Robust Vehicle Detection Using Image Processing

A dissertation submitted for the Degree of Master of …

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2024

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I would like to dedicate this thesis to my loving Family, Teachers and friends

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to all those who provided me the support to complete this research successfully. A special thanks of gratitude to my supervisor Mr. Dasun Bamunuarachchi for the contribution in stimulating suggestions and encouragements which helped me very much to coordinate my project domain.

Finally, a very special thanks to my family who helped me to collect traffic videos and with me until I achieved the goal in this project.

ABSTRACT

The escalation of vehicular traffic in a country like Sri Lanka has escalated concerns over traffic congestion and safety. This has prompted a critical need for robust vehicle detection systems to facilitating the implementation of effective traffic management strategies and understand traffic patterns. This research addresses the challenge of vehicle detection and identify vehicular categories in Sri Lankan contexts, where reliance on private transportation is leading due to the absence of an advanced public transport infrastructure. Eventhough the existence of methodologies like the Viola-Jones object detector, extracting moving vehicular feature array for vehicle detection remains a formidable task in traffic analysis. To address this problem, we propose a novel approach leveraging image processing algorithms, particularly focusing on image segmentation. Novel algorithm demonstrates a remarkable ability to extract irregularly shaped objects from traffic video streams, achieving a highest success rate in segmentation accuracy. By using the video data collected at Kottawa highway bridge and Kotte-Thalawathugoda Road using digital cameras, our methodology captures real-time traffic data and categorizes vehicles into distinct classes such as motorcycles, three-wheelers, cars, vans, lorries, and buses. Furthermore, we emphasize the importance of accurate traffic information in optimizing mobility at urban intersections, which is crucial for all road users. The proposed system not only offers insights into traffic dynamics but also contributes to the development of smart and sustainable mobility systems. However, challenges such as environmental noise, sudden illumination changes, and shadow effects necessitate further research to enhance the robustness and reliability of the proposed methodology. In conclusion, this thesis presents a comprehensive approach to address the complexities of vehicular traffic analysis in Sri Lanka, offering valuable insights for researchers, stakeholders, and policymakers. The proposed method gives a success rate of more than 95% in irregular shaped image segmentation. Results of vehicle extraction from the video sequence gives average accuracy of 94.1%. In this research six vehicle types have been considered for the results.

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CHAPTER 1 INTRODUCTION

1.1 Motivation

The increasing number of vehicles on roads in countries like Sri Lanka has led to severe traffic congestion and safety concerns. Robust vehicle detection systems can provide valuable insights into traffic patterns, helping authorities implement effective traffic management strategies and improve road safety.

1.2 Statement of the problem

In a country like Sri Lanka, where there is no advanced public transport system, most people are inclined to use their private vehicle for transportation. Vehicle category wise count collection approach in an intelligent transportation system and is useful for monitoring of traffic flow. Isolation of moving objects with perfect object boundaries in order to identify vehicular features has been a challenging problem in vehicular traffic analysis. If the segmented vehicular images contain extra garbage images, achieving pure vehicular features can not be accomplished. However isolation of real life objects with perfect object boundaries have been a challenging problem using previously found image segmentation methods. Vehicle count can be identified accurately even in high traffic conditions compared to existing methods. Collecting information such as vehicle volume is useful to realize traffic control. In this work this problem will be systematically addressed.

A video image processor is a combination of hardware and software which extracts desired information from data provided by an imaging sensor. This imaging sensor can be a IP camera, conventional camera or an infrared camera. A video image processor can detect speed, occupancy, count, and presence. Because the video image processor produces an image of several lanes, there is potential for a video image processor to provide a wealth of traffic information such as vehicle classification and vehicle movements. A video image processor generally operates in the following manner: The traffic parameters are collected by frame-by-frame analysis of video images captured by roadside cameras. The operator selects several vehicle detection zones within the field of view of the IP camera. Image processing algorithms are then applied in real time to these zones in order to extract the desired information, such as vehicle height to width ratio, speed and occupancy. Advantages of video image processor are that they are mounted above the road instead of in the road, the placement of vehicle detection zones can be made by the operator, the shape of the detection zones can be programmed for specific applications, and the system can be used to track vehicles.

The system is able to detect vehicles as they move through the camera's field of view, to track them and to classify each individual object into several categories: motorcycle, Three-wheeler, car, van, lorry and bus.

1.3 Research Aims and Objectives

The primary focus of the research is usually expressed in terms of aims and objectives.

1.3.1 Aim

The aim of this research is to develop robust algorithms for vehicle detection and recognition using traffic video streams, accurately counting vehicles in traffic video streams, and enhancing the detection and recognition of vehicle categories relevant to the Sri Lankan context, such as three-wheelers and motorcycles. Through the development of these algorithms, the project seeks to contribute to the advancement of intelligent transportation systems and improve traffic monitoring and management capabilities in urban environments, ultimately enhancing road safety and transportation efficiency.

1.3.2 Objectives

1. To develop novel algorithms to detect and recognize moving vehicles using traffic video stream

2. To output vehicle count in a traffic video stream

3. To supporting detect and recognize the vehicle categories applicable to Sri Lankan context such as three wheelers and motorcycles compared to the Viola Jones object detector

1.4 Scope

This study is based on application of image processing algorithms for vehicle count detection. Road traffic congestion has become a major issue in populated cities. So, identification of vehicle count in a specific time period in a specific location is important to manage road traffic. Motion tracking, Image feature extraction, shape matching, image edge detection are some major applications which use in this project. The expected vehicular image data collected by video recording them at a traffic intersection to have a specific feature set for different vehicle categories. Deep learning, future traffic prediction are excluded in this study.

There are boundaries and limitations exist in this study. Many practical problems effects for the results, due to changes in environmental conditions like rain, wind and climate changes. Light at night exposure and artificial light at night of the images will decrease the accuracy of the results. To avoid capturing background non vehicular images, rectangular area of the road area selects for image processing task.

Image processing is a method which converts an image into digital form and performs many operations on it to get an enhanced image as well as to extract useful information. Digital image processing is used widely in the modern age in various real-life applications. There are a number of digital image processing applications that include different areas such as robotics, medical science, environment industry, military, medical diagnosis, face finding, industrial applications, remote sensing and so on. The purpose of image processing is divided into five groups. They are: Visualization, Image sharpening and restoration, Image retrieval, Measurement of pattern and Image recognition.

Image segmentation is the process of partitioning the image into constituent parts or objects. The application of image processing like feature extraction, object detection, image scanning have relied on image segmentation as a pre-processing step. Therefore, to find an appropriate segmentation algorithm based on the type of input image and the application of the segmentation algorithm is important.

The program developed using python programming language. Python is a growing scientific programming language and many state of art image processing tools are freely available. Especially the integration of Opencv with Python contributes tremendous power for programming. Motion tracking, Image feature extraction, shape matching, image edge detection are some major applications in Opencv which have been used in this project. The program is designed to interoperate with the python numerical and scientific libraries Numpy and Scipy.

CHAPTER 2 LITERATURE REVIEW

2.1 A Literature Review

This chapter consists of past research studies which have addressed the image processing domain about feature extraction.

Mighami et al. (2018) have presented a study on vehicle detection based on the boosting technique by Viola Jones. Proposed system was tested in some real scenes of surveillance videos with different light conditions. This paper is introducing a method in order to vehicle detection by the feature of Haar-like filters. Vehicle detection can be classified into one of the following three categories such as Knowledge-based, Stereo vision-based and Motion-based. All used images are from real scene traffic in different light positions, the video formats are AVI. In order to prove the effectiveness of the algorithm, Matlab and OpenCV to simulate the experiment. Proposed method is a real-time method for detecting different vehicles by Viola Jones algorithm which is based on AdaBoost classification technique. AdaBoost combines some weak classifiers to make a strong classifier.

Singh and Kumar (2023) aim to enhance real-time vehicle detection by improving the YOLO (You Only Look Once) models, focusing on urban traffic environments. Their methodology incorporates techniques such as multi-scale feature fusion and anchor box refinement to augment the detection capabilities of YOLO models. Key findings reveal that these enhancements significantly improve detection accuracy and precision, particularly in complex scenarios with dense traffic and varied vehicle types. The improved YOLO models demonstrate high recall and precision rates, making them suitable for real-time applications in intelligent transportation systems (ITS). The study concludes that continued refinement of YOLO-based models, integrating advanced techniques to address real-world challenges, holds promise for advancing autonomous driving and traffic monitoring systems.

Khan et al. (2023) aim to provide a comprehensive overview of the state-of-the-art deep learning techniques for vehicle detection and classification from images and videos. The methodology involves an extensive literature review of various deep learning architectures, such as CNNs and R-CNNs, analyzing their training processes, performance metrics, and the role of large annotated datasets like COCO and PASCAL VOC. The key findings highlight that deep learning models have significantly improved accuracy and robustness in vehicle detection, yet challenges such as occlusions, varying lighting conditions, and real-time processing remain. The survey also discusses the benefits of transfer learning and data augmentation in enhancing model performance. The authors conclude that while deep learning has advanced vehicle detection, further research is needed to develop more efficient models and address the remaining challenges to achieve practical deployment in intelligent transportation systems (ITS).

Achanta et al. (2010) have presented SLIC superpixels image segmentation algorithm based on superpixels which can be used at a pre-processing stage in vision applications.The proposed methodology uses that cluster pixels with a combination of five dimensional color and image plane space to efficiently generate compact and nearly uniform, compact superpixels and adhere well to region boundaries. They have introduced a new distance measure that considers superpixel size. Using distance measures they enforce color similarity as well as pixel proximity, with expected cluster size and their spatial extent are approximately equal. SLIC uses k-means clustering to generate superpixels. SLIC works for both color and grayscale images. This paper proves that efficiency of superpixels in object category recognition and medical image segmentation.

Zivkovic et al. (2004) have presented color histogram based non rigid object tracking. The algorithm is able to robustly track objects in different situations and also can adapt to change in shape and scale. In the methodology, extension of mean-shift algorithm has used in making color histogram of the target object that can be used to track it in subsequent frames. The EMlike algorithm has solved the problem of adapting the ellipse in an efficient way. Human faces tracking was the primary goal of this algorithm but as experimentation done, it can be used for other objects also. Further it explains algorithm works in real time and computational cost is slightly higher than the meanshift algorithm.

Rhouma et al.(2014) has presented improving the presence of Hu moments for shape recognition. The performance of invariant moments in shape recognition has used to improve recognition rates in a variety of data sets. Set of 7 numbers calculated using central moments that are invariant to image transformations. The first 6 moments have been proved to be invariant to translation, scale, and rotation, and reflection. While the 7th moment's sign changes for image reflection. In the proposed methodology each integral or sum computed in the regular Hu moments is simply divided into 3 or 4 subdomains, and computing their invariant moments. This division does not result in any extra computations. The result is regular Hu moments tend to give way more weight to pixels that are farthest from the center of gravity used to improve shape recognition.

Ma et al. (2012) conducted a study on Canny edge detection and its improvements. Canny operator was designed to be an optimal edge detector. It takes input gray scale image and produces output image showing the positions of tracked intensity discontinuities. Canny edge 9 detector was developed to solve the weaknesses in detectors with excessive smoothing image and adaptability by parameter sigma and method to obtain high threshold. Experiments show that canny edge detector improves the balance eliminating noise getting more edge information. Edge detection is used for image segmentation in areas such as image processing, computer vision and machine vision. The main purpose of this study is to image segmentation and extract shape information thus most of the shape information of an image is enclosed in edges.

Zhao, Liu, and Wu (2023) aim to develop a fast and accurate real-time vehicle detection method using deep learning tailored for unconstrained environments. Their methodology involves enhancing the YOLO-v5 model through transfer learning and optimizing it for specific datasets, focusing on achieving a balance between high detection accuracy and computational efficiency. Key findings indicate that the enhanced YOLO-v5 model exhibits significant improvements in accuracy and processing speed, making it suitable for real-time applications even in complex and varied traffic scenarios. The study demonstrates that the model effectively handles diverse environmental conditions, such as different lighting and occlusions, which are common in real-world applications. The authors conclude that the refined YOLO-v5 model represents a robust solution for real-time vehicle detection in intelligent transportation systems, emphasizing the importance of continued refinement and adaptation of deep learning models to meet practical deployment needs.

Following table 1. consist of summary of the literature review including study category, researches, contribution and conclusion.

Study	Researches	Contribution	Conclusion
Viola jones algorithm and Haar-like features	Moghimi et al. (2018)	vehicle detection based on the boosting technique by Viola Jones This paper is introducing a method in order to vehicle detection by the feature of Haar-like filters	A real-time method for detecting different vehicles by Viola Jones algorithm which is based on AdaBoost classification technique

	Chen et al. (2007)	Generalized Haar-like features are constructed for fast face detection.	Experimental results show that the boosted face detector using the generalized Haar-like features outperforms significantly the original using the basic Haar-like features.
Deep Learning	Khan, S. et al. (2023)	Provided a comprehensive survey of deep learning techniques for vehicle detection and classification, emphasizing the performance improvements of CNNs and R-CNNs, the importance of large annotated datasets, and challenges such as occlusion and varying lighting conditions.	A comprehensive survey of some growth, successes and demerits of vehicle detection and classification and performance is conducted with a detailed investigation of the challenges faced.
	Zhao, H. et al. (2023)	Enhanced the YOLO-v5 model using transfer learning to improve detection accuracy and speed for real-time applications in diverse traffic environments. Demonstrated the model's robustness to varied lighting and occlusions.	The refined YOLO-v5 model offers a robust solution for real-time vehicle detection in ITS, balancing accuracy and computational efficiency, and is effective in handling diverse environmental conditions.
Real-Time Vehicle Detection Using Improved YOLO Models	Zhao et al. (2023)	Enhanced the YOLO-v5 model using transfer learning to improve detection accuracy and speed for real-time applications in diverse traffic environments. Demonstrated the model's robustness to varied lighting and occlusions.	The refined YOLO-v5 model offers a robust solution for real-time vehicle detection in ITS, balancing accuracy and computational efficiency, and is effective in handling diverse environmental conditions.
Image segmentation	Ma et al. (2012)	Canny operator was designed to be an optimal edge detector. It takes input gray scale image and produces output image showing the positions	The main purpose of this study is to image segmentation and extract shape information thus most of the shape information of an

		of tracked intensity discontinuities.	image is enclosed in edges.
	Achanta et al. (2010)	SLIC superpixels image segmentation algorithm based on superpixels which can be used at a pre-processing stage in vision applications	proposed method proves that efficiency of superpixels in object category recognition and medical image segmentation.

Table 1. Summary of the literature review

CHAPTER 3 METHODOLOGY

The concepts and the methods used during the research are discussed in this chapter.

3.1 A novel image segmentation algorithm

The novel algorithm for image segmentation is an algorithm capable of extracting comparatively high percentage of pixels of a moving object. The required images for the proposed work are acquired with the help of a digital camera. The novel image segmentation algorithm was first developed to extract irregular shaped objects in an image.

Each image is processed using the following image processing function.

1. Convert the color image into a grayscale image using opencv function :cvtColor

2. Convert gray-scale image into a blur image using Gaussian blur function in opencv to remove the noise in the image

3. The threshold is set in the blur image to define the boundary of objects using the gray-scale color of the object. Then the resultant image contains only black and white pixels.

4. Scan the binary image left to right and top to bottom, until you find a WHITE pixel in the image.

5. Once WHITE pixel P found, If the pixel P is not marked in the Scratch_Pad_Image_Array, mark the corresponding grey-scale pixel value to the Scratch_Pad_Image_Array.

If corresponding gray-scale pixel value is already marked in the array continue the step 4.

6. Four recursive functions initiate to call from the Eastern, Southern, Western and Northern pixels to the P.

7. Repeat step 5 in each recursive function.

8. Calculate the sum of pixels in each irregular shaped object.

9. This recursive collection of pixels bounded by an irregular shaped boundary continues until neighboring pixels are significantly different in color from the pixel of interest.

10. Calculate the height, width, mid point of the object

11. If pixel summation > minimum vehicle pixel count, Increase the objects count by 1

12. Repeat steps 5 and 6

Each video frame is processed using the following image processing functions. The novel image segmentation algorithm was modified to extract moving objects in an image.

1. Convert the color image into a grayscale image using opencv function :cvtColor
2. Convert gray-scale image into a blur image using Gaussian blur function in opencv to remove the noise in the image
3. Use background subtraction to isolate moving objects in the image.
4. Then each image is smoothing, by taking a 5X5 smoothing kernel over the entire image matrix.
5. Apply a 2D low pass filter to obtain an irregular shaped white blob corresponding to each moving object.
6. Scan the binary image left to right and top to bottom, until you find a WHITE pixel in the image.
7. Once WHITE pixel P found, If the pixel P is not marked in the Scratch_Pad_Image_Array, mark the corresponding grey-scale pixel value to the Scratch_Pad_Image_Array.
8. If corresponding gray-scale pixel value is already marked in the array continue the step 6.
9. If the white pixel P is within the selected region, four recursive functions will be calling from the Eastern, Southern, Western and Northern pixels to the P.

10. Repeat step 6 in each recursive function.
11. Calculate the sum of pixels in each irregular shaped object.
12. This recursive collection of pixels bounded by an irregular shaped boundary is continued until neighboring pixels are significantly different in color from the pixel of interest.
13. Calculate the height, width, mid point of the object
14. If pixel summation > 100, Increase the objects count by 1
15. Repeat steps 6, 7 and 8
16. Save the irregular shaped object to a folder. Image dimension equals to height and width of the object.

3.2 Calculating pixel count, Height, width and the center coordinates of the moving objects

For all objects in the image pixel count, height, width and the center coordinates are calculated. Numpy arrays are used for the calculations . Numpy is used to work with arrays. Numpy array is a grid of values of the same type and indexed by a tuple of non-negative integers. Background subtraction technique in opencv is used to isolate moving objects in a video. White pixels of the binary image are used to find the presence of a moving object. Scan the binary image left to right and top to bottom, until WHITE pixel is found in the image. Apply four path recursive algorithm, scanning the object until all white pixels are marked in the numpy array and at the same time pixels count is calculated. Pararally sum of pixels count along with the X axis and Y axis, maximum X coordinate, maximum Y coordinate , minimum X coordinate and minimum Y coordinate are recorded in a numpy array (Scratch pad image array). Above recorded data are used to find the center, height and the width of the object.

$$\text{Center X coordinate of the moving object} = \frac{\text{Sum of the pixels count along with the X axis}}{\text{Pixels count of the object}}$$

$$\text{Center Y coordinate of the moving object} = \frac{\text{Sum of the pixels count along with the Y axis}}{\text{Pixels count of the object}}$$

3.2 Extracting objects with color

In the previous methods gray-scale objects are extracted. Using the same program RGB values of the objects can be extracted to an scratch_pad_image array. But mapping colors between different color spaces may involve a huge computational load since mathematical operations used are not linear. Color histogram equalization used to enhance the contrast of RGB images. For color images histogram equalization is applied in the color channels. Figure b represents the histogram equalized image. Image enhancement methods are used in many applications such as medical images, images from satellites and images captured in remote sensing.

3.3 Identify moving vehicles in a traffic video footage

In order to identify moving vehicles in a traffic video, background subtraction technique is used for foreground detection. Background subtraction is a widely used approach for process traffic videos with a static camera. The output of this function is a binary image containing pixels belonging to moving objects. The following figure 1 and figure 2 represents the images of a traffic video and corresponding foreground mask of the image.

Figure 1, Figure 2 Images of a traffic video and corresponding foreground mask of the image

The output image obtained after background subtraction used to find the rectangular region of the moving vehicle. To avoid segment same vehicle in multiple times a rectangular selected region in the video frame is defined.

The output image obtained after performing background subtraction serves as the basis for applying a novel image segmentation algorithm. This innovative algorithm is designed to extract the maximum percentage of pixels corresponding to a moving object, ensuring high accuracy in isolating vehicular images. During this process, several key parameters of the detected vehicles are recorded, including the height, width, pixel count of the vehicular image, and the midpoint of the vehicle. Additionally, the algorithm captures the Hu-Moments of the vehicular image, which are essential for understanding the shape and orientation of the vehicle.

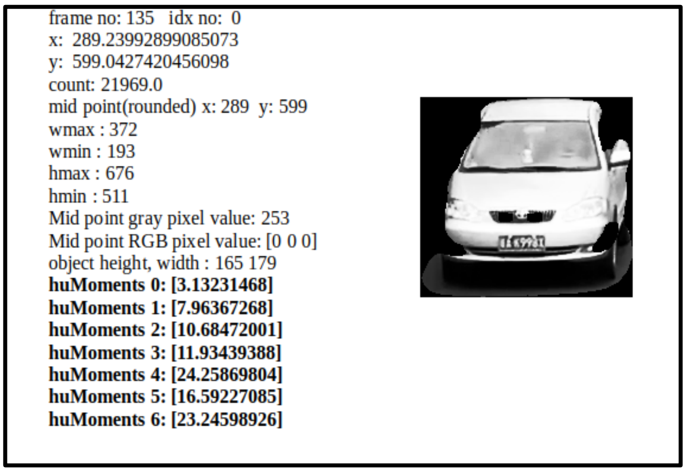

Figure 3. Data identified in a segmented vehicular image

Furthermore, relevant video frame data is meticulously recorded. This includes the number of moving objects identified within each frame and the specific video frame number, which is crucial for tracking the temporal sequence of detections. Figure 3 provides a comprehensive visual representation of the various data points identified in the vehicular image, illustrating how the segmentation algorithm processes and extracts detailed information from the video frames. This thorough recording of both vehicular and frame-specific data enhances the overall understanding and analysis of vehicle movement within the captured footage, contributing significantly to the robustness and effectiveness of the vehicle detection system.

3.4 Video data collection

A digital camera was employed to capture traffic videos at two significant locations: near the Kottawa highway bridge and along the Madiwela–Thalawathugoda road. These locations were chosen due to their high traffic flow and diverse vehicle types, making them ideal for studying vehicle movement patterns and detection accuracy. The regions of interest for these recordings are clearly depicted in Figure 4 and Figure 5, which highlight the specific areas monitored during the study. To ensure comprehensive data collection, videos were recorded continuously over an extended period, allowing for the capture of various traffic conditions and vehicle behaviors. This prolonged recording period was essential to assess the feasibility and robustness of the study, providing a substantial dataset for analysis. After reviewing the recorded footage, it was determined that the collected data was sufficient to proceed with the study, confirming the effectiveness of the chosen locations and the recording methodology. This initial phase of video recording and assessment was crucial in laying the groundwork for further research and analysis, ensuring that the study could continue with a solid foundation of reliable and relevant traffic data.

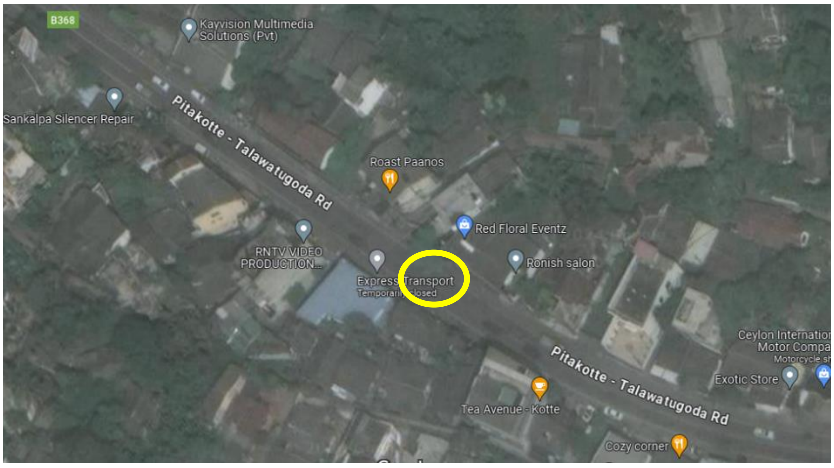

Figure 4. Traffic video data collected location at Kotte Thalawathugoda road

Figure 5. Traffic video data collected location at Kottawa highway bridge

The vehicle count sensor was calibrated to collect accurate vehicle counts using the recorded traffic videos from the designated locations. Due to variations in camera angles and positions, the feature array for the same vehicle can differ significantly. Therefore, it is crucial to identify and catalog the vehicle features corresponding to different vehicle categories across various videos. To facilitate this, vehicle features are extracted and documented in a text file, enabling the calculation of feature arrays for different vehicle categories. This extraction process is accomplished by executing the vehicle count sensor program, which involves selecting a specific rectangular region within the video frame. The selected feature arrays for different vehicle categories are then organized and entered into an Excel spreadsheet. Table 2 provides a detailed representation of the extracted vehicular features. The columns in the Excel sheet correspond to various vehicle features, while the rows are designated for samples from different vehicle categories. The recorded features include the vehicle's maximum and minimum height, maximum and minimum width, maximum and minimum pixel count, and Hu moments derived from both gray-scale and edge-detected images.

By running the vehicle count sensor program, vehicle counts for different categories are systematically collected and recorded. This detailed data collection and organization ensure that the feature arrays are comprehensive and accurate, facilitating a robust analysis of vehicle counts across different categories and conditions. The structured format in the Excel sheet aids in the efficient comparison and evaluation of vehicular features, enhancing the overall effectiveness of the study.

Sample Humoments of vehicle gray color image	Min Pix Count	Max Pix Count	Min Width	Max Width	HM0	HM1	HM2	HM3	HM4	HM5	HM6
Motor Bike-Sample1	7000	11200	60	100	2.4414	5.2062	9.0839	8.7939	17.743	11.43467	18.4023
Motor Bike-Sample2	7000	11200	60	100	2.5061	5.4444	10.6448	10.9427	22.9268	14.0101	-21.7374
Threewheeler sample1	11000	27000	100	170	2.4642	5.642	8.7545	8.084	16.5034	10.962	18.0335
Threewheeler sample2	11000	27000	100	170	2.5022	5.7131	8.0994	8.0323	16.2629	11.003	16.2353
Car sample1	20000	46000	160	250	2.7141	6.8244	9.0286	8.7849	17.7037	12.1972	-18.3253
Car sample2	20000	46000	160	250	2.8776	7.6264	11.1352	9.586	-19.9474	-13.5978	21.2098
Car sample3	20000	46000	160	250	2.918	7.6154	10.2871	10.1736	-21.2133	-14.3494	20.4093
van -sample 1	23000	60000	200	350	2.8567	7.9843	10.3484	9.3156	19.591	-13.7427	-19.1779
van -sample 2	23000	60000	200	350	2.8567	7.9843	10.3484	9.3156	19.591	-13.7427	-19.1779
Bus -sample 1	40000	98000	200	380	2.4613	5.7958	8.9864	8.9264	17.9054	11.8361	18.3857
Bus -sample 2	40000	98000	200	380	2.3765	5.4439	7.7184	7.5994	15.749	11.0871	-15.2823
Lorry - sample 1	45000	75000	200	330	2.4638	5.4921	8.0126	8.6541	17.1681	11.4955	-17.1116
Lorry - sample 2	45000	75000	200	330	2.7492	6.731	9.7049	9.319	18.9094	-12.9098	19.0904
Lorry - sample 3	45000	75000	200	330	2.7492	6.731	9.7049	9.319	18.9094	-12.9098	19.0904

Table 2. Extracted vehicular features

To ensure that the same vehicle is not segmented multiple times within a video frame, a rectangular region of interest (ROI) is defined. This approach helps to isolate and track individual vehicles accurately. To accommodate vehicles moving in various directions, multiple ROIs can be established, allowing for the extraction of moving objects from different trajectories. Figure 6 illustrates a video frame with three distinct ROIs, each designated to detect vehicles traveling in different directions at an intersection. These regions are tailored to capture vehicles of varying scales. As the depth or distance of the vehicles within these regions changes, there are corresponding adjustments in pixel count, as well as variations in the height and width of the detected vehicles. Consequently, the feature vectors representing specific vehicle models will also change, reflecting these depth-related variations. This method ensures a more robust and accurate detection of vehicles, accommodating the dynamic nature of real-world traffic scenarios.

Figure 6. Selected rectangular region in vedio frame to avoid multiple detections of a vehicle

CHAPTER 4 EVALUATION AND RESULTS

This chapter presents results obtained from the novel image segmentation algorithm applied for different traffic videos. The results were discussed based on pixels extraction and vehicle count detection.

The algorithm was used to extract different odd shaped objects. Moreover, this method has applied to real image frames of videos of vehicles. These videos have been captured from different angles and distinct traffic conditions. The pixels of vehicles have been extracted including the moving casted shadow.

Data identified in each object of a video frame are the number of objects in a frame, pixel count, height, width and midpoint of the object. The required images for the proposed work are acquired with the help of a digital camera. The frame speed of the camera was limited to 25 frames per second. The real time video sequences are acquired with the frame size of 1280 x 720 pixels resolution. In order to check the efficiency of the proposed algorithm, the experiment is performed repeatedly with different traffic videos. In this research six vehicle types have been considered for the results.

Table 1 provides a detailed representation of the accuracy percentages for the number of vehicles extracted across various vehicle types. Upon analysis, it was observed that the algorithm encountered performance issues primarily due to excessive sunlight reflection and shadow effects, which led to erroneous detections and missed vehicles. These conditions caused the algorithm to either fail in segmenting some vehicles correctly or combine them with other vehicles during extraction. The "missing number" field in Table 1 indicates those vehicles that were not segmented successfully but were instead extracted along with other vehicles. In examining the data further, the average accuracy rate depicted in Table 3 is approximately 94.1%, highlighting the overall effectiveness of the vehicle extraction process despite the identified challenges. Table 4, on the other hand, illustrates the accuracy percentages related to the extraction of image pixels for different vehicle types. The results showcased in Table 2 make it evident that the proposed algorithm is particularly well-suited for image segmentation tasks. The average accuracy for the pixel extraction process, as reflected in Table 2, stands at around 93.2%.

	Motor Bike	Car	Van	Threewheel	Bus	Truck
Actual number of vehicles	91	97	7	44	2	16
Extracted number	83	89	7	40	2	16
Missing number	8	8	0	4	0	0
Average accuracy %	91.2%	91.7%	97%	90.9%	97%	97%

Accuracy - 94.1%

Table 3. Results of vehicle extraction from the video sequence

Pixels extraction % Vehicle types	100% - 95%	95% - 90%	90% - 85%	85% - 80%	Average accuracy %
Number of Motor Bikes	55	27	1	0	94.4%
Number of Cars	45	34	9	1	93.9%
Number of Vans	4	3	0	0	94.7%

Number of Three Wheelers	14	17	9	0	92.8%
Number of Buses	1	1	0	0	92.6%
Number of Trucks	4	9	3	0	91%

Accuracy - 93.2%

Table 4. Results of pixels extraction percentage of vehicle types

Figure 7. Vehicular images extracted from the segmentation program

Detection of cyclists with an accuracy of 91.2% was obtained for video footage duration of 6 minutes video sequence which recorded on a Tuesday between 8.00 AM to 8.10 AM. Feature extraction is accomplished by applying Hu-momments for the extracted images.Cyclist category detected using Hu moments, pixel count and height to width ratio.

Actual number of cyclists	91
Extracted number	83
Average accuracy %	91.2%

Figure 8. Accuracy of cyclists detection

These accuracy percentages, though approximate, underscore the robustness and reliability of the algorithm in most conditions, while also pointing out specific areas that require further refinement, such as handling variations in sunlight and shadow effects. The comprehensive data presented in these tables serves as a valuable benchmark for evaluating and improving the algorithm's performance in real-world scenarios.

CHAPTER 5 CONCLUSION AND FUTURE WORK

An approach for vehicle count sensor program using new algorithm is presented in this thesis. Throughout this thesis the work that has been carried out on image processing domain about image segmentation for is discussed and the method has been successfully applied to identify vehicle categories in traffic video sequences. The proposed method gives a success rate of more than 95% in irregular shaped image segmentation. This work will encourage further initiatives to be taken for implementation of work in such a domain. The vehicle classification method is sensitive to various environmental variations, such as illumination, noise, vehicle shadow, angle of cameras and weather.

For the future work this study would aim at increasing mobility at intersections in Sri Lanka which will be beneficial for all road users; drivers, passengers and pedestrians equally. It is not possible always avoid traffic but with accurate traffic predictions make smarter choices that can save money, time and increase overall road mobility. Studies based on the manual traffic counts are expensive and time consuming. Therefore, this study will be highly significant to the advancement of knowledge among researchers, stakeholders, and general public in the context of Sri Lankan traffic conditions. Accurate traffic information also helps governments and organizations by supporting the development of smart and sustainable mobility systems. However, it is needed to improve robustness against environmental noise, sudden illumination and shadow effect.

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