Real-time Vehicle Detection, Classification and Counting System using Computer Vision

Keywords: intelligent transport system, vehicle detection, classification, background subtraction, traffic statistics

Abstract

The paper proposes a vehicle detection, classification and counting system that is capable of running in real-time. By using this computer vision-based system, complex traffic scenes can be analyzed and traffic interactions can be quantified. The system uses a computer vision-based detection algorithm. The system will use footage collected from CCTV cameras installed along roads to monitor traffic. The vehicles will be counted according to their class based on their sizes. The data will then be shown real-time in the video-feed and in a dashboard.

Introduction

In the last decade or so, authorities in the Philippines have increasingly depended on CCTV cameras to monitor real-time traffic especially in metropolitan areas. However, the utilization of these systems leaves so much to be desired. These camera systems are manually monitored by operators and usually only used for monitoring accidents and congestion. Quantifying the information provided by these systems would be helpful in optimizing traffic mobility and improving traffic flow. The apparent lack of comprehensive traffic flow and network analysis in the Philippines, which is crucial for urban planning and road infrastructure management is rather concerning. The most recent report of Numbeo published last January 2021 shows that the country scored 192.88 for the traffic index and 243.20 for the inefficiency index.

The use of computer vision in traffic monitoring has been steadily gaining traction over the years. These advancements have shown remarkable results and achievements. Various researches have shown that detection and classification algorithms using background subtraction techniques perform well. Thus, in an effort to improve our understanding of traffic interactions in Philippine roads, the researchers have proposed a vehicle detection and counting system. The proposed project uses a computer vision-based system to detect, classify and count vehicles in real-time. The project aims to provide a systematic solution to counting vehicles and monitoring traffic. This will provide information on the make-up of vehicles traversing these concerned road networks such as what types of vehicles traverse the roads, how many are there per size class, and what are the trends in these numbers throughout the day.

Statement of the Problem

As urban landscapes continue to rapidly sprawl in the Philippines, the need for the integration of intelligent transportation systems is also growing. There is an apparent lack of comprehensive traffic statistics especially in smaller urban areas in the country outside of the Manila area. These information and data are crucial in improving urban planning and infrastructure management to create efficient and safer road networks.

Significance/Rationale

Economy

Road congestion costs our economy a significant portion of the gross domestic product. High levels of traffic congestion and density cause huge delays in transport of goods and delivery of services, and increased fuel wastage.

Environment

The long time spent by vehicles on the road also contributes to the increase in emission of pollutants. Thus, minimizing the time spent by vehicles on the road can help lessen their carbon footprint.

Efficiency

Plenty of Filipinos spend a few hours each day stuck in traffic. Philippines is always among the top countries with longest traffic wait times. Commuters lose valuable time that can instead be spent on productive activities. Traffic costs people income opportunities. Filipinos can do away with delayed transactions and the mental and physical fatigue caused by traffic.

Safety

Efficient traffic networks also translate to safer commute and roads. With better road networks, we can significantly reduce the risk of accidents and hazards in roads.

Society

If the project is deployed successfully, especially in highly urbanized areas, it can help local governments to employ efficient routes, implement better policies, and plan effective road infrastructure projects. This could also provide road users with vital information that would help them understand traffic flow and interactions better, and consequently, navigate the roads better and more safely.

General Objective

The main objective of this project is to create a computer vision-based monitoring system that will analyze CCTV footage of highways in real time using computer vision technology to report traffic statistics.

Specific Objectives

* To create a system with the following functions: vehicle detection, vehicle classification, vehicle count, vehicle count (according to class), vehicle count (inbound/outbound)
* Deploy the system in roads with varying traffic volumes.
* Test the system in several types of environments, lighting conditions, and weather conditions.
* Publish a dashboard/web app that will show the real time data (timelines, etc.)

Related Literature

Lidasan et al (2009) published a study titled “A Needs Assessment of Transport Planning and Traffic Management of Local Cities: The Case of the Philippines.” The study assessed the technical capabilities of various cities on transport planning and traffic management. They attempted to collect data from all cities in the Philippines. However, not all cities participated. Cities were divided into three categories: large, mid-size and small. They also gathered information on the basic tools used for transport planning and traffic management. The paper identified five key areas that need to be addressed. The following are:

(i) Management and planning of public transportation operations;

(ii) Management of automobiles and trucks in cities;

(iii) Management of traffic flow at intersections;

(iv) Planning of transport networks; and

(v) Project funding.

Traffic congestion was ranked as the sixth overall among the top issues being faced by cities of various sizes. Moreover, it ranked second for large cities and fourth for mid-size cities.

The study assessed the know-how of the participating cities in Transport Planning and Traffic Management. Specifically, the participating cities self-assessed their Level of Knowledge in Transport Planning Concepts.

The following are some of the notable concepts and respective scores:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Transport Planning Concept | Small | Mid-size | Large | All |
| Planning, execution, and analysis of transport surveys to generate data for planning | 1.63 | 1.43 | 1.39 | 1.48 |
| Forecasting transport demand and analyzing how it impacts the present network | 1.41 | 1.36 | 1.30 | 1.36 |

Source: TPTM Self-assessment Survey, 2008.

Note: 1=limited knowledge, 2=some knowledge, 3=good knowledge. Figures are averages of cities in the group.

The cities’ Level of Knowledge in Traffic Engineering and Management Concepts was also assessed. Some of the relevant concepts and respective scores are:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Traffic Engineering and Management Concept | Small | Mid-size | Large | All |
| Analysis of traffic accidents and concepts to enhance road safety | 2.00 | 1.74 | 1.71 | 1.81 |
| Concepts in traffic flow management | 2.20 | 1.85 | 1.83 | 1.95 |
| Use of information and technology in traffic management | 1.83 | 1.46 | 1.52 | 1.59 |

Source: TPTM Self-assessment Survey, 2008.

Note: 1=limited knowledge, 2=some knowledge, 3=good knowledge. Figures are averages of cities in the group.

The results of the needs assessment of the paper showed the equal importance of coming up with academic research in transport and traffic management.

The interest towards using computer vision techniques for intelligent traffic systems has been growing. Thus, several vehicle detection/counting techniques have been tested by researchers in similar studies. Some of the popular algorithms used include Gaussian Mixture Model (GMM), Region Convolutional Network (R-CNN), another variation of R-CNN called Faster R-CNN, and You Only Look Once (YOLO). Some studies also used a combination of CNN-based techniques with Support Vector Machine (SVM).

Classical approaches such as the background subtraction-based Gaussian Mixture Model are widely used in these types of traffic monitoring systems. The advantages of this algorithm include fast and accurate detection. Background subtraction-based detection methods extract objects by evaluating the difference between the presumed static background and the images to be processed.

In a paper by Maqbool et al. (2018), a GMM was used to compute the variance, covariance and mean of every pixel in a frame. As a new frame arrives, these parameters are calculated again. The foreground is determined when the difference between the values for the two frames is larger than the product of actual value and standard deviation. In this method, the model is created and updated based on a singular modal distribution, such as singular Gaussian distribution.

While background subtraction is efficient for vehicle detection, Xia et al. (2016) discussed that the performance of the model can suffer in a complex environment. The variation in lighting, presence of leaves or wind, and even a slight movement of the camera can affect the effectiveness.

A paper by Guennouni et al (2014) proposed an OpenCV-based solution for multiple object detection. The study also compared the performances in a regular platform and an embedded device. Results showed that object detection can be deployed in different platforms as needed. This system is appropriate to adapt for surveillance cameras with object detection notification. The system can also be trained for any type of object to be detected for different situations. The researchers then recommended to enhance the embedded platform performance. To achieve this, several processors can be used to run separate tasks simultaneously in order to enhance performance and response time.

Chandan et al. (2018) discussed various methods for real time object detection and tracking using deep learning and OpenCV. The paper described the background subtraction method as a “rapid method of localizing objects in motion.” The footage or images used for this method must be acquired from a stationary camera. This technique separates the background from the foreground objects we are interested in using a sequence of processing steps.

In a project by Memon et al (2018), a video-based system was created using OpenCV for detection, counting and classification of vehicles. The system uses a supervised algorithm to categorize vehicles into three classes: LTV, HTV or MTV. The algorithm uses background subtraction to extract the vehicles for detection. The OpenCV algorithm used in the implementation of the system is BackgroundSubtractorMOG2. The algorithm uses an automated approach and selects an appropriate number of Gaussian mixtures for the pixel. The authors also pointed out that it is better at handling illumination changes in the scene. After the foreground is extracted, the contours are determined using cv2.findContours(). For the classification, the contour properties are extracted and compared with already assumed values to determine whether the vehicle is LTV, HTV or MTV. The researchers also tested another method of classification which uses BoF along with SVM algorithm. The results showed that the Contour Comparison method performed significantly better. However, the system needs human supervision during the determination of Region of Interest. Thus, the researchers recommended the creation of an unsupervised alternative to the system.

Li et al (2018) presented a solution to moving vehicle detection, tracking and counting using an adaptive background subtraction technology. The system was implemented using Visual C++ code with OpenCV. The footage is processed using binarization to subtract the foreground. Unlike other similar systems, the researchers proposed a method to also remove shadows of the vehicles to create a more efficient system. To count the vehicle, a technique called “Virtual Detector” was used. Contrary to similar systems, each lane is assigned a rectangular region of interest (ROI) as the virtual detector. Vehicles are detected by monitoring changes in the area of the virtual detector. Another method was also proposed to detect movement, count and trajectory. In this method, blob tracking technology was used to track and count the vehicles moving in the field of view. The results of the project showed that the accuracy rate can be up to 97.1% for the virtual detector method, and 98.4% for the blob tracking method.

Another paper by Seenouvong (2016) proposed a similar method of vehicle detection and counting system. Like other algorithms previously mentioned, the system also used background subtraction and a defined region of interest. However, a single region of interest and virtual detection zone were defined for multiple lanes. The region of interest was also divided into five zones and each zone was processed differently. This was implemented to avoid false positives in the detection of vehicles. The system was tested with seven input footages. Results showed that 646 out of 667 vehicles were detected, thus demonstrating an accuracy of 96.85%. The accuracy for each input footage also varied only from 95% to 99% which shows the great reliability of the system.

OpenCV

Background Subtraction

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The YOLO boasts quick processing speeds which makes it preferable for real time deployments. However, the YOLO algorithm is noticeably more computationally expensive than the more commonly used background subtraction method. YOLO-based systems are ideally deployed using higher-end machines with capable GPUs due to the processing involved. Various studies have been conducted that demonstrated the potential of using YOLO algorithm with OpenCV for speedy and accurate object detection and classification. The use of OpenCV alongside YOLO shows the capability of these systems to be deployed even on mid-end machines.

A project by Mittal et al (2019) proposed an object detection and classification system using YOLO with the assistance of OpenCV. In the system proposed, the object is done using a Convolution Neural Network which is applied using the OpenCV library. The project showed good results in item location with the assistance of picture dissecting field.

In the study CPU Based YOLO: A Real Time Object Detection Algorithm (Ullah, 2020), the model proposed ran the YOLO algorithm on a non-GPU computer. The model was able to process videos with minimum 10.12FPS, 80-99% confidence and with 31.05% mAP. This shows that a system like this is suitable for real time application within low cost and less effort. This particular project used an AMD Ryzen 3 machine which suggests that using a higher-end machine might yield better results.

Rahman et al (2020) presented an automatic wrong-way vehicle detection system that processes on-road surveillance camera footage. The processing is done in three stages: vehicle detection using YOLO algorithm, centroid tracking algorithm, and wrong-way driving detection. The system was tested using various traffic videos and shows that the system works well even in different light and weather conditions. The results of the experiments done with the system showed that each wrong-way vehicle was successfully detected. It is important to note however that the system was designed to only analyze one side of the road.

Another intelligent video surveillance-based vehicle tracking system presented by Al-qaness et al (2021) used a combination of the neural network, image-based tracking, and You Only Look Once (YOLOv3) to track vehicles. The system showed acceptable results even in changing scenarios. The proposed system design used the Python programming language, OpenCV library for image processing, Google Colab cloud service, and Anaconda development environment. The video stream processing algorithm used the YOLO neural network model. The developed system was tested on three real traffic videos.

Mao wrote a detailed paper in 2019 on a project that proposed vision-based vehicle detection and tracking system. The system used a YOLO neural network combined with OpenCV to realize real-time vehicle detection. Kalman filter and extended Kalman filter were applied for vehicle tracking. The system was tested using a simulated traffic scene in BeamNG and a practical experiment using real life footage. Additionally, the study also analyzed the effects of process noise and measurement noise using a variable-controlling approach. The system also employed a perspective transformation technique to transfer the coordinates from the image plane to the ground plane. Despite showing promising results, the author also emphasized the limitations of the system especially in complex circumstances. Computer vision-based algorithms are known to be hindered by spatial constraints which was also apparent in this project. The YOLO algorithm was not as effective in detecting small objects within the image. The Kalman filter method is also very sensitive to the sensor’s measurement data. Erroneous measurements would also lead to a faulty particle filtering. The tracking algorithm requires a high computational complexity and takes a relatively longer time which makes it less ideal for real-time deployment.

Methodology

The project proposes a multi-faceted system.

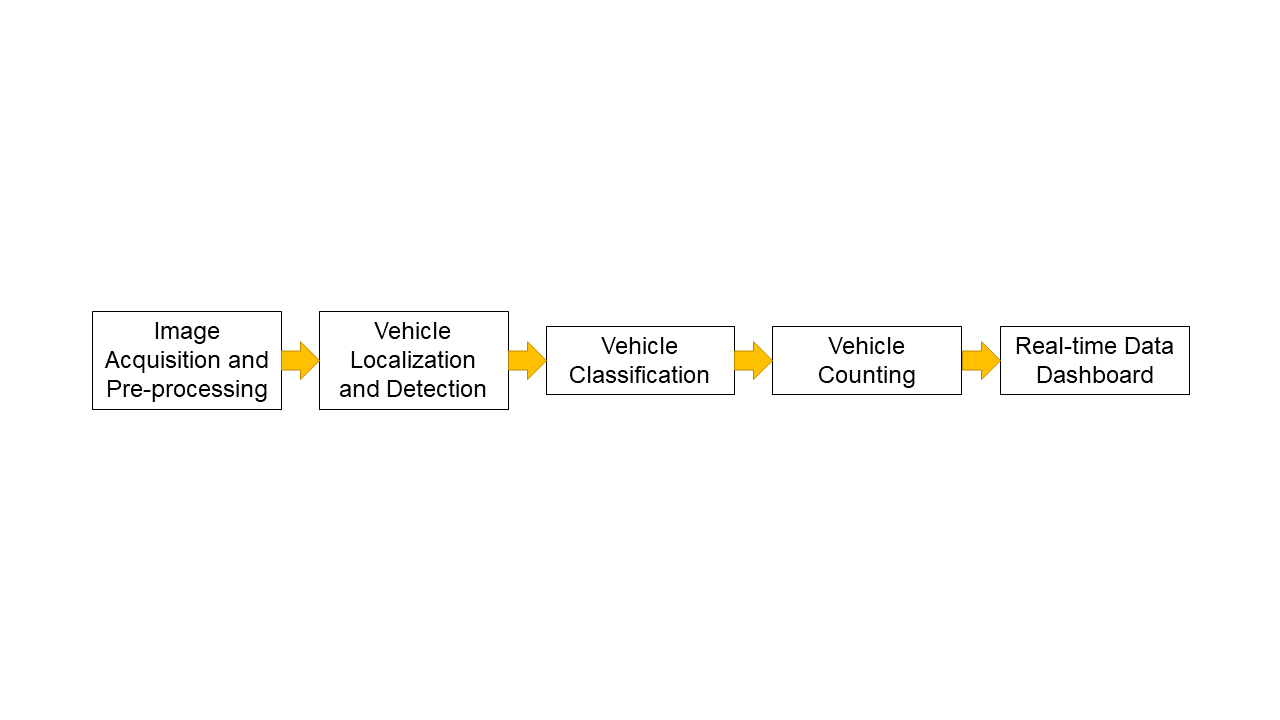
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Image Acquisition and Pre-processing

The training and testing images will be collected from CCTV cameras detected for traffic surveillance.

Real-time Data Dashboard

Aside from showing the classifications in the video feed, the real-time count and data will be reflected and published real-time in a web application/dashboard. Several visualizations such as bar (reflecting the vehicle count) and time-series (reflecting the vehicle count trend over time) charts will be published in the dashboard.

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