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Railway track detection for train geographic location based on computer vision

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Abstract

In a railway infrastructure, train geographic location (e.g., GPS) must be strengthened to adapt to the network topology (i.e., inside or outside the station, straight or curved line, passages through tunnels). Alternative solutions must be proposed to meet this need. Computer vision is one of these disruptive answers to tackle this challenge. Indeed, this technology gives meaning to geographic location by getting closer to human behaviour (i.e., human eye). This paper presents an approach detecting the rails solely by computer vision and the knowledge of certain dimensions of the railway. A case study on rail signalling is also proposed to apply this approach in a safety context.

Keywords: Computer vision, Railway detection, Rail signalling, Geographic location, Gradient analysis, Hough transform.

1 Introduction

In a railway infrastructure, train geographic location (e.g., GPS) must be strengthened to adapt to the network topology (i.e., inside or outside the station, straight or curved line, passages through tunnels). Alternative solutions must be proposed to meet this need. Computer vision is one of these disruptive answers to tackle this challenge. Indeed, this technology gives meaning to geographic location by getting closer to human behaviour (i.e., human eye). This paper presents an approach detecting the rails solely by computer vision and the knowledge of certain dimensions of the railway. A case study on rail signalling is also proposed to apply this approach in a safety context.

To accomplish this work, a number of concepts have been studied through the literature. In [1], the presented studies respectively aim to detect switch zones and rails. They essentially leverage preprocessing techniques such as Canny filters[2], Hough transform [3] and discretization [4] according to the type of lines and their orientations. In [5], the colorimetry is used to detect rails in the HSL colour space [6]. By focusing on pixels of the same row, strong variations of the H channel between each pixel are analysed for extracting the edge of the rails. A pixel-width measurement is then applied between two consecutive edges and compared with the real width of a lane. Another lane detection objective is proposed in [7], where authors mainly use the bird's flight transform by adapting a DoG mask [8] and maximum thresholding. Lastly in [9], a different approach focuses on local gradient analysis by relying on 3D projection and RANSAC algorithm [10].

The methods of the approach – called RTD (Railway Track Detector) – proposed in this paper are firstly presented. They take advantage of the above state of the art and are divided in two main stages. The first step comes to process images by filtering methods such as edge detection and vectorization. The second step aims to extract lines which characterize rails by eliminating the least relevant ones based on criteria such as lines slope. In next section, some results of the evaluation of RTD are outlined. The test dataset consists of consecutive images acquired on a same track section in different weather conditions. Finally, a use case is supplied to locate lineside signals along the train track. Some perspectives are also proposed. Figure 1 shows an example of acquisition with a freeway signal. It will serve as an example throughout this document.

Figure 1: Image containing two lanes in overcast day

2 Methods

This section presents the RTD which has been carried out in two stages:

- Selection of zone and gradient analysis
- Selection of lines characterizing the rails

2.1. Selection of zone and gradient analysis

The first objective is to delineate the boundaries of the rails area in the image. Only a part of the image is analysed by both keeping the entire width-wise and the bottom third height-wise of the image. It enables to solely contain rails by removing catenaries. Two successive filter layers are then performed to extract pixels that are eligible for rail detection.

For the first filter, horizontal contours and their orientations are determined. A mask is thus applied to discriminate pixels whose gradient values correspond to those of the rails, as illustrated in Figure 2.

The second step comes to measure the Euclidean distance between two pixels located on the same y-axis. This distance is then compared with the real distance between the two rails of the track. The filter layer consists of both verifying that the measured distance is lower or equal to the reference distance and that the gradients have the same orientation. These two steps enable to obtain the outcome of Figure 3.

Figure 2: Image showing horizontal contours by use of the Sobel filter.

Figure 3: Result after distinction of pixels according to Euclidean distance and the orientation of gradients.

2.2. Selection of lines characterizing the rails

Once the pixels filtered, the objective is to determine those aligned in order to highlight the lines representing the rails. Hough transform (1) has been chosen to achieve this, where θ represents the angle between the segment (ρ) perpendicular to the detected line and the origin.

$$\boldsymbol{\rho = x\cos\theta + y\sin\theta} \qquad \textbf{(1)}$$

Two processing operations have been implemented on these lines. The first one performs a subtraction between the values of θ of two consecutive lines (considering the x-axis). If the result of this operation is greater than a threshold, the two lines are kept (i.e., their slope is radically different). Otherwise only one of the two lines is kept. The second operation eliminates all horizontal and vertical lines. Figure 4 illustrates the obtained result.

Figure 4: Identification of the lines representing the rails

3 Results

For preparing the evaluation of RTD, the tracks must be distinguished by adding a reference point in the middle of each detected lane.

3.1. Track center determination

The identified lines must be ordained in order to discriminate the lanes. The way of proceeding lies in the calculation of intersection points between these detected lines and a drawn horizontal line (D). These points are derived from the parametric equation (1) to the Cartesian equation (2-3-4), where a and b are respectively the resulting slope and intercept of each calculation.

$$\boldsymbol{a = \cos\theta} \quad \textbf{(2)}$$
$$\boldsymbol{b = \sin\theta} \quad \textbf{(3)}$$
$$\boldsymbol{y = ax + b} \quad \textbf{(4)}$$

Each lane is then found by comparing the pixel-width distance between the x-coordinates of two successive intersection points with the reference distance between two rails. To make the identification more robust, an additional check is carried out between two successive lines to ensure they cross each over in the image. Equations (5) and (6) enable this, where (x_i, y_i) represent the coordinates of the crossing point and $_1$ and $_2$ the indexes of the crossed lines.

$$\boldsymbol{x_i = \frac{b_2 - b_1}{a_1 - a_2}} \quad \textbf{(5)}$$
$$\boldsymbol{y_i = (a_1 * x_i) + b_1} \quad \textbf{(6)}$$

Lastly, the centers of each detected track are deducted from equations (7) and (8) in Figure 5, where (xc, yc) corresponds to the coordinates of the middle point. y_D the y-axis horizontal line (D). x_l and x_r the x-coordinates of the left and right intersection points between the two rail lines and (D).

$$\boldsymbol{x_c = \frac{1}{2}|x_r - x_l|} \tag{7}$$
$$\boldsymbol{y_c = y_D} \tag{8}$$

Figure 5: Identification of two tracks whose centers are illustrated by two red dots

3.2. Tests results

To date, RTD has been developed in a nominal case. Face to the topologic complexity of the infrastructure, the function has solely been designed for tracks in straight line. Two track section videos framed in 125 consecutive images formed the test dataset. These videos were acquired from the driving cabin at approximately a rate speed of twenty images per second, with different weather conditions. Table 1 clearly shows a better accuracy in sunny conditions (i.e., 97%) than in overcast conditions (i.e., 56%).

This is because the extraction of the features that characterize the rails is not enough in the second case. Indeed, gradients describe less local variation since grey levels are less contrasted.

	Weather	Number of images	Number of bad detections
Section 1	Sunny	125	4
Section 2	Overcast	125	55

Table 1: Summary of the evaluation

4 Conclusions and Contributions

One of the objectives intended by RTD is to reinforce the train geographic location. It is necessary to offer an alternative solution for tackling the inappropriateness of existing devices in certain situations. For instance, the use of GPS can, on the one hand, lack precision from track to track and, on the other hand, be unsuccessful in areas where the network is not covered by GPS. These situations can consequently be unsafe, especially when the position of a moving train supports the rail signalling. The challenge is considerable and presents an ambitious work program. For the sake of simplicity and to evince a keen interest in further development of this solution, a concrete use case has hereafter been targeted to complete this experiment. As given in Figure 6, this implementation focuses on cropping a ROI - Region Of Interest - (i.e., the whitened area in the image) along the left train track for detecting lineside signals.

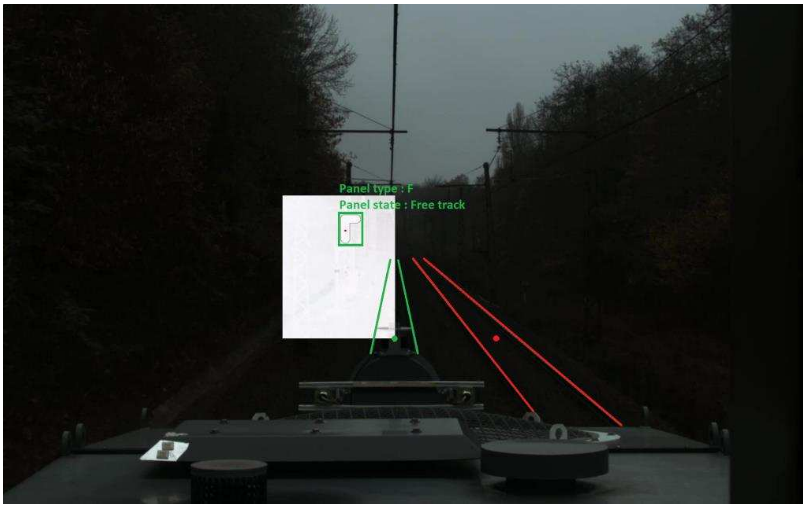

Figure 6: Implementation on lineside signals recognition

The coordinates of the ROI are made through the identification of the middle of the detected lane in green. The advantage of this processing is the reduction of the execution time since only the ROI is analysed by the recognition function. In addition, this strategy prevents from obtaining potential false positives outside the ROI.

This work is a first encouraging stage despite the inconsistency of the results of the section 2.2. The assessment of RTD has indeed indicated bad detections, in particular in overcast conditions. This means that sometimes the track can be lost and then the ROI cannot be cropped. More research needs to be conducted to make RTD more relevant.

To deal with the variability of the weather conditions, a calibration function is currently being studied to set up the RTD preprocessing. The parameters of the filters will have to be adjusted automatically to the specific conditions.

Nonetheless, tracks could still not be detected. To address this issue, an idea of tracking the ROI throughout the acquisition section is in progress. The recognition area would then be maintained once the track is missed.

To go further, RCD must be able to also extract curved rails to better follow the track profile and thus cover more use cases by providing a more robust detector. Among these cases, this consolidation could for example prevent or confirm the orientation of the train after detecting track changes in a context of station traffic.

References

[1] Karaköse, M., Akın, E., & Yaman, O. (2016). "Detection of rail switch passages through image processing on railway line and use of condition-monitoring approach".

[2] Canny, J. (1986). "A computational approach to edge detection. IEEE Transactions on pattern analysis and machine intelligence", (6), 679-698.

[3] Fernandes, L. A., & Oliveira, M. M. (2008). "Real-time line detection through an improved Hough transform voting scheme. Pattern recognition", 41(1), 299-314.

[4] R. Ross. (2012) "Track and turnout detection in video-signals using probabilistic spline curves", In Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on pages 294_299, 2012. (cited on page 23.)

[5] Min, Y., Xiao, B., Dang, J., Yue, B., & Cheng, T. (2018). "Real time detection system for rail surface defects based on machine vision", EURASIP Journal on Image and Video Processing, 2018(1), 3.

[6] Caha, J., & Vondrakova, A. (2017). "Fuzzy surface visualization using HSL colour model", Electronic Journal, 2(2), 26-42.

[7] Gschwandtner, M., Pree, W., & Uhl, A. (2010, November). "Track detection for autonomous trains", In International Symposium on Visual Computing (pp. 19-28). Springer, Berlin, Heidelberg.

[8] Birch, P., Mitra, B., Bangalore, N. M., Rehman, S., Young, R., & Chatwin, C. (2010). "Approximate bandpass and frequency response models of the difference of Gaussian filter", Optics Communications, 283(24), 4942-4948.

[9] Espino, J. C. (2014). "Rails detection, turnouts characterisation and trains localization in an automated metro's trajectory", Doctoral dissertation, Mines Paris Tech.

[10] Derpanis, K. G. (2010). "Overview of the RANSAC Algorithm", Image Rochester NY, 4(1), 2-3.