Detection and Recognition of Road Markings in Panoramic Images

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Abstract. The detection of road lane markings has many practical applications, such as advanced driver assistance systems and road maintenance. In this paper we propose an algorithm to detect and recognize road lane markings from panoramic images. Our algorithm consists of four steps. First, an inverse perspective mapping is applied to the image, and the potential road markings are segmented based on their intensity difference compared to the surrounding pixels. Second, we extract the distance between the center and the boundary at regular angular steps of each considered potential road marking segment into a feature vector. Third, each segment is classified using a Support Vector Machine (SVM). Finally, by modeling the lane markings, previous false positive detected segments can be rejected based on their orientation and position relative to the lane markings. Our experiments show that the system is capable of recognizing 93 %, 95 % and 91 % of striped line segments, blocks and arrows respectively, as well as 94 % of the lane markings.

1 Introduction

The government is responsible for the maintenance of many objects in the public space, such as traffic signs, street lights, roads and also road markings. Over time, road markings deteriorate due to the constant flow of cars, which can lead to a decreased road traffic safety. Ideally, the condition of road markings should be periodically monitored. Performing this monitoring task manually is too labor intensive and too costly, therefore an automatic or semi-automatic solution would be favorable. Because of the availability of large-scale collections of densely captured street-level panoramic images, this monitoring task can be performed much more efficiently using computer vision algorithms. Moreover, by comparing the results of images captured over different years, the deterioration can be tracked over time. In this paper, we describe the first stage of such a system, which is the detection and recognition of road markings in single panoramic images.

Although detection of road markings is an easy task for humans, we have found that creating an automated solution is not so simple, due to several reasons. The presence of shadows and illumination differences can complicate the road/line segmentation, while other vehicles on the road often (partially) occlude road

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markings. Besides this, roads can also contain regions that have a similar color as road markings. Additionally, the road surface occasionally changes abruptly in appearance and the markings themselves become deteriorated over time.

Most previous work in road marking detection has been performed in the context of Advanced Driver Assistance Systems (ADAS) and Autonomous Vehicles. In those fields, somewhat different constraints and goals apply than for our application. For example, we are interested in all type of road markings including lane markings, while ADAS typically focuses only on lane markings. Besides, there is more focus on real-time performance, the cameras have typically a lower resolution and offer lower quality, based on a smaller field-of-view (and therefore less background clutter) and they operate in more challenging weather conditions. Additionally, since the source data is typically video-based, many of the techniques described in the corresponding literature cannot be directly applied to our panoramic images. An overview of lane tracking techniques can be found in [1]. For instance, a detection and recognition method based on the Hough transform is described in [2] and [3]. A disadvantage of these methods is that they are only suitable for straight lines. In [4], the author proposes an algorithm of extracting lane markings using frequency-domain features, however this methods only supports lane markers and arrows, it is difficult to extend to other shapes and is much more complicated than our proposed method. In [5], a method of road marking detection by image moments and a Bayes classifier is proposed, however, a prior probability is required for Bayes classification. Besides this work, contour orientation [6] and a Histogram of Oriented Gradient (HOG) features [7] are also used for road marking detection. More recently, in [8], the author proposes a practical system based on matching a detected region with template images. However, their matching algorithm is quadratic in the number of features, so that with more features in the image, it becomes rather slow. A method which is capable of crosswalks and arrows recognitions, based on comparing extracted features with known models, is proposed in [9]. However, the accuracy of the comparison is constrained by scale.

There are some important differences between our system, and the previously described literature. Our system should work on high-resolution panoramic images with a very wide field-of-view (and consequently, a lot of background clutter), instead of low-resolution video. We aim to detect many different types of road markings, and it should be easy to extend support for new types of road markings. Compared to the approaches in literature we use a novel shape descriptor, and an innovative method for the modeling of lane markings.

The purpose of the work in this paper is to design a robust detection algorithm for road markings that is sufficiently reliable to handle faded markings and painted road signs. In Sect. 2, we describe the details of the processing stages of the system. In Sect. 3, the experimental results are discussed for lane markings, together with road markings such as line segments, blocks and arrows, which are mainly applied as indications for highways.

2 Road Marking Detection and Recognition

Our proposed system for road marking detection consists of three main steps. First, Inverse Perspective Mapping (IPM) is performed to generate a top-view image. Second, road marking elements are extracted by a segmentation algorithm. Finally and third, from each segment a feature vector is extracted, and a Support Vector Machine (SVM) classifier is employed to distinguish segments based on their geometric features. Since some background segments can have similar shapes as road markings, we model the lanes that appear in the image, using RANSAC and a Catmull-Rom spline [10] with the lane marking candidates classified by SVM. Many non-road marking segments can be rejected based on the lane positions and the orientation of the segments (the orientation should be consistent with the orientation of the lane markings). A block diagram of the entire system is shown in Fig. 1.

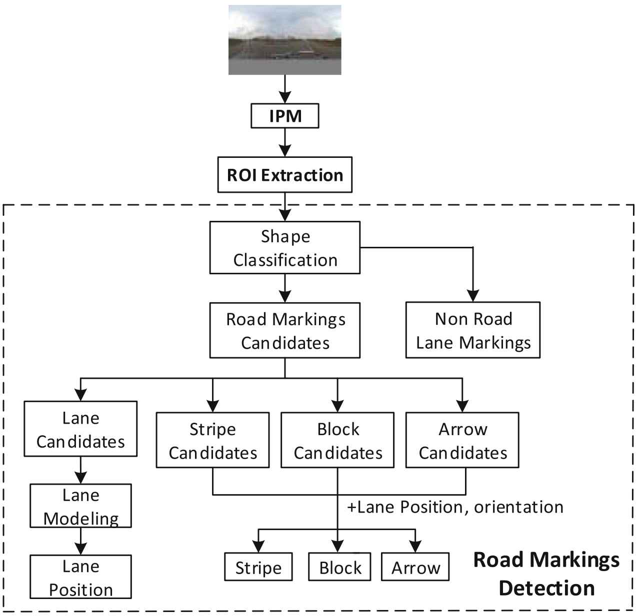


Fig. 1. Overview of the system

2.1 Inverse Perspective Mapping

The original spherical panoramic images are stored in an Equirectangular format of which an example of a panoramic image is shown in Fig. 2a. We transform the panoramic image to a top-view by applying an Inverse Perspective Mapping, similar to [2,8]. The mapping transformation between spherical panoramic images and the top-view image only depends on the camera height of the ground

(a)

(b)

Fig. 2. (a) Example of a panoramic image. (b) Top view of the original panoramic image

plane and the azimuth angle of the camera with respect to the ground plane. Since our panoramic images are well calibrated for 360° panoramics, and the orientation of the car in the image is captured by the car positioning system, we simply remap to a top-view, according to the cars position. Figure 2b shows an example of a reconstructed top-view image. The relation between the original panoramic image and the top-view image is specified by the following equations

$$y = \left(m - \frac{\arctan(d/h)}{2\pi} \times n\right) \mod m, \tag{1}$$

$$x = \left(x_{car} + \frac{\arctan(y_o/x_o)}{2\pi} \times n\right) \mod n. \tag{2}$$

In the Eq. (1), x_{car} denotes the x-coordinate of the front of the car in the panoramic image. Parameters (x, y) and (x_o, y_o) denote the pixel position of the original panoramic image and top-view image, respectively, and parameter h is the height of the camera with respect to the ground plane, d the distance between the pixel (x_o, y_o) and the center of the car in the top-view, and (m, n) is the resolution in pixels of the panoramic image.

2.2 Segmentation Algorithm

Road markings are designed to be clearly noticed and are therefore made reflective, so they can be easily observed by drivers and other road users. We design our system to work under various lighting conditions. Usually, pixels of road markings are brighter than neighboring pixels. Based on this observation, we divide our segmentation algorithm into two steps.

1. First, bright pixels are obtained by comparing the value of a pixel with the average of the surroundings. For instance, Fig. 3 shows a sketch of an image with pixel P. We choose a window centered at pixel P and make a subtraction between P and the average pixel value within the window, as in Eq. (3), where g_p is the pixel value of P and (v, w) is the pixel size of the window. If $g_p^{'}$ is larger than a manually defined threshold, then P is considered to be a candidate pixel of road markings. The size of the window is determined empirically, where it was found that a value of a 105×105 pixels provides the best performance for our data. The subtraction of the window average is specified by

$$g_p^{'} = g_p - \frac{1}{vw} \sum_{i=1}^{v} \sum_{j=1}^{w} g_{ij}. \tag{3}$$

2. The high-intensity pixels usually form connected segments. The segments that are too small to be considered as road marking regions are removed. Figure 4b shows an example of the areas of interest extracted with our segmentation algorithm. This example image has highly variable lighting, and it can be seen that the road markings are segmented correctly without being affected by the lighting conditions.

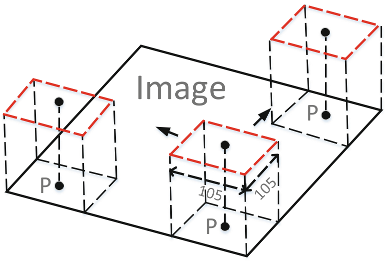
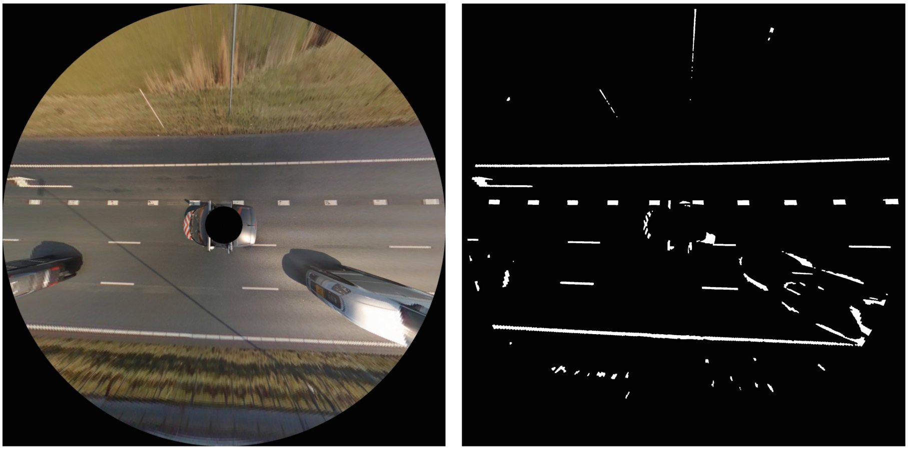


Fig. 3. Brightness normalization

2.3 Shape Classification

Each of the detected regions shown in Fig. 4b is classified into two categories based on their size: long segments and short segments. Long segments whose thickness correspond to the width of a real lane marking are assumed to be lane marking candidates, and split into smaller segments for further classification. Prior to extracting the feature vector of each segment, the centroid location, scaling and rotation should be normalized. The center of each segment is the mean of positions (x, y) of all pixels within the segment in image coordinates, hence

$$\overline{x} = \frac{1}{N} \sum_{n=1}^{N} x_n, \quad \overline{y} = \frac{1}{N} \sum_{n=1}^{N} y_n. \tag{4}$$



(a) (b)

Fig. 4. (a) Top-view image. (b) Segmented image of (a) obtained by segmentation algorithm

Therefore each segment can be aligned by subtracting the means from the coordinates,

$$x^{'} = x - \overline{x}, \text{ and } y^{'} = y - \overline{y}. \tag{5}$$

After translation normalization, a scale factor for each segment is defined based on the position of the pixel that is farthest from the center of the segment, which involves the distance computed by

$$a = \sqrt{x_{max}^{'2} + y_{max}^{'2}}. \tag{6}$$

Then scale normalization of each segment can be achieved by dividing the coordinates of all pixels in the segment by the computed distance, so that

$$x^{''} = \frac{x^{'}}{a}, \text{ and } y^{''} = \frac{y^{'}}{a}. \tag{7}$$

To implement rotational normalization, Principal Component Analysis (PCA) is employed to estimate the orientation angle θ of each segment relative to the horizontal axis, then the segment is rotated using the rotation matrix in Eq. (8)

$$R = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}. \tag{8}$$

After translation, scale and rotation are normalized, the features are then extracted by calculating the distance d_i from the center to the boundary of each segment at certain angles. In our experiment, we have chosen these angles from 0° to 360° with a step size of 30°. The value of this step size was chosen empirically and based on numerous experiments. Each segment can then be described by the vector $\boldsymbol{v} = (d_1, d_2, ..., d_{12})$. To distinguish the road markings from other regions, we apply a Support Vector Machine (SVM) [11] algorithm to classify the shapes. In our experiment, a non-linear SVM with a radial basis function kernel is used.

2.4 Lane Modeling

Non-road marking segments that have a similar shape as road markings can be misclassified. In order to decrease the number of false detections, we utilize our prior knowledge that the road is bounded by solid lane markings, and any segments found outside cannot belong to road markings. For this purpose, we model lanes, based on lane marking candidates classified by the SVM. Since lanes can appear both straight and curved in the top-view image, two models are applied consecutively: RANSAC to model straight lanes and Catmull-Rom spline to interpolate curved lanes [10]. First, by default we search to fit a straight line using RANSAC. If this method does not converge after a fixed amount of iterations, the lane marker is assumed to be curved, and as a second approach, the Catmull-Rom spline method is employed instead. This method is an efficient way to model both straight and curved lines in a reliable and straightforward manner.

Since the position of the lane in image coordinates can be interpolated by the lane model, road markings can be rejected based on their position relative to the lane markings. In our system, only road marking candidates which are confined by lane markings are preserved. In addition to the location of the segments, their rotation with respect to the lane markings is also used to reject false detections.

3 Experiments and Evaluation

Several experiments are performed to test the performance of our system. The performance is individually measured for the different kinds of road markings, such as lane markings, stripes, blocks and arrows.

A. Dataset
The dataset that we have used to evaluate the performance of our algorithm is captured by a camera mounted on the roof of a driving vehicle, and a panoramic image is captured every 5 meters under very good weather condition. A panoramic image contains a road scene with a resolution of $4,800 \times 2,400$ pixels. We use 910 highway panoramic images under various lighting conditions, and we have manually annotated all road markings that are completely visible on the top-view images of the 910 highway panoramic images. The road markings in our dataset are not damaged or faded, and the images are taken during the day-time in fair weather conditions. This is due to the fact that the panoramic images are only captured during the daytime and when the weather is good, so for this application there is no need to consider these cases. An example of an annotated top-view image is shown in Fig. 5, where different types of road markings are annotated with different colors.

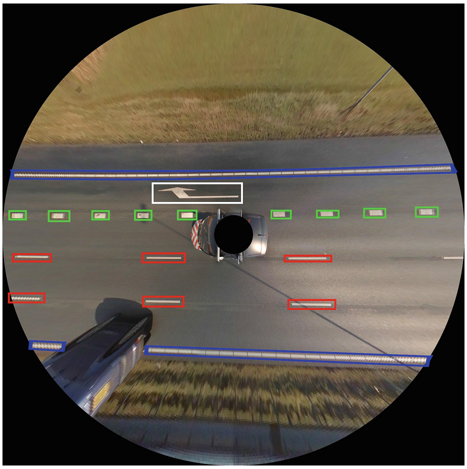
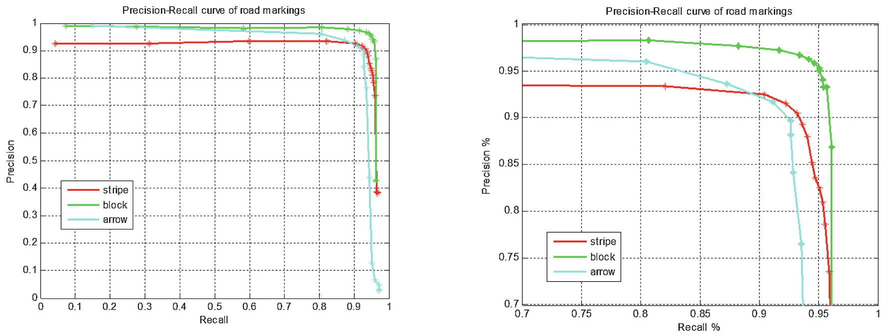


Fig. 5. Example of an annotated top-view image

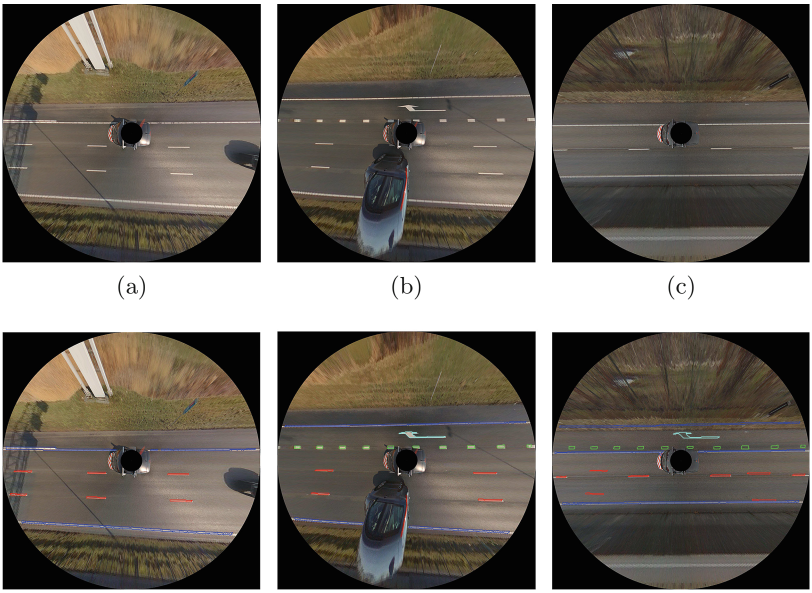
B. Evaluation metrics
We divide the found detections into two categories, road markings such as line segments, blocks and arrows as well as lane markings, as shown in Fig. 5. Detections of road markings and lane markings are compared with the corresponding annotated top-view image. A detection of a road marking is considered as True Positive (TP), if at least 90 % of the pixels of the detected segment are located within the corresponding bounding box in the annotated top-view image. If a detection of road markings is not annotated in the top-view ground-truth image, it is counted as a False Positive (FP). Since lane markings are long and usually have a variable length in each image, lane markings annotated in the ground-truth image are first split into small blocks. Similar to detections of road markings, if 90 % of the pixels of a detection of a lane marking block overlap with a corresponding annotated lane marking block in the ground-truth image, it is counted as a TP, otherwise it is counted as a FP. If 80 % of the pixels of the lane marking blocks belonging to one lane marking are detected correctly, the lane marking is considered to be correctly detected. The performance is evaluated with a Precision-Recall curve. Precision is defined as $\frac{TP}{TP+FP}$, and recall is defined as $\frac{TP}{TP+FN}$.

C. Experiments
We have tested our algorithm with the previously described dataset. In our experiment, we have selected 50 panoramic images as a training set for the Support Vector Machine, which contain road markings of line segments, blocks, arrows and lane markings. A sliding threshold is applied to the output value of the SVM to obtain a Precision-Recall curve, as shown in Fig. 6. Our algorithm achieves a recall of 93.1 %, 95 % and 91.1 % for line segments, blocks and arrows, respectively, with a corresponding precision of 90.4 %, 95.2 % and 91.7 %. Additionally, it achieves a recall of 96.4 % for lane marking blocks at a precision



(a) (b)

Fig. 6. (a) Precision-Recall curve of road markings. (b) Zoomed-in section of (a)

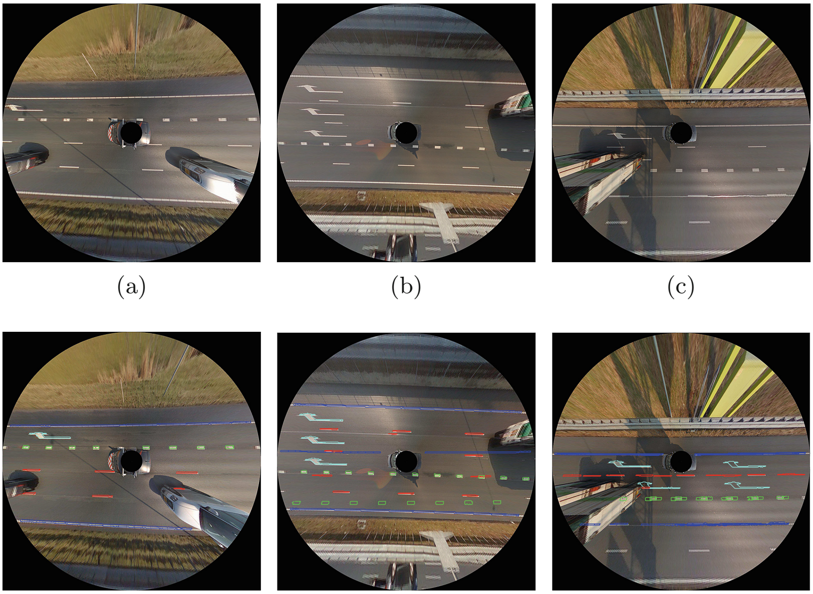


(a) (b) (c)

(d) (e) (f)

Fig. 7. Images (d), (e) and (f) show results of images (a), (b) and (c) from the system.

of 96.2 %. Considering whole lane markings, it achieves a recall of 94.3 % at a precision of 94.6 %. The performance for blocks and lane markings is thus quite promising. Figure 7 shows some visual example results from our algorithm. After evaluating the results, we have found that most false detections are caused by vehicles on the road that contain visually similar regions to road markings in the top-down image, as well as imperfections in the road surface, of which some examples are shown in Fig. 8.



(a) (b) (c)

(d) (e) (f)

Fig. 8. Examples of false positives

4 Conclusions

We have introduced a system for automatic detection and recognition of road markings in panoramic images. First, an inverse perspective transformation is applied to the image to remap it to a top-down view to modify curved lines into straight lines. Next, regions that are brighter than their surroundings are segmented. Long segments are broken up into smaller pieces, and the shape of each piece is classified using a Support Vector Machine. The shape is described with a feature vector based on boundary distance measurements taken at regular angular steps. In order to decrease the number of false positives, the lane markings are modeled using RANSAC as well as a Catmull-Rom spline for straight and curved lanes, respectively. Finally, road markings are further filtered based on the positions of candidates relative to lane markings, and their orientations. The experimental result shows that 94.3 % of lane markings as well as 93.1 %, 95 %, 91.1 % of dashed line segments, blocks and arrows, considered as road markings are correctly detected. The main cause of the false positives is due to cars on the road, as well as imperfections in the road surface. The false positives can be further reduced by combining the results from nearby panoramic images, since panoramic images are taken every 5 meters. By doing so, we expect that most of the false positives that are due to cars can be rejected. In future work, we will also extend our techniques towards additional road markings.

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