Off-Road Detection Using Vision Techniques for Hazardous Material Transportation Vehicles

LIFENG ZHAO[1], CHANGQING TIAN[2], XIANG LIU[3], LONG. LIN[4], HELIX XIE[5], NING ZHOU[6], YIPINGZENG[7], GUANGPU ZHANG[8], CHENHUI PAN[9], KANG YAO[10], XIAOXIN PI[11], T. R. CHEN[12], SHUASHUA MAO[13]

[1, 2, 3, 4] Digitalization and Information Center, Changqing Oilfield, PetroChina, Xi'an, China.
[5, 6, 7, 8, 9, 10] Zhejiang Sunleads Beidou Navigation Tech. Co., LTD., Huzhou, China.
[11, 12, 13] Mafu Laboratory, Moxin Tech., Huzhou, China.

Abstract—Ensuring the safety of hazardous material (Hazmat) transportation is critical. One of the most widely occurred traffic accidents is the run-off-road (ROR) incident. It is needed for exploring effective means of avoiding or even warning of ROR accidents for hazmat transportation. In particular, it is important to note that in many cases, vehicles are not driven on regular roads, but in "off-road" situations such as mountainous areas, where off-road detection is a hazard detection for abnormal driving. In this paper, we point out that it is a viable path for monitoring and detecting ROR incidents using an onboard camera. We reviewed existing literature in terms of the algorithm and the data that can be used. We also illustrate the shortcomings and provide insights into the future development of algorithms for detecting ROR incidents. Our research tailored a path to an effective ROR monitoring and detecting scheme that enhances the safety of hazardous material transportation.

Indexed Terms—Algorithm design, Hazardous material transportation, Safety sciences.

I. INTRODUCTION

Hazardous material (Hazmat) transportation is a type of special transport, which refers to the transport of unconventional goods by special organizations or technicians using special vehicles. In general, only those who have undergone a rigorous audit and have the appropriate facilities and equipment to ensure the safe transport of hazardous material transportation are qualified to carry out hazardous material transportation [1]. Because hazardous material is flammable, explosive, and highly corrosive, their transport is extremely dangerous. Improper transport of hazardous material transportation or accidents on the road can have serious consequences for surrounding vehicles, people, and the environment. Therefore, for the transport of dangerous chemicals, the supervisory authorities have been strictly investigated and controlled, and there can be no laxity [2]. Avoiding traffic accidents involving vehicles transporting dangerous chemicals is a very important issue in the transport of dangerous chemicals.

One of the most important types of traffic accidents is the one caused by driving off the road [3]. In some cases of improper driving, vehicles can go off the road, and collisions usually occur when there are obstacles on the side of the road. Run-off-road crashes are defined as when a vehicle leaves the road, goes into or over the shoulder, and strikes a natural or man-made object such as a tree, post, guardrail, etc. [4]. These crashes are usually single-vehicle collisions, but they often pose a significant hazard, not only to the driver of the vehicle, but also to the hazardous chemicals being transported as a result of the impact, and in many cases to the flammable roadside vegetation, which may even bring about fire and have a huge impact on the surrounding environment [5]. Therefore, there is a need for effective means of avoiding or even warning of accidents that occur when driving off the road.

Some of the previous studies have reported using machine-learning-based fiber sensing solutions for vehicle run-off-road event detection, using SNAP vibration signals as an indicator to carry out accurate off-road detection [6], as well as some radar-based solutions [7]. In this paper, however, we show that the use of onboard cameras - which are required in some regions for the transport of hazardous materials due to regulatory requirements by the authorities - can be used to determine and warn of run-off-road incidents, with the involvement of advanced machine vision tools.

In the following parts of this paper, we review current detection algorithms, relevant datasets, and data acquisition methods, summaries the shortcomings of current methods, and present a vision of future developments. This paper aims to provide a new perspective on the safety of hazardous material vehicle transport, making full use of existing hardware and improving safety during vehicle movements through software-based run-off-road detection and warning.

II. VISION TECHNIQUES OF RUN-OFF-ROAD DETECTION

Some traditional vision methods have been used to detect run-offs by detecting lanes. For example, Collado et al [8] used the spatial characteristics of lane lines and the Hough transform for lane line detection to effectively improve detection efficiency, but the detection accuracy of the method for curves is low. Sehestedt et al [9] used particle filters to identify lane lines but did not consider the robustness of the algorithm under complex conditions, and the overall detection accuracy was not high. Xu et al [10] used a road model-based approach to match lane markings and road control points. Parajuli [11] used the local gradient features of the image to determine the grey scale mutation points on the lane line position and used the local gradient value to find the edge feature points of the image. The method removes the influence of the shadow effect on lane line detection to a certain extent, but the overall detection is poor in real-time and cannot meet the needs of practical applications.

In recent years, with the development of deep learning techniques, some approaches that no longer make use of manual a priori knowledge but use a large number of samples to learn the target task have brought new means to driving scenarios [12], [13]. Specifically, in the realm of run-off road detection, for example, [14] used image segmentation-based road detection, using images captured by a monocular camera for training to obtain the drivable part of the image. The robot is first driven manually and the robot trajectory, as well as the images, are collected and used to train the classification network. Then a preliminary prediction of the current road area is obtained using the road area from the previous moment (initial values need to be calculated separately) and the current robot pose. The initial predicted area is then classified (at the pixel level) using the model to obtain a confidence map. Finally, the confidence map and the preliminary predicted region are combined to obtain the final predicted region. [15] Provides a method to give pixel-level texture direction voting to predict the vanishing point of the road (the boundary of the drivable area) in the image, and segment the main drivable area based on this vanishing point. The texture direction of each pixel is calculated and given a weight, and the vanishing point location of the road is calculated based on this information. LASV (Local Adaptive Voting) is proposed to make the weighting calculation more accurate. Finally, the final drivable area is segmented by OCR, which calculates a set of edges from the previously obtained vanishing points and then extracts the two most dominant ones as the boundaries of the drivable area. [16] introduced a method for automatic generation of training data is proposed based on stereo vision odometry. The image data (raw as video) is first collected by manual driving using a stereo camera, then the associated transfer matrix is calculated based on the video and the corresponding action sequence information, and then the labels of the drivable areas are automatically generated based on this information. Once the data is obtained, it can be trained by segmentation networks, three models are trained in the paper: FCN, VGG16, and UNet, where VGG16 is improved to obtain Segnet. after the segmentation results are obtained, the road area is finally further optimized with post-processing operations, first estimating the distance from the camera to each pixel, excluding all pixel points that are too far away, and then adding Gaussian blur is then added, while some finer areas are excluded by thresholding to obtain the final result.

The above method can adapt to more complex road conditions through sample learning, and the perception of the 'exercisable part' is more accurate than traditional methods, as it combines a priori and contextual knowledge from the data, partly combined with traditional image processing methods, to achieve better prediction results, which can be used in practical scenarios. have potential applications.

III. RUN-OFF-ROAD DATA AND ACQUISITION

For data-driven machine learning methods, data is an important factor in the accuracy of the algorithm. There is less data on vehicle run-offs, as they are very dangerous in the real world, and most of the current ones are manually acquired based on the task of the article itself, with the simulator being an important tool (video information is acquired by manual driving, and then a sequence of video and robot position changes over the period is combined to automatically generate images for training). In particular, it is important to note that in many cases, vehicles are not driven on regular roads, but in "off-road" situations such as mountainous areas and oiled areas, where off-road detection is a hazard detection for abnormal driving. Such 'off-road' datasets are rare and some work has looked at data from different scenarios, for example, the Yamaha-CMU Off-Road Dataset consists of 1076 images collected in four different locations in Western Pennsylvania and Ohio, while the Freiburg Forest dataset collected at 20 Hz with a resolution of 1024 × 768 pixels on three different days to acquire the variability in data caused by lighting conditions.

Another solution to compensate for the small dataset on the off-road side is migration learning, [17] discussed semantic segmentation in the off-road case, not specifically for drivable area detection, but some post-processing methods or classification networks can be used to isolate the segmentation part corresponding to the drivable area. This can compensate for the smaller dataset in the off-road context. Better results are obtained by using a pre-trained DeconvNet to migrate to the lightweight network designed in this paper, which focuses on the training dataset.

CONCLUSION

It is important to note that vehicle driving conditions are always complex, e.g. shadows and stains in the lane line area, foggy weather conditions, low light conditions at night, etc. can interfere with the original detection algorithm to varying degrees. Obstacles on the road and vehicles moving ahead can also affect the accuracy of detection. Deep learning methods can avoid this bias to a certain extent by learning from a large number of samples, but this also relies on a diverse and large number of samples. Some work has incorporated data augmentation or data migration algorithms that address this issue to some extent. In the future, the approaches from the mature field such as lane-detection/segmentation [18], [19] and semantic segmentation [20]–[22] in road environment can be borrowed to the ROR detection task. The use of means including domain adaptation, making full use of realistic and simulator data, or continuous learning, where new data is continuously introduced, are also available means of improving the performance of algorithms.

Overall, we propose that the detection of run-offs from the road can be carried out using on-board cameras, a device already fitted, which can alert drivers and operation centers to the occurrence of hazards and can contribute strongly to the safety of hazardous chemical transport.

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