Energy based Descriptors and their Application for Car Detection

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Abstract: In this paper, we propose a novel technique for object description. The proposed method is based on investigation of energy distribution (in the image) that describes the properties of objects. The energy distribution is encoded into a vector of features and the vector is then used as an input for the SVM classifier. Generally, the technique can be used for detecting arbitrary objects. In this paper, however, we demonstrate the robustness of the proposed descriptors for solving the problem of car detection. Compared with the state-of-the-art descriptors (e.g. HOG, Haar-like features), the proposed approach achieved better results, especially from the viewpoint of dimensionality of the feature vector; the proposed approach is able to successfully describe the objects of interest with a relatively small set of numbers without the use of methods for the reduction of feature vector.

1 INTRODUCTION

In the feature-based detectors, the selection of relevant features that are able to reliably describe the objects of interest is a key point. In the recent years, the object detectors that are based on the edge analysis that provide the valuable information about the objects of interest have been used in many detection tasks. In this area, the Histograms of Oriented Gradients (HOG) (Dalal and Triggs, 2005) are considered as the state-of-the-art method. In HOG, a sliding window is used for recognition. In the process of obtaining HOG descriptors, the window is divided into small connected cells. The histograms of gradients are calculated for each cell. It is desirable to normalize the histograms across a large block of image. As a result, a vector of values is computed for each position of window. This vector is then used for recognition, e.g. by the Support Vector Machine (SVM) classifier (Boser et al., 1992). The HOG descriptors are very useful in many detection tasks. Dalal and Triggs (Dalal and Triggs, 2005) proposed the human detection algorithm based on the HOG descriptors and a linear SVM classifier. Zhu at al. (Zhu et al., 2006) presented the nearly real-time human detector using the cascade of rejectors with the HOG features. F. Suard at al. (Suard et al., 2006) proposed the method for pedestrian detection using the HOG descriptors with the SVM classifier. Boosting HOG features for the vehicle detection in airborne videos are presented in (Cao et al., 2011).

In general, the methods that describe the edges by making use of their orientations, gradient magnitudes, positions, or length suffer from a high dimensionality of feature vectors. Furthermore, the training and classification phase can be slowed down by this drawback (a big number of training samples are required). The images that are affected by rain, noise, lack of light, misty and cloudy weather are frequent in the outdoor applications. These images cause a great difficulty in obtaining relevant features for the object description without the use of image filtering. The mentioned problems created a motivation for developing new descriptors. The preliminary versions of the presented method were used for face detection in (Fusek et al., 2013a), and for pedestrian detection in (Fusek et al., 2013b).

In essence, the method was inspired by the features that are based on HOG. We divide the image inside the sliding window into regions, and within the regions we define the sources of energy. By the transfer of energy, we will mean the transfer of heat. After the temperature transfer inside the sliding window, we investigate the movement of thermal energy from the sources. The values that we calculate are used for composing the feature vector of sliding window and the vector is then used as an input for the SVM classifier. In contrast with the HOG descriptors, the proposed method captures the object information by the energy distribution in object areas instead of

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the distribution of gradient magnitudes and directions. Using the proposed method, we are able to describe the object areas that are useful for recognition. The first advantage is that the feature vectors of relatively small dimensions are sufficient for successful recognition. The next advantage is a very good resistance to the noise. The filtering step is directly included in the calculation of proposed approach. We will show the robustness of the presented method for solving the problem of car detection.

2 RELATED WORKS

The vehicle detection systems have been very useful in the recent years. Especially nowadays in the cities, the increasing number of vehicles brings a major problem. The car detection systems can be important, especially for drivers who are looking for vacant spaces in the parking lots, for traffic analysis, for intelligent scheduling, and so on.

The information about the presence of vehicles can be provided by the intrusive (magnetometers, piezoelectric cables, micro-loop probes) and non-intrusive sensors (microwave radar, laser radar) (Mimbela et al., 2007). On the other hand, the camera-based system that is able to provide very valuable information about the situation can be used and the object detection methods that were proposed in the last years (based on the image information) can be used for vehicle detection.

For instance, Viola and Jones (Viola and Jones, 2001; Viola and Jones, 2002) proposed the very popular object detector. Haar-like features, integral images, and AdaBoost algorithm were used in their detection framework. Several improvements of this detection framework exist. The extension of the feature set of their method has been presented by Lienhart (Lienhart and Maydt, 2002). The improvement of the weak classifiers combined with Real Adaboost for the fast multi-view face detection system has been presented by Wu at al. (Wu et al., 2004). The tree structure for the construction of detector using the Vector Boosting algorithm has been presented by Huang at al. (Huang et al., 2007). The method for detecting multi-view cars has been presented by Zheng and Liang (Zheng and Liang, 2009). The authors proposed a novel set of image strip features for car detection. Their strip features are calculated using the integral image. Combined with the RealBoost framework, the authors reported good performance. Nevertheless, the authors mentioned that the strip features discard some statistical information compared with the more complex descriptors such as HOG (Dalal and Triggs, 2005). The trainable object detector for detecting faces and cars at any size, location and pose was presented by Schneiderman and Kanade (Schneiderman and Kanade, 2004). Their classifier is based on the statistics of localized parts that represent various local properties. Papageorgiou and Poggio (Papageorgiou and Poggio, 2000) described the object detector for face, people and cars using Haar wavelets with the support vector machine.

Detectors that are focused on detecting the cars in parking lot are also very useful. Several methods aimed at detecting the cars in parking lot have been presented. Three-layer Bayesian hierarchical framework for the parking lot occupancy problem was presented in (Huang and Wang, 2010). The system for parking lot vehicle detection based on the fuzzy c-means clustering classifier was reported in (Ichihashi et al., 2010). The detection system consisting of shadow removal, lens distortion correction, and parking space extraction was presented in (Fabian, 2008).

In this paper, we also focus on detecting the cars in parking lot, nevertheless, we use the classical sliding window detection approach, therefore, for comparison, we use the classical image features (e.g. HOG, Haar-like features) that are usually used in the sliding window methods.

3 PROPOSED METHOD

For determining the proposed descriptors that are based on distribution of energy (temperature), we use the sliding window (similarly as in HOG); the window is divided into a chosen number of areas (e.g. squares) called blocks (Fig. 2). For the image inside the sliding window, the distribution of temperature can be solved by making use of physical laws.

We suppose that the image is a plate that is created from a material with a certain thermal conductivity. The value of conductivity depends on the local size of the gradient of brightness or colour function (the higher is the gradient size, the lower is the conductivity). Inside each block, a source of temperature is defined through which the thermal energy can flow into the image; we use the gravity centers of blocks as the positions of sources. The method that we propose is based on determining the distribution of temperature in the image inside the sliding window after the temperature transfer, which can be performed during a chosen time. At the time $t = 0$, the temperature of the plate is zero. At the same time ($t = 0$), the source of heat with a constant temperature is attached to the gravity centers of all blocks in one position of sliding window. From the time $t = 0$, the temperature of

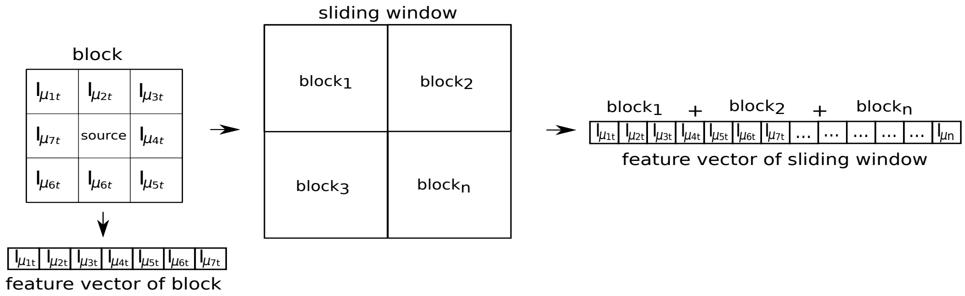


Figure 2: The vector of features.

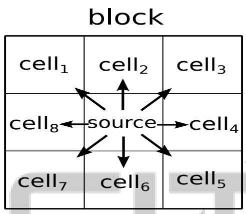


Figure 1: The block divided into cells. The source of temperature is placed to the gravity center of block. In this particular case, by appropriately placing of cells, we investigate the 8-neighborhood of source.

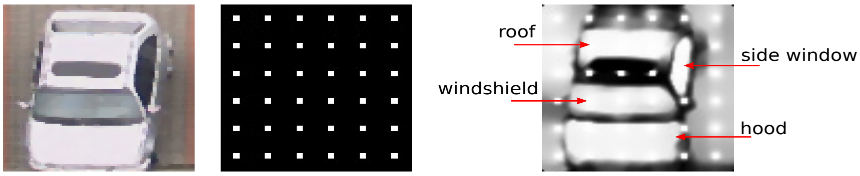
source points is held on the value of 1 (theoretically, this temperature can be held to infinity). After a certain chosen time t, the temperature of the image plate inside the sliding window is examined.

For the purpose of investigating the distribution at a chosen time t, each block is divided into cells that are placed into the neighborhood of source (Fig. 1). Let $I(x,y,t)$ be the function of temperature that was determined. We can compute the mean temperature in every cell; $I\mu_{it}$ stands for the mean temperature of the i-th cells at the time t. We use the mean cell temperatures as the values in the feature vector, i.e. the size of feature vector equals to the number of cells within the blocks. The final vector of features is composed from all mean temperatures $I\mu_{it}$ inside each block (Fig. 2). It is important to mention that the transfer of temperature from the sources is not restricted by the block size but it is computed in the entire sliding window, and the blocks and cells are only formed only for distribution measurement. We note that the heat from one source can be transported to all blocks in the window.

Before continuing to further technical details, we regard as desirable to discuss the rationale behind the method proposed above. The main idea of presented approach is that the properties of the objects of interest can be described by distribution of energy (temperature). The usefulness of temperature distribution can be illustrated as follows. Say that the values for recognition are obtained as the sample values of a function that is defined over the area of image. If it is a function of the gradient size of brightness, it is obvious that it is difficult to hit (by the samples) the places that are important for recognition (thin edges). Therefore, in the proposed method, we use the function of temperature distribution in which the information about its changes is not so important. It is sufficient to obtain the information about the areas in which the values of distribution function are approximately constant (by sampling, the information about the areas can be easily obtained). Clearly, the information about the areas also contains the information about the edges in the original image. Since the object boundary creates the thermal insulator, the area of object contains a certain distribution of temperature that reflects the shape of object. This distribution can be investigated and used for recognition.

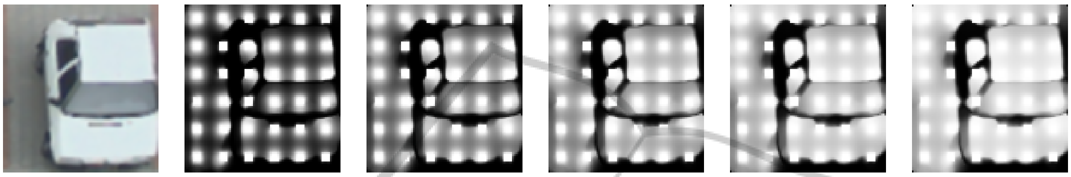
In the real images (Fig. 3(a)), the objects of interest consist of more complicated areas but the general idea from the previous paragraph can be used again. Suppose that the several temperature sources are located into this image (sliding window); say in the form of a regular grid (Fig. 3(b)). The values of temperatures that are transfered from the sources create separate segments (Fig. 3(c)). The temperature distributions inside the segments are used to encode the information about the appearance of object. For the purpose of encoding the distribution of temperature, we investigate the mean temperature of all cells inside the sliding window in several suitably chosen times of temperature transfer.

It is clear that the real images contain the areas of different sizes. At different times, we get various information about objects (Fig. 4). For the description of small areas by the temperature distribution, a lower time (lower number of iterations) during which the temperature transfer is carried out is required; small areas are filled with a certain distribution of temperature (that is sufficient for the description of these areas) in a relatively short period of time. On the other hand, the temperature sources that are located into the big areas require more time to affect the whole areas of the objects. For instance, the shape of the side win-



(a) (b) (c)

Figure 3: The real-life image (a). The regular grid of sources (b). The visualization of distribution of temperature from these sources (c). The value of temperature is depicted by the level of brightness.



orig. t = 50 t = 100 t = 150 t = 200 t = 250

Figure 4: The visualization of distribution of temperature at different times. The value of temperature is depicted by the level of brightness.

dows is visible at the time $t = 50$, however, the shape of the hood is recognizable at the time $t \geq 150$ (Fig. 4). For this reason, we compute the temperature distribution at different times. For example, we can compute two different distributions; one at the time t_1 and the second at t_2. In this particular case, the final feature vector includes the information from both these distributions. We can take the values of both distributions and compose them sequentially one after another into the final vector. The next possibility is to combine the values from both distributions together (e.g. by averaging them). In the first case, the size of the final vector is two times larger than is the size in the second case. We regard the second approach as often more suitable for recognition due to the fact that the dimensionality of final vector is not increased.

It is important to mention that the classical HOG descriptors are not rotationally invariant. Since the proposed descriptors are similar to the HOG descriptors in the sense that in both approaches the features are computed in a grid, this limitation also occurs in the proposed descriptors. Similarly as in HOG, the scale invariance is achieved by rescaling the images.

For practical realization of the method, it is important to mention that the thermal field over the one position of sliding window can be solved by making use of the following equation (Perona and Malik, 1990)

$$\frac{\partial I(x,y,t)}{\partial t} = \mathrm{div}(c\nabla I), \tag{1}$$

where I represents the temperature at a position (x,y) and at a time t, div is a divergence operator, ∇I is the temperature gradient and c stands for the thermal conductivity. For the source points and the arbitrary time $t \in [0,\infty)$, we set $I(x_s,y_s,t) = 1$, where (x_s,y_s) are the coordinates of source points (i.e. we hold the temperature constant during the whole process of transfer, which is in contrast with the usual diffusion approaches). In all remaining points, we take into account the initial condition $I(x,y,0) = 0$. We solve the equation iteratively. The conductivity in Eq. 1 is determined by

$$c = g(\|E\|), \tag{2}$$

where E is an edge estimate. We define the edge estimate E as the gradient of original image $E = \nabla B$, where B is the brightness function. The function $g(\cdot)$ has the form of (Perona and Malik, 1990)

$$g(\|\nabla B\|) = \frac{1}{1+\left(\frac{\|\nabla B\|}{K}\right)^2}, \tag{3}$$

where K is a constant representing the sensitivity to the edges (Perona and Malik, 1990). Once the temperature field over the input image is obtained (at a chosen time t), the mean cell temperature $I\mu_{it}$ can be obtained by making use of the formula

$$I\mu_{it} = \frac{\iint\limits_{M} I(x,y,t)\,dxdy}{|M|}, \tag{4}$$

where M stands for the cell area, and $|M|$ is its size.

In the next step, the SVM classifier is trained over the proposed descriptors. Let us consider a training data set (x_i, y_i) where x is the vector of proposed descriptors from training samples and y is the class label (+1 for cars, -1 for non-cars). The linear SVM determine the hyperplane $w \cdot x + b$ where w is a weight vector, x is the vector of features and b is a constant. The goal is to find the optimal decision function that maximizes the distance between the nearest point x_i and the hyperplane. In the case when it is difficult to separate the samples in a linear manner, the non-linear SVM can be used. The non-linear SVM maps the original space into a high-dimensional space using a kernel function that separate training samples. The optimal hyperplane for the non-linear SVM is obtained by the function $f(x)$:

$$f(x) = \sum_{i=0}^{N} y_i \alpha_i k(x, x_i) + b, \quad (5)$$

where N represents the number of training patterns, y_i is a class indicator (+1 for cars, -1 for non-cars) for each training pattern x_i, α_i and b are learned weights and $k(.,.)$ is a kernel function. In our case, we use the Gaussian radial basis function kernel:

$$k(x, y) = e^{\frac{|x-y|^2}{2\sigma^2}}. \quad (6)$$

4 EXPERIMENTS

For the training phase, we collected the data set consisting of 5000 samples (2500 non-cars, 2500 cars). We experimented with the parameters of our descriptors and we suggest the following configuration. The configuration is denoted as $Energy_{288}$ with the size of block: 15×15 pixels, size of temperature sources: 5×5 pixels, number of cells inside the block: 8, iterations (time) for the temperature transfer: 50, 100, 150. This configuration consists of 288 descriptors. Each training sample was resized to the size of 90×90 pixels, for the proposed detector. The example of visualizations of temperature distribution is shown in Fig. 5 (the visualizations of $Energy_{288}$ configuration at the time $t = 150$).

For comparison, we use the detectors that are based on the HOG features, LBP (Local Binary Patterns) features (Liao et al., 2007), and Haar features (Viola-Jones detection framework).

For the HOG based detectors, we created two configurations: HOG_{900} and HOG_{300}. HOG_{900} was designed with the following settings; size of block: 32×32, size of cell: 16×16, horizontal step size: 16, number of bins: 9. This configuration consists of 900 descriptors. Since the proposed method produces the relatively small number of descriptors, we designed the configuration of HOG_{300} that was used for the purpose to test these descriptors with the smaller number of features than the HOG_{900} configuration. The HOG_{300} configuration was designed with the following settings; size of block: 32×32, size of cell: 16×16, horizontal step size: 16, number of bins: 3. This configuration consists of 300 descriptors. For the HOG descriptors combined with SVM, we used the same training data set that we used for the proposed method (2500 non-cars, 2500 cars), and each sample was resized to the size of 96×96. For the detectors that are based on the Viola-Jones detection framework with the Haar features and with the features that are based on LBP, we created the cascade classifiers. The final strong classifiers consist of 20 stages for LBP and also for Haar features.

To calculate the performance of approaches, we used Matthew's correlation coefficient (MCC) that is typically used in machine learning to assess the performance of a binary classifier; MCC is useful if two classes have a different size (in our case, the numbers of TP, TN, FP, FN are different). The values of MCC are between -1 and +1. The higher value represents better predictions. We collected 28 testing images from the parking lot to evaluate the approaches. The testing images were not used in the training phase and the images were taken in several year seasons (in different weather and lighting conditions). The example of testing images is shown in Fig. 6.

The performance results obtained during our test are shown in Table 1. In fact, the table is divided into two parts. The first part shows the results of images captured in good lighting conditions. The second part shows the results for winter, rain, and night, i.e. difficult conditions.

The HOG descriptors were successful in the sunny weather and good lighting conditions. Nevertheless, the HOG based detectors failed in the bad lighting conditions especially at night, in winter and in rain. In such cases, the numbers of false positives were increased. In poor lighting situations, the HOG based detectors detect the places in the images as occupied although the cars are not present in these places. The artifacts (noise) created in the bad-lit conditions have a negative effect to the HOG descriptors, despite the fact that we used the median filter on each image. Using the HOG descriptors, we achieved the best result with HOG_{900} configuration (in this case, MCC = 0.90). The feature vector of HOG_{300} configuration (with such a small number of descriptors) was not able to describe the appearance of cars correctly and this configuration achieved MCC = 0.83 only.

In the good conditions, the Haar based detector also achieved the high accuracy (MCC = 0.94). In the worst lighting conditions, the Haar based detector (like the HOG based detectors) failed in some cases (MCC = 0.88). Haar based detector and the LBP based detector missed some of the cars in the difficult conditions (e.g. in night) and the LBP based detector even missed some of the cars in the good conditions. The detectors that are based on these features (Haar,

Figure 5: The visualization of distribution of temperature. The value of temperature is depicted by the level of brightness.

summer winter night

Figure 6: The parking lot in different conditions.

Table 1: The detection performance (occupancy detection).

	sunny					winter/rain/night					overall performance
	TP	TN	FP	FN	MCC	TP	TN	FP	FN	MCC	MCC
$Energy_{288}$	408	363	13	0	0.97	251	510	17	6	0.93	0.95
HOG_{300}	405	334	42	3	0.89	252	433	93	6	0.76	0.83
HOG_{900}	407	356	20	1	0.95	254	453	73	4	0.81	0.90
Haar	405	354	22	3	0.94	242	501	25	16	0.88	0.91
LBP	372	360	11	41	0.87	217	523	4	40	0.87	0.88

LBP) need to increase the amount of training data to achieve better detection results.

The proposed detector achieved very satisfactory results in the various weather and lighting conditions across all testing images. In the sunny weather with the good conditions, the descriptors reached the very high MCC results. In winter seasons, during nights and rain, the presented descriptors achieved much better results than the HOG, LBP, Haar feature based detectors. In general, in night images, the noise has the negative effect on image quality and especially on the quality of object edges. The proposed descriptors that are based on the temperature distribution gain the noise resistance properties from the diffusion equation and the noisy images do not cause the problem in obtaining the relevant features for the object description. In the configuration of $Energy_{288}$ of our descriptors, we achieved the best MCC = 0.95 with the 288 descriptors. The HOG_{900} configuration needed three-times more descriptors than the proposed approach to achieve MCC = 0.90.

Finally, the proposed method shows that the cars can be described with a reasonable number of features with very good detection results without need for the methods for reducing the feature space. The example of detection results of our approach is shown in Fig. 7.

5 CONCLUSIONS

This paper proposed the efficient method for computing the image descriptors that are useful for object detection. The proposed descriptors are based on the distribution of temperature and the vector of these descriptors is used as an input for the SVM classifier. In this paper, we used the descriptors for detecting the cars. The results that we demonstrated are very promising and our future work will focus on the detection of other objects of interest using this method and we will also focus on the time complexity of computation of the proposed features.

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Figure 7: The detection results of our approach.

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