Vision-Based Pavement Marking Detection – A Case Study

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Abstract. Pavement markings take responsibility to communicate with road users regarding travel regulations and guidance. Due to their irreplaceable role in ensuring the safety and order on road, it would be beneficial for road agencies to keep an as-is inventory record of the pavement markings on their roads for managerial operations. However, faced with the sheer volume of their responsible assets, manual inspection would be time-consuming and error prone. This study proposes a vision-based method to automatically detect and classify longitudinal markings using videos of road pavement. Not only line markings, audible markings, as a special category, were also identified in the images. The proposed method can achieve an average 0.89 detection accuracy for line markings and 0.82 for audible markings. Limitations and future work are also proposed. This study tests the possibility of utilising visual data to assist road agencies with an informative management of their civil assets.

Keywords: Pavement marking · Detection · Computer vision · Case study

1 Introduction

Pavement markings and signs constitute the most fundamental way to communicate with road users and they are, in most cases, the most effective way to regulate and guide traffic [1]. And this efficient communication on roads can greatly contribute to a safe and ordered traffic environment. This paper focuses on pavement markings, and especially longitudinal line markings among all the other types. Pavement markings have been designed to be highly standardised, in terms of their colour and appearance, aiming to deliver unambiguous instructions to road users and expect immediate responses from them. Colours used for road markings are limited to white, yellow and blue (very rarely). Detailed dimensions of all types of pavement markings, e.g., lines, symbols, numerals and messages, are all defined in national standards and strictly followed by local agencies.

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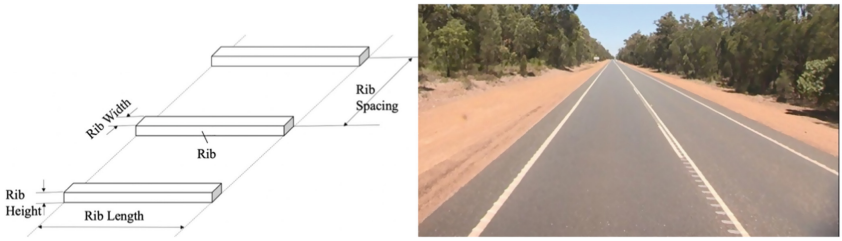
In addition to line markings, the importance of audible markings has been increasingly raised in recent years. Essentially, audible markings are created by installing a line of small projections in the road surface, on the top of or alongside ordinary line markings. Therefore, they can provide both audio and vibratory warnings to drivers who are running off the lane due to fatigue or bad driving conditions. They are generally associated with edge lines and especially beneficial for roads in rural areas. Figure 1 illustrates audible markings in concepts and real-life images.



(a) Conceptual (b) Realistic

Fig. 1. Illustrations of audible markings

To maintain road safety and efficiency for citizen's daily commutes, road agencies and traffic organizers have been making extensive efforts to ensure that pavement markings remain in satisfactory condition and keep regulating the traffic. They take responsibility to inspect and accordingly, perform proper maintenance. An as-is inventory data of all pavement markings forms a basis for managerial operations. However, manual collection of such information can be rather time-consuming and due to a lack of human resources, some local agencies and/or government fail to keep an updated record of pavement markings.

Nowadays, computer vision has gained heated attention from both the academia and industry. Its capability to save tedious manual work, automate image processing, and generate reliable detection results has been applied in many disciplines. The AEC/FM industry is, with no doubt, among them. Applications during civil assets' operation and maintenance phases include that defects on structures can be identified on images automatically, and as-is 3D model can be recreated using point clouds or photogrammetry. Such computer vision systems deploy either a combination of image processing techniques and machine learning algorithms, or deep neural networks, to achieve detection, tracking and high-level understanding.

This study collects visual data of road pavement from the Main Roads Western Australia, who governs and manages major routes in Western Australia. A vision-based method was developed and tested to automatically identify different types of pavement markings and classify them according to Australian standards. The rest of the paper is structured as follows: Sect. 2 reviews previous researches of computer vision technology in road pavement management; Sect. 3 illustrates the proposed framework for pavement marking detection and classification; Sect. 4 presents a case study using the

video data collected from a road agency in Australia; Sect. 5 indicates limitations and potential future work; and Sect. 6 concludes.

2 Related Work

A major line of studies proposed vision-based lane detection methods to support both advanced driver assistance systems (ADAS) and autonomous driving industry. On the basis of extracted lane line markings on road pavement, various models have been developed to fit the geometric shape of lanes, including, but are not limited to, linear model, parabolic model, hyperbolic model, Clothoid model and spline model. Distinctive features for lane line detection vary. For example, Son et al. [2] utilised colour information while Parajuli et al. [3] relied on local gradients. Alternatively, deep learning algorithms have been employed, for their capability in efficient and accurate object detection. For example, Zang et al. [4] adopted fully convolutional neural network to achieve pixel-wise detection of lane lines. To further assist autonomous driving, other road markings, such as arrows, speed signs and RAIL signs, are targeted for recognition and/or classification. Chen et al. [5] proposed a general framework for intelligent transportation system, by employing Binarized Normed Gradient (BING) features and PCA network to classify road markings.

Another group of studies fall into the area of digital asset management. They focused on using a combination of image processing techniques and machine learning algorithms, to obtain management information for road assets. They analyse road condition by identifying the presence of defects, classifying the damage based on their types and even evaluating their severity. Defects targeted in previous studies included cracks, rutting, potholes and patches. Regarding the first task (i.e., detection), Hoang et al. [6] developed an approach to automatically detect cracks on asphalt pavement, by combining a multi-class SVM classifier and an artificial bee colony optimizer. Chun et al. [7], otherwise, achieved this by integrating image processing techniques with a naïve Bayes-based machine learning algorithm. Similar methods were applied to detect potholes by Azhar et al. [8], which followed by explicit localisation using graph-cut segmentation. Jo and Ryu [9] used a commercial black-box camera and identified potholes based on lane detection results. Tedeschi and Benedetto [10] developed a real-time mobile-based system to recognise several common types of damage: pothole, longitudinal-transverse crack and fatigue crack. But the aforementioned studies can only deal with a particular type of distress at one time. Zalama et al. [11] classified longitudinal and transverse cracks using Gabor filters and an AdaBoost algorithm. Karaköse et al. [12] proposed an approach to further categorise pavement cracks into superficial, crocodile, linear and transverse, and their method was adaptive to different types of road.

Similar to the first application, several studies have successfully employed deep neural networks to detect road damage. By feeding raw images directly into deep learning algorithms, discriminative features of distresses are learned without any image processing techniques. For example, CrackNet, proposed by Zhang et al. [13], employed modified convolutional neural network (CNN) to achieve crack detection on 3D asphalt surfaces, with pixel-level accuracy. Fan et al. [14] modelled pavement crack

detection as a multi-label problem and solved it based on structured prediction with CNN. Zhang et al. [15] developed a transfer learning-based framework, to classify cracks and sealed cracks, and extract them at pixel level at the same time. Maeda et al. [16] proposed a smartphone-based application to determine damage status of targeted road, in terms of "no damage", "minimal damage" and "damage needs repair".

Though pavement management has been intensively studied nowadays, few studies focused on pavement marking and their condition assessment. Road agencies need such information as inspection records, and to make informed decision on repainting. An example is the use of end-to-end deep neural networks, which was proposed by Kawano et al. [17], to identify blurry road markings. Another example is done by Maeda et al. [18], who included blur detection of two types of markings, i.e., white line and crosswalk, into their multi-classifier for road damage. Therefore, an efficient framework to inspect pavement markings on images/videos and evaluate their condition with numeric indicators is still lacking in the literature. This research will propose a vision-based framework for pavement marking management, identifying line marking types for inventory purposes and estimating their severity of blur/wear for maintenance decision making.

3 Vision-Based Pavement Marking Detection

The proposed vision-based framework for pavement marking detection can be best understood as a flowchart (as shown in Fig. 2).

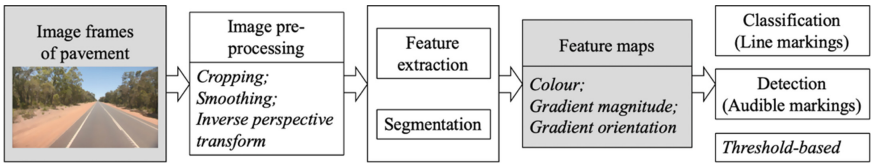


Fig. 2. Flowchart of vision-based line marking detection

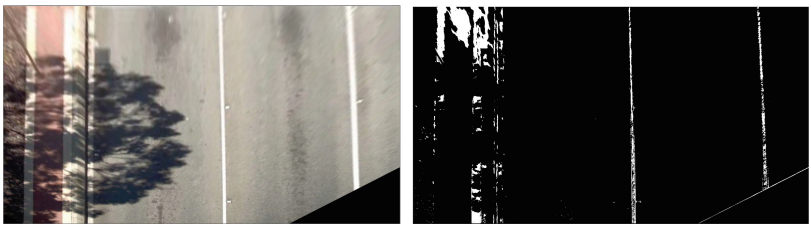
3.1 Image Pre-processing

The visual data to be used in this study are videos collected by an in-vehicle camera. The camera was mounted in the front to capture the front-view of road pavement as the vehicle moves forward. During the image pre-processing, image frames are first extracted from the video, cropped and organised in sequence. Smoothing algorithms are then applied to prepare the image for the following processing steps. Examples are Gaussian blur filter and median filter, which has been proven to be efficient in eliminating "salt-and-pepper" noise in images. Another important is image rectification, which removes the perspective effects and generates road-plane images. Inverse perspective transform (IPM) is used and a prerequisite to it is to calculate the transform matrix. One way to compute that is to conduct camera calibration and make sure the stability of the camera system throughout the data collection process. In this way, both intrinsic parameters (i.e., the optical centre

and focal length of the camera) and extrinsic parameters (i.e., the position of the camera in the 3D scene) of the entire system can be obtained. Typically, a chessboard is utilised to calibrate and several ad-hoc toolboxes [19] are available. An alternative way to achieve a proper IPM is to utilise at least two pairs of feature points in the image. Such feature pairs are selected if they locate on two parallel straight lines in the bird's eye view. After this step, line markings would be in parallel with each other in the road-plane images, which makes the segmentation of each marking instance easier to achieve. Examples of such top view images are shown in Fig. 3a.

3.2 Feature Extraction and Segmentation

The performance of feature detectors can be adversely affected by variations in lighting conditions, occlusion issues and noises. Potential noises include pavement distresses (e.g., rutting, bleeding and cracking), previous repairs, such as patches and sealed cracks, shadows of road-side facilities and plants, etc. To cope with these environmental factors, a hybrid feature detector, integrating both colour information and gradient features [20], is utilised to generate feature maps. To be specific, colour values of the saturation channel in HSL colour space are extracted to filter out yellow and white pixels in the image, while Sobel operation [21] is used to compute both gradient magnitude and orientation. This hybrid detector was tested to be efficient in eliminating noises like shadows and surface rutting, as shown in Fig. 3.



(a) Input (IPM results) (b) Output of feature extraction

Fig. 3. Test of the feature extraction method

On top of the extracted features, individual line markings are segmented. This process is also known as grouping or fitting [22]. To locate each marking instance, Canny [23] is used for edge detection, followed by Hough line Transform [24]. Outliers, such as lines with unreasonable slopes and those locating on non-marking areas, are removed. A grouping method is then applied to extract individual line marking instances.

3.3 Detection and Classification

This step aims to classify different types of pavement markings according to the specifications in Table 1. It lists common types of longitudinal line markings as specified in Standards [25]. A few categories, i.e., single barrier line, edge line, lane

line and transition line, convey different instructing messages to road users yet have the same manifestation pattern, thus they are still assembled under a single code (Code 5). The functional differences between them require further reasoning methods to be identified. In addition, a special type of line marking, i.e., audible marking, is targeted for detection.

Table 1. Category of longitudinal line marking in Australian standards

Code	Type	Standard pattern	Illustration
1	Dividing line	Broken, a 3-metre painted stripe and a 9-metre gap	
2	Barrier line (two-way)	Two parallel continuous lines	
3	Barrier line (one-way)	Two parallel lines, one continuous and the other broken	
4	Continuity line	Broken, a 1-metre painted stripe and a 3-metre gap	
5	Single barrier line; Edge line; Lane line; Transition line	Continuous line with 80, 100 or 150-mm width	

To achieve detection and classification, images of extracted and segmented line marking are first analysed and converted into numeric features, that is, width lists representing the width of marking along the vehicle's forwarding direction. Threshold-based methods are then applied on the statistical analysis results of such width lists to detect or classify. Both colour and position information are also utilised to support the process.

4 Case Study Results

To evaluate the proposed vision-based method for pavement marking detection and classification, a case study was carried out. Main Roads Western Australia (MRWA), road agency of the Government of Western Australia, archives pavement video data of their roads. The camera used for recording was mounted on a vehicle which travelled at a uniform speed and in both directions of traffic. Thus, the analysis of each image frame can only focus on the twenty-metre pavement in the near field and save the far-field regions for later. In addition, the two-direction filming is especially necessary for road segments in metro areas, since they are typically too wide to fit into the camera's field of view. The pavement video of a 28-km route in Western Australia was retrieved.

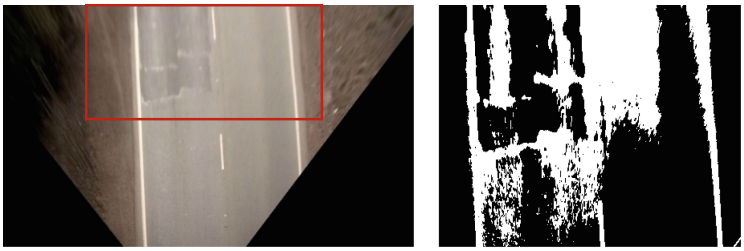
The video data in this case study included five types of longitudinal line markings, i.e., edge line, continuity line, transition line, lane line and dividing line. They were assigned to four classes, as indicated in Table 2. An additional category for classification was introduced to represent non-marking objects, such as road-side railings,

kerbs and other vehicles that appear in the region-of-interest. The threshold-based method for detection and classification mainly utilised the distinctive shape information of different line markings. Specifically, dividing lines (code "01") and continuity lines (code "03") are both broken markings with different length of strips and gaps, while marking types in code "02" all appear to be single continuous lines. As for audible markings, they are essentially densely located narrow ribs and thus, have a jagged pattern.

Table 2. Line marking classification results

Code	01	02	03	04	Overall
Type(s)	Dividing line	Edge line, transition line & lane line	Continuity line	Others	
Accuracy	0.92	0.87	0.85	0.92	0.89

Table 2 shows the accuracy of classifying line markings. The detection failures can be attributed to several environmental noises. An example is the pavement in Fig. 4 which suffers from surface distresses and leads to a misleading feature extraction result (as shown in the right image). As a result, both the left edge line and the dividing line were wrongly detected as *Others*. Occlusions by vehicles cause temporary loss of tracking, which can be compensated by referring to the context. Other noises, e.g., kerbs, islands and railings alongside the road, can also confuse the classifier.



(a) Polished pavement (b) Feature extract result

Fig. 4. Noises on the pavement

The average accuracy of identifying whether they are present reaches 0.82. The performance of detection is highly subject to variations of illuminations and the distance between the targeted markings and camera. Statistics indicate that the detection of markings which delineate the lane our vehicle ran on is more accurate than that of far-away markings (0.52). The detection loss is also partly resulted from the wear of ribs themselves due to intensive traffic.

5 Discussion and Limitation

This section discusses about a few limitations of the proposed method, given the case study results presented in the previous section. One major issue that might negatively affect its applicability in real-life projects lies in the fact that manual selection of features points for the removal of perspective effects in images is required. In addition, such human intervention is not one-off since shooting direction of the camera tends to shift while the vehicle is moving forward. There might also be incremental deviations from the initial camera settings regarding the lane throughout the data collection process. As a result, re-calibration of camera at a certain frequency would be necessary.

Also, from the practical perspective raised by our industrial partners, it would be beneficial if we can use computer vision technology to automatically measure and quantify the condition of detected pavement markings. Such condition assessment is multi-fold. One concern is the physical integrity of these painted markings. Pavement markings suffer from either the loss of a portion/patch at certain location, or general wear and tear on the entire route. Another important property of pavement markings is their reflectorisation [1], which is the capability to be seen under dark driving conditions. The level of their reflectivity can only be tested by professional consultants nowadays, which calls for the development of cost-efficient and measurable indicators. As for the audible markings, the extent of their wearing down by traffic can be informed by measuring the elevation of ribs in 3D laser-scanning profile data, as proposed by Zhang et al. [26]. Potential future agenda can be developed to use vision-based method to automate the condition assessment of various types of pavement markings.

6 Conclusion

This research proposes a vision-based method to automatically collect as-is inventory data of pavement markings. A hybrid feature detector integrating colour and spatial features was employed, individual markings were then segmented, and a threshold-based method was used to classify different types of line markings and detect audible markings as well. The detection can achieve an accuracy of 0.82 and a classification of 0.89 across all types of line markings. Future work will attempt to eliminate the need for human intervention by pre-calibrating the camera system and maintaining its stability throughout the data collection. Vision-based methods for condition evaluation will also be explored.

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