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POLARIZATION-BASED CAR DETECTION

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ABSTRACT

Road scene understanding is a vital task for driving assistance systems. Robust vehicle detection is a precondition for diverse applications particularly for obstacle avoidance and secure navigation. Color images provide limited information about the physical properties of the object. This results in unstable vehicle detection caused mainly from road scene complexity (strong reflexions, noises and radiometric distortions). Instead, polarimetric images, characteristic of the light wave, can robustly describe important physical properties of the object (e.g., the surface geometric structure, material and roughness etc). This modality gives rich physical informations which could be complementary to classical color images features. In order to improve the robustness of the vehicle detection purpose, we propose in this paper a fusion model using polarization information and color image attributes. Our method is based on a feature selection procedure to get the most informative polarization feature and color-based ones. The proposed method, based on the Deformable Part based Models (DPM), has been evaluated on our self-collected database, showing good performances and encouraging results about the use of the polarimetric modality for road scenes analysis.

Index Terms— Car detection, polarization, feature selection, DPM, road scenes

1. INTRODUCTION

For an intelligent device in road scenes, cars appear to be one of the most frequently observed yet dangerous objects. Car detection has broad range of applications such as autonomous driving or obstacle detection and avoidance. It is a challenging problem due to its large structural and appearance variations.

Dalal et al. [1] proposed a single filter based on Histogram of Oriented Gradients (HOG) features to represent an object. The model is a single filter that slides throughout the image. A score is computed with each position and scale. Based on this effective feature, Felzenswalb et al. [2] proposed Deformable Part Models (DPM). The object is modeled by several deformable parts to better handle the object appearance points of view (frontal, rear, left side or right side) and to inte-

grate the intra-class variations. Specifically for car detection, Wu [3] proposed a reconfigurable hierarchical and/or model to integrate the context and the occlusion patterns, in which the DPM is utilized as the deformable feature.

Classical color-based detection methods [4],[5],[6] including those mentioned above, depend extremely on outdoor illumination conditions. These conditions, in the road scene context, are most of the time hard and complex (strong reflexions, presence of transparent objects, occlusions, bad weather conditions) making RGB images poor and limited [7].

The polarization of the reflected light is strongly linked to the physical properties of the surface [8]. Compared to other sensors, polarimetric imaging systems have the advantage to characterize the geometric aspect of the surface (orientation, reflexion angle, degree of polarization), to identify the material nature of each object (refraction index, material type) and to offer physical and optical information (reflexion, transmittance, depolarisation). Polarization is able to bring additional information of an object other than its intensity [9].

In this paper, we propose to use polarization features as a complementary information to color-based ones in order to improve car detection results. To our knowledge, this is the first work in the literature that attempts to use polarization-based features for outdoor object detection. A feature selection process is performed to select the most informative polarization feature. The detection scheme is carried out using DPM detector. Polarization-based DPM detector and a color-based DPM detector are trained independently and different score maps are produced by the two models. A fusion rule that takes the polar-based model as a confirmation to the color-based one is proposed to achieve the final detection. Experiments performed on our self collected dataset, show that fusing polarization and color features reduces strongly false alarm rate (false bounding boxes), and improve effectively the car detection accuracy.

2. POLARIZATION FORMALISM

The main applications of polarization imaging are related to distinguish metallic object from dielectric surface [10], [11]. Polarization imaging permits likewise to give three-dimensional information of specular [12], [13] and transparent objects [14]. The physical principle of the polarization

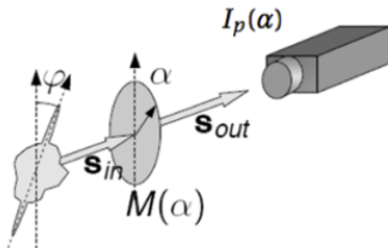


Fig. 1. The polarization device principle.

of the light is that after being reflected, an unpolarized light wave become partially linearly polarized depending on the surface normal and on the refractive index of the material it impinges on [8], [9], [15]. The reflected partially linearly polarized light is described by a measurable vector, named the Stokes vector $S = [S_0, S_1, S_2]$. The first component S_0 relates to the object intensity, the two others describe the physical properties of the object. From these three components, other physical properties are derived such as the light magnitude I , the degree of polarization (DOP) ρ and the angle of polarization (AOP) φ [16]. In order to measure the polarization parameters, at least three images are required. For this purpose, a rotating linear polarizer around three angles $(\alpha_i)_{i=1:3}$ is placed in front of the camera. Figure.1 gives an example of a polarization device. For each angle (α_i) , an intensity $I(\alpha_i)$ is measured by the camera. The relationship between the acquired images and the Stokes vectors is given by :

$$I(\alpha_i) = \frac{1}{2} [1, \cos(2\alpha_i), \sin(2\alpha_i)] \cdot [S_0, S_1, S_2]^t \quad (1)$$

The DOP is calculated as $\rho = \frac{\sqrt{S_1^2 + S_2^2}}{S_0}$ and the AOP as $\varphi = \frac{1}{2} \tan^{-1} \frac{S_2}{S_1}$

3. FEATURE EXTRACTION

3.1. Polarization feature selection

Because of the noisy nature of the polarization parameters, a feature selection is required to find the most informative polar-based feature for the detection model training. In our case, the feature selection procedure is trained by the Dalal-Trigg detector [1] by replacing the HOG feature by the polarization features.

To train the Dalal-Trigg detector, similar to the original HOG features, the polarization features are extracted based on blocks and cells. A 8×8 block was divided into four 4×4 cells. For each pixel in the cell, a feature vector is extracted, which contains the 3-dimensional Stokes vector, the DOP (ρ) and the AOP (φ). The feature vector $[S_0, S_1, S_2, \rho, \varphi]$ of a

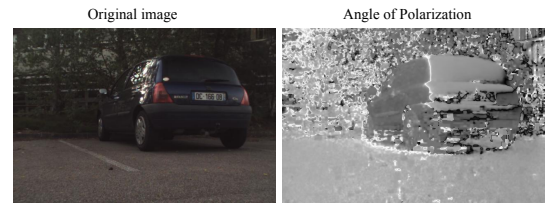


Fig. 2. The original image and its corresponding AOP.

cell is represented by the mean feature vector of all the pixels inside the cell. Each cell holds a 5-dimensional feature vector. The feature vector of the block is the concatenation of the feature vectors from the four cells. The derived 20-dimensional features ϕ_{20-d} of all the examples are used to train the Dalal-trigg detector in order to get the filter f that indicates the weight of each feature. Larger weight is, better the relevancy of the corresponding feature. The advantage of the feature selection is twofold : first, it allows to leverage from the most relevant polarimetric information and second, it reduces the dimension of the feature vector, making the detection faster.

By applying the feature selection process presented above, the AOP was selected as the most informative feature with regards to the car detection purpose.

3.2. The Angle of polarization

The AOP refers to the direction of the polarization of the reflected light. It is determined by the angle of the incident light (generally for outdoor applications, the incident light is assumed to be unpolarized), the surface orientation of the object and the material of the object. For rough surface, as surface orientations of neighboring pixels change a lot, the AOP changes in an irregularly way. For smooth surfaces, however, the AOP changes smoothly and continuously. Up to the road scenes analysis, especially for car detection tasks, the AOP on the car surfaces changes gradually according to the surface geometry structure, while it is noisy for other objects. This phenomena is illustrated in Figure. 2 where the AOP image on the tree area is highly noisy, on the road it is better but still much noisy than on the car. It can be observed that the AOP image describes the geometry structure of the car, which is even more clear than that from the color image.

We can conclude that, the AOP describes the geometry structure that cannot be captured from the color image. In addition, it highlights the area of the car among the noise.

4. DETECTION MODEL

The DPM model proposed by Felzenswalb [2] is known to be an efficient method that handles the intraclass variations of an object. The DPM is a filter-based detector applied throughout

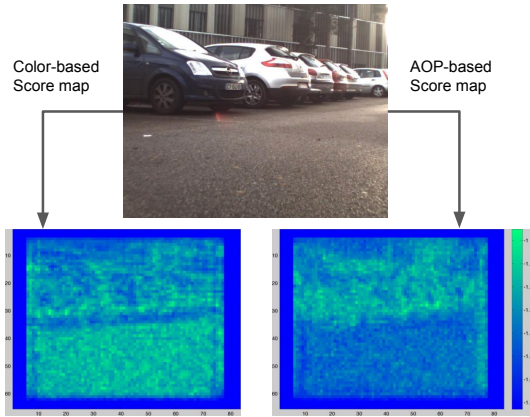


Fig. 3. The score map given by color-based and AOP-based methods.

a feature map to get a detection score. A feature map is an array that each entry is a d -dimensional feature vector computed from the corresponding image location. Let Φ be the feature map, with $\phi(x, y)$ corresponds to the entry at the location (x, y) . The filter f shares the same dimension as the feature map, and the detection score is computed as the dot product $f \cdot \phi(x, y)$. The detection score for a given location is proportional to the possibility of the existence of an object on that location (refer to Felzenszwalb [2] for more details about the initialization and optimization process).

5. FUSION RULE

As polarization provides complementary information that is not accessible from color images, the fusion of polarization and color improves the result provided by color-only methods [17] [18]. In order to improve the detection results, we have proposed a fusion rule by taking the polarization result as a confirmation to the color one.

Following the training process, we obtained a polar-deformable part model M_p using the AOP image and a color-deformable part model M_c using the color image. Since each location is scored by the model, a score map is formulated for each domain (polarimetric and color). The higher score a location gets, the stronger the possibility that a car appears at this location. The result is given by simply thresholding the score map by a trained threshold. The idea is that the score location on which M_c produces high scores are confirmed by the score of M_p . If both M_c and M_p produces high score, this location is then considered as an object, and vice versa.

The score map given respectively by M_c and M_p are shown with the original image in Figure 3. It can be seen that on the color-based score map, both the car area and the road area get high scores, which consequently generates false positive.

The score M_p is used as a confirmation to M_p in order

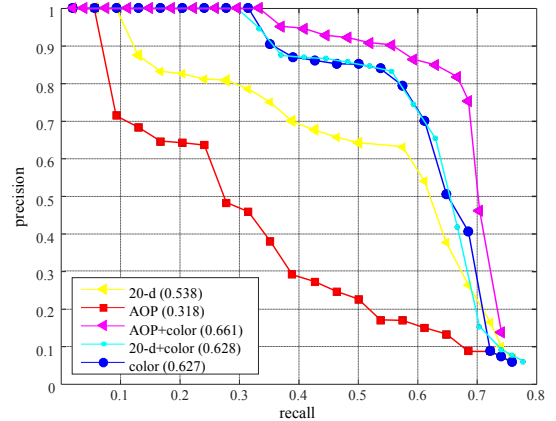


Fig. 4. Precision recall curve on the test set

to exclude the false detection provided by the color-only method, thus improving the detection accuracy.

6. EXPERIMENTS

6.1. Data-set and configuration

Since there does not yet exist a public polarization-based data set, our experiment was implemented on a self-collected data set¹. It contains 153 scenes, with three images I_0 , I_{45} and I_{90} for each scene taken manually by the corresponding polarizer angles. All the cars in the image were labeled by bounding boxes. We divided the data set so that 115 scenes were used for the training and 38 scenes for the model evaluation. The parameters of the DPM model are set as proposed by Felzenszwalb et al [2].

6.2. Results

As a standard evaluation, the detected bounding boxes on the test set was assessed by the evaluation scheme provided by the PASCAL VOC data set [19].

The Precision-Recall Curve (PRC) is firstly computed and shown in Figure 4. The PRC of respectively the AOP-based model, the color-based model and the fusion of AOP with color are shown in the same figure. We trained a model with the 20-dimensional polarization features (the features described in section 3), fused with the color based model. The results are noted in Figure 4 by $20 - d$ (polar-based model) and $20 - d + color$ (fusion). The corresponding Average Precision (AP) of each curve is shown in Table 1.

It can be observed from both Figure 4 and Table 1 that the fusion of AOP with color produces the best result, followed by the fusion of $20 - d + color$ which performs only slightly better than the color only one. The $20 - d$ or the AOP alone

¹<http://pagesperso.litislab.fr/fwang/fichiers/>



Fig. 5. Detection results. The first and third rows refer to the polar-based model whereas the second and fourth rows are the corresponding color-only based model.

Source	AOP	$20 - d$	$20 - d$ + color	color	AOP +color
AP (%)	31.8	53.8	62.8	62.7	66.1

Table 1. The Average Precision (AP) rate

does not provide comparable results, this is because the noise still strongly present in polarization acquisitions.

This result confirms that once the AOP is properly fused with the color model, it provides complementary information that improves the AP by 3.4%. The $20 - d$ is more stable than the AOP, however, with all the redundant features and the more complex model, it almost does not improve the color-based result (0.1% can be even neglected). Moreover, the AOP alone achieves 31.8% of AP, which is important comparing to the 53.8% performed by the whole polarization feature $20 - d$. This result shows that the AOP has an important impact on the detection process. According to the above analysis, it can be concluded that our proposed pre-selection method is valid. By using the selected feature (AOP) and the proposed fusion rule, the polarization features provided useful information which improved and reinforced the color-based method.

To evaluate the improvement provided by the fusion of $AOP + color$, we compare the detected bounding box by $AOP + color$ method with the color-only one. This comparison is shown in Figure. 5, The first and third rows show the results of the detection with the $AOP + color$ fusion and the second and fourth rows show the corresponding color-only detection method. It is worth to note that, after fusing the two different sources of information via the proposed fusion scheme, while keeping the true positive bounding boxes, the false detection are effectively removed.



Fig. 6. Main limitations. False alarms are reduced however not new true positive detection boxes are generated.

7. DISCUSSION

The detection results have shown that the proposed methodology largely reduced the false detection rate and enhance the robustness of the model. Our approach confirmed that polarization-based features can provide useful information for car detection. False alarms were reduced by a simple but effective fusion rule. However, as it can be seen in Figure. 6, the polarization-based feature model does not generate new true positive detection boxes. This limitation is caused by the And-fusion used scheme, which is too much selective.

Our first objective by this work is to prove that polarization is the suitable alternative to color-based models for improving the detection result. This first observation is encouraging to continue our investigation in this direction. As a future work, the polarization feature should be properly fused with the color one inside a training loop. A stable model which integrates the color-based feature and the polar-based feature by an early-based fusion scheme might be able to both reduce the false detection and produce new true positive bounding boxes as well. Other more recent methods like the transfer learning based on the Deep learning networks, that shown interesting performances in several computer vision applications even for vehicle detection [20], should be tested in the polarization domain.

The enhancing of the polarization images quality is not to be missed. Because of the noise reaching polarization acquisitions, it was difficult to leverage from the whole polarimetric information. For example, the DOP coupled with the AOP could give better results in the detection process provided that the DOP is properly calculated. An adapted (physical) filtering process is thus necessary to get better results.

The last point that deserves a discussion in this work is the real time constraint. The proposed algorithm takes around 5 seconds for the detection task on an image of 320×240 , without tacking into account the learning step time. It is far away to be a real time achievement. The use of speed up tools like Open CV implementation and GPU configuration should make faster the detection task .

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