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Two-wheeler Detection Research using Modified Histogram of Oriented Gradients Algorithm Based on Global and Local Feature

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Abstract

Many kinds of transportation system have been developed to help the people to move things or people. This paper presents an enhanced algorithm for the detection rate to classify the two-wheelers with riding people using new innovative global and local feature extraction and comparison method; the difference of Gaussian (DoG), the normalized cross correlation (NCC) and its application of histogram of oriented gradients (HOG). Applied new features are calculated by DoG which present edge components and NCC algorithm which is used to make a match from template images, local weighting values are calculated from template cell features. And the combined cell features are classified by using a boosting algorithm (Adaboost). The improvement detection rates are confirmed through experiments using bicycles and motorcycles data set for 60 and 90 degrees.

Keywords: *HOGs, Difference of Gaussian, Normalized Cross Correlation, Adaboost, Two-wheelers*

1. Introduction

But while a simple device or vehicle to move things may be in the past, in addition to advancement in scientific technology, the means of transportation has been developed in several types or shapes and including variety function. In these days, the degree of injury to drivers and passengers in a vehicle caused by a traffic accident is reduced gradually by many safety device techniques, because the development of transportation systems has been concentrated on not only improving performance but also to protect the people mounted in and outside of vehicle, for the last few years [1]. And the road environment is also changing to protect the vehicles, passengers, pedestrians, *etc.*

Although many researchers have focused to develop an intelligent vehicle using variety of algorithms to detect the vehicles, pedestrian and lanes, the research of vulnerable road users (VRUs), such as a small device for riding (bicycle-adults and kids, motorcycle-two and four wheels, *etc.*) is gradually expanded with bicycle as the center. So this research is still a hot subject for the study field in the intelligent transportation system. Unlike the vehicle and pedestrian detection system for the intelligent vehicle, VRU detection appears as a combination of human and complicated devices (bicycles and motorcycles). VRUs also move more slowly than vehicles on the road, except motorcycles. Because people on the two-wheelers are always exposed to a harmful road environment, the research have to be expanded to protect the VRUs for the intelligent vehicles.

Vision based intelligent vehicle systems have mainly focused on the pedestrian and vehicle development system and design. As this paper previously alluded to the similarity of the shape of pedestrians and two-wheelers, the two-wheeler detection algorithm also closely resembles the pedestrian. Because of this reason, this paper describes the pedestrian detection algorithms. Generally speaking, the literature on pedestrian detection system is abundant. Features can be distinguished into global features, local features,

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single features, and multiple features depending on how features are measured and used [2, 3, 4]. Global features operate on the entire image of datasets such as principal component analysis (PCA) [5]. On the other hand, local features are extracted by dividing a sliding window into a different subset region of an image, with one or more kinds of features extracted in each subset region [6, 3]. Similarity, Mikolajczyk, *etc.*, [7] divided whole body detection and body part detection as the local features. The advantage of using part-based research is that it can deal with variations in human appearance due to body articulation. However, the disadvantage of using this approach is that it is difficult to calculate due to the complexity of the pedestrian detection problem [8]. Widely used single features for pedestrian and object detection in the literature are edge [9], shapelets [10], local binary pattern (LBP) [11], histogram of oriented gradients(HOGs) [12], local representative field [13], wavelet coefficient [14], Haar-like features and its application features [15]. Contrary to this, approaches based on multiple features combine several types of the above single features.

Two wheelers consist of a human and a machine; usually the human is the upper part and the machine is the lower part in the shape. HOG [12] based detector system has slow performance because of its dense encoding scheme and multi-level scale images. Porikli [16] solved this problem using the concept of “Intelligent Histogram” to speed up the feature extraction process. Because of the above reasons, we tried to use a modified HOG algorithm to select the best features and Adaboost to improve detection rate

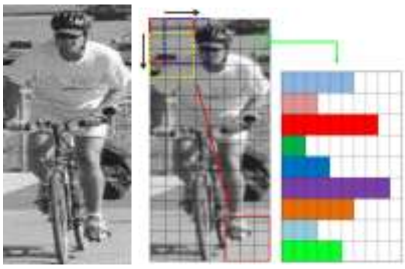
In this study, we invented a new algorithm based on an adapted HOG value which is calculated difference of Gaussian (DoG) from the original images and normalized cross correlation coefficient between a global area and local area (each cell). The motivation of this paper is as follows. Firstly, the two wheeler detection system is still not a considerable time investment needed to find a good algorithm. Secondly, it is familiar with pedestrian detection which has accuracy and efficiency in still images. But it is one of the most difficult studies due to the range of various image poses, as well as environmental conditions, cluttered backgrounds, and composite objects (showing several shapes other than pedestrians, according to the view point). Thirdly, human part and object part edge is well presented by DoG from original image and NCC is calculated for each basis function (in this paper cell) instead of the whole template. So in this paper, we suggest a new algorithm to detect the two-wheelers using subimage periodicity for the weak part on the road.

This paper is organized as follows. In Section 2, this paper explains the original feature set using general HOG algorithm, DoG method using the two stage edge detection process, and the NCC to measure the resemblance between two signals. Section 3 describes the framework and training procedure of the proposed two wheeler detection system. The results of their evaluation and a detailed performance analysis are presented in Section 4. Section 5 concludes this paper.

2. Feature Extraction

2.1. Histogram of Oriented Gradients (HOG)

Histograms of Oriented Gradients (HOG) descriptors which are one of the well-known methods for object detection are the feature descriptor using edge intensity in a local region. HOG is feature descriptors used in computer vision and image processing for the purpose of object detection. It [13, 17] converts the distribution directions of brightness for a local region into a histogram to express them in feature vectors, which is utilized to express the shape characteristics of an object. This method is similar to that of edge orientation histograms, scale-invariant feature transforms descriptors, which uses normalized local spatial histograms as a descriptor, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. And it is little influenced from the effect of illumination by converting the distribution of near pixels for a local region into a histogram, and has a strong feature for a geometric change of local regions.



(a) (b) (c)

Figure 1. The Example of Two Wheelers HOG Normalization. (a) Original Image (b) Cells and Blocks (A Block is 3x3 Cells) Sliding (c) A Cell Histogram

Dalal and Triggs [12] described Histogram of Oriented Gradients descriptors in the context of human detection. Their proposed method is based on evaluating well normalized local histogram of image gradient orientations in a dense grid, computed over blocks of various sizes. The main idea is that local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients or edge directions. This is achieved by dividing the image into cells and for each cell a dimension histogram of gradient directions over the pixels of the cell is calculated. Then each block in the image consists of a number of cells, as shown in Figure 1.

After calculating x, y derivatives (dx and dy), the magnitude $|m(x,y)|$ and orientation $\theta(x,y)$ of the gradient for each pixel $I(x,y)$ is computed from

$$|m(x,y)| = \sqrt{dx^2 + dy^2} \tag{1}$$

$$dx = I(x+1,y) - I(x-1,y), \quad dy = I(x,y+1) - I(x,y-1) \tag{2}$$

$$\theta(x,y) = \tan^{-1}(dy/dx) \tag{3}$$

One thing to note is that, at orientation the computation radian to degree method is used, which returns values between -180° and 180°. Each histogram divides the gradient angle range into a predefined number of bins. In this paper, each cell, as shown Figure 1 (c) and (d), is represented by 8x8 pixel size and has 9 bins covering the orientation for [0°, 180°] interval. For each pixel's orientation, the corresponding orientation bin is found and the orientation's magnitude $|m(x,y)|$ is voted to this bin. A contrast-normalization is used on the local responses to get better invariance regarding illumination, shading, *etc.* To normalize the cell's orientation histograms, it should be grouped into blocks (3x3 cells). A cell feature is expressed as $F_i = [f_1, f_2, \cdots f_9]$. The characteristic quantities of *k'th* block may be expressed as:

$$B_k = [F_1, F_2, \cdots F_9] \tag{4}$$

This is done by accumulating a measure of the local histogram value over the blocks. Normalization processing is expressed in Figure 1 (c), where the movement of the block is based on the fact that it is moved to the right side and to the lower side by a cell each way (back arrow). Although there are four different methods for block normalization suggested by Dalal and Triggs [12], L2-norm normalization Π is implemented using equation (5),

$$\Pi = \frac{B_k}{\sqrt{\|B_k\|^2 + \varepsilon^2}} \tag{5}$$

where ε is the small constant instead of zero for the denominator. Here, the overlapping processing is done to ensure the important feature information of each cell is saved as a concatenated method. For the 128x64 pixels input image, the number of HOG feature vectors with 6804 dimension is obtained using the 9 histogram dimension, 8x8 pixels for a cell, 3x3 cells for a block, and a cell sliding.

2.2. Normalized Cross Correlation

similarity in which two series as a signal of the lag of one relative to another are correlated, in image processing, pattern recognition, and other fields. To overcome several disadvantages for the cross correlation, NCC (Normalized Cross Correlation) algorithm [18], [19] which is an improved method to measure the resemblance between two signals is used to decide the similarity between two images. Equation (6) is shown as a basic definition for the normalized cross correlation coefficient γ.

$$\gamma = \frac{1}{n}\sum_{x,y}\frac{[f(x,y)-\bar{f}_{u,v}][t(x-u,y-u)-\bar{t}]}{\{[f(x,y)-\bar{f}_{u,v}]^2[t(x-u,y-u)-\bar{t}]^2\}^{0.5}} \tag{6}$$

where $f(x,y)$ is the intensity value of the image f of the size $M_x \times M_y$ at the point (x, y), $x \in \{0,\ldots,M_x-1\}$, $y \in \{0,\ldots,M_y-1\}$. Template t of size is $N_x \times N_y$. And $\bar{t}$ is the mean of the feature and $\bar{f}_{u,v}$ is the mean of $f(x,y)$ in the region under the feature which is calculated by

$$\bar{f}_{u,v} = \frac{1}{N_x N_y}\sum_{x=u}^{u+N_x-1}\sum_{y=v}^{v+N_y-1}(fx,y) \tag{7}$$

A common way to calculate the pixel (u, v) of the pattern in the image f is to evaluate the normalized cross correlation value γ at each point (u, v) for f and the template t, which has been shifted by u steps in the x direction and by v steps in the y direction. The denominator in (7) is the variance of the zero mean image function $f(x,y)$ - $\bar{f}_{u,v}$ and the shifted zero mean template function $t(x-u,y-v)$ - $\bar{t}_{u,v}$. Due to this normalization, $\gamma(u,v)$ is independent to the change in brightness or the contrast of the image, which are related to the mean value and the standard deviation.

2.3. Difference of Gaussian

The Difference of Gaussian (DoG) module is similar to the Laplacian of Gaussian (LoG) in that it is a two stage edge detection process. And it works by performing two different Gaussian blurs on the image [20]. The resulting image is a blurred version of the source image. The final image is then calculated by replacing each pixel with the difference between the two blurred images and detecting when the values cross zero, *i.e.* negative becomes positive and vice versa. The image is first smoothed by convolution with Gaussian kernel of certain width

$$G_{\sigma_1}(x,y) = \frac{1}{\sqrt{2\pi\sigma_1^2}}\exp\left(-\frac{x^2+y^2}{2\sigma_1^2}\right) \tag{8}$$

to get $g_1(x,y) = G_{\sigma_1}(x,y) * f(x,y)$. With a different width σ_2, a second smoothed image can be obtained

$$g_2(x,y) = G_{\sigma_2}(x,y) * f(x,y)$$

Finally, the DoG as an operator or convolution kernel is defined as

$$DoG = G_{\sigma_1} - G_{\sigma_2} = \frac{1}{\sqrt{2\pi}}\left(\frac{1}{\sigma_1}e^{-(x^2+y^2)/2\sigma_1^2} - \frac{1}{\sigma_2}e^{-(x^2+y^2)/2\sigma_2^2}\right) \tag{9}$$

We show the example of DoG generation using the scale space, as below Figure 2

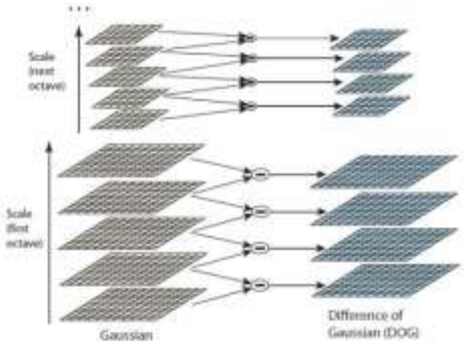


Figure 2. The Generation of DoG Using the Scale Space

3. Classification

Adaboost is a simple learning algorithm that selects a small set of weak classifiers from a large number of potential features according to the weighted majority of classifiers. The training procedure of Adaboost is a greedy algorithm, which constructs an additive combination of the weak classifier. Our boosting algorithm is basically the same as P. Viola's algorithm [21].

Given training set: $(x_1, y_1), \cdots, (x_n, y_n)$

Where $x_i \in X, \quad y_i \in Y = \{+1, -1\}$

1) Initialize weights $w_{1,i} = 1/2m, 1/2l$ for $y_i = +1, -1$

m : the number of positive image (two-wheeler, +1)

n : the number of negative image (non-two-wheeler, -1)

2) For t=1 $\cdots T$:

(a) Normalize the weights, $w_{t,i} = w_{t,i} \Big/ \sum_{j=1}^{n} w_{t,j}$, so that $w_{t,i}$ is a probability distribution of ith training image for tth weak classification

(b) For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_i

$$\varepsilon_j = \sum_i w_j \left| h_j(x_i) - y_i \right|.$$

(c) Choose the classifier, h_t, with the lowest error ε_t

(d) Update the weights:

$w_{t+1,i} = w_{t,i}\beta_t^{1-\varepsilon_i}$, where $\varepsilon_i = -1$ if example x_i is classified correctly, $\varepsilon_i = +1$ otherwise, and $\beta_t^i = \varepsilon_t / (1 - \varepsilon_t)$

3) Output the final hypothesis:

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right),$$

where $\alpha_t = \log(1/\beta_t)$

The final hypothesis H is a weighted majority vote of the $\boldsymbol{T}$ weak hypotheses where α_t is the weight assigned to h_t. Using the two strong classifications, this paper suggests the use of 2nd stage cascade method. It improves the recognition rate due to the complementary role for two feature vectors of quite different types.

In Stage 1), initial input value x represents the training feature for the image and y represents classification of positive (+1) and negative (-1), such as two-wheeler and non-two-wheeler. Stage 2) conducts the initial values and updates the weighting factors, and creates weak classifiers in which it selects a weak classifier having a minimum error and imposes a weighting factor on the classifier.

4. Experimental Result

Two-wheeler data used in the experiment includes photos taken on the street and others obtained from the internet randomly. For our purposes, it is hypothesized in the experiment for the following two cases: rear and front appearance. The experiment was done for the attitude of 90 degrees and within ±60 degrees on the basis of a horizontal line. 2,353 pictures were used with a size of 128x64 from the taken photos with a size of 640x480. They were utilized by dividing training and experimental images. The number of non-two-wheelers used in the training was equal to the number of two-wheelers, and 3,000 pictures were used as non-two-wheelers. The experiment was carried out with an ordinary user computer environment consisting of a Pentium 3.1 GHz and Visual C++ 6.0 program and Matlab

Our dataset contains only front and rear views with a relatively limited range of poses (60° and 90°) which are scaled to size 16x128 pixels. And the negative (non-two wheelers) samples used in our experiments were extracted randomly from general street images. All our dataset examples used in this paper are shown in Figure 3.

Figure 3. Examples of Training and Test Samples for Positive and Negative

Each training set ratio of positive and negative is 1:1. For more details, the bicyclist training images are 340 examples for the 60degree view and 845 examples for 90 degrees. And motorcycle driver training images are 96 examples for the 60degree view and 234 examples for 90 degrees. We also mixed the two degrees and types (bicyclist and motorcycle driver). In the first experiment, the performance of the traditional HOG and Haar-like feature are shown in Figure 4 (a) and (b), according to the data type and degree.

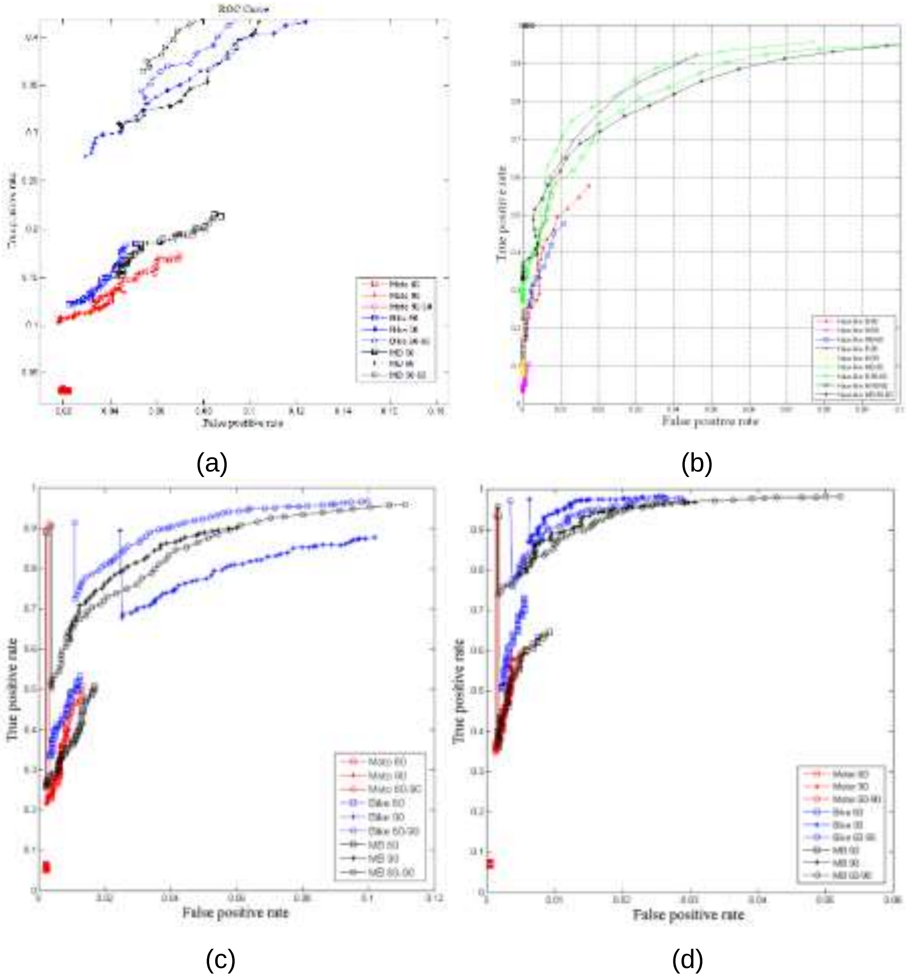


Figure 4. Experiment Results (a) Results of an ordinary HOG Method, (b) Results of the Haar-like Experiment, (c) Results of the G_HOG Experiment by Applying the Global Target, (d) Results of the L_HOG Experiment by Applying the Local Target

Secondly, the experiment was carried out by the DoG and NCC method using the weighting value which is suggested in the study. A range of thresholds of -20 to 20 was utilized in classification, and confusion matrix, true positive rate (TPR) and false positive rate (FPR) were used for analyzing experimental results per angles for the methods, and ROC curves are shown in Figure. 4, by applying Eq. (10) below:

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN} \tag{10}$$

where "TP" is True Positive", "FP" is False Positive", "TN" is True Negative and "FN" is False Negative. In Figure 4, "Moto" means motorcycle, "Bike" means bicycle, and "MB" is a mixture of motorcycles and bicycles, respectively. Also, the numerals behind each of the abbreviations "60" signifies within 60˚, "90" within 90˚, and "90-60" a mixture of 90˚ and 60˚ , respectively, as well. In Figure 4, we confirmed that the mixed front view (90 degree) showed a bigger area for the receiver operating characteristic (ROC) curves than non-mixed degree.

For the HOG features, we have used 8x8 pixels for a cell and 3x3 cells for a block. DoG is calculated by two window kernel, by applying eq. (11) below:

$$I_{DOG} = (\sigma_2 - \sigma_1) \times I \tag{11}$$

where I is original image, σ_1 and σ_2 is 3x3 window kernel. Used σ_2/σ_1 value is 1.6. The result of I_{DOG} image is shown Figure 5.

(a) (b)

Figure 5. The Result of DoG Operator (a) Original Image, (b) The Result of 3x3 Window Kernel

From the obtained DoG image, new magnitude feature M is calculated using Eq. (12)

$$M = m + m_{\_DOG} \tag{12}$$

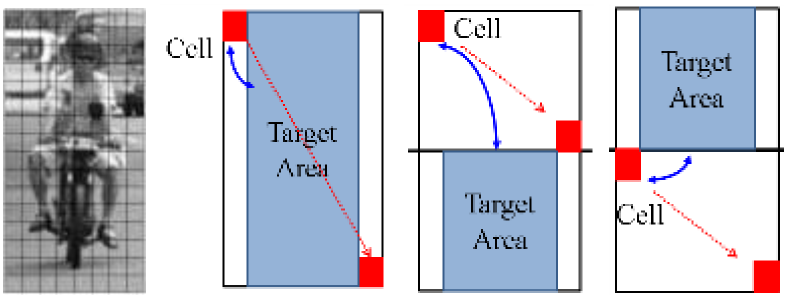
Where m is calculated from original image and m_{DOG} is calculated from I_{DOG} image.

To use the NCC, consider two series $f(x)$ and $t(x)$ which are histogram features where $x \in \{0, \ldots, N-1\}$. By the equation (6), the proposed NCC(W_γ) is defined as

$$W_\gamma = \frac{1}{n}\sum_{x,y}\frac{[f(x)-\bar{f}][t(x-u)-\bar{t}]}{\{[f(x-\bar{f}]^2[t(x-u)-\bar{t}]^2\}^{0.5}} \tag{13}$$

where $f(x)$ is local cell histogram features, $t(x)$ is target histogram features, $\bar{f}$ and $\bar{t}$ are the means of corresponding histogram features.

In general, a positive image which contains a bicycle or motorcycle consists of a bicycle or motorcycle, human, and background, as shown in Figure 6 (a). In this paper, the special area was established as the blue region which is used as the target histogram features in Figure 6. The target histogram features are the average value of each bin of cells for the target area.



(a) (b) (c) (d)

Figure 6. Displayed Target Area. Upper Area is the Upper Body of a Human, and Lower Area is a Part of the Riding Machine, which also Includes a :Part of the Body (Legs), (a) An Example of an Image of Front View, (b) Target is Body and Machine (Whole Area, Except Left and Right Margin), (c) Target is the Lower Area (d), Target is the Upper Area

Using this target histogram, the proposed new two wheeler detection method using the modified HOG is calculated as follows:

$$H_j = \begin{cases} C_j * |W_\gamma|, & m_{-DOG} > TH \\ C_j \quad , & else \end{cases} \tag{14}$$

where C_j means *j*th cell histogram using the result of Equation (12) and H_j is new histogram features which is weighted NCC value between local cell histogram features and target histogram features. TH means threshold value, in this paper used 20.

Table 1. Accuracies for Each of the Methods (%)

Angle(°) \ Method		HOG	Haar-like	G_HOG	L_HOG
60	**M**	61.1	79.3	54.9	68.7
	B	71.2	92.8	91.2	96.3
	MB	76.7	87.7	91.2	94.4
90	**M**	74.9	81.3	86.2	95.0
	B	78.3	94.8	95.5	98.4
	MB	76.1	94.6	94.8	97.4
90-60	**M**	77.8	98.0	81.7	93.7
	B	75.5	93.5	93.8	97.6
	MB	73.1	92.5	93.7	97.2

In Figure 4 (a), the ordinary HOG method, it is shown that the experiment according to B90 has the best results among these experiments, but the recognition rate is significantly low. However, Figure 4 (c) shows that the results of B90 experiments according to the proposed method which is used Figure 5 (b) type have a higher recognition rate than ordinary HOG. And also, Figure 4 (d) shows that 90 degrees and 90-60 degrees experiment according to the proposed method using Figure 5 (c) and (d) type have a higher recognition rate than other methods. When the proposed algorithm was applied to the other characteristic vector method, a higher recognition rate could be obtained, and the results are listed in Figure 3 (b). The highest accuracies for each of the methods were calculated with equation (15) [22] and the results are listed in Table 1.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{15}$$

As shown in Table 1, Bike (bicycle) has higher accuracies than Moto (motorcycle) for the G_HOG, signifying that bicycle has a trend of better classifying characteristics than motorcycle. In our opinion, the reason is that motorcycle becomes complicated by loading baggage in the rear or by loading high baggage. In the experiment of mixture of the two kinds of two-wheelers, the results of accuracies have partially confused patterns for angles and kinds, but for the whole mixture (90-60) the suggested method has a higher accuracy than the existing algorithm.

The results of the experiment per angle showed that the B and MB result of 90 degree have a higher system performance than 60 degrees, and the results of the mixture (noted as 90-60 in the Figure) has an average performance level of the two angles. Reasons for these results may be analyzed by the following two ideas: first, the number of trainings within 60 degrees was lower than 90 degrees, and second, since the characteristics of narrower ranges, which were almost similar to pedestrians, were utilized in the case of 90 degrees, that characteristics of wider ranges were induced in the case of 60 degrees, which led to diffused characteristics, which is judged by us to increase the probability of false recognition. Recognition conduction time was analyzed as approximately 20ms in the suggested method for one image whose characteristics has been extracted, and in the other methods the time was analyzed similarly.

For the same database, a comparison of the performance results for other different feature types (LBP) is shown in Figure 7. The result of LBP features shows lower performance than HOG and the proposed algorithm, because of a concentrated lower area in Figure 7.

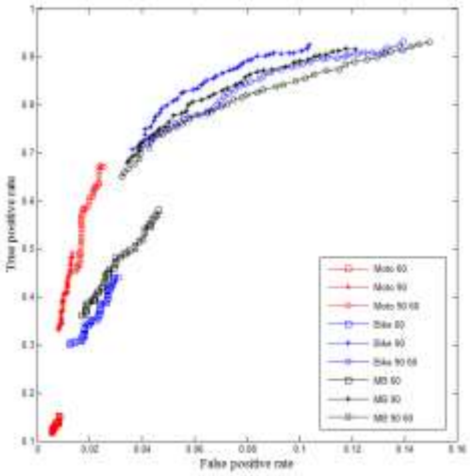


Figure 7. The Result of Local Binary Pattern (LBP) Using Same Database

5. Conclusion

For accuracy and efficiency, two wheeler detection with riders in a still image is one of the most difficult works due to a variety of poses, as well as environmental conditions and cluttered backgrounds. A novel system for detecting two-wheelers was suggested by applying the saving method of new characteristic vectors. In this study, we have introduced that a new practical implementation of the solution for weak object (vulnerable road users) on the road using DoG and NCC weighting value for modified HOG features. The Adaboost Method was applied for a speedy classification of two-wheelers; the results compared with existing methods have been shown that it has highly improved system performance. When applied in an actual system, it has a much higher accuracy than the existing methods, as well. The characteristics that can be better classified in cases similar to two-wheelers, as demonstrated in the experiments, will be developed and the bicycles with different attitudes and shapes will be analyzed more precisely in future studies. It has been experimentally demonstrated that the proposal using the G_HOG method as weighting value leads to better classification results than other traditional methods from ROC. Among the several angles and poses, the B90 showed a higher detection rate than others.

From the experimental results, we proved that the processing of two wheeler detection system may use smaller local features, lower dimensions and less computation than earlier. For further research, we have to go on to include the occluded region, object change according to the weather, night environment, other degrees of view, and *etc.*

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