Paper:

Novel Discriminative Method for Illegal Parking and Abandoned Objects

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Computer vision techniques have been widely applied in Intelligent Transportation Systems (ITSs) to automatically detect abnormal events and trigger alarms. In the last few years, many abnormal traffic events, such as illegal parking, abandoned objects, speeding, and overloading, have occurred on the highway, threatening traffic safety. In order to distinguish illegal parking and abandoned object events, we propose an effective method to classify these types of abnormal objects. First, abnormal areas are detected by feature point extraction and matching. The transformation relation, between the world and image coordinate systems, is then established by camera calibration. Next, different-height inverse projection planes (IPPs) are built to obtain the inverse projection maps (IPMs). Finally, the 3D information describing the abnormal objects is estimated and used to distinguish illegally parked vehicles and abandoned objects. Experimental results from traffic image sequences show that this method is effective in distinguishing illegal parking and abandoned objects, while its low computational cost satisfies the real-time requirements; furthermore, it can be used in vehicle classification.

Keywords: illegal parking, abandoned object, camera calibration, vehicle model, inverse projection maps

1. Introduction

In recent years, the increasing volume of traffic has caused traffic accidents to occur much more frequently. There are many factors that lead to these accidents, including personal, vehicle, road and environmental factors [1]. Illegal parking and abandoned objects are important causes of traffic accidents due to their contingency and randomness. Moreover, they occupy road space, affect traffic order, and cause congestion. In order to reduce the loss of lives and property, it is necessary to detect and handle such events as quickly as possible.

Traditional detection methods mainly rely on manual supervision. This is inefficient and does not allow real-time monitoring. Moreover, traditional detection methods waste a large amount of human and financial resources. In recent years, a method based on surveillance video has received increasing attention [2–4]. This method provides the advantages of high accuracy, good real-time performance, low cost, and easy collection of evidence. State-of-the-art methods for object detection include model-based training, video background-based difference, and feature-based methods. The model training method [5] uses training data and machine learning to obtain a classification model; this model is then used to detect objects. The video background difference method [4] subtracts the pixel value of the current frame image from the background image to obtain a difference image; this difference image is then binarized to obtain an image of the foreground object. The feature-based method [6–10] extracts an object's local feature points and obtains a local descriptor. These features can be used to detect and recognize objects. In this study, we used the feature-based method owing to its low computation costs, since model training and real-time updates of the background are not required.

Since illegally parked vehicles and abandoned objects are temporary static objects in the traffic scene, many existing methods focus on the detection of these static objects [11–14]. Because if the camera is stationary, then there were no velocity or motion about illegal parked vehicles or abandoned objects. Although many researchers have focused their attention on object detection, there is little research into illegally parked vehicles and abandoned objects. [3, 4] designed an intelligent monitoring system for illegal parking, but they focused on hardware and software system designs respectively, and did not do an in-depth study on illegal parking detection. Frail et al. [15] proposed a method based on the Hidden Markov model, which first extracted the vehicles' trajectories, and divided these trajectories into four types: forward, left, right, and stop. Bevilacqua et al. [16] proposed a method of detecting the center position of tracked objects in a short time interval in order to detect illegal parking. In this method, the foreground object is first obtained by subtracting the background, then the optical flow method is used to track the object and the central position of each vehicle is analyzed to determine illegal parking. Fatih et al. [17] proposed a method for detecting abandoned objects based on dual foregrounds. Unlike other subtractive background methods, this method detects only abnormal events by subtracting the background without using related tracking techniques. In addition, this method uses different time constants to obtain two different backgrounds: the long-term and short-term backgrounds. The background model adopted is a mixed Gaussian model which uses the on-line Bayesian mechanism to update the background in real time. The long-term background is the background in the usual sense, while the short-term background consists of the objects which have recently become stationary. Beynon et al. [18] used multiple cameras to capture the video data which they used to detect abandoned objects. Wang et al. [19] proposed an illegal parking detection system based on machine vision. They used a Gaussian mixture model to extract the background, then analyzed the characteristics of the illegal vehicles to get the experimental results. However, most of these methods are not able to distinguish between illegal parking and abandoned objects in the same traffic scene. This is because they use 2D images or videos that may lose some 3D information about the objects due to scale changes and geometric deformation during the process of camera imaging. Therefore, we suggest a novel way to solve this problem.

In this paper, we propose a method to distinguish illegally parked vehicles and abandoned objects with estimated 3D information. We employ inverse projection maps to recover the related information from a 2D image in the inverse projection planes. The proposed method achieves good performance in tests with different traffic scenes.

The rest of this paper is organized as follows. Abnormal area detection is discussed in Section 2, Section 3 describes the discrimination method, Section 4 displays the experimental results, and finally Section 5 provides conclusions.

2. Abnormal Area Detection

First, feature points of the foreground objects must be extracted. Several methods are available for this such as SIFT [6], SURF [7], ORB [8], MSER [9], BRISK [10], and A-KAZE [20]. We used the ORB descriptor to detect the feature points and hamming distance required to achieve the matching. In order to obtain the abnormal area we adopted a strategy to determine abnormal objects. The steps are as follows:

- Use ORB to obtain the feature descriptors for the corners in each frame-difference image and use non-maximum suppression to select the feature points.
- Use the Hamming distance to achieve matching tracking within the neighborhood window W of the feature points in the previous frame.
- Record the distance D between the two feature points if the two feature points are matched. If $D_{i+1} - D_i < \xi$, where $0 < \xi < 1$, the counter CN is increased by 1.
- If $CN > \eta$, the counter of feature point CF is increased by 1. If $CF > \lambda$, record the position of these feature points

Where ξ, η and λ are the threshold values, $CN > \eta$ means that the position of the feature point remains unchanged during consecutive T_1 frames, and $CF > \lambda$ means that the area of these feature points is abnormal. The abnormal area which contains these abnormal feature points can then be obtained.

3. Discrimination Method

We used a special method to reconstruct the 3D information from 2D image points. First, the camera was calibrated using the transformation relation between the world and image coordinate systems given by

$$\lambda \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = K \begin{bmatrix} R & t \end{bmatrix} \begin{bmatrix} X_W \\ Y_W \\ Z_W \\ 1 \end{bmatrix}, \quad \cdots\cdots\cdots \quad (1)$$

where K is the internal, and R and t are the external camera parameters. The internal and external parameters were calculated using the method described by Kanhere et al. [21]. In particular, we used the method that employs the position of two vanishing points and the known camera height (VVH).

The image captured by the camera is a projection of a 3D space scene to a 2D plane, this is called a perspective transformation process. The transformation from a 2D image plane to a 3D space is called the inverse perspective transformation (IPT). According to the imaging model of the camera, if a point is projected from 3D space to a 2D image, the result is unique. On the contrary, if a 2D point is back-projected to 3D space, the result is uncertain because of the scale factor. Therefore, we pre-determine an inverse projection plane (IPP) in a calibrated 3D traffic scene to get a single result, as shown in **Fig. 1**. Then, the information from the IPP which corresponds to the position of the pixels in the image can be obtained using the perspective relation. We call this back-projected information the inverse projection map (IPM). We utilize the IPP and IPT to calculate mp from p, as shown in **Fig. 2**, where m represents a small grid in the IPP, p is the image pixel, and mp is the pixel corresponding to m. If the position of the IPP is known, we can reconstruct the 3D information about the IPP using the 2D image by Eq. (1). Then the IPM can be obtained based on the IPP and the 2D image.

However, different positions of the IPPs can produce different 3D information. In order to distinguish illegal parking from abandoned objects in a practical and effective manner, we constructed the IPPs parallel to the ground because it is difficult to determine the position of the IPPs in the other two directions for different calibration scenes. Moreover, since vehicle height is limited, the

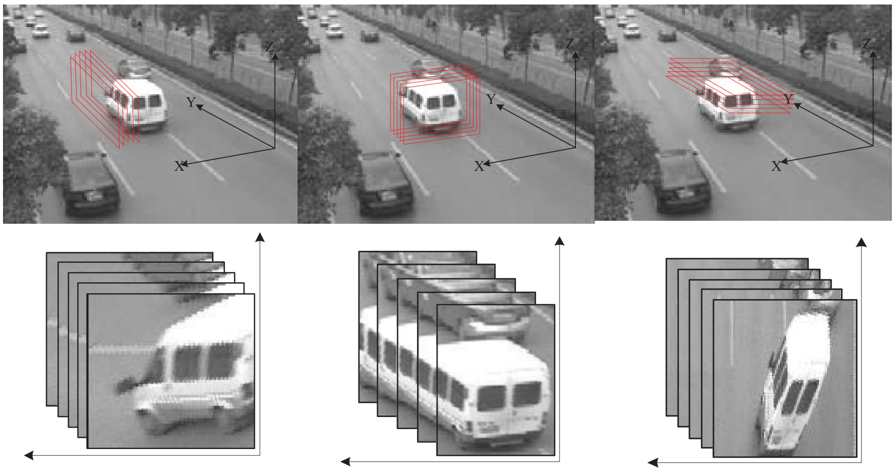

Fig. 1. Different inverse projection planes and the corresponding inverse projection maps.

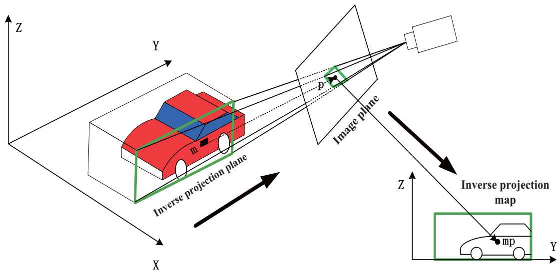

Fig. 2. Inverse projection plane and inverse projection maps.

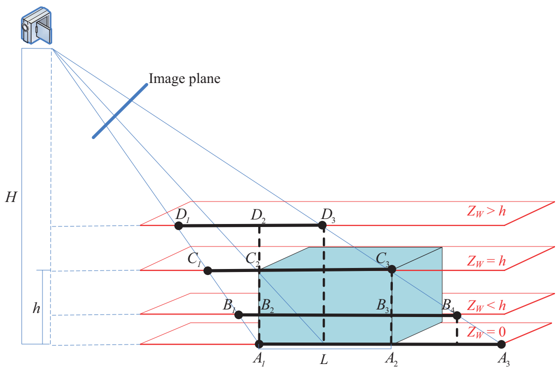

Fig. 3. Correlation between different-height inverse projection map and actual size of object.

maximum height of the IPPs in this paper does not exceed 4 m. As shown in **Fig. 3**, we regarded the vehicle as a cuboid. Its IPM is a specified height and it contains not only the true information about the object, but also some fake information produced by the higher and lower positions. The fake information is called pseudo-projection (PP). It can be seen that $A_1A_2C_3C_2$ is a lengthwise section of the cuboid, A_1A_3 is the projection of $A_1A_2C_3C_2$ on the IPP with $Z_W = 0$ m, A_1A_2 is the true 3D length (L) of the cuboid, and A_2A_3 is the PP that is produced from the higher part of the cuboid. Similarly, B_2B_3 and C_2C_3 indicate the 3D length (L) of the cuboid, and B_1B_2, B_3B_4, C_1C_2, and D_1D_3 are all PPs. Therefore, it can be shown that

$$\begin{cases} A_1A_3 \cap B_1B_4 > L \\ A_1A_3 \cap C_1C_3 = L \\ A_1A_3 \cap D_1D_3 < L. \end{cases} \quad \text{. . . . . (2)}$$

It can be seen that if the height of IPP is h, we can obtain the true 3D information about the cuboid. Therefore, we use different 3D heights to build IPPs for the abnormal area in order to get the corresponding information of objects. Once combined with 3D information about the vehicle model, we can use the different sizes of vehicles to distinguish events of illegal parking and abandoned objects. The steps are as follows:

- Construct the IPPs for the abnormal area at different heights ($Z_W = 0$ m, 0.1 m, $\ldots, 3$ m) and calculate the IPMs.
- Extract the binary image of the abnormal object from the IPMs using the background difference method.
- Do the AND operation between the different-height ($Z_W > 0$ m) IPMs and the IPM with $Z_W = 0$ m.
- Distinguish illegally parked vehicles and abandoned objects using the 3D information. If it matches the vehicle model library, the abnormal object is considered to be a certain type of vehicle. Otherwise, it is an abandoned object.

4. Experimental Results

In order to demonstrate that the proposed method is effective and robust, it has been tested with real video sequences of highways. The proposed method was implemented using Visual studio 2013 and the sampling frequency of the video was 25 FPS. All the videos are captured by our research group, they mainly contain the Second South Ring Road of Xi'an, Yanqing Road of Beijing

(a) Feature points.

(b) Tracking results.

Fig. 4. ORB detection and tracking.

(a) Abnormal area.

(b) Detection results of abnormal area.

Fig. 5. Abnormal area in the traffic scene.

Chongqing Highway, Outer Ring Road of Shanghai and Fuxing Road Tunnel of Shanghai. The camera for standard definition was set up beside the road and was approximately 9 m high, thus all the traffic scenes could be calibrated by the VVH method.

We have tested the proposed method in different traffic scenes. As shown in **Fig. 4**, we first use ORB to detect the feature points and achieve match tracking. Throughout all of the test videos, several abnormal areas were obtained. If the abnormal area appears as show in **Fig. 5(a)**, our method used the position of the feature points to recognize the abnormal area, as shown in **Fig. 5(b)**. Then, we used the position of these abnormal areas to construct the IPPs, as shown in **Fig. 3**. In addition, in terms of the calibrated traffic scene in this paper, a pixel in x direction of the IPM is 0.025 m, and a pixel in y direction is 0.1 m.

From **Fig. 6**, it can be seen that the size of abnormal objects are different for different IPMs. The result after the AND operation are shown in **Fig. 7**. The bottom region represents the IPM with $Z_W = 0$, and the upper region represents the IPM with $Z_W > 0$. Then the bounding boxes of the object in different-height IPMs can be obtained by

$$\begin{aligned} Width &= |Right - Left| \times 0.025 \text{ m} \\ Length &= |Top - Bottom| \times 0.1 \text{ m}, \end{aligned} \quad \ldots\ldots \quad (3)$$

where Top, $Bottom$, $Left$, and $Right$ are the top, bottom, left, and right boundary values in IPM, respectively. In the experiments, the interval of the enumeration height was 0.1 m. This means that there was an IPP at intervals of 0.1 m. **Tables 1** and **2** show the experimental results of **Fig. 8**.

Fig. 6. Inverse projection maps with different heights.

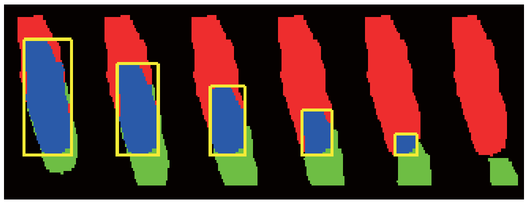

Fig. 7. Results of AND operation.

Table 1. Results of illegal parking.

No.	Length [m]	Width [m]	Height [m]	No.	Length [m]	Width [m]	Height [m]
1	10.8	2.075	0.1	16	3.3	1.420	1.6
2	10.3	2.025	0.2	17	2.8	1.420	1.7
3	9.9	1.950	0.3	18	2.3	1.395	1.8
4	8.9	1.875	0.4	19	1.9	1.370	1.9
5	8.4	1.800	0.5	20	1.4	1.345	2.0
6	8.0	1.725	0.6	21	0.9	1.320	2.1
7	7.5	1.650	0.7	22	0.8	1.320	2.2
8	7.0	1.570	0.8	23	0.6	1.295	2.3
9	6.6	1.545	0.9	24	0.5	1.270	2.4
10	6.1	1.545	1.0	25	0.5	1.245	2.5
11	5.6	1.520	1.1	26	0.4	1.220	2.6
12	4.8	1.495	1.2	27	0.3	1.195	2.7
13	3.9	1.495	1.3	28	0.2	1.170	2.8
14	3.6	1.470	1.4	29	0.1	0.725	2.9
15	3.4	1.445	1.5	30	0.0	0.000	3.0

Table 2. Results of abandoned object.

No.	Length [m]	Width [m]	Height [m]
1	0.40	0.53	0.10
2	0.20	0.35	0.20
3	0.00	0.00	0.30

(a) Illegal parking vehicle. **(b)** Abandoned object.

Fig. 8. Abnormal events in the traffic scene.

Since vehicles are usually higher than abandoned objects, the test number for illegal parking was much larger than that for abandoned objects until the result of the AND operation was zero. Moreover, the size of illegally parked vehicle must satisfy the 3D vehicle models, while the abandoned objects may be irregular. Based on prior knowledge of vehicle sizes, 3D vehicle models can be built as shown in **Table 3**.

Table 3. Vehicle model classification.

Types	Length [m]	Width [m]	Height [m]
Minicompact	3.3–3.6	1.4–1.6	1.4–1.5
Compact car	4.1–4.7	1.5–1.8	1.5–1.6
Mid-size car	5.0–5.5	1.7–2.2	1.7–2.4
Full-size car	≥ 6	≥ 2	≥ 2.5

Therefore, if the detection data matched the vehicle model library, the abnormal object was considered to be an illegally parked vehicle. Otherwise, it was taken as an abandoned object.

In addition, the proposed method has been tested in different traffic scenes as shown in **Fig. 9**. In order to evaluate the proposed method, we defined the recall rate and precision rate.

$$Recall\ Rate = \frac{ATN}{TN}, Precision\ Rate = \frac{ATN}{AN}. \quad (4)$$

where AN is the number of alarms for abnormal objects (illegal parking or abandoned object) using the proposed method, ATN is the number of true alarms in AN, and TN is the true number of abnormal objects (illegal parking or abandoned object) in the traffic scene by artificial data. Some experimental results can be seen in **Tables 4** and **5**. It can be seen that the proposed method is able to detect and distinguish events of illegal parking and abandoned objects in complex traffic scenes such as urban road with

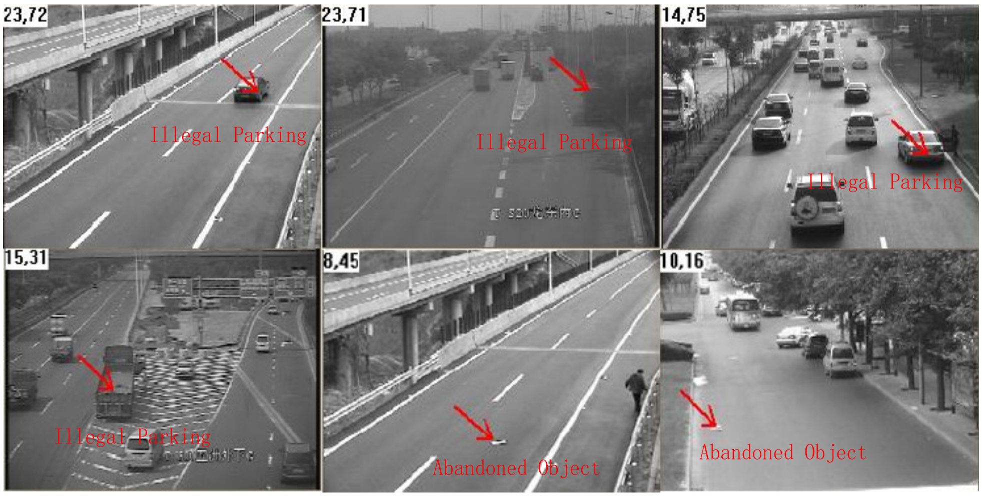

Fig. 9. Results of detection.

Table 4. Results of illegal parking in different traffic scenes.

Scenes	TN	AN	ATN	Recall Rate	Precision Rate
Second South Ring Road of Xi'an	38	39	37	97.37%	94.87%
Yanqing Road of Beijing	52	54	49	94.23%	90.74%
Chongqing Highway	43	45	42	97.67%	93.33%
Outer Ring Road of Shanghai	60	63	58	96.67%	92.06%
Fuxing Road Tunnel of Shanghai	26	28	25	96.15%	89.29%

Table 5. Results of abandoned object in different traffic scenes.

Scenes	TN	AN	ATN	Recall Rate	Precision Rate
Second South Ring Road of Xi'an	14	15	13	92.86%	86.67%
Yanqing Road of Beijing	19	22	18	94.74%	81.82%
Chongqing Highway	16	18	15	93.75%	83.33%
Outer Ring Road of Shanghai	15	17	14	93.33%	82.35%
Fuxing Road Tunnel of Shanghai	13	14	12	95.31%	85.71%

large traffic flow, highways and tunnels. The recall rate of illegal parking and abandoned objects reached 94% and 92%, respectively. Moreover, all of the abnormal events were alarmed within 5 s. Furthermore, if the abnormal object was determined to be illegal parking, the 3D information of the vehicle could be estimated. As shown in **Table 3**, tests No. 14 and 15 satisfied the designed vehicle model in **Table 2**. It satisfied the vehicle model of a Mini-compact, we then used the average value of the two tests to estimated 3D parameters of the vehicle. Thus, the proposed method can be used to give a rough classification of vehicle types.

5. Conclusion

In this paper, we have proposed a method to distinguish illegal parking and abandoned object events. The IPM was utilized to extract 3D information of the abnormal objects, which improves the robustness of the proposed method. Experimental results from tested video show that the proposed method can not only distinguish illegally parked vehicles and abandoned objects, but it also can classify the vehicles in the illegal parking events into different types.

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References:

[1] M. Bédard, G. H. Guyatt, M. J. Stones, and J. P. Hirdes, "The independent contribution of driver, crash, and vehicle characteristics to driver fatalities," Accident analysis and prevention, Vol.34, No.6, pp. 717-727, 2002.

[2] W. Hu, X. Xiao, D. Xie, and T. Tan, "Traffic accident predictionusing 3-D model-based vehicle tracking," IEEE Trans. on Vehicular Technology, Vol.53, No.3, pp. 677-694, 2004.

[3] H. Ikeda, Y. Kaneko, T. Matsuo, and K. Tsuji, "Abnormal incident detection system employing image processing technology," Proc. of IEEE/IEEJ/JSAI Int. Conf. on Intelligent Transportation Systems, pp. 748-752, 1998.

[4] Y. K. Ki and D. Y. Lee, "A Traffic Accident Recording and Reporting Model at Intersections," IEEE Trans. on Intelligent Transportation Systems, Vol.8, No.2, pp. 188-194, 2007.

[5] J. E. Espinosa, S. A. Velastin, and J. W. Branch, "Vehicle Detection Using Alex Net and Faster R-CNN Deep Learning Models: A Comparative Study," Int. Visual Informatics Conf., pp. 3-15, 2017.
[6] D. G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," Int. J. of Computer Vision, Vol.60, No.2, pp. 91-110, 2004.
[7] H. Bay, T. Tuytelaars, and L. V. Gool, "SURF: SpeededUpRobust Features," 9th European Conf. on Computer Vision (ECCV 2006), 2006.
[8] E. Rublee, V. Rabaud, K. Konolige, and G. R. Bradski, "ORB: An efficient alternative to SIFT or SURF," 2011 Int. Conf. on Computer Vision, pp. 2564-2571, 2011.
[9] P. E. Forssén and D. G. Lowe, "Shape Descriptors for Maximally Stable Extremal Regions," 2007 IEEE 11th Int. Conf. on Computer Vision, pp. 1-8, 2007.
[10] S. Leutenegger, M. Chli, and R. Siegwart, "BRISK: Binary Robust invariant scalable keypoints," 2011 Int. Conf. on Computer Vision, pp. 2548-2555, 2011.
[11] S. Sivaraman and M. M. Trivedi, "Looking at Vehicles on the Road: A Survey of Vision-Based Vehicle Detection, Tracking, and Behavior Analysis," IEEE Trans. on Intelligent Transportation Systems, Vol.14, pp. 1773-1795, 2013.
[12] M. Jayebhaye, "Comparative Analysis and Detection of Street Parked Vehicles using Spatiotemporal Maps and Corner Detection Methods," Int. J. of Computer Applications, Vol.6, pp. 42-49, 2016.
[13] T. D'Orazio and C. Guaragnella, "A Survey of Automatic Event Detection in Multi-Camera Third Generation Surveillance Systems," Int. J. of Pattern Recognition and Artificial Intelligent, Vol.29, No.1, 2015.
[14] Y. l. Tian, R. S. Feris, H. Liu, A. Hampapur, and M. T. Sun, "Robust Detection of Abandoned and Removed Objects in Complex Surveillance Videos," IEEE Trans. Systems, Man, and Cybernetics, Part C, Vol.41, pp. 565-576, 2011.
[15] R. Fraile and S. J. Maybank, "Vehicle Trajectory Approximation and Classification," British Machine Vision Conf. 1998 (BMVC 1998), 1998.
[16] A. Bevilacqua and S. Vaccari, "Realtime detection of stopped vehicles in traffic scenes," IEEE Conf. on Advanced Video and Signal Based Surveillance, pp. 266-270, 2007.
[17] P. Fatih and H. Tetsuji, "Robust Abandoned Object Detection Using Dual Foregrounds," Eurasip J. on Advances in Signal Processing, Vol.2008, No.1, pp. 1-11, 2007.
[18] M. D. Beynon, D. J. V. Hook, M. Seibert, A. Peacock, and D. Dan, "Detecting Abandoned Packages in a Multi-Camera Video Surveillance System," Proc. of IEEE Conf. on Advanced Video and Signal Based Surveillance, pp. 221-228, 2003.
[19] D. Wang et al., "Detection and recognition algorithm of illegal parking," J. of Jilin University (Engineering and Technology Edition), Vol.40, No.1, pp. 42-46, 2010.
[20] P. F. Alcantarilla, A. Bartoli, and A. J. Davison, "KAZE Features," European Conf. on Computer Vision (ECCV), pp. 214-227, 2012.
[21] N. K. Kanhere and S. T. Birchfield, "A Taxonomy and Analysis of Camera Calibration Methods for Traffic Monitoring Applications," IEEE Trans. on Intelligent Transportation Systems, Vol.11, No.2, pp. 441-452, 2010.

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- "LDPC-based lossless compression of nonstationary binary sources using sliding-window belief propagation," IEEE Trans. on Communications, Vol.60, No.11, pp. 3161-3166, 2012.
- "DAC spectrum of binary sources with equally-likely symbols," IEEE Trans. on Communications, Vol.61, No.4, pp. 1584-1594, 2013.
- "Asymmetric Slepian-Wolf coding of nonstationarily-correlated M-ary sources with sliding-window belief propagation," IEEE Trans. on Communications, Vol.61, No.12, pp. 5114-5124, 2013.
- "Improved binary DAC codec with spectrum for equiprobable sources," IEEE Trans. on Communications, Vol.62, No.1, pp. 256-268, 2014.
- "Hamming distance spectrum of DAC codes for equiprobable binary sources," IEEE Trans. on Communications, Vol.64, No.3, pp. 1232-1245, 2016.

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- "Dempster-Shafer Multifeature Fusion for Pedestrian Detection," Advances in Mechanical Engineering, Vol.7, No.1, pp. 454058-454058, 2014.
- "Early ramp warning using vehicle behavior analysis," Soft Computing, Vol.22, No.5, pp. 1421-1432, 2018.