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# IMPROVED VEHICLES DETECTION & CLASSIFICATION ALGORITHM FOR TRAFFIC SURVEILLANCE SYSTEM

**Synh Viet-Uyen Ha* [1], Long Hoang Pham* [2], Ha Manh Tran[3], and Phong Ho Thanh[4]**

[1] School of Computer Science and Engineering, International University – Vietnam National University HCMC,
Block 6, Ward Linh Trung, Thu Duc District, Ho Chi Minh, Vietnam
*hvusynh@hcmiu.edu.vn*

[2] Department of Industrial and Systems Engineering, International University – Vietnam National University HCMC,
Block 6, Ward Linh Trung, Thu Duc District, Ho Chi Minh, Vietnam
*phlong@hcmiu.edu.vn*

[3] School of Computer Science and Engineering, International University – Vietnam National University HCMC,
Block 6, Ward Linh Trung, Thu Duc District, Ho Chi Minh, Vietnam
*tmha@hcmiu.edu.vn*

[4] Department of Industrial and Systems Engineering, International University – Vietnam National University HCMC,
Block 6, Ward Linh Trung, Thu Duc District, Ho Chi Minh, Vietnam
*htphong@hcmiu.edu.vn*

***Abstract*: Vehicles detection and classification are the most popular subjects in the computer vision researching field, and also are the most important parts in any traffic monitoring or surveillance system. Although there has been a considerable amount of ideas to accommodate this problem since the 90s, many problems are still unresolved due to the complexity of traffic systems and the variety of vehicles. This paper is a work-in-process that proposes a new approach to detect and classify vehicles based on the traffic system in Vietnam. The main goal of this method is to group vehicles into 2 main classes, which are 2-wheeled and 4-wheeled vehicles, based on low-level traffic parameters in urban areas.**

***Keywords*:** segmentation, object detection, contours detection, distance transform, vehicle classification**.**

## I. Introduction

In recent years, there has been an increasing interest in using traffic monitoring systems, especially in developing countries such as Vietnam. The basic function of these systems is to detect and classify vehicles. Most of the existing technologies monitor traffics by using transportation tag reader and antennas, or inductive loop detector to obtain traffic information. The vehicles must also be integrated with many signal-supporting devices such as GPS, IR laser, magnetic loop detector, etc..., which are only compatible with cars. However, these systems create an enormous amount of data, not to mention the huge investment that cannot be afforded by many developing countries. Additionally, in the developing countries, especially Vietnam, the large amount of small vehicles (e.g. bicycle, motorcycle) as well as the disorder movement of these vehicles makes these systems inoperative. Under these circumstances, a new trend has been emerged, based on the usage of traffic video processing. The computer vision-based traffic monitoring system is becoming popular due to its flexibility in installation, maintenance and upgrade. This method can utilize the existing surveillance system on some big routes to reduce costs while still reserve the function of count and classifying vehicles.

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Recently, there is noticeable work in the area of vehicles detection and classification such as [1, 2, 3]. The most recent study on vehicle segmentation is [4], in which a model-based approach is employed using 3-D box models. There are also many other studies on the model-based method [5, 6, 19], which compare and match the detected vehicles with a set of sample images and models. Another approach for this problem is using features detection [7]. By using this approach, [8] presented a quite successful solution to classify vehicles into three main classes, Sedan, Semi, and an additional class, Truck + SUV + Van. However, these methods only work on specific traffic systems, which are unique for each country. About two years ago, [9] provided a traffic monitoring system, which is capable of analyzing the vehicle flow on urban streets in Vietnam. However, this system has two disadvantages; (a) it can only work with the camera which is installed in the middle-above of the street; (b) the result from this classifying method cannot clearly distinguish bike and car.

The objective of this research is to achieve an improvement method in detection and classification vehicles into two main class, 2-wheeled and 4-wheeled vehicles, using data of traffic video. The research inherits one core idea from [8], which is using the low-level features from the video to detect the best observation zone. This model-based system can give us a good result, providing a set of models for every vehicle. However, in developing countries where routes are not properly divided into lanes for different means of transport (e.g. cars, bikes, motorbikes, pedestrians, and others), these models seem to be impossible to create. Moreover, the model-based system requires the vehicles to be in the right traffic lane, which is uncommon in these countries. For example, in Vietnam, the urban roads are always in a state of chaostic because of a massive number of motobike (over 37 millions by the end of 2013). The situation is even more complex as many types of vehicle all travel on the same road. Therefore, the proposed system will follow the non-model based approach to solve the problem of complex traffic scene.

Compared to [9], our system can find a better observation zone, which can remove most unclear objects, and can work with any camera position toward which the traffic flow heads. Furthermore, the system can utilize the low quality videos from the surveillance system of Vietnam.

(a)

(b)

**Figure 1.** Example of complex traffic scene. (a) Ho Chi Minh city at mid-day. (b) Hanoi at morning rush hour.

Because the location of each surveillance camera is different, we apply one simple technique but it can give a significant effect to our method for finding the best observation zone. We name it "observation zone technique", and the idea can be described as follow. Firstly, we divide the input frame into particular zones. Further explanations of the zones are shown in section II-B. Secondly, we use some statistical method to get the best zone in which we can detect and classify the vehicles almost perfectly. After having the best observation zone, we apply the ratio estimation to classify vehicles. What makes our method stand out from the conventional ones is that it classifies vehicles using only the low-level features from the objects' ellipse. The evaluation function takes into account 2 criteria, which are dimensional ratio $R_{Dimension}$ and density ratio $R_{Density}$, dividing vehicles into 2 classes (2-wheeled and 4-wheeled vehicles). Further information of this function is show in section II-C.

The rest of the paper is organized as follow. Section II-A describes briefly the preparation step including the optical flow and contour detection. Then section II.B introduces the technique to detect the best observation zone automatically and section II.C provides the evaluation function for detecting vehicle. Experiments are discussed in section III, followed by the conclusion in section IV.

## II. Proposed Method

### A. Camera Angle

The surveillance camera angle is an important factor in a monitoring system because vehicles' features (example size and shape) are different in each angle of view. In the proposed method, the detection and classification algorithm are heavenly depended on these features. Furthermore, a good camera angle can reduced many cases of vehicles occlusion.

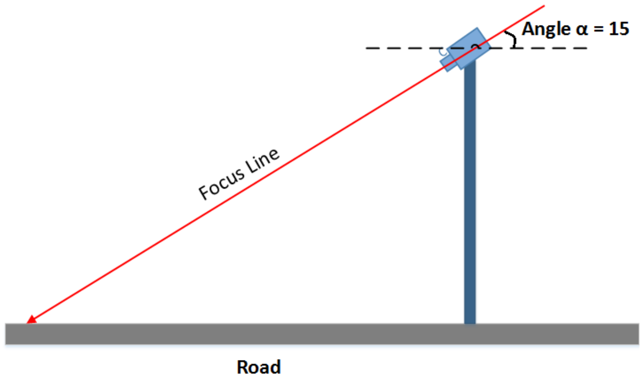



**Figure 2.** Camera Angle

The camera must be setup at an angle $\alpha$ that can capture all vehicles in the road. If the value of $\alpha$ is big, the field view will be too small and it definitely cannot capture a big vehicle (ex: a bus or a truck) as a whole. If the angle $\alpha$ is to small, the view may not cover the whole road. Figure 3 illustrates serveral views of different camera angle. Figure 3a shows a good view of the road and vehicles. In the other hand the angle in Figure 3b is too steep that a normal 4-seated car takes nearly half the frame.

(a)

(b)

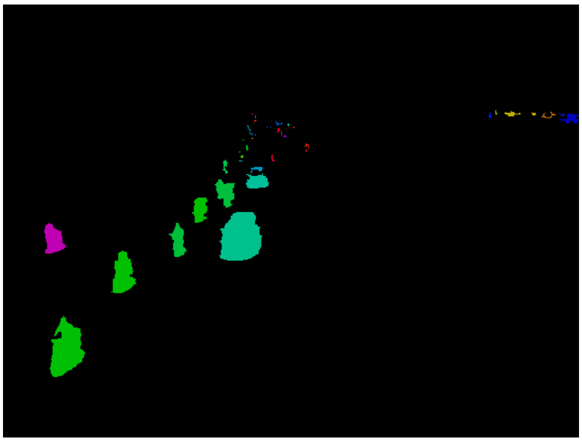
**Figure 3.** Different angle of view. (a) $\alpha = 15°$. (b) $\alpha = 30°$.

In the context of this paper, we choose to observe only the lane which vehicles coming to the camera. The camera angle is $15°$. It is the angle that gives the best view of the road and vehicles of all angles. It is also the angle that is mostly used in many currently installed surveillance camera in Ho Chi Minh city.

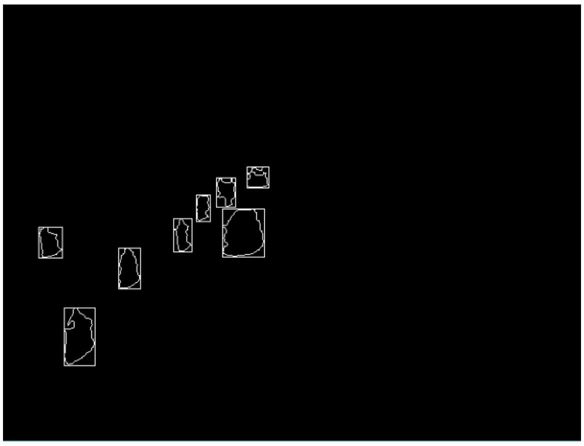
### *B. Vehicle Detection*

The main goal of the proposed system is to segment, count and classify moving vehicles in surveillance videos. Therefore, static objects are obsolete and need to be removed. For this study, the optical flow and background subtraction modules from [10, 11, 12, 13, 22] were used to produce the traffic flow of the street from the input video. In this paper, the result of optical flow is represented by the color flow, which is the moving vehicles or objects being extracted from the background (Figure 4 - b).

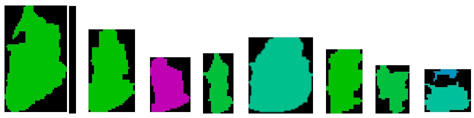
(a)



(b)



(c)



(d)

**Figure 4.** Traffic flow example. (a) Original images (sequence VVK1 – frame 350 and 355). (b) The traffic flow. (c) Contour extraction and bounding boxs. (d) Extracted vehicles

After obtaining the traffic flow, each object is extracted from the image by determining its contour. These contours are prepared by adapting the procedure used by [14]. More details about contour tracing algorithm discussion can be found in there.

The contour extraction method can also filter noises and obsolete objects to obtain a better foreground blobs. Then, we calculate the area of each contour and eliminate the object that has too small area by using the Green formula. This small step helps reducing the potential noises and eliminates obsolete objects.

In order to successfully perform the classification process, vehicles must be extracted into separated images. Since, the contour of each vehicle has already been extracted, it is easy to locate the vehicle in the image, and therefore, cropping the vehicle into a separated sub-image becomes a simply task. Each contour is wrapped with a bounding box, which will as a region of interest (ROI). Then using the ROI as a mask, the vehicle in the traffic flow image is cut and pasted into a new image.

The whole vehicle detection process is fully described in Figure 4.

### C. Observation Zone

Since the cameras are installed along the streets, the best observation zone is the one where the sizes of vehicles do not change significantly in several consecutive frames. Generally, the surveillance video can be divided into 3 distinct zones: the top, the middle and the bottom one. The vehicles in the top zone are further from the camera, which are smaller to the vehicles located in the bottom zone. One common characteristic of these 2 zones is that the sizes of objects change significantly after two or more consecutive frames. On the other hand, when the vehicles travel through the middle zone, their sizes slightly change. Since the vehicles classification method significantly depends on the low-level information of objects such as the shape size or the middle zone, the observation zone must be defined.

It is so difficult to define the observation zone because not all surveillance cameras are set up at the same heights and angles. In fact, most cameras are installed on the 6-meter traffic lights, while the rests are positioned on the pedestrian walking bridges on the street. In order to address this issue, we propose a method to automatically and accurately define the best observation zone. Let $x$ be the location of a vehicle on a frame and $f(x)$ be its contour size. We will track the location and size of some vehicles when they travel through the camera range. Then we calculate the second derivative to obtain how fast the objects' size is changing. By using these values, we can determine the range of locations where the magnitudes of second derivative are between 0 and 1 ($0 \leq f''(x) \leq 1$).

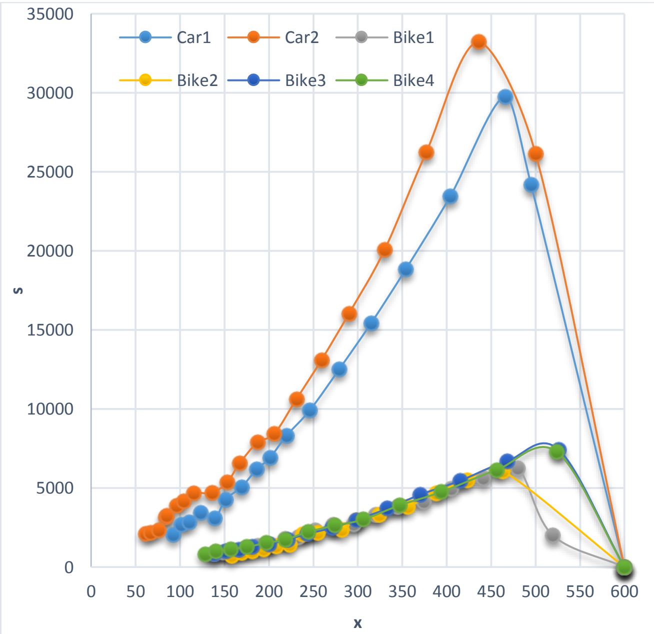



**Figure 5**. Vehicle's size vs. location

| $x$ | $f(x)$ | $f'(x)$ | $\lvert f''(x)\rvert$ | Description |
|---|---|---|---|---|
| 158 | 732 | 15.40 | 0.6964 | Top zone (Vehicle appear) |
| 169 | 901 | 7.74 | 0.0621 | |
| 181 | 994 | 8.48 | 0.4677 | |
| 194 | 1104 | 14.56 | 0.4945 | |
| 208 | 1308 | 7.64 | 2.4488 | |
| 223 | 1423 | 44.37 | 2.6807 | |
| 238 | 2088 | 4.16 | 0.1799 | **Observation zone** |
| 255 | 2159 | 7.22 | 1.1465 | |
| 282 | 2354 | 38.18 | 1.5194 | |
| **298** | **2965** | **13.87** | **0.0693** | **Best stable location** |
| 324 | 3325 | 15.67 | 0.3394 | **Observation zone** |
| 356 | 3827 | 26.53 | 0.0920 | |
| 388 | 4676 | 23.59 | 0.2619 | |
| 423 | 5501 | 14.42 | 1.4697 | Bottom Zone |
| 463 | 6078 | -44.37 | | |
| 480 | 0 | | | |

*Table 1*. The result of $f(x)$ and $f''(x)$ of Bike 1

Figure 5 represents the function $f(x)$ of both car and motorbike from the sample video VVK1. Next, Figure 6, 7 shows the magnitude of $f''(x)$. In TABLE 1, at $x = 298$, the value of $f''(x)$ is the smallest and almost equal to 0. Furthermore, the best observation for bike 1 is from 238 to 388 ($238 < x < 388$). Figure 6 and Figure 7 show more examples. After analyzing the dataset VVK1, it is concluded that the observation zone for the surveillance camera is within the range of $200\ and\ 300$ $(200 < x < 300)$, where $|f''(x)|$ is in the range of $[0,1]$.

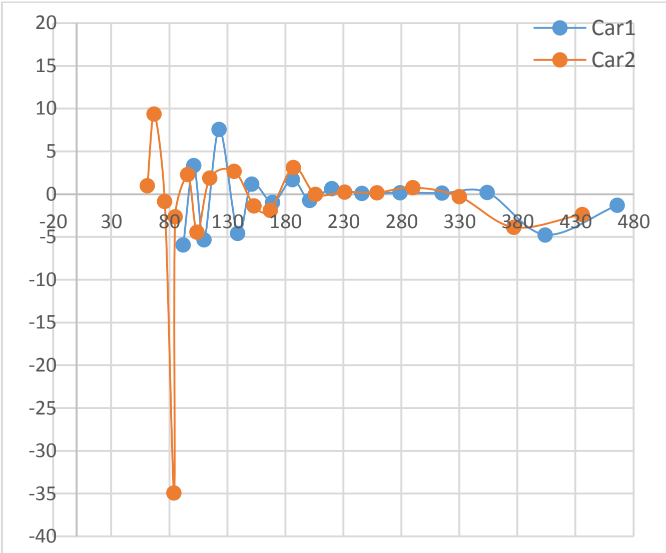



**Figure 6**. Second derivative for 4-wheeled

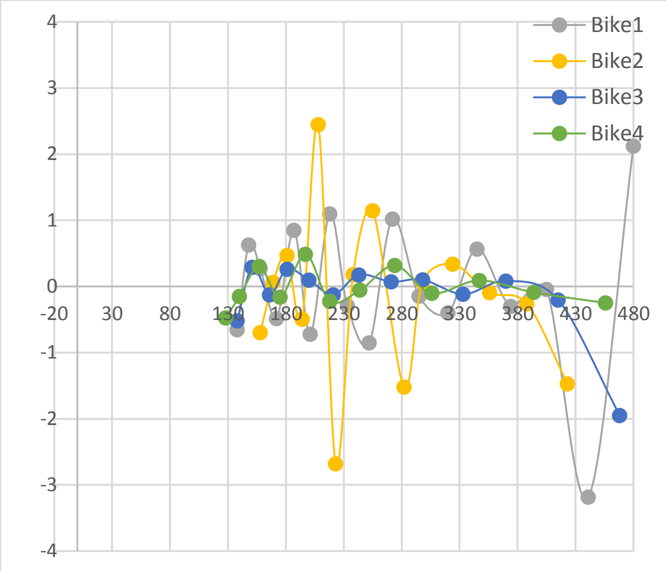
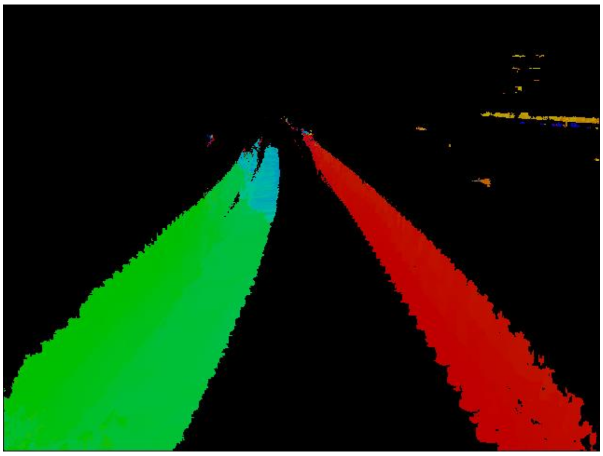


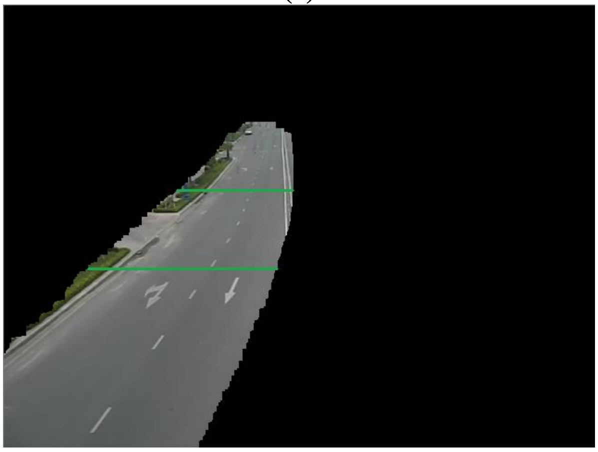

**Figure 7**. Second derivative for 2-wheeled

In this paper context, each camera will monitor only incoming vehicles. Therefore, all lanes that contain incoming vehicles must be extracted. The optical flow method in [22] can also be used to create a lane image as show in Figure 8-a, which separates lanes on the road based on vehicles' direction. Using the color ruler in [22], we can easily extracted the incoming lane, which is the green lane in this case. Then we apply the top and bottom boundaries to the lane image to obtain 4 corners of the observation zone (Figure 8-c). Finally the draft observation zone is drawn using these 4 corers in Figure 8-d. In some cases when some parts of the interested lane are missing because there is no vehicle travels through those parts in the learning process. Therefore, in those cases, we should calibrate the draft observation zone so that it can cover the lane completely. Figure 9 shows the final observation zone of the dataset VVK1



(a)

(b)



(c)

(d)

**Figure 8**. Extract observation zone from lane image. (a) Lane image. (b) Filter out unwanted lane. (c) Apply top and bottom boundaries. (d) Draft observation zone

After obtaining the observation zone, a middle line, which is the most stable location to detect and classify vehicles, is drawn and will be used as a vehicle counting line. When a vehicle enter the first half part of the observation zone, it's size and shape are not stable and can be fluctuated greatly. In addition, many cases of vehicles occlusion may occured in this part. In the another hand, the lower part of the observation zone is a better part to count and classify the vehicles. The vehicles have better shapes and sizes. Some occlusion problems can be solved because distances between the occluded vehicles are clearer and can be recognized easier.

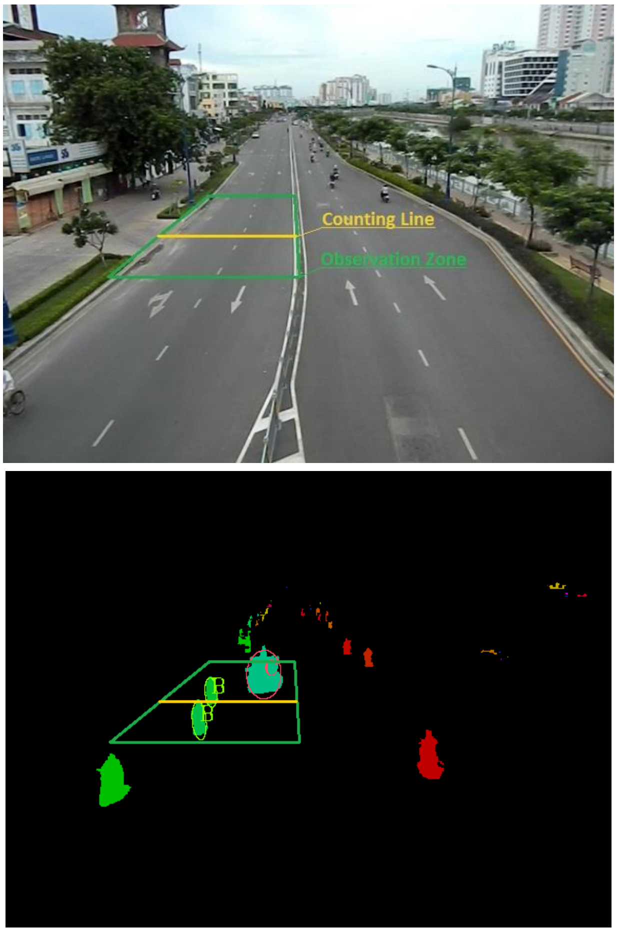



**Figure 9**. Observation zone of dataset VVK 1

Beside improving the accuracy of the vehicle dection and classification, the observation zone improves the system performance by only performing the classification process in a smaller sub-image. We can also use the observation zone as a tool to filter out unwanted objects, which are usually created by swinging trees along roadsides. Furthermore, since the main goal of the proposed system is to count the number of vehicles in a lane, the observation zone can also be used to serve this goal.

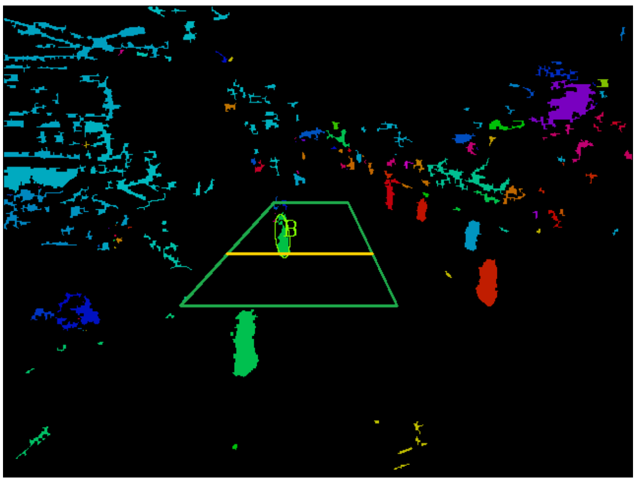
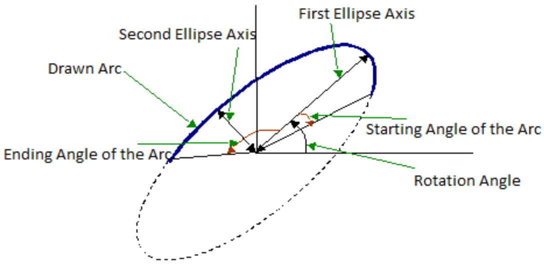


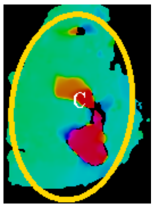
**Figure 10**. Filter out noises created by swinging tree on the roadside

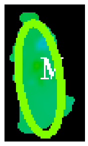
### *D. Vehicles Classification*

After some preparation steps to identify the objects and extract their contours information from the input frame, the system performs a classification process. In order to extract useful low-level features, each vehicle is bounded by ellipse. [15] provides an algorithm to calculate the ellipse that fits best (in a least-squares sense) to a set of 2D points. The extracted ellipse-bounding vehicles can be visualized in Figure 10-a:




(a)





(b) (c)

**Figure 11**. (a) The extracted ellipse's features. (b) Extracted car. (c) Extracted motorbike (sequence VVK1 – frame 355)

What makes our method stand out from the conventional ones is that it classifies vehicles using only the low-level features from the objects' ellipse. The proposed method uses ratio estimation to classify vehicles. The evaluation function take into account 2 criteria, which are dimensional ratio $R_{Dimension}$ and density ratio $R_{Density}$, dividing vehicles into 2 classes (2-wheeled and 4-wheeled vehicles).

Let $O$ be the object that need to be classify and $E$ is the bounding ellipse of $O$. The dimension ratio is the fraction of the ellipse's width and height:

$$R_{Dimension} = \frac{E_W}{E_H} \quad (1)$$

Where $E_W$ is the ellipse's width and $E_H$ is the ellipse's height

Since the ellipse has a property that its width is always smaller than height, the dimensional ratio is in the range of $0 < R_{Dimension} < 1$. The dimensional ratio is used as the primary criterion to classify 2-wheeled and 4-wheeled vehicles.

As suggested by Fig 11-c, the ellipse bouding a 2-wheeled vehicle, for instance a motorbike, has a small $R_{Dimension}$ value due to the great difference between dimensions. The reason is that the motorbike and the rider are grouped together as one moving object which makes the bounding ellipse thinner. In most cases, the ellipse's height is 2 times larger than its width. In constrast, the value $R_{Dimension}$ of a car is large since its height and width are not so different.

The dimensional criterion alone can work well in most cases, but there are remaining problems due to the variety of motorbike. When 2-wheeled vehicles are far from the camera, their shapes can be similar similar to 4-wheeled ones. In order to separate vehicles efficiently, the second criterion – desity ration, must be used. The density ratio is calculated by dividing the number of the object's pixels (non-zero pixels) by the total pixels of the ellipse. According to the image above, cars are uniform rectangles that are fitted into the ellipses, while motorbikes are not. So the density ratio of 4-wheeled vehicles will be larger than 2-wheeled ratio.

$$R_{Density} = \frac{\sum_{p \in O} p}{\sum_{p \in E} p} \quad (2)$$

Figure 12 shows the distribution of 2-wheeled and 4-wheeled vehicles ratios taking from a set of samples.

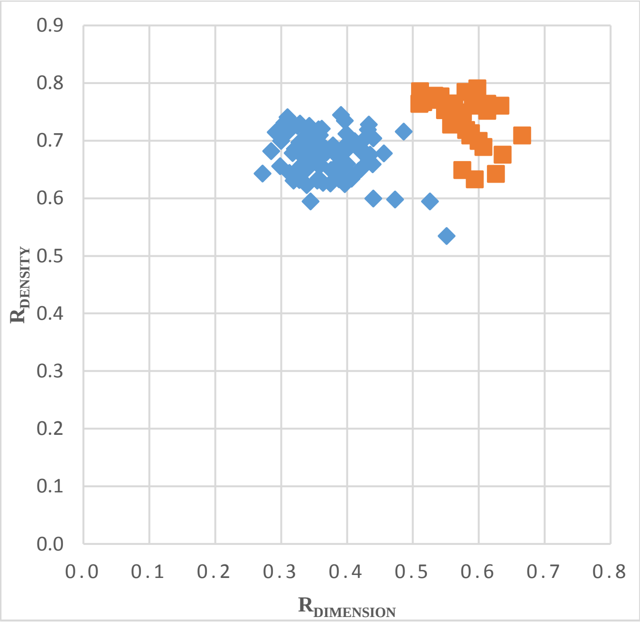



**Figure 12**. The blue dots represent 4-wheeled vehicle. The orange dots represent 2-wheeled vehicles.

Along the dimensional axis, most of the 2-wheeled vehicles distribute in the range of $0.2 < R_{Dimension} < 0.5$ and the 4-wheeled vehicles are in the range of $0.6 < R_{Dimension} < 1$. The range $0.5 < R_{Dimension} < 0.6$ is the ambiguous zone, where the dimensional ratio alone cannot clearly distinguish 2-wheeled and 4-wheeled vehicles. Therefore, the density ratio could be used to improve the classification process. In the ambiguous zone, the value of 4-wheeled $R_{Density}$ is larger than that of 2-wheeled $R_{Density}$. The means and variances are as are as Table 2:

| | $R_{Dimension}$ | | $R_{Density}$ | |
|---|---|---|---|---|
| | 2-wheeled | 4-wheeled | 2-wheeled | 4-wheeled |
| **Mean** | 0.3591 | 0.6640 | 0.6126 | 0.7858 |
| **Variance** | 0.00252 | 0.00161 | 0.00295 | 0.00406 |
| **Standard Deviation** | 0.0502 | 0.0401 | 0.0544 | 0.0637 |

*Table 2*. Table of mean and standard deviation of VVK1

## III. Experiment Results and Discussion

### *A. Testing Proposed Method's Accuracy*

The experiment input data is selected specially for testing the proposed algorithm. Each testing video sequence includes a mix of 4-wheeled (cars) and 2-wheeled (motorbike) vehicles. The video has the frame rate of 30 frames per second in the standard VGA $(640 \times 480)$ resolution. Since the camera is installed on top of a bridge, the best observation areas are the one that is near the camera, and the bottom half. The final goal is to classify the vehicles at this observation area.

The 2-wheeled vehicles are marked with the letter "B" (stand for motorbike) and bounded by green ellipses. The 4-wheeled vehicles are labelled by the letter "C" (stand for car) and bounded by red ellipses (Figure 13, 14, 15). The system can clearly detect and classify well when the vehicles in the observation area.

Sometimes, bad situations happen in the input sequence. In particular, two or more motorbikes driving so close to each other with the same speed will create a shape similar to the shape of a car, which causes incorrect results. In Table 3 and 4, we make some statistic calculations for a random set of frames from the sequence VVK1 at different times to test the exactness of the proposed algorithm. The results show that most of the errors are caused by the occlusion of 2-wheeled vehicles running at the same speed. Since it is still a work-in-process, more improvements will be made to enhance the accuracy of the classification algorithm.

| | **Count by human** | **Count by system** | **Deviation** | **Percent** |
|---|---|---|---|---|
| **Total Vehicles** | 736 | 684 | 52 | 92.93% |
| **4-wheeled** | 72 | 64 | 8 | 88.88% |
| **2-wheeled** | 664 | 620 | 44 | 93.37% |

*Table 3*. Statistical calculation base on a random set of 18000 frames from sequence VVK1 in afternoon rush hour

| | **Count by human** | **Count by system** | **Deviation** | **Percent** |
|---|---|---|---|---|
| **Total Vehicles** | 375 | 362 | 13 | 96.53% |
| **4-wheeled** | 38 | 49 | 11 | 77.55% |
| **2-wheeled** | 337 | 313 | 24 | 92.88% |

*Table 4*. Statistical calculation base on a random set of 18000 frames from sequence VVK1 at midday

### *B. Testing the performance*

It is essential that the detection and classification must run in real-time if it is going to be integrated into a traffic monitoring system. In order to test the performance of the detection and classification algorithm, four short traffic surveillance video, which each has exactly 1000 frames are selected. Firstly, an optical flow module will process the video and produce traffic flow images. These images will then be passed through the detection and classification module.

We are going to perform 2 kinds of test. In the first test, the module will process each video individually. In the second test, we will try to run all 4 video simultaneously. The first testing hardware system consists of an Intel core i7 720QM, which runs at 1.6GHz, and 4GB of RAM. Table 4 reveals the run-time results:

| Video | Run-time | Frame per second |
|---|---|---|
| VVK1_01 | 44.07s | 22.69 fps |
| VVK1_02 | 42.36s | 23.61 fps |
| PVD1_01 | 39.77s | 25.14 fps |
| PVD1_02 | 41.27s | 24.23 fps |
| All 4 video | 45.03s | 22.21 fps |

*Table 5*. Proposed method performance test 1

Another more powerful hardware system was also tested with the proposed system. The computer consists of a third generation Intel core i5 3230M, which runs at 3GHz, and 4GB of RAM.

| Video | Run-time | Frame per second |
|---|---|---|
| VVK1_01 | 34.28s | 29.17 fps |
| VVK1_02 | 30.32s | 32.98 fps |
| PVD1_01 | 29.52s | 33.87 fps |
| PVD1_02 | 29.50s | 33.89 fps |
| All 4 video | 40.67s | 24.59 fps |

*Table 6*: Proposed method performance test 2

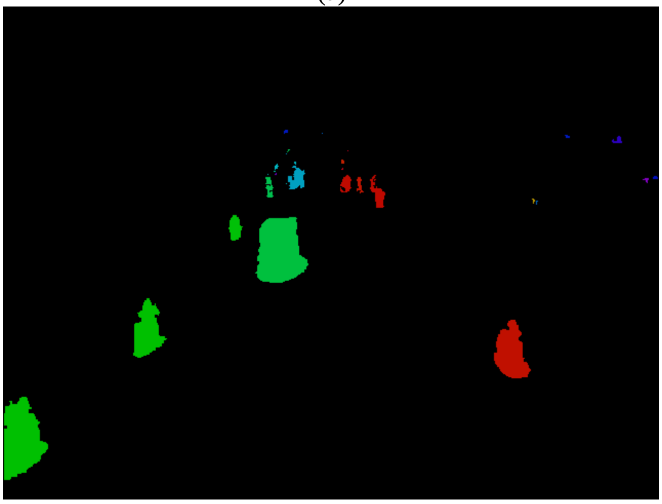
The results shows that our detection and classification module can run in real-time. Moreover, the module can process 4 video in parallel at the speed of 24.59 fps.

## IV. Conclusion

In this paper, we presented a new method that can detect and classify vehicles in low quality monitoring videos. Our proposed method first finds motion vectors associated with the moving vehicles and then marks and extracts them. Then the system bounds each vehicle with an ellipse and obtains low-level features. Moreover, we also apply the "observation zone technique" to help our method to get a better result. Although the idea of this one is simple, it helps the system a lot by removing all of the noise zones from the input scene. For example, the bottom zone can contain some cars that have gone out from the middle of the scene. Therefore the shape that we get is not a full-car shape, which can lead to an error in computing the result. Using these features, the classification function applies 2 ratio criteria to divide the vehicles into 2 main groups: 2-wheeled and 4-wheeled. The experiments on the suggested algorithm show some promising of results. Most the vehicles are detected and can be classified successfully. The system can run 4 video simultaneously in real-time at an average 23.41 frame per second.

The future works will focus on solving the case when two or more vehicles overlapping each other to improve the accuracy of the proposed algorithm.

(a)



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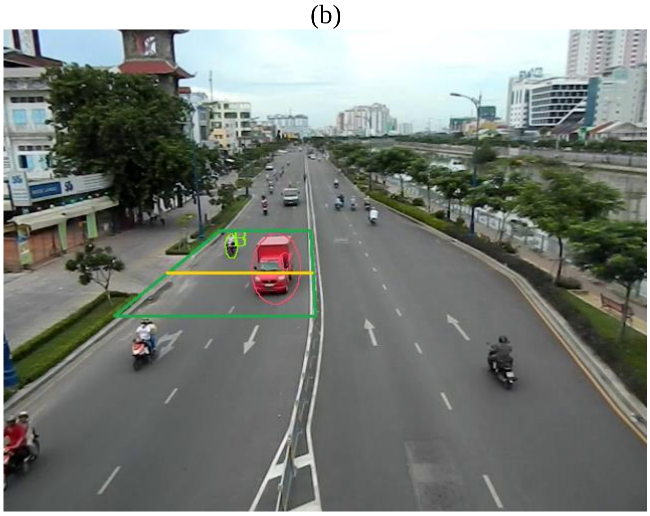
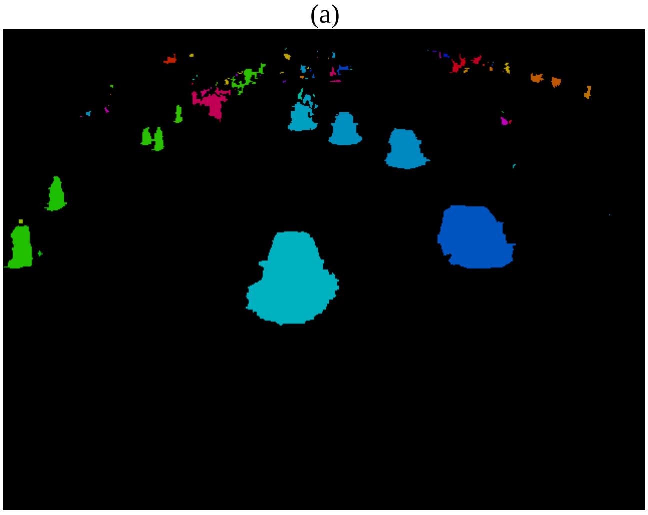


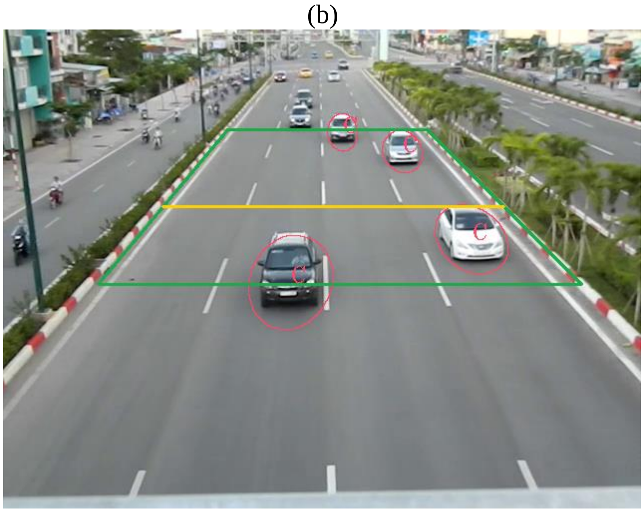
(c)

**Figure 13**. Experiment result from frame 510 to frame 515 of dataset VVK1. (a) original frame. (b) trafic flow. (c) segmentation and classification result

(a)



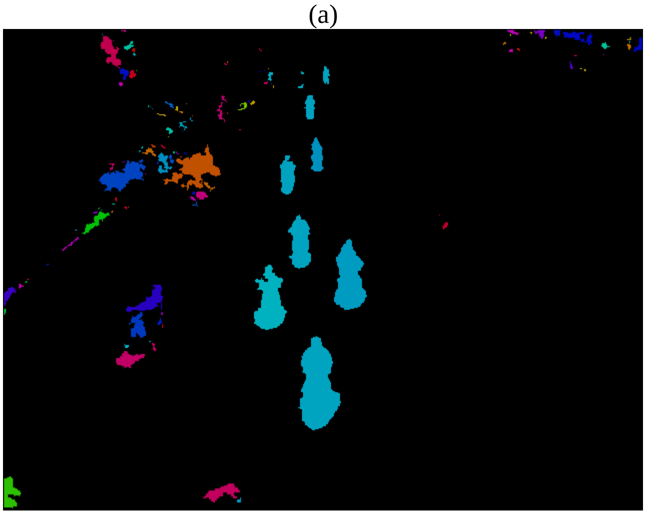
(b)



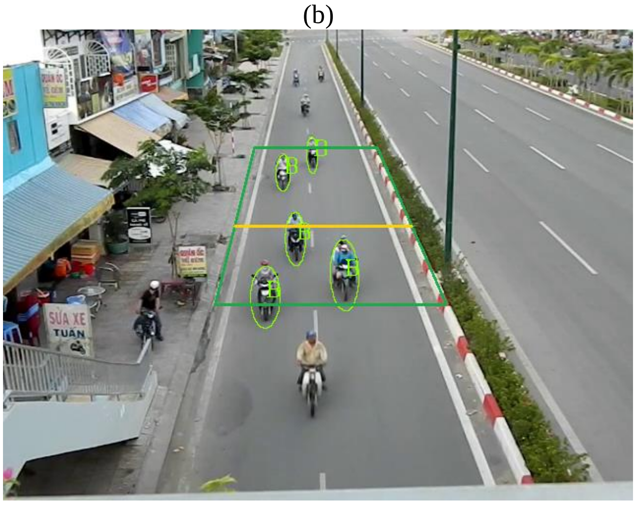
(c)

**Figure 14**. Experiment result from frame 50 to frame 55 of dataset PVD1. (a) original frame. (b) trafic flow. (c) segmentation and classification result

(a)



(b)



(c)

**Figure 15**. Experiment result from frame 230 to frame 235 of dataset PVD2. (a) original frame. (b) trafic flow. (c) segmentation and classification result

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## Author Biographies

**Synh Viet-Uyen Ha** is a lecturer at the School of Computer Science and Engineering, International University - Vietnam National University. He received an engineer degree from Ho Chi Minh City University of Technology (HCMUT), Vietnam in 1996; and a M.Sc. degree from Ho Chi Minh University of Natural Science (HCMUNS), Vietnam in 1999, both in computer science and engineering. He received a Ph.D. degree from School of Information and Communication Engineering, Sungkyunkwan University, Suwon, Korea in 2010. His research interests include computer machine, computer vision and image processing.

**Long Hoang Pham** is a senior student and is completing a B.Sc. degree in computer science and engineering from International University – Vietnam National University HCMC, Vietnam. He has been doing research related to image processing and computer vision under the supervision of Dr. Synh Viet-Uyen Ha. His research interests include image processing, computer vision, artificial intelligence and robotics.

**Ha Manh Tran** is a lecturer at the School of Computer Science and Engineering, International University – Vietnam National University. He received his doctoral degree in 2009 from Jacobs University Bremen, Germany. His research interests include network management, fault management, parallel and distributed computing, information retrieval and artificial intelligence. He serves as technical program member and reviewer of several international conferences and journals in the area of network and system management.

**Phong Ho Thanh** is an associated professor, the rector of International University and the head at the Department of Industrial and Systems Engineering, International University – Vietnam National University. He received an engineer degree in mechanical from Ho Chi Minh City University of Technology (HCMUT), Vietnam in 1982. He received a M.Sc. degree, in 1994, and a Ph.D. degree, in 1997, from Asian Institute of Technology (AIT), both in industrial and systems engineering. His research interests include multiple criteria decision making in industry, stochatic processs in industry and production management.