Building a HOG Descriptor Model of Pedestrian Images Using GA and GP Learning

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Abstract

For detecting a pedestrian by using features of images, it is generally needed to establish a reference model that is used to match with input images. The support vector machine (SVM) or AdaBoost Cascade method have been generally used to train the reference pedestrian model in the approaches using the histogram of oriented gradients (HOG) as features of the pedestrian model. In this paper, we propose a new approach to match HOG features of input images with reference model and to learn the structure and parameters of the reference model. The Gaussian scoring method proposed in this paper evaluates the degree of feature coincidence with HOG maps divided with angle of the HOG vector. We also propose two approaches for leaning of the reference model: genetic algorithm (GA) based learning and genetic programming (GP) based learning. The GA and GP are used to search the best parameters of the gene and nonlinear function representing feature map of pedestrian model, respectively. We performed experiments to verify the performance of proposed method in terms of accuracy and processing time with INRIA person dataset.

Keywords: HOG model, Genetic algorithm, Genetic programming, Learning, Pedestrian detection

1. Introduction

Machine vision has attracted much attention in recent decades of years because it is important for various application areas such as surveillance, car safety, and robotics. Recently, various researches on machine vision have been actively applied smart vehicles for driving safety and autonomous driving. The recent progresses in smart vehicles have growing needs to be endowed with pedestrian detection. This study aims at propose an approach to pedestrian detection with enhanced accuracy and reduced processing time.

In recent years, the number of approaches to detect pedestrians in monocular images has grown steadily. Benenson et al. [1] categorized the main paradigms for pedestrian detection into Viola-Jones variants, HOG+SVM rigid templates, deformable part detectors (DPM), and convolutional neural networks. Viola and Jones [2] recognized objects by combining Haar wavelet-like features. Instead of recognizing an object using a single classifier, they used several multiple cascade classifiers to recognize the object. Viola et al. [3] also developed a superior classifier progressively through a boosting method for detector training. Dollar et al. [4] evaluated that the ideas of Viola et al. [3] had served as a foundation for modern detectors. YOLO [6] and faster R-CNN [7] are currently considered as the state of the art

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techniques where real-time deep learning techniques are applied.

Dalal and Triggs [8] created the HOG, which is a method to generate a histogram by accumulating the magnitude in terms of angles of gradient and recognize the shape of the object through it. In addition, they used SVM as a learning machine to utilize the HOG features in detecting pedestrians. The DPM of Felzenszwalb et al. [9] utilized the method of Dalal and Triggs [8] as a building block. Zhu et al. [11] improved the speed of calculation in the study of Dalal and Triggs [8] by applying the cascade technique to HOG features. There is a difference between the conventional HOG and cascade HOG in that the cascade HOG transforms the size of the model variably and selects an excellent model among the converted models through the boosting learning, whereas the conventional HOG recognizes the object by fixing the size of the model.

Since their introduction, the number of variants of HOG features has proliferated greatly with nearly all modern detectors utilizing them in some form. Maji et al. [12] considered fast approximations of non-linear kernels. Dollar et al. [5] recognized pedestrians by utilizing various channels such as color and edge, unlike the HOG using a gray channel. Felzenszwalb et al. [10] determined the similarity between the whole model and partial model of the pedestrian model after their generation and finally judged whether it is a pedestrian or not. In most of studies using the HOG such as studies of Dalal and Triggs [8] and Felzenszwalb et al. [10], pedestrian recognition is carried out by using learning based approach in which discriminative features are extracted from each candidate and then, they are passed through the learning machine or classifier such as SVM. In this paper, we propose a new approach for matching and training of pedestrian model using the HOG features.

2. HOG Descriptor Model of Pedestrian Images

2.1 Pedestrian Detection

In this paper, we use a matching technique using the pedestrian HOG feature model as a method for pedestrian detection through a vision sensor. After distinguishing features and similarities in the input image with the pedestrian HOG feature model, the detector judges whether it is a pedestrian or not. To determine the similarities, we propose a scoring method using the Gaussian function in this paper. The scoring method divides the HOG features by each angle, accumulates the score values calculated at each angle and obtains the final score.

If the pedestrian HOG feature model is configured with a

single pedestrian image, there might be caused errors that detect only a specific pedestrian by characteristics such as clothing, hair style and posture of the pedestrian. Therefore, it is necessary to train the pedestrian HOG feature model to express the generalized pedestrian characteristics. The HOG feature model is learned using genetic algorithm. In addition, we use genetic programming to learn the nonlinear function expressing the reference model which is used to calculate the final score value to determine the detection of pedestrian.

2.2 Gaussian Scoring

In this research, we divide the HOG feature values ranging from 0° to 360° degrees by the angle and determine the similarity between the model and an input image with respect to the feature values on each divided angle space. This paper proposes a Gaussian scoring to determine the degree of similarity for each angle as given in Eq. (1).

$$Score(I, M) = e^{-\frac{(I-M)^2}{2(kM)^2}}, \quad (1)$$

where, I and M represent the HOG value of an input image and the model, respectively. The constant k is introduced to generate higher scoring to relatively larger HOG values compared to smaller HOG values. The final scoring function for the input image cell is derived as Eq. (2).

$$angle\ score_{(x,y,l)} = \frac{\sum_{(i,j)} Score(I_{(x+i,y+j)}, M_{(i,j)})}{w \cdot h}, \quad (2a)$$

$$Cell\ score_{(x,y)} = \frac{\sum_l angle\ score_{(x,y,l)}}{N_l}, \quad (2b)$$

$$if\ (Cell\ Score > Threshold)\ Pedestrian\ Detect, \quad (2c)$$

where w , h and N_l represent the width and height of the model and total number of divided angle, respectively.

When the scoring based decision is applied to pedestrian detection, a huge amount of calculation is needed because the scoring is performed through the exponential function for all cells. Therefore, a lookup table is used to improve the calculation speed. Eq. (1) for Gaussian scoring function can be expressed in terms of parameter j as given in Eq. (3).

$$Score(I, M) = e^{-\frac{(j-1)^2}{2k^2}}, \quad j = \frac{I}{M}. \quad (3)$$

Since the value of the Gaussian function is determined by the ratio of the HOG value of the input image to the reference model as shown in Eq. (3), the Gaussian function value according to

the ratio can be configured with a lookup table. In addition, as the ratio j approaches to small or large value, the scoring value approaches to zero. Since the scoring value approaching to zero means that the feature of the model and input image are far each other in similarity, we can regard the scoring value in these cases as 0 to improve the calculation speed. The proposed Gaussian scoring is calculated with the ratio j value as shown in Eq. (4).

$$\begin{aligned} \text{If } \left(\frac{1}{n} \leq j \leq \frac{2n-1}{n} \right) \quad & \text{Score}(j) = e^{-\frac{(j-1)^2}{2k^2}}, \\ \text{else} \quad & \text{Score}(j) = 0. \end{aligned} \quad (4)$$

The scoring function (4) can be approximated by lookup table configured at discrete value j and linear interpolation given in Eq. (5)

$$\begin{aligned} \text{Score}(j) = & \text{GauLUT}(j_{\text{index}}) \\ & + \text{GauLUT}(j_{\text{index}} + 1) \times (j - j^*), \end{aligned} \quad (5)$$

where *GauLUT* represents the Gaussian lookup table array, j_{index} represents the array index corresponding to the ratio value, and j^* represents the j value corresponding to j_{index} , respectively.

3. Learning of the Pedestrian HOG Model

3.1 Learning of the Model by using GA

GA was first developed by John Holland in 1975 as an intelligent algorithm that solves the optimization problems based on Darwin's theory of evolution. It was developed by mimicking the biological evolution and explores the best genes through crossover, mutation and selection operations. Many studies have reported that GA and GP provide an efficient and robust alternative for solving complex and highly nonlinear optimization problems utilizing global search procedures. The GA and GP model and their optimization procedures can be applied to solve the problem of establishing and training of the reference pedestrian model because it belongs to highly nonlinear optimization problem.

This paper proposes a HOG model training method using GA and applies the model to detection of general pedestrian characteristics. The INRIA person dataset is used for the training image of the HOG model, and the pedestrian HOG model is trained using 1, 216 pedestrian images and 1, 218 background images. The genetic configuration of the pedestrian model is

Figure 1. Genetic configuration of the pedestrian HOG model.

shown in Figure 1.

In order to apply GA to learn the HOG pedestrian detection model, the model image and training images need to be presented as genes. A pedestrian model image is divided into cells as shown in Figure 1. A gene represented by P in Figure 1 consists of chromosomes (G) whose number is equal to the number of divided cells in the image.

GA needs to evaluate the fitness of gene to learn the parameter of the model. In order to construct the fitness function, we define the average score of the pedestrian images and non-pedestrian images. The average score is obtained by averaging the Gaussian scorings of the whole image of the pedestrian and non-pedestrian, respectively, with the GA HOG model as shown in Figure 2 and Eq. (6).

$$S_P = \frac{1}{N_P} \sum_{i=1}^{N_P} \text{Score}(PD_i, \text{GA Model}), \quad (6a)$$

$$S_N = \frac{1}{N_N} \sum_{i=1}^{N_N} \text{Score}(ND_i, \text{GA Model}). \quad (6b)$$

In Eq. (6), S_P and S_N represent the average score of pedestrian images and the non-pedestrian images, N_P and N_N represent the number of positive data and the negative data, and PD_i and ND_i represent the i th pedestrian and non-pedestrian image, respectively. Now, we can regard S_P and S_N as measures for representing matching degree between GA model and pedestrian image and non-pedestrian image, respectively.

It can be noted that the high value of S_P means the corresponding GA model has high degree of measure for representing the general pedestrian characteristics. On the other hand, when S_N is high, the measure can be regarded that the model hardly

Figure 2. Calculation of the average score S_P and S_N .

Figure 3. Effect of score variance to detect pedestrian.

distinguish the pedestrian and non-pedestrian characteristics. Therefore, the larger the difference between S_P and S_N , the easier it is distinguish between the general pedestrian and non-pedestrian characteristics, which is the more advantageous to detect pedestrians. On the other hand, if the variance value of the pedestrian score and the non-pedestrian score becomes larger, it is difficult to separate the pedestrian and non-pedestrian characteristics. Figure 3 shows changes in pedestrian detection rates of the pedestrian classification according to changes of score variance.

In graphs of Figure 3, S_P and S_N values are 6 and 4, respectively. Under the assumption that pedestrians are recognized based on the red solid lines, the detection rate is 100% in Figure 3(a), but the rate is 28.5% in Figure 3(b). Therefore, in order to train GA HOG model to have good performance, it is advantageous to reflect the variance of the pedestrian score and the non-pedestrian score in the evaluation function. Thus, we derived the fitness function to evaluate the GA HOG model as shown in Eq. (7).

$$Fitness = sw_1 \frac{S_P}{S_N} + w_2 (S_P - S_N) - w_3 (v_P + v_N), \quad (7a)$$

$$\begin{aligned} \text{If } (S_P < Threshold) \quad & s = 0, \\ \text{else} \quad & s = 1, \end{aligned} \quad (7b)$$

where w_1 , w_2 and w_3 represent weights, v_P and v_N represent variance of scores for pedestrian images and non-pedestrian images, respectively. In Eq. (7), we can note that $S_P - S_N$ value is applied to the fitness function because the larger the difference between S_P and S_N , the better the pedestrian model. In addition, $v_P + v_N$ is added because the model having smaller variance is advantageous to distinguish between the pedestrian and non-pedestrian images as explained above. We designed the fitness function to have the term S_P / S_N , the ratio of the score on the positive data to the score on the negative data, because it is another representation of characteristic difference between positive data and negative data to the model.

3.2 Learning of the Model by using GP

The overall flow of GP algorithm [13] is similar to GA, but the structure of genes is different from each other. While GA has a fixed structure due to its bit string or real-number string, GP has a variable structure as the genes are expressed in a tree structure. Since the genetic structure of GP is variable, it has been widely applied to practical optimization such as searching for complex nonlinear functions or designing the system model itself.

$$Wf1 = \alpha \times Tree_0 + (1 - \alpha) \times Tree_1, \quad (8a)$$

$$Wf2 = (1 - \alpha) \times Tree_0 + \alpha \times Tree_1. \quad (8b)$$

The cell score consists of average value of angle scores corresponding to the scores for each angle in Eq. (2a). Since angle score is a score for each angle, and we divide the angle by 20° in this paper, there exist 18 angle scores for each image. In Eq. (2b), the average value of the angle scores is obtained to calculate the cell score. In this case, the weights of all angle scores are same. However, there might be specific angle score that can well fit the general pedestrian characteristics.

We can train cell score function of Eq. (2b) using GP to the direction of increasing the weight for this type of angle score. The number of terminals used in cell score learning is 19 in total, including 18 angle score values from angle score 0° to angle score 340° and any constant values from 0 to 1. In this paper, GP functions consist of 11 items, which are +, |-, *, /, |sin|, |cos|, avg, Wf1, Wf2, min, and max. The terminal and function of GP are summarized in Table 1.

Through the Gaussian scoring of INRIA person dataset and

Table 1. Configuration of GP terminal and function

Node	Arity	Description
R	0	Arbitrary values ranging from 0 to 1
angle score _{0~340}	0	Score values of each angle
Sin	1	Absolute value of Sin function
Cos	1	Absolute value of Cos function
+	2	Sum of two channels
-	2	Absolute value of difference between two channels
*	2	Product of two channels
/	2	Division of two channels
Avg	2	Average of two channels
Wf1	2	Weighted sum of two channels
Wf2	2	Weighted sum of two channels
Max	3	Maximum value among three channels
Min	3	Minimum value among three channels

Figure 4. Angle score calculation process.

GA HOG learning model introduced for learning the score, the angle score is obtained as shown in Figure 4, and it is utilized as a GP terminal.

Based on the angle score value obtained as in Figure 4, a GP tree is configured to obtain the final score. In order to evaluate the fitness of the GP tree, the average score S_P^{GP} of positive image through GP model and the average score S_N^{GP} of negative image are calculated. The GP explores the tree with the largest difference between S_P^{GP} and S_N^{GP} . The calculation process of S_P^{GP} and S_N^{GP} is shown in Figure 5, and the equation is shown in Eq. (9).

$$S_P^{GP} = \frac{1}{N^P} \sum_{i=1}^{N^P} GP\ Score_i(angle\ score), \quad (9a)$$

Figure 5. GP score average calculation process.

$$S_N^{GP} = \frac{1}{N^N} \sum_{i=1}^{N^N} GP\ Score_i(angle\ score). \quad (9b)$$

GP fitness is similar to the fitness of GA HOG model learning. As in the GA model, the larger the difference between S_P^{GP} and S_N^{GP} and the smaller the variance of scores are, the easier it is distinguish between the pedestrian and non-pedestrian characteristics. Thus, we designed the fitness function of GP model to reflect the difference and the variance of the average scores. Through the Gaussian scoring of an input image and the learned GA HOG model, the angle score is obtained, and the final score is calculated by using it as an input of the learned GP scoring. The final decision whether the input image is a pedestrian image or not depends on the threshold. Thus, the performance of pedestrian detection is affected by the threshold settings. Therefore, we propose a method for setting appropriate threshold values as shown in Figure 6 and Eq. (10).

$$P_d = s_P - \sqrt{v_P}, \quad (10a)$$

$$N_u = s_N + \sqrt{v_N}, \quad (10b)$$

$$d = P_d - N_u, \quad (10c)$$

$$T = P_d - d \cdot \frac{\sqrt{v_P}}{\sqrt{v_P} + \sqrt{v_N}}. \quad (10d)$$

P_d and N_u represents the lower positive and upper negative reference, respectively. These are obtained by subtracting the standard deviation from the average score. The difference between P_d and N_u is represented by d , which can be a measure for evaluating how good classifier is generated. The threshold can be raised or lowered by the standard deviation value of positive score and negative score from the median value. This means that data with larger standard deviation has wider score width, and therefore the threshold T is adjusted accordingly.

Figure 6. Threshold setting.

Table 2. Results division table

		Predicted	
		Yes	No
Actual	Yes	True Positive	False Negative
	No	False Negative	True Negative

4. Experiments

In order to verify the performance of the scoring learning technique using GP and pedestrian HOG model learning using GA and Gaussian scoring proposed in this paper, the pedestrian detection test was performed with the testing image of INRIA person dataset. We used ACC (Accuracy), CSI (Critical Success Index) and PAG (Post Agreement) as the performance indexes for the experiment of pedestrian image detection. Table 2 shows the result division table for performance index parameters, and the performance indexes are calculated with the parameters as shown in Eq. (11).

$$ACC = \frac{TP + TN}{TP + FP + TN + FN}, \quad (11a)$$

$$PAG = \frac{TP}{TP + FP}, \quad (11b)$$

$$CSI = \frac{TP}{TP + FP + FN}. \quad (11c)$$

We verify the performance of pedestrian detection through GA HOG model and GP scoring and compare the performance with a pedestrian classifier using SVM of HOG features. The parameters used in GA learning are summarized in Table 3, and Figure 7 shows the average score of the best GA HOG model.

We experimented GP learning with the parameters given in Table 4, and the result of best GP are shown in Figure 8. Table 5 shows a summary of the analysis on the performance comparison of the pedestrian detection using the conventional

Table 3. GA parameter values

Parameter	Value
Population size	50
Max generation	100
Crossover rate	0.9
Mutation rate	0.1
Select method	Tournament (size= 7)

Figure 7. Best GA model.

Figure 8. Best GP model.

SVM and the algorithm proposed in this paper.

In Table 6, GS represents the Gaussian scoring, and GU means the Gaussian lookup table. The detection accuracy of GS and GA model was about 4% better than that of SVM, and the performance of GS+GA+GP model showed about 9% better in accuracy compared to SVM. In addition, the execution time of the proposed methods was measured, and the results of the time taken to execute a single input image with a resolution of 640×480 are summarized in Table 6. All the algorithms proposed in this paper are much better than SVM in terms of the

Table 4. GP parameter values

Parameter	Value
Population size	1, 000
Max generation	200
Crossover rate	0.9
Mutation rate	0.1
Select method	Tournament (size= 7)
Initial depth	6-8
Max depth	17
Initial population	Half and half

Table 5. Experimental results of pedestrian detection performance

	Efficiency index		
	ACC	PAG	CSI
SVM	0.847	0.801	0.724
GS	0.743	0.752	0.592
GS + GA	0.890	0.889	0.802
GS + GA + GP	0.927	0.925	0.871

Table 6. Comparison of execution time

	Execution time (FPS)
GS + GA	44 ms
GS + GA + GP	53 ms
SVM	148 ms
GU + GA	19 ms
GU + GA + GP	28 ms

execution time, and the execution time of the algorithm using the Gaussian lookup table proposed in this paper was about 2.3 times faster than the conventional GS.

5. Conclusion

This paper proposed a Gaussian Scoring method for matching images and GA/GP based learning to establish a reference model for pedestrian detection.

In the conventional approaches using HOG feature for matching, the HOG feature map consists of vectors representing the magnitude and angle of gradient for each pixel, and a reference model is trained with learning algorithms such as SVM and AdaBoost cascade method. In this paper, we consider the HOG value separately for each divided angle and evaluate the

degree of HOG feature coincidence using the GS. By evaluating the HOG feature for each divided angle, it allowed us to visualize the features and make it easy to analyze it. This has a major advantage over the conventional HOG matching technique that cannot ensure the visualized representation due to large dimension of the HOG vector. In order to solve the problem of processing time to calculate the Gaussian score for all cells of the input images, we proposed a method to improve the processing time by using the Gaussian lookup table. In this paper, we also proposed GA and GP based training methods for the reference model. The GA and GP are used to search the best parameters of the gene and nonlinear function representing feature map of pedestrian model, respectively.

We performed experiments to verify the performance of proposed method in terms of accuracy and processing time with INRIA person dataset. The experimental results showed us that the accuracies of pedestrian detection using GA model and GP model were about 4% and 9% higher, respectively than the SVM method. In terms of processing time, the results showed us that the GA model using Gaussian lookup table has the best performance and 7.8 times faster than the SVM model. For future works, it is challenged to devise a model and training algorithm for recognizing the pedestrian even from input images where various size of pedestrian is appeared or a part of pedestrian is covered by something.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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