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GRADIENT-BASED VEHICLE DETECTION USING A TWO-SEGMENT DETECTION FIELD

Summary. This paper presents a method of vehicle detection using the conversion of images from a source image sequence into binary target images. This conversion is performed on the basis of small image gradients. The location of binary values after conversion is in accordance with the edges of the converted image. For all processed images, a detection field is defined, which is composed of two segments. In the area of each segment, the sum of the edge values is calculated. On the basis of the calculated sums within the segments, an adjusted sum of the edge values is established, which allows for the determination of the state of the detection field. Vehicle detection is carried out by recognition of distinctive changes in the state of the detection field caused by the passing vehicle. Experimental results are provided.
Keywords: vehicle detection; image conversion; detection field

1. INTRODUCTION

Contemporary road traffic systems use image data for the determination of traffic parameters and traffic surveillance. Processing and analysis of image data allow for vehicle detection. In [1], a feature-based tracking system is presented. This system employs corner features for vehicle detection. In [3], static and dynamic analyses of segmented images is

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applied. Static analysis is used for one processed image, while dynamic analysis involves the comparison of a current image and a previous image. In [6], vehicle tracking at intersections with the use of a stochastic algorithm is presented. The applied algorithm assumes the division of an image into square blocks. In [4], vehicles are separated from the background by segmentation involving the determination of the difference between the current image and the background. Furthermore, in [5], the difference between the current image and the background is calculated. In the next stages, lane-dividing lines are determined. In [2], a rule-based method is applied. In this approach, high-level and low-level processing modules are applied. In [7], time-spatial images are applied for vehicle detection. The time-spatial images are obtained from the virtual lines set in the frames of the input video sequence.

The proposed method of vehicle detection uses the gradient-based conversion of images from the source image sequence into binary target images. The applied detection field is composed of two segments. Analysing changes in average adjusted sums within the detection field allows for vehicle detection. The proposed method of vehicle detection is intended for road traffic systems using image data.

2. ALGORITHM OF VEHICLE DETECTION

Gradient-based vehicle detection using the two-segment detection field is carried out on the basis of the video stream obtained from a camera mounted over a road. Consecutive frames taken from the video stream create a source image sequence. Images from the source image sequence are processed separately, one by one. The processing of each individual image from the source image sequence consists of the following stages:

- conversion into a binary target image
- definition of a two-segment detection field
- summation of the edge values within the segments of the detection field
- determination of the adjusted sum within the detection field
- description of the state of the detection field

Individual images differ in terms of the number of objects and object locations. The properties and the quality of the images in the source image sequence depend on the parameters of the applied camera. The time of day and changeable weather conditions can also influence the features of images in the input image sequence.

3. CONVERSION INTO BINARY TARGET IMAGES

Images of the source image sequence are converted from the bitmap format into the binary target images. Conversion is carried out by analysis of small gradients in the images of the source image sequence. The source image sequence consists of greyscale images of size M xN pixels. The coordinate of columns is denoted by m and the coordinate of rows is denoted by n. The position of each image in the source image sequence points to the integer number denoted by i.

The results of conversion are written into the binary matrix $\mathbf{B} = [b_{n,m}]$ of the dimensions N x M. All elements of matrix $\mathbf{B}$ are set to 0 at the beginning of the conversion of each source image. For all pixels of the converted source image, except border pixels, the magnitude of the small gradients is calculated for the current pixel at coordinates (m, n) relative to the pixels at coordinates (m - 1, n), (m, n - 1), (m -1, n - 1), (m + 1, n - 1) in rows, columns and diagonal directions, respectively. If the obtained value of the magnitude is greater than the preset threshold value:

$$|G(m,n)| > T_G , \tag{1}$$

the element of matrix **B**, corresponding with the current pixel at coordinates (m, n), is set to 1

$$b_{n,m} = 1 . \tag{2}$$

The elements of matrix **B**, corresponding to the pixels at coordinates (m - 1, n), (m, n - 1), (m - 1, n -1), (m + 1, n - 1), are also appropriately set to 1 for gradient magnitudes greater than the threshold value.

Matrix **B** contains logical values obtained as a result of the conversion of the source image into the binary target image. The location of values equal to 1 in matrix **B** corresponds to edges in the source image; thus, these values are called edge values.

4. DEFINITION OF THE DETECTION FIELD

A detection field is defined for each considered road lane. The rectangular detection field is specified by coordinates describing the vertices: the left column m_L, the right column m_R, the upper row n_U and the bottom row n_B. The detection field covers the road lane in terms of width, while it is small in height, such that the changes in the features of the detection field could involve two-state properties. Samples of the source images, which show the vehicle passing the area of the detection field, are shown in Fig. 1 (the detection field is marked by black rectangles).

Fig. 1. Samples of the source images within the detection field

The detection field is composed of two segments, which partially cover each other. The first segment, denoted by A, is specified by coordinates describing the vertices: the left column $m_{(A)L}$, the right column $m_{(A)R}$, the upper row $n_{(A)U}$ and the bottom row $n_{(A)B}$. Similarly, coordinates $m_{(B)L}$, $m_{(B)R}$, $n_{(B)U}$, $n_{(B)U}$ describe the second segment denoted by B.

Both segments of the detection field are the same in width and height. The height of the segments is the same as the height of the detection field. The width of the segments is smaller than the width of the detection field and can be expressed by the equation:

$$w = w_{(A)} = w_{(B)} = \text{ent}\left[(m_R - m_L + 1) \cdot d\right], \tag{3}$$

where:
ent – signifies the integer part of the expression in brackets
d – denotes the constant of proportionality, which is less than 1

The samples of the source images with the marked segment *A* and segment *B* are shown in Fig. 2 and Fig. 3, respectively.

Fig. 2. Samples of the source images within segment *A*

Fig. 3. Samples of the source images within segment *B*

The segments of the detection field are of the same size and displaced in parallel, relative to each other inside of the detection field.

5. SUMMATION OF THE EDGE VALUES

The arithmetic sums of the edge values are calculated within both segments of the detection field for the current image *i*. These sums of the edge values, calculated in the areas of segment *A* and segment *B*, are given respectively by the following equations:

$$S_{(A)i} = \sum_{n=n_{(A)U}}^{n_{(A)B}} \sum_{m=m_{(A)L}}^{m_{(A)R}} b_{n,m} : b_{n,m} = 1 ,$$
$$S_{(B)i} = \sum_{n=n_{(B)U}}^{n_{(B)B}} \sum_{m=m_{(B)L}}^{m_{(B)R}} b_{n,m} : b_{n,m} = 1 . \tag{4}$$

Samples of target images, with the marked segments *A* and *B*, are shown Fig. 4 and Fig. 5, respectively. The black points signify the edge values, while the segments of the detection field are marked by black rectangles.

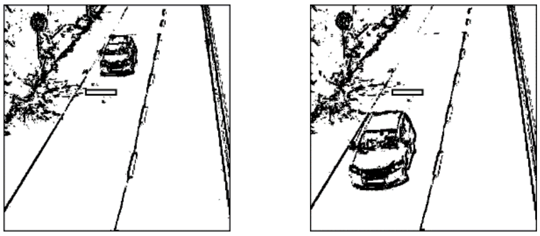

Fig. 4. Samples of the target images within segment *A*

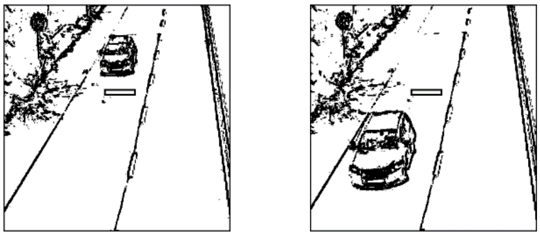

Fig. 5. Samples of the target images within segment *B*

The maximum value of the arithmetic sums of the edge values within segments *A* and *B* is determined according to the expression:

$$S_{(\max)i} = \max\left[S_{(A)}, S_{(B)}\right]. \tag{5}$$

On the basis of the maximum arithmetic sums of the edge values, the adjusted sum of the edge values in the area of the detection field is calculated using the equation:

$$S_{(\mathrm{adj})\,i} = S_{(\max)i}\,\frac{(m_R - m_L + 1)}{w}. \tag{6}$$

Samples of the target images, with the edge values signified by black points and the detection field marked by black rectangles, are shown in Fig. 6.

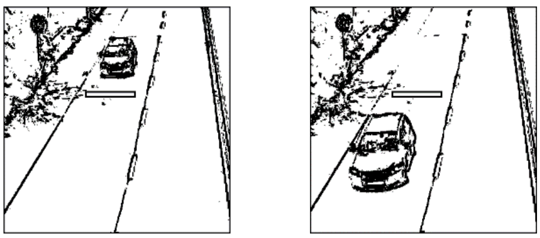

Fig. 6. Samples of the target images in the detection field

Considering the current image *i* and *P* previous images, the average adjusted sum of the edge values within the detection field is determined for the current image *i* as follows:

$$R_{(\mathrm{adj})\,i} = \frac{1}{P+1}\sum_{j=i-P}^{i} S_{(\mathrm{adj})\,j}\,. \tag{7}$$

The determination of the average adjusted sums of the edge values in the area of the detection field corresponds to the low-pass filtering operation carried out on the adjusted sums of the edge values.

6. VEHICLE DETECTION

For the current source image, following conversion into the target image, the arithmetic sums of the edge values are calculated: the sums within the segments *A* and *B*, the adjusted sum within the detection field and finally the average adjusted sum. The worked-out average adjusted sum is appropriate, compared to the preset threshold values, for determining the state of the detection field.

The state of the detection fields changes from “free detection field” to “occupied detection field” if the average adjusted sum of the edge values is greater than the preset threshold value for the detection field in the “occupied detection field” state:

$$R_{(\mathrm{adj})\,i} > T_O \,. \tag{8}$$

The return change from the “occupied detection field” state into the “free detection field” state occurs when the average adjusted sum of the edge values is less than the preset threshold value for the detection field in the “free detection field” state:

$$R_{(\mathrm{adj})\,i} < T_F \,. \tag{9}$$

The state of the detection field is determined by analysis of the average adjusted sums of the edge values in the area of the detection field for the consecutive images from the source image sequence. A vehicle driving into the detection field changes its state from the “free detection field” to the “occupied detection field” state. Next, after a period of time depending on the speed and length of the vehicle, the vehicle leaves the detection field and changes its state from “occupied detection field” to “free detection field”. Vehicle detection is carried out by the recognition of the sequence “free detection field-occupied detection field-free detection field” in the changes of the state of the detection field. The appearance of such changes in the state of the detection field indicates the passing vehicle.

7. RESULT OF EXPERIMENTS

Experiments have been carried out for one road lane in good weather conditions and different light conditions. Short source image sequences, presenting various traffic scenes, have been analysed. One camera of average quality has been applied. Traffic conditions were changeable without congestion.

The source images sequence is composed of greyscale images with a size of 384 x 384 pixels and an intensity resolution of 8 bits per pixel. The source images are signified by their ordinal numbers, while the size of the detection field is set to 80 x 5 pixels. The constant of proportionality is set at $d = 0.6$. The samples of the processed images are shown in Fig. 7. The source image is placed on the left side of the fig. and the target image is situated on the right side of the figure. The detection field is marked by black rectangles, while black points signify the edge values in the target images.

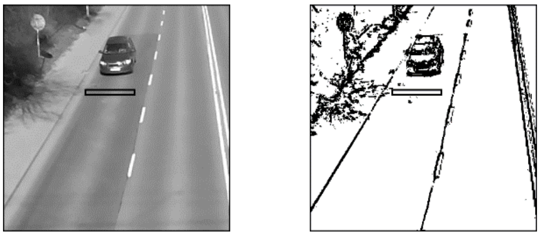

Fig. 7. Samples of the processed images

After conversion of the current source image *i* into the target image, the arithmetic sums of the edge values are calculated in the segments of the detection field. The changes of the arithmetic sum of the edge values in segments *A* and *B* are shown in Fig. 8 and Fig. 9, respectively.

The adjusted sum of the edge values is calculated on the basis of the sums of edge values in segments *A* and segment *B*. The changes in the adjusted sum of the edge values within the detection field are shown in Fig. 10.

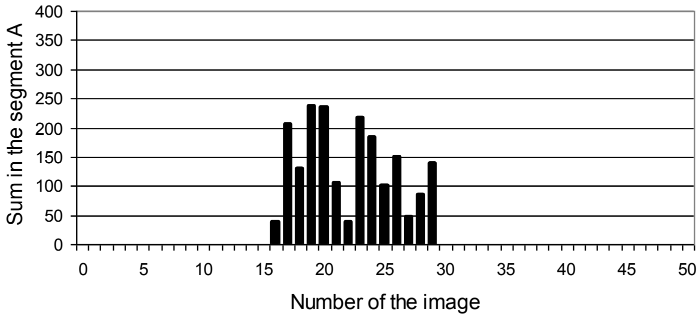

Fig. 8. Changes in the arithmetic sum of the edge values in segment *A*

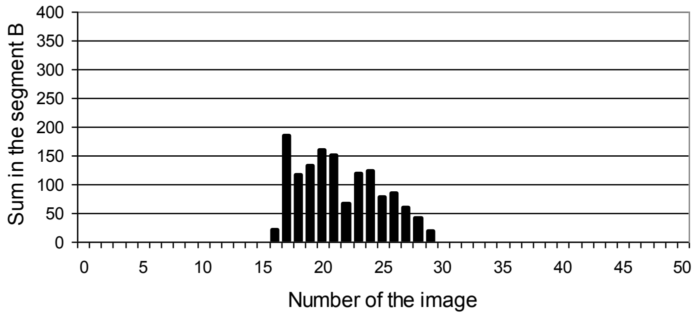

Fig. 9. Changes in the arithmetic sum of the edge values in segment *B*

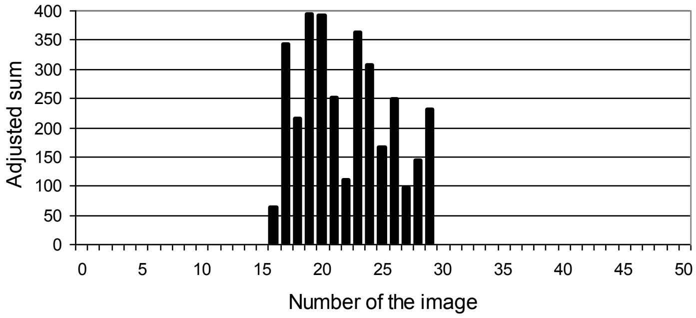

Fig. 10. Changes in the adjusted sum of the edge values within the detection field

On the basis of the adjusted sums of the edge values within the detection field, the average adjusted sums are determined. The number of the previous images is set at $P = 3$. The changes in the average adjusted sum of the edge values within the detection field are presented in Fig. 11.

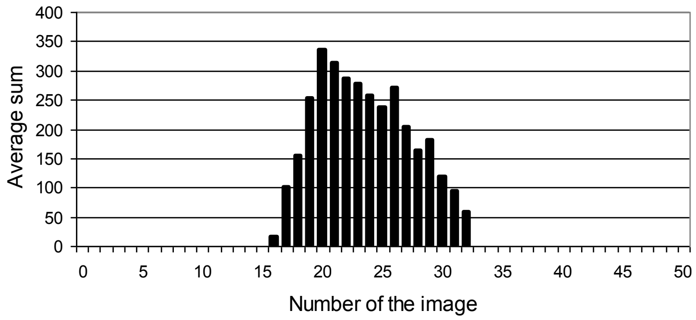

Fig. 11. Changes in the average adjusted sum of the edge values within the detection field

For the analysed source image sequence, the state of the detection field has been determined on the basis of the average adjusted sum of the edge values as follows:

- For images $i = 0$ to $i = 15$, the vehicle approached the detection field and the state of the detection field was “free detection field”
- For images $i = 15$, the vehicle drove partially into the detection field and the state of the detection field was still “free detection field”
- For images $i = 16$, the vehicle drove into the detection field and the state of the detection field changed to “occupied detection field”
- For images $i = 17$ to $i = 32$, the vehicle remained in the area of the detection field and the state of the detection field was “occupied detection field”
- For images $i = 33$, the vehicle drove out of the detection field and the state of the detection field changed to “free detection field”
- For images $i = 34$ to $i = 50$, the vehicle drove away from the detection field and the state of the detection field was “free detection field”

Calculation of the adjusted sums of the edge values causes an increase in the number of the edge values assigned to the detection field. Enlargement of the sum of the edge values facilitates the detection of vehicles, particularly vehicles whose depiction contains large surfaces without edges. Application of the two-segment detection field allows for detecting various types of vehicles: passenger cars, vans, trucks, buses, articulated lorries and motorcycles.

8. CONCLUSIONS

Vehicle detection can be performed on the basis of image gradients. The source images are converted into binary target images. This conversion is based on local gradients in the source images. Positions of the edge values in the target images are in accordance with the edges of objects contained in the source images. The main advantage of the proposed method lies in analysis of the state of the detection field, based simply on the sums of the edge values. The application of a detection field composed of two segments improved the effectiveness of vehicle detection and enhanced the response of the detection field in relation to the passing vehicle. Similar to other methods using image data, the presented method is not very resistant to changeable weather and light conditions. The proposed method of vehicle detection is intended for the detection of various types of vehicles, but not directly for vehicle classification.

Gradient-based vehicle detection using the two-segment detection field requires a small number of operations, as well as being simpler than the majority of the widely known methods. The detection of vehicles based on image gradients is fast and uncomplicated. The proposed method of vehicle detection is intended for road traffic systems, e.g., surveillance or measurement systems, for vehicle location and counting.

References

1. Coifman Benjamin, David Beymer, Philip McLauchlan, Jitendra Malik. 1998. "A real-time computer vision system for vehicle tracking and traffic surveillance." *Transportation Research Part C* 6(4): 271-288. DOI: 10.1016/s0968-090x(98)00019-9.
2. Cucchiara Rita, Piccardi Massimo, Mello Paola. 2000. "Image analysis and rule-based reasoning for a traffic monitoring system." *IEEE Transaction on Intelligent Transaction Systems*, 1(2): 119-130. DOI: 10.1109/6979.8809.69.
3. Fernandez-Caballero Antonio, Francisco J. Gomez, Juan Lopez-Lopez. 2008. "Road traffic monitoring by knowledge-driven static and dynamic image analysis." *Expert Systems with Applications* 35(3): 701-719. DOI: 10.1016/j.eswa.2007.07.017.
4. Gupte Surendra, Osama Masoud, Robert F.K. Martin, Nikolaos P. Papanikolopoulos. 2002. "Detection and classification of vehicles." *IEEE Transaction on Intelligent Transportation Systems* 3(1): 37-47. DOI: 10.1109/6979.994794.
5. Hsieh Jun Wei, Shih-Hao Yu, Jung-Sheng Chen, Wen-Fong Hu. 2006. "Automatic traffic surveillance system for vehicle tracking and classification." *IEEE Transaction on Intelligent Transportation Systems* 7(2): 175-187. DOI: 10.1109/tits.2006.874722.
6. Kamijo Shunsuke, Yasuyuki Matsushita, Katsushi Ikeuchi, Masao Sakauchi. 2000. "Traffic monitoring and accident detection at intersections." *IEEE Transactions on Intelligence Transportation Systems* 1(2): 108-118. DOI: 10.1109/6979.880968.

7. Mithun Niluthpol Chowdhury, Nafi Ur Rashid, S.M. Mahbubur Rahman. 2012. "Detection and classification of vehicles from video using multiple time-spatial images." *IEEE Transaction on Intelligent Transportation Systems* 13(3): 1215-1225. DOI: 10.1109/tits.2012.2186128.

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