.1. Step 1: Closing

Morphological closing is applied to the edge map and a horizontal line SE is used. Closing consists of a dilation followed by an erosion using the same SE. Its primary effect is to fill small holes and close gaps in contours. In this context, applying closing with a horizontal line SE specifically targets the connection of horizontally aligned edge segments that might have been fragmented during Sobel detection. This is particularly relevant for bridging gaps in the top and bottom boundaries of the rectangular license plate, making the plate outline more continuous without excessively thickening vertical edges.

2.3.2. Step 2: Dilation

The closed edge image is dilated, and a small disk-shaped SE is used. Dilation expands the foreground regions (the edges). This small dilation aims to further reinforce the connectivity of the edge structures, ensuring that the boundaries form closed contours before the filling operation, thereby making potential plate regions more solid.

2.3.3. *Step 3: Hole Filling*

Holes within the connected foreground regions are filled using 'holes' method. This operation identifies background pixels that are surrounded by foreground pixels (connected components) and changes them to foreground pixels. Based on the assumption that license plates are solid objects, this step converts the outlined plate regions (formed by the connected and dilated edges) into solid, filled blobs. This transformation is essential for enabling subsequent analysis based on regional properties like area and solidity.

2.3.4. *Step 4: Intermediate Filtering*

Additional filtering step is applied to the filled image before erosion. This involves calculating properties ('Area', 'BoundingBox', 'Solidity', 'Extent') for all regions in filled image using region-props. This step acts as an early pruning mechanism. By removing regions that are clearly too large, have highly non-plate-like aspect ratios, or are very non-solid/sparse even after filling, it aims to reduce the number of candidate regions processed in the subsequent, potentially more computationally demanding, erosion and final region-props analysis stages.

2.3.5. *Step 5: Erosion*

The image resulting from the previous step is eroded, and a disk-shaped SE used. Erosion shrinks the boundaries of foreground objects. Applying erosion at this stage serves multiple purposes: smoothing the contours of the filled blobs, removing thin protrusions or bridges that might have formed during dilation and filling, and separating objects that were weakly connected. Using a 'disk' SE ensures that the shrinking effect is isotropic (uniform in all directions).

2.3.6. *Step 6: Area Opening*

Loosely connected components are removed from the eroded image. This is a noise removal step that eliminates small, isolated blobs (connected components) whose area is below the specified threshold. These small regions are considered unlikely to be valid license plates and are treated as noise artifacts resulting from the preceding operations.

2.4. Region Analysis and Candidate Selection

After the morphological processing pipeline, the resulting binary image contains cleaned, solid blobs representing potential license plate candidates. The next stage involves analyzing the geometric properties of these blobs to filter out non-plate regions.

- **Property Measurement:** The region-props function is used to measure a set of specified geometric properties for each connected component (8-connectivity for 2D) in cleaned image. The properties measured are: 'BoundingBox', 'Area', 'Extent', 'Solidity', 'Eccentricity', and 'Orientation'.
- **Measured Properties Definitions:**
  - **Area:** The actual number of pixels belonging to the region (scalar). Used to filter based on expected plate size.
  - **BoundingBox:** The smallest rectangle enclosing the region, returned. Used to calculate aspect ratio and define the final output box.
  - **Extent:** The ratio of the region's 'Area' to the area of its 'BoundingBox' (scalar, 0 to 1). Measures how well the region fills its bounding box; expected to be high for rectangular plates.
  - **Solidity:** The ratio of the region's 'Area' to the area of its convex hull (scalar, 0 to 1). Measures the convexity of the region; expected to be high for solid rectangular plates without significant indentations or holes.
  - **Eccentricity:** The eccentricity of an ellipse with the same second moments as the region (scalar, 0 to 1). Measures elongation; 0 for a circle, 1 for a line segment. Rectangular plates are expected to have high eccentricity.
  - **Orientation:** The angle between the x-axis and the major axis of the ellipse with the same second moments as the region. Used to filter out regions that are significantly tilted.
- **Geometric Filtering:** The algorithm iterates through each region identified by region-props. A region is considered a valid license plate candidate only if all its measured properties satisfy a set of predefined constraints (hard thresholds) specified in the params structure.

2.5. Geometric Scoring and Final Selection

The properties and bounding boxes of all regions that pass the geometric filters are stored. For each valid candidate, a geometric score is calculated using a weighted sum of its properties, designed to measure its "plate-likeness". The candidate region achieving the maximum geometric score is selected as the final detected license plate.

2.6. Bounding Box Generation

The final step involves retrieving the bounding box of the selected candidate and scaling it back to the original image's coordinate system.

- **Retrieving Scaled Box:** The bounding box is retrieved from candidate boxes.
- **Rescaling:** A scaling factor is calculated based on the ratio of the original image height to the resized image height. Each element of the selected bounding box is multiplied by this rescale factor. A function is used to convert the resulting floating-point coordinates and dimensions to integers.
- **Validation:** A final check ensures the rescaled bounding box has positive width and height.
- **Output:** The function returns the final, rescaled bounding box as a vector of four integers representing the top-left corner coordinates (x, y) and the dimensions (width, height) in the original image space.

3. Experimental Study

The application developed using MATLAB and as a test dataset 50 images with licenses plates under varying conditions used. To test the algorithm, basic user interface developed. F1 score metrics chosen to determine performance of application on 50 given images.

Preprocessing	imResizeHeight	480
Edge Detection	edgeMethod	sobel
Morphology (Close)	seCloseShape seCloseSize	line 7.75
Morphology (Dilate)	seDilateShape seDilateSize	disk 1
Morphology (Erode)	seErodeShape seErodeSize	disk 2
Morphology (Clean)	minNoiseBlobArea	180
Intermediate Filter	intermediateMaxFilledAreaFactor intermediateMinFilledSolidity intermediateMinFilledExtent intermediateMinFilledAspectRatio intermediateMaxFilledAspectRatio	10 0.15 0.15 2.27 7
Geometric Filtering	targetAspectRatio geoScoreWeightAR geoScoreWeightExtent geoScoreWeightSolidity geoScoreWeightEccentricity geoScoreWeightOrientation	4.5 0.75 1.75 1.75 0.8 0.5
Geometric Scoring	minArea maxArea minAspectRatio maxAspectRatio minExtent minSolidity minEccentricity maxAbsOrientation	175 6000 2 6.5 0.3 0.3 0.8 20

Table 1: Parameters Used

3.1. Evaluation Metrics and Results

To quantitatively assess the performance of the LPD system, standard object detection metric was considered:

- **Precision:** The fraction of predicted bounding boxes that correctly match a plate (TPs) out of all predicted bounding boxes (TPs + False Positives, FPs). High precision indicates the system generates few false alarms

$$\frac{TP}{TP+FP} = \frac{42}{42+3} = \frac{42}{45} \approx 0.93 \quad (1)$$

- **Detection Rate (Recall):** The fraction of actual license plates that were correctly detected (TPs) out of the total number of plates (TPs + False Negatives, FNs). High recall indicates the system misses few actual plates. This is a special case, which we included 3 FPs as FN because there are 5 cases where our algorithm does not even make predictions.

$$\frac{TP}{TP+FN} = \frac{42}{42+8} = \frac{42}{50} \approx 0.84 \quad (2)$$

- **F1 Score:** The harmonic mean of Precision and Recall, providing a single measure that balances both metrics.

$$2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} = 2 \times \frac{(0.93 \times 0.84)}{(0.93+0.84)} = \approx 0.88 \quad (3)$$

3.2. Illustrative Results

Figure 1: Input Image

Figure 2: Edge Map Result

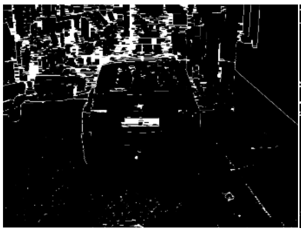

Figure 3: Close Op Result

Figure 4: Dilate Op Result

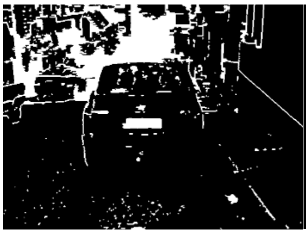

Figure 5: Fill Op Result

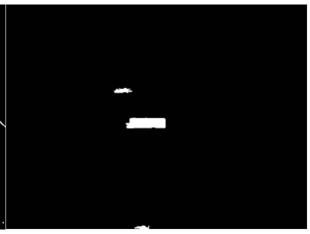

Figure 6: Intermediate Filter

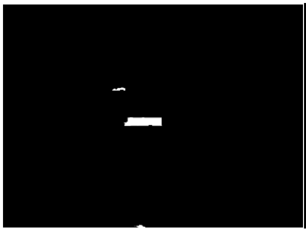

Figure 7: Erode Op Result

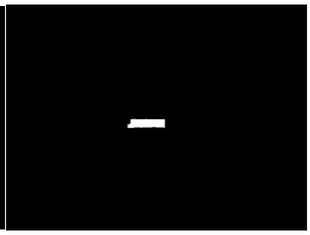

Figure 8: Area Open Result

Figure 9: Geometric Scoring

Figure 10: Final Result

As seen from the above, the algorithm aggressively fills the edges then filters objects that do not fill or resemble a rectangle. Thanks to this our algorithm generalizes well in common cases.

4. Conclusions

The implemented approach demonstrates a systematic pipeline for LPD using classical image processing techniques. Its strengths lie in the use of well-understood algorithms like Sobel edge detection and standard morphological operations, combined with explicit geometric filtering based on regionprops measurements. This makes the algorithm relatively interpretable, as the purpose of each step and the rationale behind the filtering criteria are clear.

However, the approach also exhibits several inherent weaknesses characteristic of traditional methods. Its performance is likely highly sensitive to the tuning of the numerous parameters defined in the params structure. The chosen values (e.g., SE sizes, area thresholds, geometric filter limits, scoring weights) may work well for a specific set of conditions or plate types but might require significant readjustment to generalize to different datasets, camera setups, or environmental conditions. The reliance on hard thresholds for geometric filtering creates a "scoring" problem. Plates that are slightly outside the defined ranges (e.g., due to perspective distortion or non-standard design) will be missed, even if clearly visible. Also, when plate is scored alongside with other rectangle artifacts that failed to be filtered/cleaned, there are cases in the dataset (21,28) that algorithm choses artifacts than plate.

The initial Sobel edge detection struggles in low-contrast scenarios or with significant image noise, potentially leading to fragmented edges that the morphological closing step cannot fully repair. In the given dataset this problem encountered in many cases (3, 18, 20, 23, 24, 41)

Compared to modern deep learning-based object detectors, this traditional pipeline sacrifices robustness and generalization capability for interpretability. Deep learning models can learn complex features automatically from large datasets, often achieving higher accuracy in challenging "in-the-wild" scenarios without requiring manual feature engineering or extensive parameter tuning for specific geometric properties.

5. References

[1] D. Dharun, "License Plate Localization: A Review," *International Journal of Engineering Trends and Technology (IJETT)*, vol. 10, p. 13, 2014, Accessed: May 05, 2025. [Online]. Available: https://ijettjournal.org/assets/volume-10/number-13/IJETT-V10P322.pdf

[2] A. Zenath and S. Shriram, "Licence Plate Localization And Recognition Using Mser And Swt Algorithms," vol. 142, pp. 2278–2834, Accessed: May 05, 2025. [Online]. Available: https://www.iosrjournals.org/iosr-jece/papers/Conf.15011/Volume%201/iosr%2023-142-147.pdf

[3] Soora, N.R., Kotte, V.K., Dorthi, K., Vodithala, S., Kumar, N.C.S. (2024). A comprehensive literature review of vehicle license plate detection methods. Traitement du Signal, Vol. 41, No. 3, pp. 1129-1141. https://doi.org/10.18280/ts.410304

[4] "Vertical-Edge-Based Car-License-Plate Detection Method," *SlideShare*, 2017. https://www.slideshare.net/slideshow/verticaledgebased-carlicenseplate-detection-method/77459765 (accessed May 05, 2025).

[5] X. Zhai, Faycal Benssali, and S. Ramalingam, "License plate localisation based on morphological operations," *University of Hertfordshire Research Archive (University of Hertfordshire)*, Dec. 2010, doi: https://doi.org/10.1109/icarcv.2010.5707933.

[6] Narasimha Reddy Soora, V. K. Kotte, Kumar Dorthi, Swathy Vodithala, and N. C. S. Kumar, "A Comprehensive Literature Review of Vehicle License Plate Detection Methods," *Traitement du signal*, vol. 41, no. 3, Jun. 2024, doi: https://doi.org/10.18280/ts.410304.

[7] G. Sharma, "Performance Analysis of Vehicle Number Plate Recognition System Using Template Matching Techniques," *Journal of Information Technology & Software Engineering*, vol. 08, no. 02, 2018, doi: https://doi.org/10.4172/2165-7866.1000232.

[8] A. Ismail, Maroua Mehri, Anis Sahbani, and B. Amara, "A dual-stage system for real-time license plate detection and recognition on mobile security robots," *Robotica*, pp. 1–22, Jan. 2025, doi: https://doi.org/10.1017/s0263574724001991.