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Half and Full Helmet Wearing Detection in Thailand using Haar Like Feature and Circle Hough Transform on Image Processing

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***Abstract*—Helmet detection has a wide area of applications in image processing. A new helmet detection technique is proposed in this paper. The technique combines two methods for helmet detection to achieve better detection rates. The two methods are face detection using haar like feature for detection between without helmet and full helmet and circle hough transform for detection between without helmet and half helmet. In the first module of the technique, we proposed a fast algorithm for detecting helmet in color images. The algorithm uses haar like feature to detect helmet regions. that, face / nose / mouth / left eye / right eye detection method can not detection between full and half helmet. So, the second module of the technique, the circle hough transform is applied for detection it. In experiments on images, our technique has achieved high detection rates and low false positives due to the application of the new algorithm.**

Keywords—Helmet detection, haar like feature, circle hough transform

I. INTRODUCTION

An accident is a specific, unexpected, unusual and unintended external action which occurs in a particular time and place, with no apparent and deliberate cause but with marked effects. Carelessness of the driver is the major factor of such accidents [1]. The traffic authorities give a lot of instructions to the vehicle operators. But many of them do not obey the rules. Nowadays most of the countries in Thailand are forcing the motor riders to wear the helmet and not to use the vehicles when the person is in drunken condition. But still the rules are being violated by the users. In order to overcome this we introduces an intelligent system, Smart Helmet, which automatically checks whether the person is wearing the helmet and has non- alcoholic breath while driving.

A traffic accident is defined as any vehicle accident occurring on a public highway (i.e. originating on, terminating on, or involving a vehicle partially on the highway). These accidents therefore include collisions between vehicles and animals, vehicles and pedestrians, or vehicles and fixed obstacles. In higher-income countries, road traffic accidents are already among the top ten leading causes of disease burden in 1998 as measured in DALYs (disability-adjusted life years). In less developed countries, road traffic accidents were the most significant cause of injuries, ranking eleventh among the most important causes of lost years of healthy life. In Indian road system, widening of the road is not an alternative solution to avoid traffic in such a cities. Our work is closely related with the study of helmet detection methods [1-10]. We divided into 6 algorithms as Vision based method, it is one of the most popular techniques for traffic surveillance due to low hardware cost. Background subtraction, this is one of the method where image background is extracted for further processing. It is the best approach for detecting objects from videos taken by static cameras. There are many techniques and both expert and new comers can be confused about limitations and benefits of it. This method based on static background hypothesis not applicable in real environments. Object detection, it is process of finding instance of real world objects such as face / nose / mouth / left eye / right eye. We can use Local Binary Pattern, Histogram of Oriented Gradients and Hough transform descriptors Local Binary Pattern, it is used for face recognition in computer vision. In this method [5] image is divided into several small segments and from which features are extracted. It consists of binary patterns and describe surrounding of pixels. The features from segment are joint into single feature histogram. This method provides good result in term of speed. Histogram of Oriented Gradients Descriptor, provides better performance than other existing feature sets. It is used to extract human feature from visible spectrum images. It has been determined that when LBP combined with HOG descriptor improves, detection, performance considerably on some data sets. Hough transform descriptor, it is a technique and can be used to isolate features of particular shape with an image. It requires some features in parametric form.

The main contribution of this work is to propose a new method to combine 2 features for helmet wearing detection problem. The rest of this paper is organised as follows. In Section II, we describe the modality of helmet detection that is used in this paper. Section III describes the experimental results with comparison to the other method. Conclusions are given in Section IV.

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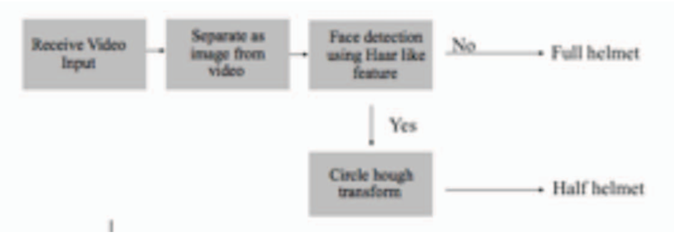

Fig. 1, The flowchart of the proposed approach

II. HELMET DETECTION

Our face / nose / mouth / left eye / right eye detection system consists of these steps. The first step is to classify each pixel in the given image as without helmet or full helmet. The second step is to identify different helmet regions in the helmet detected image. The final step is to decide whether each of the helmet regions identified is a full helmet or half helmet.

A. *Face / nose / mouth / left eye / right eye detection using haar like feature for detection between without helmet and full helmet [11-13]*

Isolated pixel values do not give any information other than the luminance and/or the colour of the radiation received by the camera at a given point. So, a recognition process can be much more efficient it is based the detection of features that encode some information about the class to be detected. This is the case of Haar like features that encode the existence of oriented contrasts between regions in the image. A set of these features can be used to encode the contrasts exhibited by a human face / nose / mouth / left eye / right eye and their spacial relationships. One of the problems that these kind of approaches present is the computation effort that is required to compute each of the features as a window sweeps the whole image at various scales. Fortunately, each of the used features can be computed by peeking 8 values in a table (the integral image) independently of the position or scale. Our feature pool was inspired by the over complete Haar like features and their very fast computation scheme proposed. More specifically, we use 14 feature prototypes shown in Fig. 1 which include 4 edge features, 8 line features and 2 centre-surround features. These prototypes are scaled independently in vertical and horizontal direction in order to generate a rich, over-complete set of features.

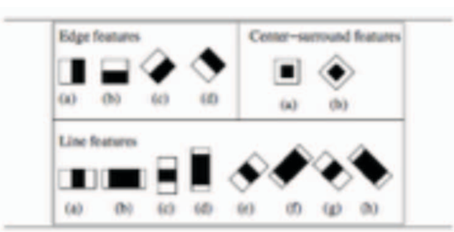

Fig. 2, Examples of the used Feature prototypes

Given a feature set and a training set of positive and negative sample images, any number of ma- chine learning approaches could be used to learn a classification function. A variant of AdaBoost is used both to select a small set of features and train the classifier. In its original form, the AdaBoost learning algorithm is used to boost the classification performance of a simple (also called weak) learning algorithm. Recall that there are over 117,000 rectangle features associated with each image 24 × 24 sub-window, a number far larger than the number of pixels. Even though each feature can be computed very efficiently, computing the complete set is prohibitively expensive. The main challenge is to find a very small number of these features that can be combined to form an effective classifier. In support of this goal, the weak learning algorithm is designed to select the single rectangle feature which best separates the positive and negative examples. For each feature, the weak learner determines the optimal threshold classification function, such that the minimum number of examples are misclassified. A weak classifier $h_j(x)$ thus consists of a feature $f_j(x)$, a threshold θ_j and a parity p_j indicating the direction of the inequality sign:

$$h_j(x) = \begin{cases} 1, p_j f_j(x) < p_j \theta_j \\ 0, otherwise \end{cases} \tag{1}$$

where x is a 24 × 24 pixel sub-window of an image.

This section describes an algorithm for constructing a cascade of classifiers which achieves increased detection performance while radically reducing computation time. The key insight is that smaller, and therefore more efficient, boosted classifiers can be constructed which reject many of the negative sub-windows while detecting almost all positive instances. Simpler classifiers are used to reject the majority of sub-windows before more complex classifiers are called upon to achieve low false positive rates.

A cascade of classifiers is degenerated decision tree where at each stage a classifier is trained to detect almost all objects of interest while rejecting a certain fraction of the non-object patterns see in Fig. 3. Each stage was trained using the Adaboost algorithm. At each round of boosting is added the feature-based classifier that best classifies the weighted training samples. With increasing stage number, the number of weak classifiers, which are needed to achieve the desired false alarm rate at the given hit rate, increases.

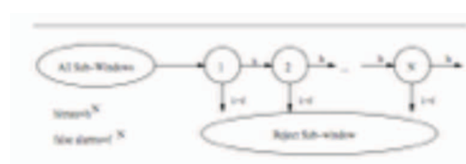

Fig. 3, Cascade of Classifiers with N stages.

B. Circle hough transform for detection between without helmet and half helmet [14-19]

The Hough transform can be applied to detect the presence of a circular shape in a given image. It is used to detect any shape or to locate the helmet. The characteristic equation of a circle of radius r and $center(a,b)$ is given by

:

$$(x-a)^2+(y-b)^2=r^2 \qquad (2)$$

This circle can be described by the two following equations:

$$\begin{aligned} x &= a + r\cos(\theta) \\ y &= b + r\sin(\theta) \end{aligned} \qquad (3)$$

Thus, the role of the Hough transform is to search for the triplet of parameters (a,b,r) which determines the points (x,y) Two cases may be presented as described in Fig 4.

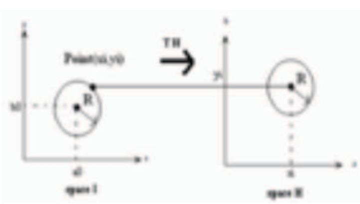

Fig 4, Transformation of a point in circle[10]

If we know the radius of the circle to be detected in the image, the parameter to search is reduced to a pair (a,b) and the H space is 2 dimensional.

We consider a circle of radius R and centre (a_0,b_0), the transformation for each point (x_i,y_i) in space I yields a circle in space H having a center (x_i,y_i) and radius R.

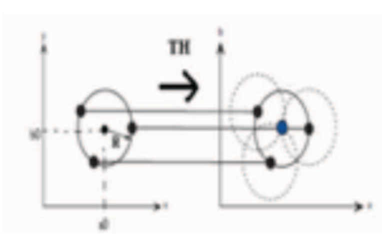

Fig 5, Representation of HT for several points in circle[10]

Similarly, we transform all points of the circle in image. The result will be more circles where their intersection is the point (a_0,b_0). This point is obtained by searching the maximum of the accumulator. The black circles indicate a set edge points within the image. Each edge point contributes a circle of radius R to an output accumulator space indicated by the grey circles. The output accumulator space has a peak where these contributed circles overlap at the center of the original circle. In this work, the edge orientation information is used to increase the CHT performance.

III. Experimental Results

The proposed algorithm was tested using the video sequences. The images were acquired at a frame rate of 30 fps and have a spatial resolution of 480 × 640 pixels. The proposed algorithm performs in real time in a standard PC, despite the fact that it was programmed in Matlab. The following values were adopted in all the experiments: maximum vehicle area, Amax = 300 pixels, smallest distance between blobs, R = 10 pixels. These values were chosen by trial and error and were not changed during the experiments. To assess the algorithm, the target position and size (bounding box) was manually annotated for all the test images. Then we compute recall and precision.

$$recall = \frac{TP}{TP+FN} \qquad (4)$$

$$precision = \frac{TP}{TP+FP} \qquad (5)$$

where TP (true positives) denotes the number of detected vessels, FN (false negatives) the number of non-detected vessels and FP (false positives) the number of detected non-vessels, aka false alarms. We consider the boat as detected if the overlap between the detected bounding box and the bounding box of the true vessel together with its trail is larger than 30%. Table 1 shows the recall and precision achieved by the system after each of the main processing blocks. The first block tracks most of the vessel in most of the frames (92%). However, the precision is very low (9%) .

I. Recall and Precision Achieved and Comparison to the Other Method

Algorithm	Recall	Precision
Circle hough transform for helmet detection	89	11
LBP for helmet detection	82	14
Our proposed	95	7

IV. CONCLUSION

We described a real-time vision-based helmet waring monitoring system that can be used to detect in a sequence of images. The system used a moving object detection method and resolved full and half helmet problems using a proposed full and half helmet detection and segmentation method. The proposed full and half helmet detection and segmentation method used the visual face / nose / mouth / left eye / right eye detection using haar like feature and circle hough transform to identify classes of full and half helmet. This system overcame various issues raised by the complexity of full and half helmet detection problems. Experimental results obtained with complex road and helmet style images revealed that the proposed system could successfully segment and detect various full and half helmet. full and half helmet problems with motorcycles in traffic jams will be the subject of future work.

Fig. 6, Example of face / nose / mouth / left eye / right eye detected

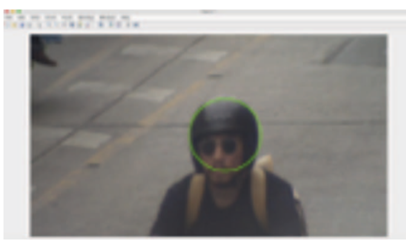

Fig. 7, Example of half helmet detected

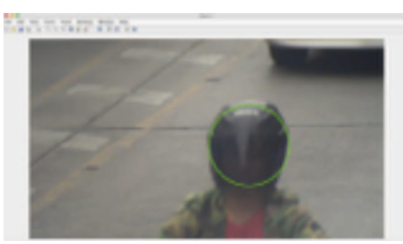

Fig. 8, Example of full helmet detected

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REFERENCES

1. A. Leelasantitham and W. Wongseree, “Detection and classification of moving thai vehicles based on traffic engineering knowledge,” in *ITST 2008*, oct. 2008, pp. 439 –442.
2. B. Duan, W. Liu, P. Fu, C. Yang, X. Wen, and H. Yuan, “Real-time on-road vehicle and motorcycle detection using a single camera,” in *ICIT 2009*, feb. 2009, pp. 1 –6.
3. V. Milanés, D. F. Llorca, J. Villagrá, J. Pérez, C. Fernández, I. Parra, C. González, and M. A. Sotelo, “Intelligent automatic overtaking system using vision for vehicle detection,” *Expert Systems with Applications*, vol. 39, no. 3, pp. 3362 – 3373, 2012.
4. S. Sheik Mohammed Ali, B. George, L. Vanajakshi, and J. Venkatraman, “A multipleinductive loop vehicle detection system for heterogeneous and lane-less traffic,” *Instrumentation and Measurement, IEEE Transactions on*, vol. 61, no. 5, pp. 1353 –1360, may 2012.
5. S. Messelodi, C. Modena, and M. Zanin, “A computer vision system for the detection and classification of vehicles at urban road intersections,” *Pattern Analysis & Applications*, vol. 8, pp. 17–31, 2005.
6. C.-C.Chiu,M.-Y.Ku,andH.-T.Chen,“Motor cycle detection and tracking system with occlusion segmentation,” in *WIAMIS '07*. Washington, DC, USA: IEEE Computer Society, 2007, pp. 32–. [Online]. Available: http://dx.doi.org/10.1109/WIAMIS.2007.60
7. J. Canny, “Finding edges and lines in images,” Cambridge, MA, USA, Tech. Rep., 1983.
8. M. Zengqiang, P. Cunzhi, H. Ke, and C. Qiandong, “Research on segmentation of overlapped vehicles based on feature points on contour,” in *FBIE 2009*, dec. 2009, pp. 552 –555.
9. K. Takahashi, Y. Kuriya, and T. Morie, “Bicycle detection using pedaling movement by spatiotemporal gabor filtering,” in *TENCON 2010 - 2010 IEEE Region 10 Conference*, nov. 2010, pp. 918 –922.
10. S. Sonoda, J. K. Tan, H. Kim, S. Ishikawa, and T. Morie, “Moving objects detection at an intersection by sequential background extraction,” in *ICCAS 2011*, oct. 2011, pp. 1752 –1755.
11. J. Chiverton, “Helmet presence classification with motorcycle detection and tracking,” *IET*, vol. 6, no. 3, pp. 259–269, 2012.
12. Viola, Paul and Michael Jones (2001). Rapid object detection using boosted cascade of simple features. In: Proceedings IEEE Conf. on Computer Vision and Pattern Recognition 2001.
13. Yang, Ming-Hsuan (2002). Detecting faces images: A survey. IEEE Transations on Pattern Anal- ysis and Machine Inteligence 24(1), 34–58.
14. Turk, M.A. and A.P. Pentland (1991). Face recog- nition using eigenfaces. In Proc. of IEEE Conference on Computer Vision and Pattern Recognition pp. 586 – 591.
15. H. Rhody Chester F. ‘’Hough Circle Transform‘’, Carlson Center for Imaging Science Rochester Institute of Technology October 11, 2005.
16. Duda, R.O. and P.E Hart, 1972. Use of the Hough transformation to detect lines and curves in picture. Commun. ACM, pp: 11-15.
17. Kimme, C., D. Ballard and J. Sklansky, 1975. Finding circles by an array of accumulators. Proc. ACM, 18: 120-122.
18. Ioannou, D., W. Duda and F. Laine, 1999. Circle recognition through a 2D Hough Transform and radius histogramming. Image and Vision Computing, 17: 15-26.
19. Guil, N. and E.L. Zapata, 1997. Lower order circle and ellipse hough transform. Pattern Recognition, 30: 1729-1744.