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A New Vehicle Detection Method based on Color Integral Histogram

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Abstract

In this paper, a novel vehicle detection algorithm is proposed that utilizes the color histogram of the image. The color histogram is used to search the image for regions with shadow, block symmetry, and block non-homogeneity, thereby detecting the vehicle region. First, an integral histogram of the input image is computed to decrease the amount of required computation time for the block color histograms. Then, shadow detection is performed and the block symmetry and block non-homogeneity are checked in a cascade manner to detect the vehicle in the image. Finally, the proposed scheme is applied to both still images taken in a parking lot and an on-road video sequence to demonstrate its effectiveness.

Key Words : Vehicle Detection, Symmetry Detection, Integral Histogram

1. Introduction

Since the early 90's, the paradigm of the vehicle safety system has moved from passive safety to active safety. The passive safety system includes safety-belts and air bags, while the active safety system includes an adaptive cruise control system, a lane departure warning system, and etc. Since the late 90's [1], these active safety systems have begun to be implemented into commercial cars. Thus, the detection of on-road preceding or nearby vehicles has become an essential yet challenging problem and a variety of sensors have been employed to solve the problem. Cameras are certainly among them and much research has been conducted.

The most difficult problem in the visual vehicle detection based on cameras is to find vehicles in a given image or image sequence. One popular approach is to use the symmetry of the vehicle, in order to detect a vehicle in an image. This approach uses the fact that the images of vehicles are symmetric in the horizontal direction when observed from the front or the rear. A. Kuehnle and T. Zielke *et al.* utilized symmetry to detect the vehicles in [2] and [3], respectively. In these papers, the average intensity computed over blocks was used to detect the symmetric parts of the image. However, the block intensity lost information from the image and sometimes detected wrong vehicles. A. Bensrhair et al. and G. Alessandretti *et al.* also adopted symmetry in [4] and [5], respectively. Unlike in [2] and [3], edge symmetry was introduced instead of intensity symmetry to detect the symmetric region. When the background is complex, edge symmetry also has problems.

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Another popular approach in vehicle detection in images is finding the shadow beneath the vehicle. This approach was initially discussed by Mori and Charkai [5] and used by Dickmanns *et al.* [6], Tzomakas *et al.*[7], and Alessandretti [8]. This approach shows relatively good detection performance, but it has limitations when the shadow is cast adjacent to the vehicle. Several other methods regarding visual vehicle detection were proposed, including methods that use gabor filtering [9], Haar-like features [10], and histograms [11].

In this paper, a new vehicle detection algorithm is proposed that is based on a color integral histogram. This method combines symmetry and the shadow beneath the car, in order to detect the vehicle. Unlike previous methods in which either the block intensity or the edge was used to detect symmetry, a color histogram is employed in the proposed method. Symmetry that is based on color is more robust than symmetry that is based on an edge, since an edge is susceptible to noise. Further, instead of searching the image for symmetric color parts on a pixel basis, the candidate region is decomposed into blocks and a search for symmetric parts on a block basis using the color histogram is utilized. Unlike the simple block intensity, the color histogram maintains the detailed color information of the blocks. The limitation of the color histogram method is its high computational cost. To decrease the amount of computation time for the block color histograms, the color integral histogram is adopted [12]. Using the color integral image, the color histograms of a number of blocks can easily be computed for each instant, enabling a real time application.

The paper is organized as follows. In Section 2, the integral histogram is explained and expanded to a multi-channel case. In Section 3, a new vehicle detection algorithm is proposed by combining shadow detection, symmetry check, and the non-homogeneity check. In Section 4, the proposed method is applied to still images and video sequences and the experimental results are presented. Finally, some conclusions are drawn in Section 5.

2. Histogram for Multi-Channel

2.1 Integral Image

The integral image was introduced by Viola *et al.* [13] and used for various Haar-like features [13, 14] and fast histogram extraction [12]. Assume the parameter of interest in the coordinate system (x,y) is given by $f(x,y)$.The parameter of interest could be intensity, color components, etc. The integral image sums up all of the $f(x,y)$s over the rectangular region which contains the origin and (x,y). That is, if the image is $N_1 \times N_2$, the integral value at position (x,y) is represented by

$$F(x,y) = \sum_{i=1}^{x}\sum_{j=1}^{y} f(x,y), \tag{1}$$

where the range is $1 \leq x \leq N_1$ and $1 \leq y \leq N_2$. Here, (1) can be rewritten in a recursive manner into

$$\begin{aligned} F(x,y) &= f(x,y) + F(x-1,y) \\ &+ F(x,y-1) - F(x-1,y-1)' \end{aligned} \tag{2}$$

by defining

$$F(x,y) = 0 \text{ if } x=0 \text{ or } y=0 \tag{3}$$

Provided the integral image, the parameters over the block

$$F_B(x_1,y_1,x_2,y_2) = \sum_{i=x_1+1}^{x_2} \sum_{j=y_1+1}^{y_2} f(i,j) \tag{4}$$

can be computed by

$$\begin{aligned} F_B(x_1,y_1,x_2,y_2) &= F(x_1,y_1) - F(x_1,y_2) \\ &- F(x_2,y_1) + F(x_2+y_2)' \end{aligned} \tag{5}$$

as shown in Fig. 1.

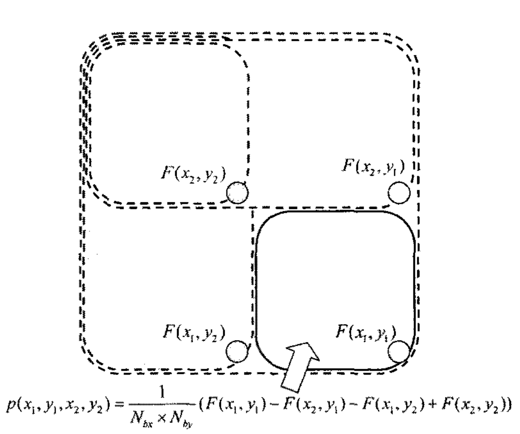

Fig. 1. Integral Algorithm Blocks.

Further, the block parameter is normalized by the size of the block, as in

$$\overline{F_B}(x_1,y_1,x_2,y_2) = \frac{F_B(x_1,y_1,x_2,y_2)}{(x_2-x_1)\times(y_2-y_1)}, \tag{6}$$

to eliminate the effect of the block size on the block parameter. By plugging (5) into (6), (7) is obtained.

$$\begin{aligned} &\overline{F_B}(x_1,y_1,x_2,y_2) = \\ &\frac{F(x_1,y_1) - F(x_1,y_2) - F(x_2,y_1) + F(x_2,y_2)}{(x_2-x_1)\times(y_2-y_1)}. \end{aligned} \tag{7}$$

2.2 Integral Histogram

An integral histogram is a special version of the integral image. The histogram is used as the parameter $f(x,y)$ of the integral image. Assume N_{bin} bins in the histogram and let the upper and lower boundaries of the kth bin be denoted as B^k_{upper} and B^k_{lower}, respectively, as shown in Fig. 2.

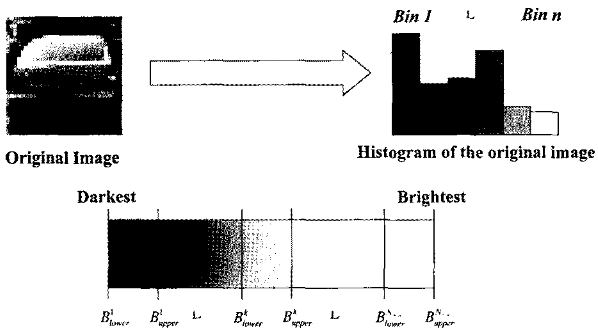

Fig. 2. Bins defined for histogram.

The function $b: R^2 \to \{1,2,\cdots,N_{bin}\}$ associates the pixel at (x,y) to the index $b(x,y)$ of its bin in the quantized feature space of the image $I(x,y)$, as in Fig. 2. Then, the k th bin $H_B(x_1,y_1,x_2,y_2)$ of the block histogram

$$\begin{aligned} &\boldsymbol{H_B}(x_1,y_1,x_2,y_2) = \\ &[H_B(x_1,y_1,x_2,y_2,1),\cdots,H_B(x_1,y_1,x_2,y_2,N_{bin})] \end{aligned} \tag{8}$$

is represented by

$$H_B(x_1,y_1,x_2,y_2,k) = \sum_{i=x_1}^{x_2}\sum_{j=y_1}^{y_2} \delta(b(i,j)-k), \tag{9}$$

where $\delta(\cdot)$ is the Kronecker delta function. As in the integral image, if the integral histogram is defined by

$$H(x,y,k) = \sum_{i=1}^{x}\sum_{j=1}^{y} \delta(b(i,j)-k), \tag{10}$$

then $H_B(x_1,y_1,x_2,y_2,k)$ is computed by

$$\begin{aligned} &H_B(x_1,y_1,x_2,y_2,k) = \\ &\quad H(x_1,y_1,k) - H(x_1,y_2,k) \\ &\quad - H(x_2,y_1,k) + H(x_2,y_2,k) \end{aligned} \tag{11}$$

and the normalized k th bin $\overline{H_B}(x_1,y_1,x_2,y_2,k)$ is computed by

$$\overline{H_B}(x_1,y_1,x_2,y_2,k) = \frac{H_B(x_1,y_1,x_2,y_2,k)}{(x_2-x_1)\times(y_2-y_1)}. \quad (12)$$

The normalized block histogram becomes

$$\overline{\boldsymbol{H}_B}(x_1,y_1,x_2,y_2) = [\overline{H_B}(x_1,y_1,x_2,y_2,1),\cdots,\overline{H_B}(x_1,y_1,x_2,y_2,N_{bin})]^{\cdot} \quad (13)$$

In the case of the multi channel color space, the normalized block histogram is represented as

$$\overline{\boldsymbol{H}_B}(x_1,y_1,x_2,y_2) = [\overline{H_B^1}(x_1,y_1,x_2,y_2,1),\cdots,\overline{H_B^{N_c}}(x_1,y_1,x_2,y_2,N_{bin})] \quad (14)$$

$$\overline{\boldsymbol{H}_B}(x_1,y_1,x_2,y_2) = [\overline{H_B}(x_1,y_1,x_2,y_2,1),\cdots,\overline{H_B}(x_1,y_1,x_2,y_2,N_{bin})]^{\cdot} \quad (15)$$

where c is the channel index for the color image. For example, using the CG space, N_c is 2 and if RGB, HSI or Lab space is used, then is 3.

3. New Vehicle Detection Algorithm based on Color Histogram

In this section, a new vehicle detection method is proposed that is based on a color histogram. This method combines three features including the *shadow* cast beneath the vehicle, the *color symmetry* of the vehicle, and *non-homogeneity* of the vehicles. First, we use the shadows beneath vehicles since every vehicle has a *shadow* between the ground and the bottom of the vehicle. The second feature is the *color symmetry* of the vehicle. When viewed from the rear or the front, the symmetric shape of the vehicle includes the wheels, trunk, and backlights. The third feature is *non-homogeneity* of the vehicles. Even though vehicles are a single color in general, the rear images are composed of different colors due to the tires and backlights. Thus, some candidates can be eliminated, which have a single color over the whole area. The RGB color coordinate system is used. This means that the number of channels N_c is 3. The first bin is the darkest bin and N_{bin} th bin is the brightest bin in the histogram.

3.1 Shadow Detection

In general, shadow areas in the image are concentrated in the dark bin of the block histogram. If the value of darkest bin exceeds a certain threshold, then the area is classified as a shadow region. First, the lower quarter of the candidate region is chosen and marked as "shadow region," as indicated in Fig. 3. We denote the region by $B_s(x_1^{B_s},y_1^{B_s},x_2^{B_s},y_2^{B_s})$. Then, the block histogram of $B_s(x_1^{B_s},y_1^{B_s},x_2^{B_s},y_2^{B_s})$ is computed and it is determined whether the block belongs to the shadow or not by

$$\overline{H_s^c}(x_1^{B_s},y_1^{B_s},x_2^{B_s},y_2^{B_s}) \le \delta_s \text{ for all } 1 \le c \le N_c \quad (16)$$

where δ_s is the threshold for shadow.

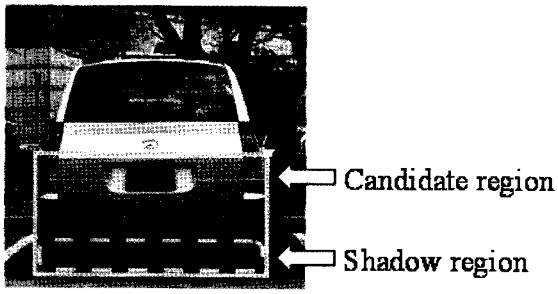

Fig. 3. Shadow Region in a Vehicle Candidate.

3.2 Histogram Symmetry Detection

Vehicles are symmetric with respect to the horizontal axis when viewed from the rear or from the front. The symmetric area is searched for on a block basis instead of a pixel basis. The pixel-based search is not only computationally expensive but also inaccurate. Thus, the candidate region is decomposed into $2N\times M$ blocks $B_{i,j}$, where i is the horizontal position in the range $1 \le i \le 2N$ and j is the vertical position in the range $1 \le j \le M$, as shown in Fig. 4.

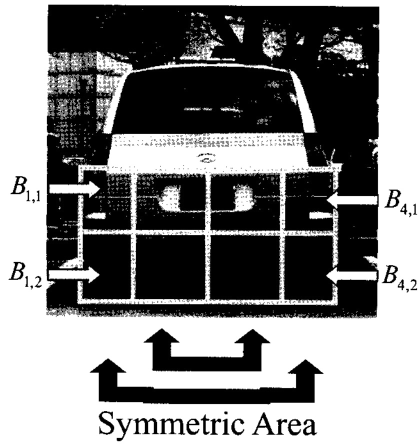

Fig. 4. Blocks in the Candidate Region for Symmetry Check and Non-Homogenity check

Since the left half and the right half of the vehicle, with respect to the centerline, should have the same histogram, the block $B_{i,j}$ will have a similar histogram to block $B_{2N+1-i,j}$. The symmetry between two blocks can be easily determined by using the norm of two histograms. If

$$\| H_{B_{i,j}} - H_{B_{2N+1-i,j}} \| \le \delta_s, \quad (17)$$

is satisfied, then two blocks are symmetric, where δ_s is the threshold. Since the vehicle candidate region is composed of $2N\times M$ blocks, the symmetry of the candidate region is tested by the following two approaches:

1) Sum approach

$$\sum_{i=1}^{N}\sum_{j=1}^{M} \| H_{B_{i,j}} - H_{B_{2N+1-i,j}} \| \le \delta_{sum}, \quad (18)$$

2) Probabilistic approach

$$\prod_{i=1}^{N}\prod_{j=1}^{M} N(H_{B_{i,j}} - H_{B_{2,N+1-i,j}};0,\sigma_X^2) \geq \delta_{prod} \quad (19)$$

where δ_{sum} is the threshold for the sum approach (18); $N(\cdot)$ denotes a normal distribution and σ_X is its variance. δ_{prod} is the threshold of the probability for the probabilistic approach (19).

3.3 Non-homogenity Check

If only the color histogram symmetry is used for vehicle detection, a single color region such as a black wall will be selected as a vehicle candidate. In order to eliminate the single color non-vehicle candidates, the histogram of the blocks in the region is computed and removed, if all of the blocks in the region have the same histogram. Otherwise, if one block histogram is different from the other blocks, the candidate region is not homogeneous and is kept. In the non-homogenity check, only the left (or right) half of the region can be tested, since the candidate regions have already passed the symmetry check. The non-homogenity check is formulated as

$$\begin{aligned} &\| \boldsymbol{H}_{B_{i1,j1}} - \boldsymbol{H}_{B_{i2,j2}} \| \geq \delta_{\text{homo}} \\ &1 \leq i_1, i_2 \leq N, 1 \leq j_1, j_2 \leq M, (i_1, j_1) \neq M(i_2, j_2) \end{aligned} \quad (20)$$

If (20) is not satisfied, the area is homogeneous and the area could not be vehicles. If (20) holds, this area is non-homogeneous and the region is selected as a vehicle candidate.

3.4 Finding the Candidate

To detect vehicles in an image, the whole image must be searched with a variety of window sizes for the vehicle candidates. The strategy is simple but requires much computation time. To avoid high computational cost, initially the integral histogram of the image is built. Then, the window size is initialized to $W \times H$ and a search for the candidate region begins by shifting the window. After the completion of each scan, the window size is increased by 1.2 times and the procedure is repeated. The vehicle detection algorithm is summarized in Table 1.

4. Experimental Result

In this section, experiments are performed to demonstrate the effectiveness of the proposed method. In the experiments, two data sets are used. The first data set is composed of still images that were taken in a parking lot by a digital camera. The second data set is composed of two video sequences that were taken on different roads.

The test was performed on a PC with Intel Pentium IV 2.6 GHz Processor and Windows XP. The data set is composed of images that were taken in the parking lot of Yonsei University. Pictures were collected only from the rear to simulate the rear side of vehicles on actual roads.

Table 1. The proposed vehicle detection algorithm

```
Generate Integral Histogram.
Set the window size to
For predetermined iterations,
  For entire image area (by shifting the window),
    decompose the window region into 2N ×M
    blocks.
    If shadow constraint (16) and non-homogeneous
    color constraint (20) is satisfied, calculate symmetry.
    If the block satisfies the symmetry constraint
    (18) or (19) ,
      put in to the candidate set
    else
      The area is not symmetric.
    End if
  End for
  Increase the window size by 1.2 times
End
For all the candidates,
  From the candidate set c, find the candidates which
  are not included by a larger candidate.
  Store in candidate set
End
```

Table 2. Parameters used in the experiment.

Parameter Name	Value
Bin Size	6
Block Dimension	6 × 2
Shadow Percentage	18.75%
Minimum Distance	1

The images are resized to 160x120. Windows with 9 different sizes were used. The height and width were increased from 24x12 to 124x62, by multiplying the window size by 1.2 each time. The experiments were performed with 156 images, which included 353 vehicles. The parameters used in the experiments are given in Table 2.

In the experiments, two conditions and were examined for the symmetry check. In the sum approach of , the true detection rate is 84.33% and the false detection rate is about 7.12%. On the other hand, in the probabilistic approach of , the true detection rate is 80.63% and the false detection rate is about 9.7%. The experimentation results are shown in Fig. 5 and summarized in Table 3.

It can be seen that the sum approach shows slightly better performance than the probabilistic approach . The false detection is mainly due to (1) the shadows cast from the nearby trees and vehicle wheels and (2) the unexpected symmetry made by two identical vehicles parked consecutively. Further, the time consumption to compute the algorithm was investigated.

Table 3. Parameters used in the Expariment.

	Sum Method (18)		Probablistic Method (19)	
	# of objects	%	# of objects	%
Number of Vehicles	351	100%	351	100%
True detection	295	84.33%	283	80.63%
False Detection	25	7.12%	34	9.69%

Fig. 5. Images taken from parking lot of Yonsei Univ. and the detection resuls of the proposed method.

5. Conclusion

In this paper, a vehicle detection method has been introduced that is based on an integral histogram. The proposed method consists of shadow detection, symmetry detection, and homogeneity elimination. Compared to conventional methods, which were based on edge symmetry and shadow, the proposed method is more robust and can detect vehicles in more complex environments. In addition, homogeneity was combined to improve the detection rate. Finally, the performance of the proposed method was demonstrated by applying it to both still images and video sequences. Future work will combine the developed vehicle detection method with the tracking method such as the Mean Shift [15] or Particle filter [16] and involve installation into the experimental vehicle.

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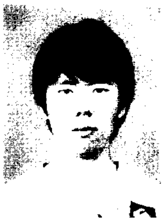

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