Machine Vision Techniques for Motorcycle Safety Helmet Detection

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***Abstract*— Although motorcycle safety helmets are known for preventing head injuries, in many countries, the use of motorcycle helmets is low due to the lack of police power to enforcing helmet laws. This paper presents a system which automatically detect motorcycle riders and determine that they are wearing safety helmets or not. The system extracts moving objects and classifies them as a motorcycle or other moving objects based on features extracted from their region properties using K-Nearest Neighbor (KNN) classifier. The heads of the riders on the recognized motorcycle are then counted and segmented based on projection profiling. The system classifies the head as wearing a helmet or not using KNN based on features derived from 4 sections of segmented head region. Experiment results show an average correct detection rate for near lane, far lane, and both lanes as 84%, 68%, and 74%, respectively.**

***Index Terms*—object recognition, machine vision, supervised learning, vehicle detection, vehicle safety**

I. Introduction

In many Asian countries, a motorcycle is a popular mean of transportation, due to its lower price compares to other four-wheeled cars, and due to the lack of efficient mass transportation. Thailand is one of those countries, which motorcycles are widely used. According to key statistics of Thailand 2012 [1], Thailand had more than 17 million officially registered motorcycles in 2010, while in the same year Thailand had its population of 63.9 million. With high number of vehicles comes high number of road accidents, according to WHO Global Status Report on Road Safety 2013 [2] the estimated road traffic death rate per 100,000 populations for Thailand was high as 38.1 compared to 20.5 for China, 11.4 for the U.S. and 9.1 for New Zealand, which made Thailand the third highest road traffic death rate in the world. From annually reported number of road traffic deaths in the recent decade, 60 - 75% of fatalities are from riders with motorized two- or three-wheelers [2]-[4]. Despite many attempts from both governmental and non-governmental organizations to increase road safety via many local and nation-wide campaigns, the reported mortality rate from motorcycles is still high. Motorcycle safety helmets are widely known for effectiveness in preventing head injuries and saving lives of motorcycle riders and passengers, and it has been one method used by Thai authorities in reducing mortality rate from motorcycle. Although Thai authorities are enforcing traffic law that requires both riders and passengers to wear safety helmets, unfortunately, the use of the helmets is as low as 54% for riders and 24% for passengers [4]. One of the reasons that made many helmet laws and campaigns unsuccessful was the lack of police manpower to monitor motorcyclists and enforce the laws.

This paper proposes an approach to automatically recognize motorcycle riders and passengers whether they are wearing helmets or not and is an extension of preliminary work reported in [5]. The method focuses on detecting helmets in light traffic scenes, especially in a university campus in Thailand. This proposed method may reduce the labor-intensive work of enforcing helmet laws and hence ultimately reduce the mortality rate involving motorcycle accidents. The organization of the rest of this paper is as follows. Section 2 reviews previous studies related to detecting motorcycle helmets. Section 3 describes our algorithm of the motorcycle helmet recognition system. Section 4 presents the experiments and results of our algorithm. Finally, the conclusion of the paper is given in Section 5.

II. Related Work

Recently, studies on automatic detection of safety helmets are mostly based on data from still images or video sequences using computer vision and image processing techniques. Some of these studies are automatic vehicle classification systems based on the assumption that a motorcyclist usually wears a helmet in order to classify and track motorcycles in traffic scenes. Chiu and Ku et al. [6], [7] proposed algorithms to detect occluded motorcycles using the visual length, visual width, and Pixel Ratio. They assume that motorcycle riders usually wear helmets to detect motorcycles in the scene. However these studies do not explicitly focus on detecting a helmet for safety reasons but use a helmet as a cue to identify a motorcycle. For the studies focusing on helmets detection,

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Liu, Liao, Chen, and Chen [8] presented a technique to find a full-face helmet in a scene using circle fitting on its Canny edge image. Similar techniques were introduced by Wen and his colleagues [9], [10] to detect helmets based on Circle Hough Transform. They developed this method to be used in surveillance systems in banks or at ATM machines. These techniques work well on full-face helmets with easily extractable circles or circular arcs. More recently, Chiverton proposed a system for the automatic classification and tracking of motorcycle riders with and without helmets [11]. In this system, the motorcycle riders are automatically segmented from video data using background subtraction, and support vector machines (SVM) are used to train histograms derived from head region image data of motorcycle riders to classify whether or not the riders are wearing helmets. However, this technique is not designed to distinguish each rider or count people on a motorcycle.

III. The Proposed Method

A. Overview

An overview of the automatic motorcycle safety helmet detection system is shown in Fig.1. Input of the system can be either real-time video sequence captured from a common web camera or a pre-recorded video clip.

The first part of the system is the moving object detection, which is a combination of algorithms to extract any moving objects in a scene. This part consists of background subtraction followed by a connected component labeling and a detection of moving direction. The extracted object is then classified as a motorcycle or other objects using K-Nearest Neighbor (KNN) classifier. For the third part, heads of the riders are counted and extracted from a motorcycle region. The last part classifies the extracted head as wearing a helmet or not based on KNN. Features used in this part are based on circularity, average intensity, and average hues of each head quadrants.

B. Moving Object Detection

The first part of the system is the moving object detection. In this paper, after applying a low-pass filter to all the input images to reduce noise, we firstly construct a background image using the mixture model algorithm and doing background subtraction as described in [12] and [13]. This algorithm provides good results with decent performance and works well for shadow removal. After background subtraction, images were binarized so that moving parts were marked white and stationary parts were marked black. Morphological closing is performed on the obtained binary images to reduce noise. Fig. 2 shows the results of this algorithm, which (a) and (b) are extracted moving objects and their corresponding results after applying closing operation, respectively.

A typical traffic scene in a university campus or in a road with light traffic usually consists of image frames that do not contain many vehicles or do not have any moving object at all. It is sufficient to process only one instance of a vehicle when it is within the camera frame. From the above reasons and to reduce computational load and memory consumption of the computer, instead of recognizing every frame in the sequence, we capture only an instance of a moving object when it passes exactly in front of the camera. To do that, a virtual vertical line which we call the "*detection line*" is drawn in the middle of a binary input image.

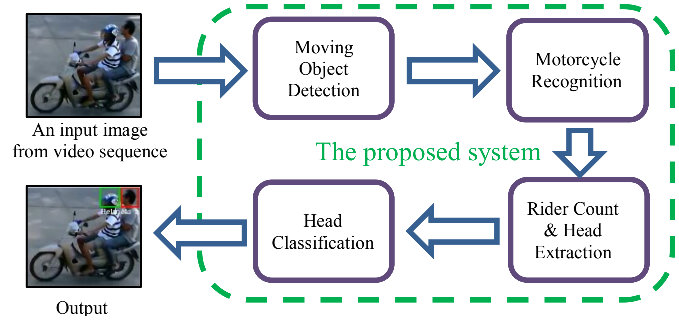

Figure 1. Overview of the system

(a) (b)

Figure 2. Moving object detection, a) binary extracted moving object, b) closed binary moving object with the detection line and the object centroid

Whenever any white pixels which belong to a moving object touch this line, the rest of the process is executed; otherwise the system is still in idle state. The detection line also serves another purpose. It is used to determine the direction of a moving object. When a white pixel touches the line, a connected component labeling algorithm based on contour analysis as in [14] and [15] is performed on the binary image. A moving direction can be found from the spatial relationship between the position of the detection line and the centroid $(\bar{x}, \bar{y})$ of the region that touches the line. For example, if the centroid $(\bar{x}, \bar{y})$ of the region is on the right side of the detection line, says $\bar{x} > x_{line}$, then the object is identified as moving from right to left. Fig 2 (b) illustrates the detection line and the centroid of an object. The acquired direction can be used to identify the driving lane of a moving vehicle. As Thailand uses left-hand traffic, in which traffic keeps to the left side of the road, so that an object that moves from right to left is considered to be an object in the near (closer to the camera) lane, while an object that moves from left to right is considered to be in the far lane.

C. Motorcycle Recognition

The purpose of this system is to detect safety helmets worn by people riding on motorcycles in a traffic scene. Hence, firstly, a motorcycle must be distinguished from other moving objects. To achieve this goal, we extract 3 features from the moving *blob* (connected region) that touches the detection line. These features are:

(a) (b)

Figure 3. The areas used in feature computation based on S.D. of hues are marked as red rectangles a) on a motocycle, and b) on a car.

Feature 1: Area of bounding rectangle

The first feature extracted from the blob of interest is the area of its bounding rectangle. This feature is used based on the fact that a motorcycle is usually smaller than other forms of vehicle on the road. This feature is normalized to make it range within 0.0 to 1.0 by dividing the rectangle area by the area of the whole frame.

Feature 2: Aspect ratio of bounding rectangle

The aspect ratio of bounding rectangle is defined as the ratio of the length of the shorter side of the bounding rectangle to the length of its longer side. This feature is used because from our observation, we noticed that the aspect ratio of the bounding box of a motorcycle is closer to 1.0 (closer to a square) than other moving objects e.g. cars, buses, trucks, and pedestrians.

Feature 3: Standard deviation of hue around blob center

The third feature is the standard deviation (S.D.) of hue (H in the HSV color model) in a small rectangular area around the blob's centroid. This feature is used based on the observations that an image part at the center of each motorcycle region has more variation of colors due to the motorcycle parts, riders' legs, and shadows compared to the same area of cars as shown in Fig. 3. The areas used in S.D. computations are marked by red rectangles in Fig. 3 (a) and Fig. 3 (b).

After all 3 features are extracted from the moving blob, the K-Nearest Neighbor (KNN) [16] classifier is applied on these features to classify either the blob is a motorcycle or other moving object.

D. Rider Count and Head Extraction

The heads of motorcycle riders are usually in the upper part of a motorcycle blob. Thus, the top 25% of the height of a motorcycle blob is defined as the region of interest (ROI) for counting and extracting motorcycle riders' heads. Fig. 4 (a) depicts the *top ROI* of Fig. 3 (a), while Fig. 4 (b) shows the background-subtracted image of the top ROI in Fig. 3a. From this top ROI, heads in the region can be counted and extracted as follows:

1) Vertical projection

After background of the image is subtracted, small holes and small isolate regions in binary image of ROI are eliminated using morphological closing as in Fig. 4 (c). The top ROI is vertically projected to construct vertical projection profiles. A projection profile is a frequency distribution of the projected head pixels onto the projection line. The projection profiles provide information about the number of white pixels that aligned along the vertical direction. A moving average is then performed on the projection profiles to smooth the curves and reduce noise. The black shaded curves in Fig. 4 (d) are the smoothed projection profiles of Fig. 4 (c).

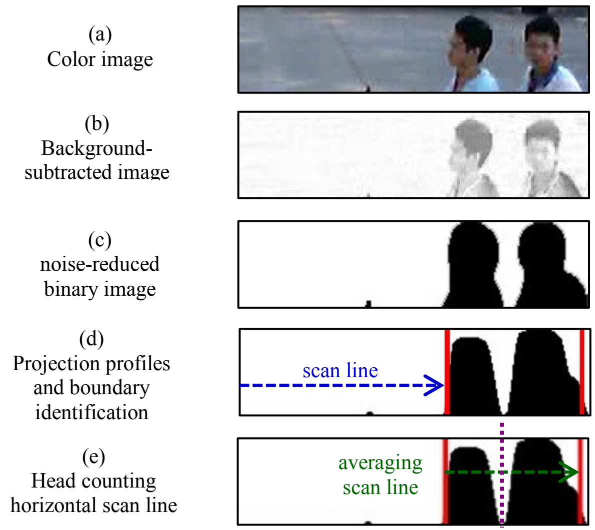

Figure 4. The process of rider heads detection and counting, a) the ROI of original frame, b) the background-subtracted frame, c) the enhanced binary image, d) the vertical projection profiles of the binary image and their defined boundaries, and e) the head counting scan line.

2) Profile boundaries identification

The next step is to determine left and right boundaries of heads' projection profiles. To find these boundaries, pixels along a horizontal line of the smoothed projection profiles are scanned from left to right starting from the leftmost border of the ROI and stops when the first pixel of a profile is found as shown in Fig 4 (d). The process is repeated with the opposite direction starting from the rightmost pixel and scanning from right to left until the first pixel on the right of the profile is found. The positions of the first pixels of projection profile found from both directions are defined as the left and right boundaries and were shown with red vertical lines in Fig 4 (d). To avoid a few small regions which usually resulted from the motorcycle mirrors, the horizontal scan line is picked at the 30% of the height of the projection profile image.

3) Head counting

From the vertical projection profiles image as in Fig 4 (d), the number of people (heads) in the top ROI equals the number of peaks of the projection profiles. To count the number of peaks from the projection profiles, another horizontal scan line is used. This new scan line scans the pixels inside the boundaries from the left boundary to the right boundary. The height of this scan line is the averaging of all the projection profiles inside the left and right boundaries. A scanning process is then performed along this line in order to count any changes from a black pixel to a white pixel followed by another change from a white pixel to a black pixel. In other words, this process counts the number of valleys in the projection profiles. The number of peaks (heads) in the projection profiles equals this counting result plus one.

Fig. 4 (e) depicts the head counting process, which the averaging scan line is drawn in green.

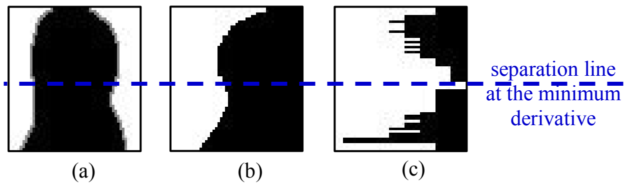

Figure 5. Head extraction process, a) a head binary image, b) horizontal projection profiles, and c) first-order derivatives

4) People and head image extraction

The presence of one or more valleys in the vertical projection profile means that there are two or more heads on that motorcycle. In that case, the midpoints of the valleys are used as dividing points to separate each head as depicted as the dotted purple line in Fig. 4 (e). The portions of the image, which lies on the left and right sides of a valley are considered to be separate heads from different riders.

After a rider is separated, the rider's head is then segmented using first order derivatives of the rider's horizontal projection profiles. The first order derivatives represent slopes of the projection profiles curve at each point. The position with the minimum derivatives is assumed as the point between the chin and neck boundary of the rider. Fig. 5 shows the head extraction process described earlier. Fig 5 (a) depicts the separated rider from Fig. 4. Fig 5 (b) is the horizontal projection profiles of Fig. 5 (a). Fig. 5 (c) shows the first order derivatives of the horizontal projection profiles in Fig. 5 (b). The separation line drawn in blue dash found at the minimum of the second-order derivatives shown in Fig. 5 (c).

E. Helmet-Head Classification

After each head region is separated and extracted, the head region is then divided into four independent quadrants according to the moving direction of that motorcycle. The quadrant division is performed firstly by finding the head region centroid. This centroid is used as a dividing point for both vertical and horizontal divisions as shown in Fig. 6. The first and fourth quadrants denoted as Q_1 and Q_4 in Fig. 6 are on the back of the rider's head, while the second and third quadrants denoted as Q_2 and Q_3 are on the forehead and lower face of the rider, respectively. For instance, if the motorcycle is moving from right to left (near lane), the face side of the head (Q_2 and Q_3) is on the left of the head region and the back side of the head (Q_1 and Q_4) is on the right side.

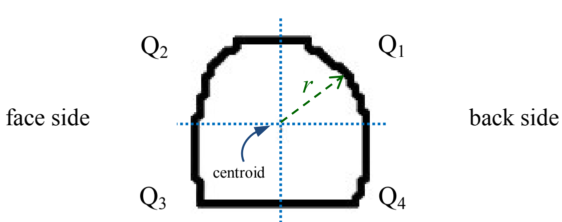

Figure 6. Head quadrants division

These quadrants of head region are then treated as inputs of head classification algorithm described in detail below.

1) Feature extraction

The total of 9 features is derived from the four quadrants of head region. The followings are the detail descriptions of these features:

Feature 1 to Feature 4: Arc circularities

The first 4 features extracted from the quadrants are arc circularities. The arc circularity measures the similarity between the arc and a circle. We apply this measurement based on the circularity, *C*, described in [17] as:

$$C = \mu_r / \sigma_r \tag{1}$$

where μ_r and σ_r are the mean and S.D. of the distance, *r*, from the head centroid to the head contour in each quadrant, respectively. Fig. 6 illustrates the distance *r*, the centroid, and the contour of the head region.

The circularity measure, *C,* increases monotonically as the arc becomes more circular. These features are used because the fact that a head wearing a helmet is more circular than a head without a helmet, especially on the top and the back of the helmet which reflects in high circularity of head contour in quadrants Q_1, Q_2, and Q_4. These features are normalized by the maximum of the circularity found in the training set.

Feature 5 to Feature 8: Average intensities

The next 4 features extracted from the quadrants are average intensities. The average intensity, μ, is computed individually from a grayscale image of each quadrant as:

$$\mu_I = \frac{1}{N} \sum_{i=0}^{N-1} I_i \tag{2}$$

where I_i is an intensity of the i^{th} pixel in the quadrant, while *N* is the number of head pixels in the quadrant. These features are used because the intensity of the head especially on the top and the back of the head without helmet are mostly dark as most Thai are black hair compared to a variety of shades of helmets. These features are normalized by the maximum grayscale intensity.

Feature 9: Average hue of the third quadrant

The last feature is the average hues (in the HSV color model) of the facial part of the head in the third quadrant Q_3. The average hue is computed exclusively only in Q_3 as:

$$\mu_H = \frac{1}{N} \sum_{i=0}^{N-1} H_i \tag{3}$$

where H_i is a hue of the i^{th} pixel in the third quadrant, and *N* is the number of head pixels in this quadrant. This feature is applied based on the fact that if a rider is wearing a helmet, a large portion of her face (third quadrant) is covered by her helmet and varies the average of the hues. On the other hand, a rider without a helmet has certain average hues of skin color.

2) Classification

For the classification of head, we applied K-Nearest Neighbor (KNN) [16] as a classifier. KNN is a method for classifying objects based on closest training examples in the feature vector. In this work, a head is classified by a majority vote of its neighbors, with the head being assigned to either "wearing a helmet", "not wearing a helmet", and "undefined" classes. The neighbors are taken from a set of heads for which the correct classification is known and labeled. The Euclidean distance is used in this study.

IV. Experiments and Results

A. Experiments

We set up experiments inside Naresuan University campus. The width of the campus road where we set up the instrument is 6 meters. A web camera with 4.4 mm focal length was attached to a 4-meter-high pole on the sidewalk. The pole was set 5 meters away from the center of the road. The camera produced video sequences with resolution of 640x480 pixels and 30 frames per second. The system was implemented in C# on MS Windows 7 operating system that ran on a 2.4 GHz CPU. We tested 3 main components of our systems individually which are motorcycle recognition, rider head counting, and head-helmet classification. These experiments were tested separately, so that the results of each test are independent from other tests and error from the previous algorithm steps were not propagated. The overall performance of the system with error propagation was also tested. We performed all KNN classifications with *K* varied from 1 to 9 and 10-fold validation settings, each fold with approximately 400 training images and approximately 40 testing images. Each experiment had different images in training and testing sets. Feature selection was also performed on each test. Weka software [18] was used in testing the classifications Fig. 7 shows some examples of the test images.

B. Results

The accuracy of the motorcycle recognition algorithm was 95 % at *K* = 11 and the detail is shown in the confusion matrix in Table I. The diagonal cells show the percentages of correct recognized object of each class, while other cells show the percentages of incorrect recognized objects. All three features (area and aspect ratio of bounding rectangle, and SD of hue around blob center) were selected as the classification features. For the rider heads counting algorithm, we tested with 828 manually cropped motorcycle images, the results showed the accuracy at 83.82% and the detail is shown in the confusion matrix in Table II. The helmet classification algorithm with manual cropped heads images as inputs was 89% with *K* was set to 11 and 6 features were selected, which were arc circularities of Q1 and Q2, average intensities of Q1, Q2, and Q3, and the average hue of Q3. The results are shown in the confusion matrix in Table III.

For the overall performance of our system, we also studied the classification accuracy under three conditions. Condition 1 is the set of input from moving objects that the system detected as in the near (closer to the camera) lane. Condition 2 is the set of input from moving objects that the system detected as in the far lane. Condition 3 is the set of input from moving objects in both lanes. We also tested the results of various *K* and features in the KNN classifier.

(a) (b)

Figure 7. Examples of test image; a) two riders without helmet, and b) one rider with a helmet

(a) (b)

Figure 8. Examples of errors; a) two objects overlap when touching the detection line, and b) riders sit too close to each other

For condition 1, the best value for *K* was 5 with accuracy of 84%. Seven features were selected, which were arc circularities of Q1 to Q4, average intensities of Q1 and Q2, and the average hue of Q3. Table IV is the confusion matrix of this condition. For condition 2, the best value for *K* was 11 with accuracy of 68%. Three features were selected, which were arc circularities of Q1, Q3, and Q4. Table V is the confusion matrix of this condition. For condition 3, the best value for *K* was 5 with accuracy of 74%. Eight features were selected, which were arc circularities of Q1 to Q4, average intensities of Q1, Q2, and Q4, and the average hue of Q3. Table VI is the confusion matrix of this condition.

TABLE I. CONFUSION MATRIX FOR MOTOCYCLE RECOGNITION

Actual class (%)	**Predicted class (%)**	
	motorcycle	***other***
motorcycle	96	9
other	4	91

TABLE II. CONFUSION MATRIX FOR PEOPLE COUNTING

Actual class (%)	**Predicted class (%)**		
	1 rider	***2 riders***	***> 2 riders***
1 rider	81.1	1.0	0.0
2 riders	17.5	91.8	0.0
> 2 riders	1.5	7.2	100.0

TABLE III. CONFUSION MATRIX FOR HELMET RECOGNITION

Actual class (%)	**Predicted class (%)**	
	with helmet	***no helmet***
with helmet	87	9
other	13	91

TABLE IV. CONFUSION MATRIX FOR NEAR LANE PERFORMANCE

Actual class (%)	Predicted class (%)		
	helmet	***no helmet***	***undefined***
helmet	80	16	4
no helmet	15	81	5
undefined	5	4	91

TABLE V. CONFUSION MATRIX FOR FAR LANE PERFORMANCE

Actual class (%)	Predicted class (%)		
	helmet	***no helmet***	***undefined***
helmet	58	33	4
no helmet	32	60	11
undefined	10	7	85

TABLE VI. CONFUSION MATRIX FOR BOTH LANES PERFORMANCE

Actual class (%)	Predicted class (%)		
	helmet	***no helmet***	***undefined***
helmet	58	33	4
no helmet	32	60	11
undefined	10	7	85

From our experiments, we found some common errors of the system. Most error occurs in the recognition of the far lane. This suggests that the low resolution of input images play very important role in accuracy of the system. Another type of error occurs when a moving object touches the detection line while it also overlaps with other objects, the system would treat them as one object and results in wrong classifications. Fig. 8 (a) shows an example of this type of error. Another type of error occurs when riders on the same motorcycle sit too close to each other or a passenger is leaning on the back of the rider. Fig. 8 (b) shows some examples of these errors.

V. CONCLUSION

We proposed a real-time motorcycle safety helmet detection system. The system used a moving object detection method and classified heads using the proposed techniques which consists mainly of head extraction and classification. The extraction method is based on vertical and horizontal projection profiling methods, while the classification method is based on features derived from head regions. The experimental results show that our methods accurately detected helmet wearing at the rate of 74% for both lane. This system can be combined with an automatic license plate recognition system to provide a novel automatic helmet wearing monitoring system to reduce laborious work of policing and law enforcement.

REFERENCES

[1] Statistical Forecasting Bureau, "Key Statistics of Thailand 2012," National Statistical Office, Ministry of Information and Communication Technology, Bangkok, Rep., 2012.

[2] World Health Organization, *Global Status Report on Road Safety 2013: supporting a decade of action*. Geneva: World Health Organization, 2013.

[3] Y. Tanaboriboon and T. Satiennam, "Road Accidents in Thailand," *J. Int. Assoc. of Traffic and Safety Sci., IATSS Research*, Vol. 29, No.1, pp.88-100, 2005.

[4] Thai Road Foundation and Thai Health Promotion Foundation. (2012). "ผลสำรวจอัตราการสวมหมวกนิรภัยของผู้ใช้รถจักรยานยนต์ในประเทศไทย ปี 2553 และ 2554 [Survey Results of Helmet Using Rate of Motorcyclists in Thailand during 2010 and 2011] [Online]. Available: http://www.roadsafetythailand.com/main/files/data1/2012-01-01-helmet-wearing-rate-2554.pdf

[5] C. Tangnoi, N. Bundon, V. Timtong, and R. Waranusast, "A Motorcycle Safety Helmet Detection System Using KNN Classifier," *Proc. 2013 2nd ICT Int. Student Project Conf.*, pp. 97-100, 2013.

[6] C. C. Chiu, M. Y. Ku, and H. T. Chen. "Motorcycle Detection and Tracking System with Occlusion Segmentation," *8th Int. Workshop on Image Anal. for Multimedia Interactive Services*, 2007. 32-32.

[7] M. Y. Ku, C. C. Chin, H. T. Chen, and S. H. Hong. "Visual Motorcycle Detection and Tracking Algorithms," *WSEAS Trans. Electron.*, Vol. 5, No. 4, pp. 121-131, Apr. 2008.

[8] C. C. Liu, J. S. Liao, W. Y. Chen, and J. H. Chen. "The Full Motorcycle Helmet Detection Scheme Using Canny Detection," *18th IPPR Conf. on CVGIP*, 2005. 1104-1110.

[9] C. Y. Wen, S. H. Chiu, J. J. Liaw, and C. P. Lu. "The Safety Helmet Detection for ATM's Surveillance System via the Modified Hough transform," *IEEE 37th Annual ICCST*, 2003. 364–369.

[10] C. Y. Wen. "The Safety Helmet Detection Technology and Its Application to the Surveillance System," *J. Forensic Sci.*, Vol. 49, No. 4, pp. 770-780, Jul. 2004.

[11] J. Chiverton, "Helmet presence classification with motorcycle detection and tracking," *IET Intelligent Transport Systems*, Vol. 6, No. 3, pp. 259-269, Sep. 2012.

[12] Z. Zivkovic and F. van der Heijden, "Recursive unsupervised learning of finite mixture models," *IEEE Trans. Pattern Anal. and Mach. Intell.*, vol. 26, no. 5, pp. 651–656, May 2004.

[13] Z. Zivkovic, "Improved adaptive gausian mixture model for background subtraction," in *Proc. Int. Conf. Pattern Recognition*, vol. 2. 2004, pp. 28–31.

[14] G. Bradski, and A. Kaehler. "Contours," in *Learning OpenCV: Computer Vision with the OpenCV Library*, Sebastopol: O'Reilly Media, 2008, pp. 222-264.

[15] S. Suzuki, and K. Abe, "Topological Structural Analysis of Digital Binary Images by Border Following," *Computer Vision, Graphics and Image Processing*, No. 30, pp. 32–46, 1985.

[16] T. Cover, P. Hart, "Nearest-Neighbor Pattern Classification," *IEEE Trans. Inf. Theory*, pp. 21-27, Jan. 1967.

[17] R. M. Haralick, "A Measure of Circularity of Digital Figures," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. SMC-4, 1974, pp. 394-396.

[18] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA Data Mining Software: An Update," *SIGKDD Explorations*, Vol. 11, Issue 1, 2009.