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Identifying the Weight of a Moving Vehicle using Computer Vision

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ABSTRACT

Computer vision-based weigh-in-motion (WIM) systems are designed to monitor heavy vehicles. Computer vision is a field of artificial intelligence (AI) that enables computers and systems to derive meaningful information from visual inputs such as digital images, videos – and perform actions or make recommendations based on information. The system accurately estimates the contact between the tire and the road to calculate weight. This is based on the simple physics that force is equal to pressure multiplied by area. In this study, a computer vision system is developed using edge detection and optical character recognition. Edge detection is used to detect the location and presence of edges by changing the intensity of the image. Optical character recognition (OCR) is the process of converting text images into a machine-readable text format. The WIM system includes a camera and computer vision software to measure tire deformation parameters so that it can accurately estimate the tire's contact area with the road surface and recognize tire wall markings from images.

KEYWORDS Computer Vision, Weigh-In-Motion, Edge Detection, Optical Character Recognition.

INTRODUCTION

Large vehicles, especially those that exceed the permissible weight, not only pose a hazard to traffic in general but also put undue strain on transportation infrastructure such as bridges and roads. It is estimated that nearly 6% of trucks on the road carry illegal loads, and enforcing vehicle weight restrictions is a difficult task due to a lack of effective weighing methods. The traditional static weighing method currently used requires redirecting heavy vehicles to the weigh station, causing significant traffic disruption and delays. Additionally, static weighing systems are not economically viable due to the need for on-site personnel. Recognizing the inadequacies of static weighing, the development of Weigh-in-Motion (WIM) technology has gained importance. WIM technology allows vehicles to be weighed while in motion without any interruptions. Various approaches have been explored to develop WIM systems, such as measuring axle loads using sensors embedded in the pavement. These pavement-based WIM systems employ technologies like wheel or axle scale plates, capacitive strips, piezo-electric cables, bending plates, and load cells with strip sensors to measure vehicle weight while the vehicle is in motion. However, these systems come with drawbacks, including high costs for hardware, installation, and maintenance. In recent studies, attempts have been made to utilize bridges for weighing passing vehicles. However, this method requires precise knowledge of the bridge's stiffness, which is often unknown, and the accuracy is affected by the roughness of the bridge deck. Consequently, these factors have hindered the widespread implementation and approval of such systems for enforcement purposes. To overcome the challenges associated with weighing vehicles in motion, a cost-effective computer vision-based method is proposed. This method allows for non-contact and remote measurement and estimation of moving vehicle weights.

LITERATURE SURVEY

Computer vision system developed in this research consists of a camera and computer vision software for measuring tire deformation parameters and recognizing tire sidewall markings from images of individual tires of a moving vehicle [1].Computer vision techniques such as edge detection and optical character recognition are applied to enhance the measurement and recognition accuracy [1] .The tire-road contact area is estimated by measuring two essential tire deformation parameters using computer vision, and the overall diameter of the tire and constant coefficients computed empirically using tire technical parameters provided by the tire manufacturer are used in the estimation process [1].

Weigh-in-motion (WIM) systems record axle loads in addition to vehicle counts and classification .WIM systems incorporate a refined vehicle classification scheme by considering some load characteristics such as gross vehicle weight (GVW) and steering axle weight [2] .WIM systems consist of one or more traffic sensors embedded onto the roadway surface and a controller data acquisition system .Traffic sensors used in WIM systems include bending plates, load cell plates, quartz piezo strips, polymer piezo strips, and strain gauged strips .WIM data are widely used for pavement design, bridge design, freight planning, and load enforcement screening purposes [2] .

The study proposes a Weigh-in-Motion (WIM) model based on the beetle swarm optimization (BSO) algorithm and the error back propagation (BP) neural network [3]. The structure and principle of the WIM system used in this study are analyzed. The WIM signal is denoised and reconstructed using wavelet transform, which is a widely used transform analysis method in fault detection, image processing, and signal analysis [3]. A BP neural network model optimized by the BSO algorithm is established to process the WIM signal. The experimental results show that the BSO-BP WIM model has fast convergence speed and high accuracy, with a relative error of 1.41% for the maximum gross weight and 6.69% for the maximum axle weight [3].

The paper proposes a novel methodology for acquiring the weights of vehicles in motion on a bridge, based on the extraction of structural dynamic response patterns and deep learning algorithms [4]. The method involves recording the response patterns caused by vehicles passing over the bridge using an accelerometer and converting the raw signal into a two-dimensional spectral image through time-frequency analysis to extract output the corresponding image samples. Object classification is then performed using a deep convolutional neural network (DCNN) to automatically learn features, while applying optimization analysis improves the performance of the trained network [4].

This paper presents a non-contact motion weighing method based on computer vision for monitoring heavy vehicles to prevent infrastructure deterioration [5]. Determining vehicle weight, especially overweight trucks, is essential for infrastructure owners, law enforcement agencies, and the general public. The accuracy of the method will be further evaluated in the future using a statistically significant sample of trucks. Future studies will address how extreme weather conditions, terrain conditions, and camera resolution may affect the accuracy of computer vision measurements. The actual value of the contact area is obtained by the spray paint method, in which tire traces on white paper are photographed and processed to extract the contact area [5].

There are two main classifications of WIM solution methods: static WIM and dynamic WIM. Dynamic WIM methods can be further divided into low-speed WIM (LS-WIM) and high-speed WIM (HS-WIM) LS-WIM weighs the vehicle while it moves across the scale at low speed, typically less than 15 kmph, while HS-WIMs can weigh the vehicle weight at full highway speeds .This study focuses on using Vehicular Telematics (VT) data from onboard diagnostics modules and smartphones to infer the payload of a vehicle, which falls under the dynamic WIM category [6].The experiment conducted in this study aimed to find the correlation between VT data and the payload of a vehicle, and feature engineering was done to find the best regression model .The results of the experiment showed that using VT data for nonintrusive measurement of the weight of a vehicle in motion is feasible [6].

The study proposes an information-fusion-based method for load identification on bridges, using a weigh-in-motion system (WIMs) and multiple cameras arranged along the bridge. The method aims to simultaneously identify transverse and longitudinal loads on the full deck of the bridge [7].The WIMs system at the beginning of the bridge captures the weight of vehicles, while the multiple cameras calculate the vehicle's trajectory and location. The weight and location data are matched when the vehicle in the video crosses the piezoelectric sensor of WIMs for the same time as the weight information is recorded. The proposed method is verified using multi-view 3D simulated topography and terrain data from a steep bridge, demonstrating its reliability and accuracy [7].

Evaluate the effects of extreme loads caused by different types of trucks on bridges. Procedures are proposed for conducting probabilistic assessments of the relative severity of heavy truck loads on simply supported bridges [8]. Use Wisconsin Scales in Motion (WIM) data to analyze the heaviest 5% of trucks in each truck axle group. Determine the best statistical distributions for axle loads and axle spacing within each truck type axle group. Limitations: Sensitivity to data quality Span length limitation (20 to240 ft bridges) [8].

The paper proposes a bridge weigh-in-motion (BWIM) methodology that considers nonconstant vehicle speed and improves the accuracy of axle weight estimation [9].The methodology uses strain measurements from transducers installed on the bottom chord of a truss bridge to estimate axle weights and gross vehicle weight (GVW) [9].The methodology involves several components, including speed detection, lateral load distribution determination, influence line determination, speed correction, and axle weight determination .The methodology can be applied to estimate axle weights and GVW of unknown vehicles by using strain measurements and the obtained information on lateral load distribution and influence line of the bridge [9].

The study discusses the history of bridge weigh-in-motion (B-WIM) technology, including early work on weigh-in-motion (WIM) technologies [10].Research initiatives in Australia and Europe have focused on improving B-WIM accuracy, with the moving force identification (MFI) method showing promise in modeling the dynamic fluctuation of axle forces on the bridge [10].The accuracy of B-WIM installations reported in the literature varies, with current accuracy levels being sufficient for selecting vehicles to be weighed using static scales but insufficient for direct enforcement .An accuracy class of C (15) or better has been suggested as sufficient for pre-selection requirements, with B-WIM systems generally being more accurate for gross weight than for individual axles [10].

The SIM system is unique due to its textured measuring surface that represents a typical "textured" road surface [11].The system allows for the quantification of tri-axial tire contact force distributions in the three orthogonal directions X, Y, and Z for single, dual, or full axle truck tire configurations [11].The SIM system has been used for real tire (or truck) rolling conditions and has been shown to provide satisfactory characterizations of tire contact measurements .The stress outputs from the SIM system are calculated by dividing the measured tire forces from the sensing elements with a constant effective area of 250.28 mm2 [11] .

Weigh-in-Motion (WIM) technologies have been developed to improve overload screening and enforcement, contributing to safer and more efficient operation of trucks [12].The B-WIM technology offers portability, allowing transducers and electronics to be quickly attached, removed, and reinstalled on different bridges [12].This is particularly useful in harsh climates and on busy highways where lane closures are difficult. On-board WIM systems are a promising alternative to traditional roadside enforcement, offering potential solutions to compliance officers. They can be part of advanced driver assistance systems (ADAS) to improve road safety and reduce road wear. Traditional processes to meet weight limits include static weighing, but the trend is to abandon the use of discs and instead use belt sensors for operational and economic reasons [12].

Weigh-in-motion (WIM) systems require calibration to ensure accuracy. Static weight measurement error can affect the performance of the WIM system [14]. ASTM and COST protocols provide calibration guidelines. Long-term pavement performance (LTPP) data were used to study the effects of static weight. The data analyzes address two main concerns (1) modeling gross vehicle weight (GVW) errors while calculating static weight and WIM weight errors, and (2) quantifying the impact of gross vehicle weight (GVW) error. Multiple WIM sites with varying performance level [14].

Traffic load simulation is important in bridge design and maintenance. Non-contact machine vision offers an alternative to WIM in gathering vehicle information. Enhanced YOLO-v5 detector with k-means++ clustering improves vehicle type recognition [15]. Merging data sources creates a comprehensive vehicle database. Advantages: Improved vehicle detection, spatio-temporal tracking [15].

METHODOLOGY

Objective: The main goal of this paper is to create a non-contact weigh-in-motion system using computer vision technology to measure the tire deformation parameters and estimate the tire-roadway contact area accurately.

Components:

A camera is used to capture images of individual tires on moving vehicles. These images are essential for subsequent analysis. Computer vision software is employed to process the captured images.

Weight Estimation: W= $\sum F = \sum P.A$

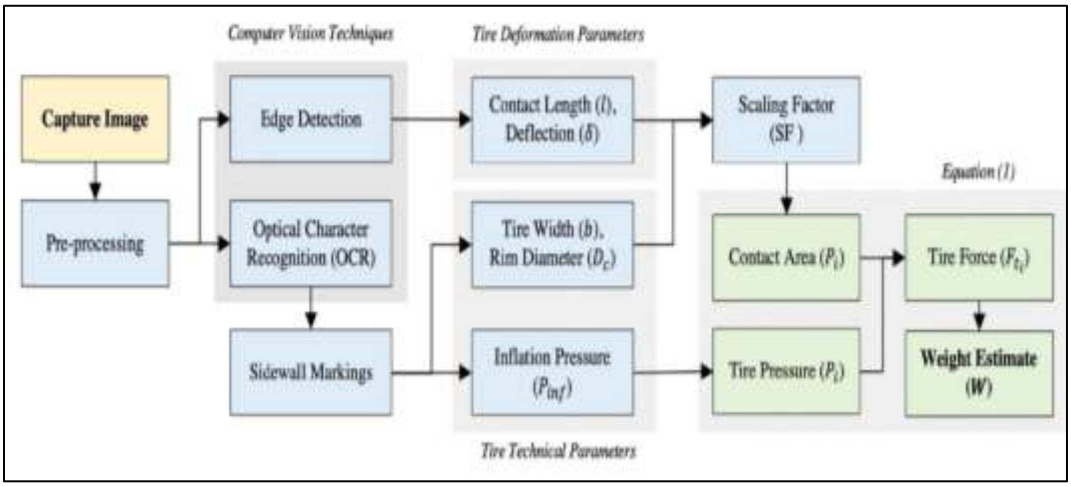
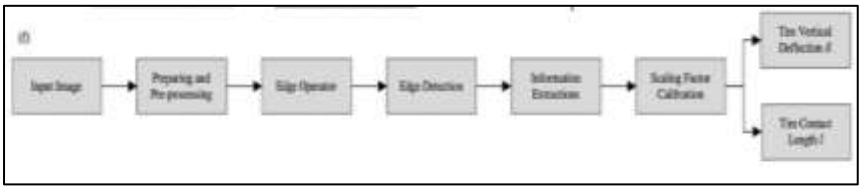


Fig 1: Work Flow

Techniques:

Edge Detection:

- This technique is used to identify the boundaries and contours of objects in the images. It is applied to detect changes in the tire shape and identify the regions of interest.
- The use of edge detection techniques ensures precise measurements of the tire deformation parameters, leading to consistent high accuracy.



Optical Character Recognition:

- OCR technology is employed to recognize and convert text information found on tire sidewall markings in the images into machine-readable text. This is essential for extracting information about the tires.
- Identifies and recognizes the texts—tire brand, model, and size—of the sidewall markings from a tire image.

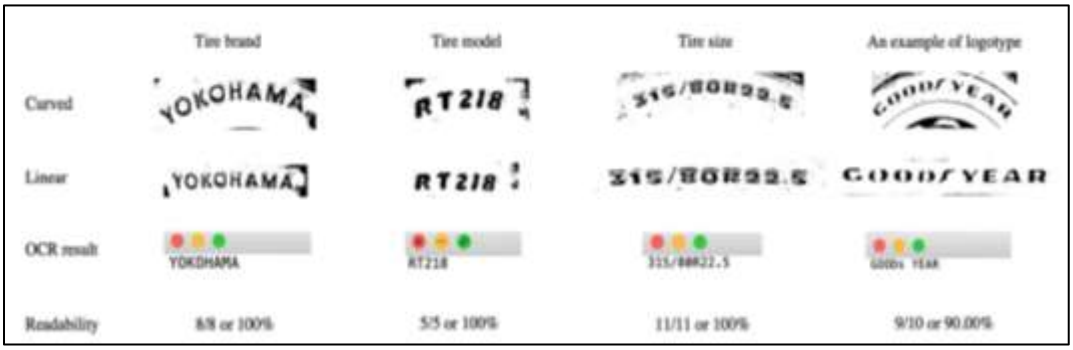
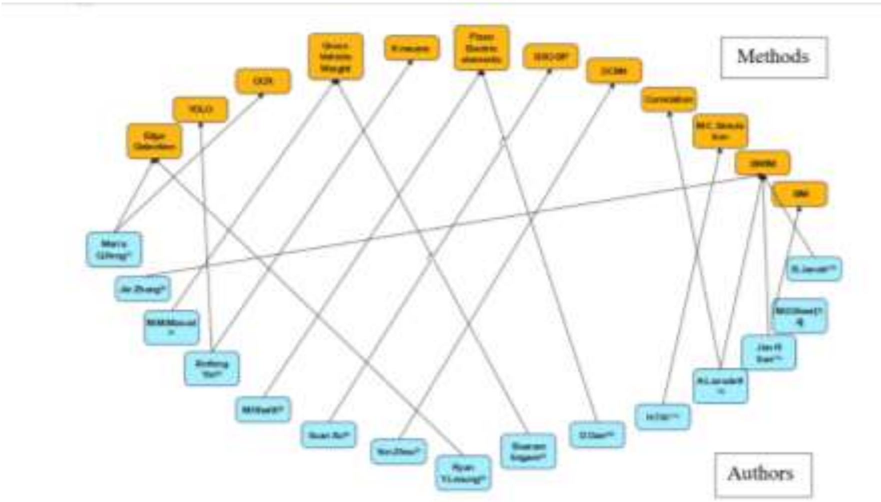


Fig 2: Samples of tire brand, tire model, tire size, and logotype in curved, linear forms and their OCR results and readabilities

Graphical representation with literature Survey



CONCLUSION

This paper presents a cost-effective computer vision-based solution for non-contact weighing of moving vehicles by analyzing the contact force between the tire and the road. Using roadside cameras, the system measures tire deformation parameters, such as contact length and longitudinal deflection, to estimate the contact area. It also recognizes markings on the tire sidewall to achieve the recommended inflation pressure. Innovative optical character recognition (OCR) technique significantly improves the readability rate of sidewall text to over 90%. Field experiments with 12 vehicles, including sport utility vehicles and concrete trucks, confirmed the system's accuracy with a weight estimation error of ±4% compared to static weighing. The proposed system eliminates the need to install permanent or destructive sensors on the road or on vehicles. Despite its success, future research may address issues related to image blurring at higher speeds and image quality degradation in adverse weather conditions. Overall, this low-cost computer vision-based solution provides a promising, accurate and non-intrusive vehicle weighing method, demonstrating its superiority over traditional static methods and other.

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