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A New Computer Vision Based Rail Detection Method Using Entropy and Support Vector Machines

Kağan Murat
Computer Engineering Department
Firat University
Elazig, Turkey
Email: kaganmurat [AT] gmail.com

Mehmet Karaköse
Computer Engineering Department
Firat University
Elazig, Turkey
Email: mkarakose [AT] firat.edu.tr

Erhan Akın
Computer Engineering Department
Firat University
Elazig, Turkey
Email: eakin [AT] firat.edu.tr

Abstract—**Condition monitoring in railways is an important and critical process in terms of travel safety. However, this process is generally done based on observation or with various equipment. Therefore, it is costly and has a high probability of error. In this study, a computer vision-based method for rail detection for condition monitoring in railways is proposed. In addition to the features obtained from the images, a new feature is calculated using entropy. Rail detection is provided by classifying these features with Support Vector Machine (SVM). It has been seen that the proposed method works successfully and provides improvement in the monitoring process.**

Keywords-classification; entropy; support vector machine; image processing; railways

I. INTRODUCTION

Transportation by rail is a form of transportation with high travel safety and low cost. Therefore, its use is still increasing today for both human and freight transportation. According to the data of the International Union of Railways (UIC), approximately 4 trillion passengers/km of passengers and approximately 11 trillion tons/km of freight were transported in the world in 2018. When these values are compared with 2010, an increase of approximately 25% is observed [1]. With the increasing use of this mode of transportation, condition monitoring and maintenance studies are also becoming important. These routine processes are usually carried out using human-based observation or some devices. However, there are some disadvantages such as cost in device and equipment processes and personnel experience in human processes.

In recent years, especially with the development of camera technologies and the decrease in their costs, camera equipment has started to be used in many fields together with different disciplines. The images taken with the help of the camera are converted into digital features by image processing methods and the obtained outputs are used for many purposes such as monitoring, measurement, diagnosis and detection. In a study on face detection, in principle, pre-processed the facial images and fixed the lighting-related problems [2]. Then, they classified the values obtained by the feature extraction processes with the SVM method and enabled the detection of six different facial expressions. In a study conducted to measure food consumption developed a method for measuring calories and nutrition in humans [3]. For this, foods were determined by image processing methods using shape, color and volume features and calorie calculations were made for each of them. In this way, it has been tried to make the process of determining a diet program easier. In a study in the field of health, conducted a study to prevent mistakes that may arise from the observations of radiologists [4]. In the study, the detection and classification of brain tumor was provided by using magnetic resonance images (MRI) images. It is aimed to obtain more accurate results.

In the field of railway transportation, camera technologies and computer vision-based studies are generally carried out for contactless defect detection and inspection. In general, maintenance, monitoring and detection operations are costly in terms of both financial and time since they are maintenance tools or human-made operations. However, it can also cause some accidents due to negligence and mistake. In order to prevent these deficiencies, many studies are carried out for error detection and monitoring. In some of these studies, it is aimed to determine the rail surface and the components that make up the rails and to find the defects that may occur in these components. In another study a method for detecting faults that may occur on the rail surface [5]. In the study, images were taken by means of a thermal camera. The detection process consists of two main stages. The first step is to process the received images and convert them into signals. The second step is to provide the identification process with a complex fuzzy automaton. Two different cameras following the same track were used in a different study [6]. The images taken from the cameras were combined using image processing methods and it was aimed to find the defects on the rail surface. In a railway monitoring method was developed a method for the detection of rail surface and rail components [7]. A maintenance vehicle is designed to monitor the railway. Cameras are placed on the vehicle that can see both rail lines. On the images obtained from the cameras, the rails were tried to be determined by the Canny edge extraction method. With the help of a mask, the connection plates on the rail track edges were fixed. An interface has been developed to detect and monitor defects that may occur in this component. Prepared a method for the control of the rail surface and pantograph catenary system in another study [8]. The system uses three different thermal cameras. A camera is located above the locomotive and the pantograph monitors the catenary system. The other two cameras follow the rails in the lower front of the locomotive. Complex fuzzy automata method was used to classify the data obtained from the images. The results obtained are given separately for the rails and the pantograph catenary system. A study tried to detect damage on the rail line using a Convolutional Neural Network (CNN) [9]. Histogram equalization, segmentation and morphological image processing methods were applied. CNN was used for the classification of defective and non-defective rails on the obtained data. The results obtained by the method are shown by increasing data in the training set. A study aimed at developing less cost, proposes a method to prevent the deficiencies caused by human experience in maintenance and inspection operations at railway switches [10]. They classified the data they obtained using the images with the support vector machine. As a result of classification, defects were detected. The results are shared by comparing the Native Bayes and BP artificial neural network methods. A study proposed a method for the detection of defects caused by joggled fishplate, which is an important connection component in railways [11]. Images were taken from high altitude by drone. By creating a template mask, fishplates were detected on the images. It is mentioned that the method is not affected by different weather conditions.

There are many studies in the literature for the monitoring and inspection of railway. One of them proposes an approach using geometry-based vision to detect rail lines in the study [12]. By placing a camera on the upper-front part of the locomotive, images of the rail lines are taken. These obtained images were processed with a projection filter in a preprocessing stage. A pattern was tried to be obtained by dividing the image and the rail lines were determined by means of this pattern. The method has been tested with images taken from the real environment. In another study used dynamic programming to detect the railway line and the gap in between [13]. The method works in two main stages: feature extraction and path detection. For the first step Sobel filter, threshold value and Hough transform methods are used. In the second stage, a graph structure was designed using image pixels. A block diagram of this method is given in Fig. 1. In a different study, transforms the images they obtained of the railway into an inverted projection image [14]. Then, lane tracking methods on highways were used for rail detection. The developed method was applied on the frames and the results were compared. Images taken from unmanned aerial vehicles for rail line detection in study [15]. After making feature extraction on the images, a classification was made using the k-NN algorithm. The output obtained as a result of the classification is shown by marking on the original images. Proposed a method for detecting rail and other components in study [16]. A preprocessing was performed on the images obtained by unmanned aerial vehicles for the purpose of noise reduction and improvement. An intuitive method has been developed using the lighting and geometric properties of the rails. With the method, it is tried to detect the rail defects.

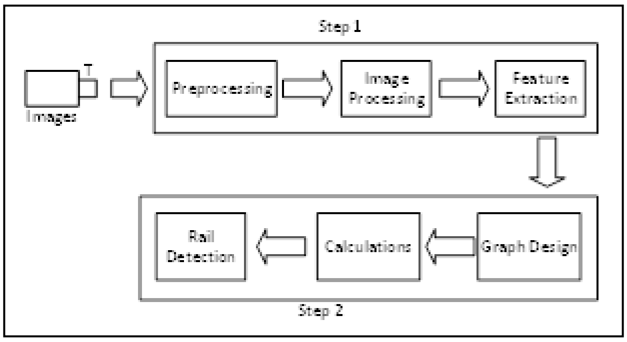


Figure 1. Diagram of the method using dynamic programming method.

In a study converted images to Hue, Saturation, Value (HSV) color space in the study [17]. By using the value ranges of the colors in the images, ray detection was made with mathematical expressions. In addition, a measurement system has been developed by obtaining some values of the rails. AlNaimi et al. Developed a method for the detection of rail line breaks to prevent accidents on railways in [18]. Images are taken with the help of a robot on the rails. The captured image is processed on the local computer. If a defect is found, the results are transferred to the cloud server together with the location information. In this way, it is aimed to provide storage advantage in the cloud server.

In this study, a method is proposed to improve the condition monitoring processes in railways. With the help of a camera placed in front of the locomotive, images of the rails are taken. From these images, data about possible rail lines are obtained by extracting features with image processing methods. A new local feature is calculated from this data using entropy. Obtained features are used for training and testing of the SVM classifier. The study aims to make rail detection more accurate and efficient with the output from the classifier.

II. RAILWAY MONITORING AND INSPECTION

With the developments in railway transportation, the use of this type of transportation in the field of human and freight transportation is increasing. The safety of railways is also gaining importance in relation to its use. Therefore, the railway must be constantly monitored and inspected.

However, the fact that this process is done by people causes some shortcomings: inexperience, carelessness, fatigue, time cost, financial reasons. Many methods have been developed to overcome these disadvantages. These methods are generally contact and non-contact based methods. Contact methods are ultrasonic, acoustic or magnetic-based methods using equipment such as radar and sensors [19-23]. The disadvantage of these methods is that they bring economic cost burden. In addition, in the event of a malfunction, it can cause negative consequences that can affect train services. The other type of control is contactless methods [24-26]. These methods are generally based on computer vision, image processing and machine learning. Different number of cameras can be used. The images taken with the help of the camera are processed. In this way, data can be obtained from the image. Then, using machine learning methods and these data calculations and formulations, conclusions are drawn for monitoring, inspection and measurement. Such methods are less costly and efficient than contact methods. In addition, since it does not involve any contact with the railway and its components, it does not directly affect the railway transportation in case of failure.

In this study, a computer vision-based method has been developed to take advantage of the non-contact inspection methods. Rail images were taken by placing a camera on the upper front of the train so that it could follow the rails. Data were obtained using image processing methods and the concept of entropy, and these data were classified by SVM method. Thanks to this method, both the economic costs in the monitoring and inspection processes and the time cost will be reduced. As a result, the detection of the rail line has been achieved quickly and successfully.

III. PROPOSED METHODOLOGY

In this study, a computer vision-based method for rail detection is proposed. Images of the railway are taken while cruising with a camera placed on the front upper part of the locomotive. The collected images go through a preprocessing step for noise reduction and enhancement. Then, by obtaining the gray level image, the lines showing the possible rails in the image are detected with the help of threshold value filtering and Hough transform methods. A classification process is performed using SVM to select the rail among the lines. A value calculated by the length, angle and entropy of the lines is used to train the classification process. The trained SVM system is tested by giving different images. A block diagram showing the main stages of the developed method is shown in Fig. 2.

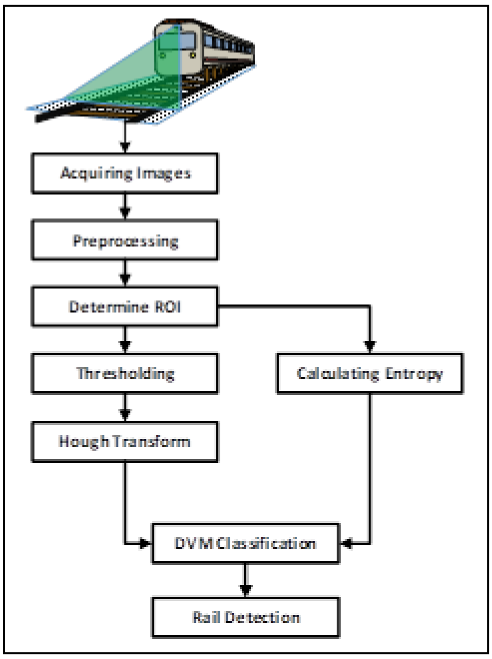


Figure 2. Diagram of the proposed method.

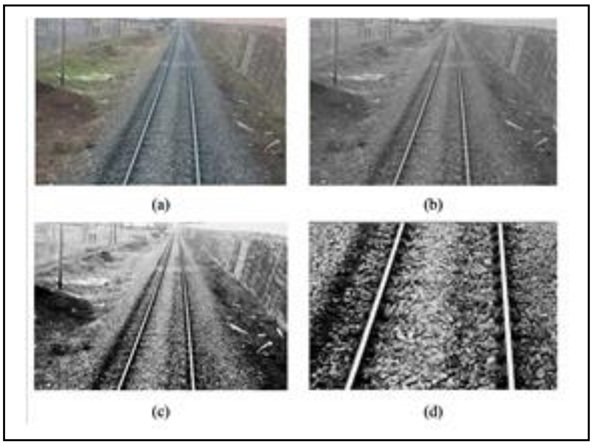


Figure 3. Image processing stages

A. Preprocessing

Images are taken with the help of a camera placed in the upper-front part of the locomotive. In these images, the processing is performed on each frame. Each frame image is converted to gray level format. Then, histogram equalization process is performed in order to provide improvement. The color values of the pixels are balanced by histogram equalization. Thanks to histogram equalization, some problems caused by the light in the image are overcome.

B. ROI determination

There may be some elements on the raw image that belong to the environment and negatively affect the image processing process. ROI detection is performed in an area close to the locomotive to remove areas in the image that may interfere with operation or are not needed. In this way, the rails can be perceived more clearly.

C. Thresholding

The thresholding method is segmentation operation. The image is converted to binary format with a threshold value to separate the unwanted parts on the image. The thresholded image ensures that areas outside the rail lines are removed. However, in addition to possible rail lines, non-rail lines can also remain on the image.

Fig. 3 shows the operations performed on each image. (a) is the first image taken from the camera. (b) and (c) are images obtained as a result of gray-level conversion and histogram equalization processes applied during preprocessing, respectively. (d) is a partial view after ROI determination applied to eliminate unwanted areas.

D. Hough transform

Information is extracted from the image with the Hough transform method. After the threshold value is applied, the length and angle of the lines remaining in different lengths and directions in the image are determined. Among these lines, the lines that are short and have the wrong direction are eliminated.

E. Calculating entropy

Considering the possible situations of an event, if the probability of any of these situations is uncertain or if the number of possible situations is greater than one, there is uncertainty for the situation of this event at any time. The numerical equivalent of this uncertainty is determined by the concept of entropy. Entropy is a computational method in the field of information theory that gives a measure of the disorder of data in a field [27]. In the study, this concept is used for information extraction. Before the image processing process, linear entropy is calculated on some images by using the gray level density values of the rails by using (1). When examined (1), p(x) is the ratio of the number of pixels with the same value with any pixel in the image to be calculated to the total number of pixels. The formula for the value of p(x) is shown in (2). As seen in Fig. 4, the number of all pixels with the same value is calculated after the gray level image of a pixel is taken during the calculation. The ratio of this number to all pixels in the image gives the expression p(x). Using the entropy equation in (1), the entropy value in the image fragment is calculated. As a result of this calculation made on each image, it is seen that the entropy values of the rail lines move between a certain range. In Fig. 5, the entropy values of 10 sample images showing the rail are shown. As seen on the graph, entropy values vary between approximately 28-36. Considering this calculated value, it is aimed that the lines that can be detected outside the rail line are not considered as a result of the classification.

$$H(X) = -\sum_i p(x)_i \log p(x)_i \tag{1}$$

$$p(x) = \frac{\text{number of pixels with same value}}{\text{number of all pixels}} \tag{2}$$

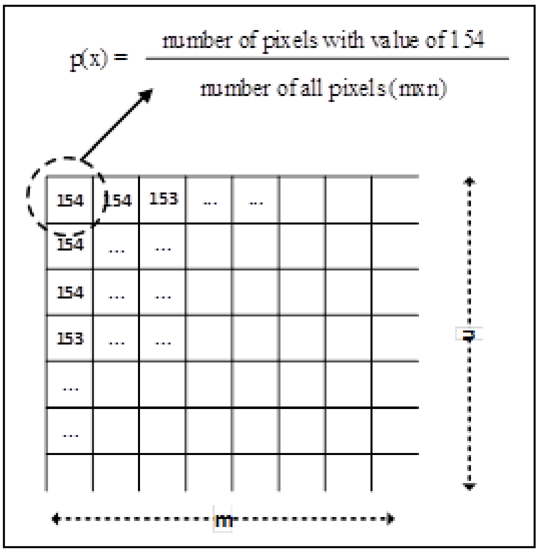


Figure 4. Calculating the p(x) value

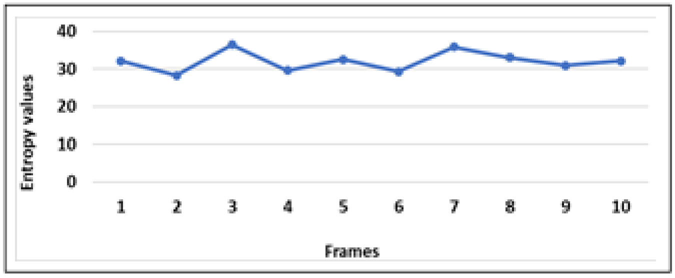


Figure 5. Samples of calculated entropy values

F. Classification by DVM

SVM is a supervised training algorithm that provides binary classification [28]. By means of the determined support vectors, the data can be divided into predetermined classes. A general support vector machine drawing is given in Fig. 6. Square and circular objects represent two different data types. The data shown in red and blue are considered as support vectors. The decision line (w) is determined between the data by means of support vectors. The separated data is labeled as 1 or -1. In the previous stages, angle, length and line entropy values were calculated in the Hough transform and entropy calculation steps. These obtained values are used as the input parameters of the SVM for training. A linear type of SVM training is carried out. The output parameter determines whether the line is a rail. In this way, the line determined as the rail is marked on the image. Some examples of training data are given in Table 1.

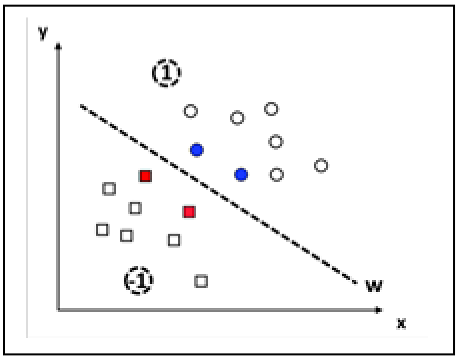


Figure 6. Support Vector Machine

TABLE I. SOME VALUES USED FOR SVM TRAINING SET

Inputs			Output
Angle	**Length**	**Line Entropy**	**Label**
95	149	9.39	Rail
69	159	29.36	Rail
77	152	38	Rail
163	58	20	Not Rail
83	149	39	Rail

IV. Experimental Results

In this study, a method for computer vision-based rail detection is proposed to improve monitoring and inspection processes on railways. The method acquires images via a camera placed in the front upper part of the locomotive. After processing these images, some lines are obtained. All of these lines may not belong to the rail line. Angle, length and entropy values of these lines are calculated. By using these three parameters as inputs, classification is provided with a SVM. In particular, during the threshold application, different numbers of lines can be detected on the images for different threshold values. As the number of detected lines increases, rail detection becomes more difficult. The proposed method is able to eliminate unnecessary lines as much as possible. In this way, more successful and accurate detection can be made.

In Table 2, sample images determined for this purpose are given. The threshold value determination in the images was made using the OpenCV library and the threshold() and HoughLinesP() methods. The number of lines obtained as a result of three different threshold value parameters and the detected rail lines are given. The second column, “Threshold() method”, shows images with different thresholds applied. The third column “Line count by HoughLinesP() method”, shows the number of lines detected in the image. The last column “Detected rail”, shows the detected rail line. Different threshold values are applied to the image in rows 1,2 and 3 in the table. Then, line detection process was performed on these images. Although there were 62, 6 and 91 lines, respectively, the rail line was determined correctly in all cases.

TABLE II. Rail Detection Results with Different Threshold Values

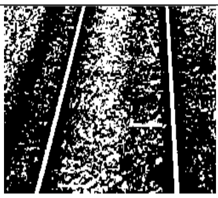
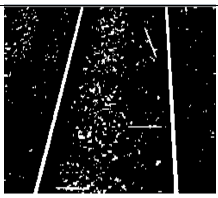
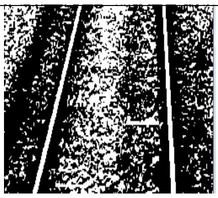
No	Threshold() method	Line count by HoughLinesP() method	Detected rail
1		62	
2		6	
3		91	

TABLE III. The effect of the training set on the success rate

Training Set	Test Set	Real rail count	False Detections	True Detections	Success Rate
20	10	20	8	12	%60
30	10	20	7	13	%65
50	10	20	4	16	%80

In addition, as the training dataset used in the classification process on the SVM is expanded, its positive contribution to the results has been observed. When the values given in Table 3 are examined, when 20 rail images are used in the training set and when tested with 10 rail images (assuming that two rail lines must be found in each image), it is seen that there are 8 false positive lines that are detected as rails, although there are no rails. When the number of images used for training is 50, it is seen that there are 12 lines. In this way, the accuracy of the method can be increased.

V. Conclusions

In this study, a method has been developed for rail line detection, which is an important element in monitoring and inspection studies in railways. The proposed method is based on image processing. The study is based on non-contact tracking of the rail track using SVM and entropy. The images taken from the camera placed on the upper front of the locomotive were processed using ROI determination, threshold value application and Hough transform, and some data about the rail lines were obtained. However, the entropy values of the rail lines in the images were calculated. It is aimed to determine the rail line on the image by classifying these obtained values through SVM. Considering the studies in the literature, it has been seen that contact methods use tools such as multiple cameras, radars and sensors, and therefore their costs are high. In non-contact inspection-based methods, it has been seen that the elements outside the rail line within the camera angle make it difficult to find the rail line and negatively affect the accuracy of the method. In addition, the design of a maintenance tool for monitoring the rails is also a factor affecting the cost. With the method proposed in this study, a non-contact method is developed to ensure that the detection of the rail line is less costly and more accurate detection is achieved by eliminating unwanted lines.

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