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Computer Vision Based Approach for Traffic Violation Detection

Akila Peiris¹, EATA Edirisuriya², CD Athuraliya³, Isuru Jayasooriya⁴

^{1,2}Department of Computer Science, Faculty of Applied Sciences, University of Sri Jayewardenepura, Sri Lanka ^{3,4}LIRNEasia, Colombo, Sri Lanka

#ananda@dscs.sjp.ac.lk

Abstract -The ever growing number of vehicles in a country present a variety of problems including but not limited to; infrastructural problems, air and water pollution and accidents with the latter being the most apparent. The main cause for this being traffic violations. This research was carried out with the intention of detecting motor traffic violations using CCTV footages. While there have been attempts to create automated traffic violation detection systems over the years, these studies have mostly been focused on more streamlined and sparse traffic conditions such as highways. But, the type of traffic conditions observed in Sri Lanka among other developing countries are unruly and chaotic. This paper proposes an automated real-time traffic violation detection system for highly congested and unruly road traffic conditions. The proposed system uses computer vision techniques, machine learning technology in creating a traffic violation detection system.

Keywords - Computer Vision, Traffic Violation Detection, Kalman Filter, Haar Detection.

Introduction

The ever growing number of vehicles on roads present numerous problems to a country. Especially in a developing country like Sri Lanka where the existing infrastructures are insufficient to cater to all these vehicles. Two of the biggest problems posed by this vehicle population are traffic accidents and heavy traffic congestion. These are caused largely due to negligence and violation of traffic rules. In Sri Lanka, the existing methods for detecting traffic violations are highly dependent on the police personnel thus, subject to human error. The idea here is to analyze the inputs gathered in the form of CCTV footages by utilizing computer vision and machine learning concepts. The reason for using CCTV infrastructure as the data source is due to the fact that, the infrastructure is easy to implement, maintain and expanded.

Problem Definition

The challenge was to create an automated motor traffic violation detection system using CCTV footage that may facilitate ease of enforcing law and can be integrated into a complete advanced urban traffic management system. This system had to be feasible and easily maintainable to be implemented for a developing country. And the system must be robust against unruly traffic conditions.

Literature Review

The methodological pipeline used in most of the previous works has several common steps; vehicle (object) detection, vehicle identification, tracking and traffic violation detection.

A research paper[1] proposed a way to detect vehicles using Gaussian mixture model. Detecting traffic violations is based on event detection. And events have to be considered as spatiotemporal data. Hence the goal of event detection is to identify spatio-temporal patterns of a particular nature.

A team of researchers have developed a system[2] to detect spatio-temporal patterns





(human actions) such as picking up a dropped object or waving a hand in videos of crowded areas. This system uses spatiotemporal shapes for event detection in highly dynamic and cluttered videos. The spatio-temporal event parts and their configurations are matched to a template to identify the events.

A research paper[3] has provided a comparative analysis and evaluation of Linear and Unscented Kalman Filters process models for urban traffic applications.

A team of Korean researchers proposed an image processing algorithm[4] for individual vehicle trajectory monitoring. This is done by utilizing detailed information such as speed, volume, etc. on each individual vehicle and conflict evaluation techniques.

A system, capable of counting and tracking vehicle speeds and trajectories in multi-track highways, has been proposed in an article[5] In this system, Foreground detection is done by utilizing the Gaussian

Mixture Model and then the detected foreground is morphed to reduce noise. Tracking is done using Kalman Filter. Gaussian Mixture Model handles illumination and background variation automatically.

A group of researchers[6] have developed an algorithm to address the issue of occlusion in traffic monitoring systems. They have developed an algorithm, called the Spatiotemporal Markov Random Field model which tracks each pixel in each frame and their transitions on a two-dimensional plane through the set of frames (time). And combining this with Hidden Markov Model (HMM) they have developed a system to detect traffic violations at intersections by identifying event chains.

Methodology

Vehicle Detection

After testing multiple methods of object detection varying from simple background subtraction methods to state of the art Deep learning methods such as Faster RCNN, we have selected Haar Cascade detection as the object detection technique for this system for its performance and accuracy.

Initially developed as a solution for face detection issues, this method can be trained to detect any form of object classes. Haar cascade uses a sliding window technique to test all possible positions to determine whether one or more objects of interest exist within the image[7].

In order to use Haar detection, first we have to train a Haar cascade classifier using a set of positive (images of objects of interest, in this case vehicles) and a set of negative (images of non vehicular objects) images which are approximately the same size. this previously trained classifier is then used in determining whether an area on an image contains an object of interest (vehicle) or otherwise.

The results are returned as bounding box positions in the (left x coordinate, top y coordinate, right x coordinate, bottom y coordinate) format.

After the initial detection, it is done at a discrete interval of the frame sequence (once in every 4 frames) and the detected data(bounding box positions) are compared with the bounding box positions of the existing KalmanBoxTracker objects(tracking data objects) using an Intersection Over Union (IOU) matrix.

If the newly detected objects do not correspond to any currently existing tracking data objects, they are passed into the next phase of the pipeline.

The tracking objects with a corresponding detected objects, the hit streak attribute is



increased by 1 and time since update attribute is set to 0 in the corresponding KalmanBoxTracker object. This attribute keeps the score of how many consecutive track detect position matches each tracking object has observed.

3) If there are tracking objects that do not correspond to any of the detected objects, the hit streak attribute is set to 0 and time since update attribute is increased by 1 in the corresponding KalmanBoxTracker object. If the hit streak value falls below the number of minimum number of hits or the frame count exceeds the minimum number of hits while the time since update is 0, the object is removed from the tracking object list.

hit_streak attribute keeps track of the number of consecutive of a particular object. time since update attribute keeps track of the number of frames processed since the hit streak attribute is updated. (A hit is a bounding box of a tracked object which shares an IOU value of more than 0.5 when compared to the bounding box of a detected object.

Vehicle Tracking

Then the results obtained from the haar detection are converted into the (x coordinate, y coordinate, bounding box area, width to height ratio) format.

These bounding box values are then fed into model called an instance of а KalmanBoxTracker along with a unique id assigned to each object. Then the newly created KalmanBoxTracker object is inserted into a list of such objects. This list holds the information about all the objects being tracked. During the data association phase, objects representing the newly detected objects are added and the objects which are found obsolete are removed from the list Kalman filter[8], or Linear Quadratic Estimation (LQE) is an optimal estimation algorithm. It was first used in the 1960s where it was used in the Apollo project to calculate the trajectory of spacecrafts. Kalman filter has 2 main usages; it can be used to estimate system states that cannot be measured directly using indirect measurements and it can calculate the optimal measures of state by combining measurements from multiple sensors when the measurements are prone to noise.

Kalman filter combines the measurement and the prediction from the mathematical model to predict an optimal value for the next location of an object. In our context, this is very useful in situations where partial or complete occlusion is present.

Violation Detection

The traffic violations are identified using the angles of the edges that connect the points of the vehicle's path.

For this purpose, we have selected to detect a specific type of traffic violation, disobeying lane laws, i.e. vehicles changing the travel path rapidly/ suddenly. We have used our own mechanism here to calculate the angles of the path of the vehicles. For every frame, we calculate the angle between 2 lines that connect the current position (P_k) and the 2nd previous position (P_{k-2}).

2nd previous position (P_{k-2}) and the 2nd point previous to that (P_{k-4}) .



Figure 1: Vehicle path and previous positions

i.e. in a series of points where the current position is (P_k) , previous position is (P_{k-1}) and so on, we calculate the angle made at (P_{k-2}) by points (P_k) , (P_{k-2}) and (P_{k-4}) . and if the angle



exceeds a certain value, the system detects it as a violation.



Figure 2: Change of angle

The reason that we calculate the angle by skipping a previous position (angle between P_k and P_{k-2} instead of P_k and P_{k-1} and so on is to reduce the effects of noise and small errors of the predicted tracking positions.

Results



Figure 3: A violation being detected

The system we have developed produces results with a high MOT A (Multiple Object Tracking Ac-curacy) value when considering tracking accuracy. The overall system has a MOT A (Multiple Object Tracking Accuracy) value of 0.90. This value was achieved by testing 5 sets of frames, with each set having 80 frames.

The overall system was able to identify 2 out of 3 lane rule violations committed by the vehicles it tracked.

Conclusion

Since the system is pipelined, a bottleneck in accuracies in any stage affects the accuracies in the next stage. Therefore, it is important for the detection method to achieve a low false negative rate to achieve higher accuracies in tracking and violation detection stages. Using a set of predefined areas to conduct detection and tracking and combining the results together can improve the speed and overall accuracies of the results. This is because we can avoid tracking vehicles that are too far and limit our scope to one direction at a time which is especially in complex junctions.

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