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Assessing Road Conditions for Driving Safety of Hazardous Materials Transport

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***Abstract*: Ensuring the safety operation of hazardous materials transport is critical. Many previous works have reported various method to promote safety, while in this work, we identified and explored an overlooked aspect that affect the safety -- the real-time road conditions. For example, the slippery wet road or road with holes cause accidents for hazardous materials transport. Therefore, we argue that it is necessary to monitor the road conditions in real-time, and computer vision algorithms can make it possible. The advances in computer vision techniques shed light on the realm of road condition assessment. We reviewed and compared existing algorithms in this work. We also listed the existing road condition datasets and provided insights into how to apply the monitoring process with the safety framework of hazardous material transport.**

***Keywords*: Algorithm design, Hazardous material transportation, Road condition, Safety sciences.**

1. Introduction

Hazardous chemicals, including compressed and liquefied gases, flammable liquids, flammable solids, spontaneous and wet flammable substances, oxidants and organic peroxides, drugs and corrosives, are essential in everyday life. It is well known that the transport of dangerous chemicals is high-risk and, in the event of an accident, is likely to result in mass death and injury, leading to serious social repercussions.[1]-[3] Hazardous chemicals are highly susceptible to dangerous accidents during transportation because they can be affected by various factors. Therefore, when implementing the work of transporting hazardous chemicals, it is important to take into account the actual situation and increase the efforts to implement safety management work so as to ensure the safety of transporting hazardous chemicals.

Past work has described a number of measures to improve safety levels in the transport of dangerous chemicals [4]-[6], such as strengthening staff training and vehicle management, using GIS methods for careful route planning, and even adding intelligent systems for the safe monitoring and control of the transport of dangerous chemicals to achieve timely and effective monitoring of the safe transport of dangerous chemicals, which can be done at the first instance by means of video of transport vehicles, drivers and the specific situation of the goods. [7] The specific situation of transport vehicles, drivers and goods can be transmitted to the supervision centre through video, thus playing an active and effective role in protecting the lives of transport staff and the safe transport of dangerous chemicals.

However, in order to ensure good safety during the transport of dangerous chemicals, it is most important to strengthen the safety management of transport roads to avoid dangerous accidents and to improve the stability of the transport of dangerous chemicals. The existing methods of monitoring road conditions and video feedback do not reflect well the information on the road surface during the driving process. In fact, we would like to point out that the condition of the pavement itself is also crucial to formal safety. [8] Common pavement distresses include transverse cracks, longitudinal cracks, rutting, waves, potholes, delamination and leaks. [9], [10] Transverse cracks tend to appear more readily than longitudinal cracks and can develop from a crack less than 0.5 mm wide and 2 cm deep. Such cracks are difficult to see in sunny weather, but are detectable after rain. This is because while the surface water evaporates, water remains in the crack. Small cracks need to be treated promptly to prevent them from developing into large cracks. Large cracks are often more than 1 mm wide and 5 cm deep and can be several metres long. If large cracks are not sealed, delamination and shrinkage can ensue. If the bond between the pavement and the concrete slab is reduced, the overlay can debond from the concrete slab surface. Most potholes caused by cracks or leaks are the result of reduced adhesion. Localised delamination may extend over a few square centimetres, but such cracks are difficult to detect as the road surface remains intact. Large delaminations may develop into large cracks in the pavement and eventually lead to large potholes and breakdowns. Hazardous chemicals may be sensitive to such vibrations and extra care needs to be taken. In addition to cracks, water is another factor that can affect driving safety. In the rain, drivers' vision clarity is reduced, tyre friction with the ground is reduced and the road surface is complicated by water, which can not only cause the vehicle to stall if it inadvertently enters deep water, but can also endanger the lives of the vehicle owner and passengers. [11] Therefore, a method

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is needed that can detect the road surface in real time to promote driving safety. In the following article we will first review some of the methods and corresponding data for assessing road conditions before pointing out the possibilities of combining these methods with the transport of dangerous chemicals. The work in this paper will provide yet another dimension in the advancement of safety in the transport of dangerous chemicals.

2. Method of Road Condition Assessment with Visual Clue

Recent years witnessed the rapid development of computer vision technologies. Neural networks have made great strides in computer vision and have demonstrated powerful advantages in a wide range of image classification and tracking tasks [12]-[16], road information understanding [17]-[19], and even the transport of hazardous materials [20], [21]. Not much work has been reported about road safety assessment, and the following is an overview of some of the work that is informative.

Dewangan et al. [22] carried out a pavement four-classification task: dry, rough, ice, wet, adding a dense layer and upsampling on top of the general CNN. Cheng et al. [23] carried out a pavement five-classification task by self-designed CNN: distinguishing between dry, wet, snow, mud, and other categories, where some improvements were made to the activation function. [23] carried out a pavement binary classification task using SqueezeNet: dry/wet, day/night, above-zero temperature/below-zero temperature; for three binary classification tasks (for complex environments), a six-dimensional vector was output directly using softmax. [24] carried out a more detailed assessment of road surface conditions by dividing the road classes into six categories. The article first uses ROI to select regions of interest and then uses CNN to classify them. The article also mentions that the idea of road type classification can be extended using CNN to further evaluate the friction coefficient of the road surface. [25] measures the friction of the road (corresponding to the type) that is related to many parameters (which can be obtained through experiments), and different types of roads have more obvious distinctions in terms of friction coefficients, etc. Therefore, this phenomenon can be used to develop a decision tree and further optimise the output of the neural network to determine the final result. The overall process of the algorithm is as follows: firstly, the neural network accepts four parameters such as friction coefficient and vehicle speed as input, outputs the road coefficients, and then determines the final road type based on the value of this output. The abovementioned works provide valuable tools in road assessments and can be readily applied to hazardous material transportation.

3. Datasets for Road Assessment

Although the above-mentioned learning-based algorithms can capture the feature information of images more effectively than the traditional methods to promote higher accuracy road condition assessment, they all rely on high-quality training data. This training data needs to be general enough to cover a wider range of situations. At present, there are still few publicly available relevant road condition datasets.

Some of the work uses publicly available road datasets such as RobotCar [26] and KITTI [27] for re-labelling, with the latest released KITTI-360 dataset [28] is also available as an option, where the RobotCar dataset contains over 100 consistent routes through Oxford, UK, captured over a period of over a year. The dataset captures many different combinations of weather, traffic and pedestrians, as well as long-term changes such as construction and roadworks. There are also datasets that specifically include road surface characteristics, such as [29], which contains roads of different surface types: asphalt changes, other types of pavement, and even unpaved roads. It also includes road damage (e.g., potholes). These images were taken from a moving vehicle in the cities of Á GUAS mornas and Santo Amaro Da Imperatriz near Florianopolis, Santa Catalina, Brazil. These data These data provide an important contribution to the use of machine learning methods for road assessment. It is important to note that some of the data augmentation methods adopted in other fields could be used, such as Domain Adaptation or augmenting the data by methods such as GAN [30].

4. Conclusion and Discussion

Ensuring the safe transport of dangerous chemicals is a very important matter. Much past work has given ways of improving the safety of the transport of dangerous chemicals. In this paper we point out that in addition to the consideration of road conditions and road network conditions. We further point out that the road conditions on which vehicles are travelling can be monitored in real time, and that possible unsafe situations can be warned and communicated to the command centre as a basis for subsequent route arrangements. This monitoring can even be combined with assisted driving systems to help the driver to better control the vehicle. This paper reviews relevant research on the use of machine learning methods for road situation recognition, as well as some of the current datasets. It is noted that these methods provide a useful tool for monitoring road conditions while hazardous chemical vehicles are in motion. In the future, more datasets will need to be captured to allow for better generalisation of the network. More lightweight real-time algorithms will also need to be developed to enable real-time road condition detection and transmission at edge devices in real time. Road detection swarms consisting of large numbers of vehicles could even provide urban infrastructure providers and road builders with a real-time basis for information about roads.

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