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VEHICLE DETECTION BY THE VARIOUS VEHICLE PARTS USING SVM TECHNIQUE

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Abstract

Traffic scrutiny is an essential topic in intelligent transportation systems. Vigorous vehicle detection and tracking is one difficult problem for complex urban traffic surveillance. As the traffic problems in urban areas are leaving to increase traffic surveillance systems based on record are involved over precedent decades. These systems are very much practical to observe and supervise various traffic situations such as traffic management, preclusion of calamity, also secure transportation. Vehicle detection has been the serious part of the traffic observation system for lots of years. However, vehicle detection method is at rest challenging discrepancy morphology ultimate side view is used to remove the vehicle routinely from the traffic image. This paper propose a rear-view automobile detection and tracking method based on multiple vehicle relevant parts using a still camera. We show that spatial modeling of these vehicle parts is decisive for overall performance.

Keywords: people counting, vehicle detection, vehicle tracking, part-based object detection.

Introduction

With quick expansion of urbanization, traffic jamming, occurrence, and abuse fake huge challenges for traffic administration system. Vision, as an in sequence collection access of real-world environment, has attracted much attention in intelligent transportation systems. processor vision techniques are largely used to amass traffic parameter and investigate traffic behaviors for traffic scrutiny. First, the vehicle is treated as an object unruffled of several significant parts, together with the license plate and rear lamps. These parts are local using their unique color, surface, and region feature. besides, the detected parts are treated as graph nodes to create a probabilistic graph using a Markov random field model. The aim of people counting is to belief the number of pedestrians or the compression of the throng in a monitor situation [1]–[8]. To work with cameras that have diverse settings, we propose a communication judgment algorithm that maps each segmented group of pedestrians in one vision to the corresponding cluster in a further view. We call these equivalent groups harmonized globule clusters, each of which enable information to be shared between cameras. The intra-camera chart cues (captured by one camera) and inter-camera diagram information (transferred from other cameras) are built-in in every view. It follows that we present a two-pass regression framework for multi view people counting. particularly, the first-pass repressors uses the visual skin texture extract from the intra-camera video frames to estimate the size of a crowd.

In this paper, we plan to expand vehicle detection and tracking system mainly for urban traffic scrutiny below various environments in China. The system utilizes a rear-view still camera to capture the image succession. In practical traffic scenario, occlusion among vehicles time and again occurs; therefore, it is irrational to delicacy the vehicle as a total. Much explore has detected the purpose by detecting its parts foremost and measure their spatial relationships; this is called a part based model. In our system, we treat the vehicle as an object collected of numerous parts. Unlike other vehicle detection methods, we choose relevant vehicle parts, including the license plate and rear lamps, which usually stay alive on each vehicle. Then, we coalesce these parts into a vehicle by using a Markov arbitrary field (MRF) to model their spatial relationships. We further track the detected vehicles by employ a Kalman filter (KF) to obtain vehicle trajectories. A detection-by-tracking strategy is realize to recover vehicle detection performance. The main charity of this paper lie in the following. First, narrative methods are projected to limit vehicle parts. We localize the Chinese license plate and the rear lamp using their distinguishing color, texture, and region features. Second, we propose a part based vehicle detection model using the MRF. Detected vehicle *parts are shared into a vehicle using an MRF model in which parts are treat as graph nodes. Our method can get used to partial occlusion and various illumination setting.*

Related works

The activity is get in [1] using equation of spherical bulge to guess the vehicle speed. Lucas-Kanade-Tomasi algorithm is used for movement tracking. The various algorithms which are residential for vehicle detection and tracking has reviewed in [2].In this paper is based on background subtraction. In background subtraction and background modeling is nearly everyone vital. The range of method of moving vehicle speed discovery is Inductive loops, RADAR gun, LASER Gun, Manual count [3]. The methods of background pulling out from color image [4] based on normal value, median filter and common region. Also running regular, median algorithm, Mixture of Gaussian [5] are residential, these are based on DCT. Numerous times first frame or frame differencing is used for setting totaling. To remove misdetection of vehicle [6] due to vehicle travelling from other road or other tiny activities such as tree wave can be avoided by using ROI extraction. The background is multiply with ROI mask. So that vehicles are detected correctly. In addition thresholding and morphological operations are used to diminish noise. In range of threshold value is based on a range of methods. The threshold value can be selected yourself or automatically [7].

In superior and constant illumination setting, moving object detection methods are largely used for vehicle detection in ITSs. These methods can be confidential into background modeling, frame differencing, and optical flow [3], [4]. They can handle enlightenment modify and affect to multimode and minor background change. However, there is some drawback in that they are powerless to detect a immobile vehicle and the detected moving object is not essentially a vehicle. Therefore, much delve into utilize the visual features of the vehicle to detect it in a still outline [5], [6]. Features such as Gabor, color, edge, and corner are habitually used to signify the vehicle. Then, they are feed into a deterministic classifier and a generative model to make out vehicles. In addition, researchers usually utilize a two step method, as well as suggestion time band and hypothesis proof [7], to situate the vehicle. This method works fit for the period of the luminous day time but may fall short through poor illumination conditions of the night.

[8], a vehicle is measured to be collected of a skylight, a crown, wheels, and extra parts. These parts are frequently cultured and detected by using their manifestation, edge, and shape appearance [9], [10]. After element detection, the spatial relationship, motion cues, and multiple models are usually used to detect vehicles. Winn et al. [11] decomposed an entity into more than a few local regions to detect them. The relationships between them were used to improve detection performance by a layout conditional random field model. Hoiem et al. [12] further expanded this method by using 3-D models to mark the learning samples. In addition, vehicle parts can be selected and learned automatically in a deformable part-based model [13]. Niknejad et al. [14] employed this model composed of five components, including the front, back, plane, front shortened, and back condensed. Each component contained a root filter and six part filters, which were learned using a latent support vector machine and a histogram of oriented gradients features. To use the part-based model in parameter transfer learning, Xu and Sun [15] proposed a essential knowledge framework named part-based transfer learning. All the composite errands are regarded as a collection of constituent parts, and each task can be divided into several parts, respectively. Transfer learning between two complex tasks can be accomplished by sub transfer learning tasks between their parts. To avoid negative transfer and improve the effectiveness of transfer learning, Sun et al.

People counting

[10], [11]. but, we only believe computer-vision based methods, which can be divided into two category, counting-by-detection and counting-by-regression methods. The methods planned in [12]–[15] exploit various low-level casing manner to search for human heads or moving objects. Stimulated by the progress of deceitful powerful hiker detectors [16]–[19], methods in this category often employ a strider detector to unearth people [20], [21]. Since the guidance samples are regularly of a high ruling without occlusions, the detectors' concert deteriorates notably when the under fire pedestrians are incompletely occluded or in shape images. Moreover, the computational cost of the detection point is typically too high to bear real-time response. The methods in this class are fairly efficient. They educated guess the size of a group by extract low-level features to represent the analogous region, which is usually generated by background subtraction or action segmentation [3]–[5], [22]. However, these methods cannot explain the localization impede or establish the accurate number

of people. They are only suitable for estimating the level of compactness. Following the methods that linearly map a set of respectively normalize the features to the number of people [22]–[24], nonlinear deterioration model, such as neural network, Gaussian process model, and Poisson course model, have been operate recently to develop the concert of people counting systems [1], [3], [25], [26].

Part based vehicle detection

We treat the vehicle as an article collected of multiple relevant parts, together with the license plate and rear lamps, which frequently exist on both vehicle. These parts are contained using their typical color, texture, and region features. Then, an MRF model is constructed to model the spatial associations among these parts to conclude and localize the vehicle. Even if some parts are occluded, vehicles can be correctly detected. in the intervening time, our method can survive with several weather and illumination circumstances. An illustration of the vehicle detection conduit.

License plate localization

License plate localization is grave equipment in ITS applications for traffic administration and scrutiny. In this section, we localize the Chinese license plates with a coarseto-fine strategy. It has its unique texture features that are renowned from the other vehicle parts. The Chinese license plates include a blue background character plate, a yellow setting character plate, a white or black background and-red character plate, and a black background and white character plate. Here, we take a white–blue pair as an example. This type of plate is the mainly general in China. To get the width of the plate for every image synchronizes, we utilized the calibration toolbox in the OpenCV library for traffic prospect calibration.

Vehicle rear lamp localization

A vehicle rear lamp is an noticeable feature of the vehicle. According to the Chinese national standard, the color of the vehicle rear lamp is red and falls within a individual range. We adopt the multi threshold segmentation and connected module scrutiny to extract as many aspirant rear lamps as possible. In this section, we focal point on contender rear-lamp localization without coupling them.

Vehicle detection using MRF

Possibility Model Representation: At first, we created an MRF graph model and definite its model parameters. Vehicle parts were treated as the graph nodes, and the dealings between them were the graph edges. First, we chose one detected license plate as a graph node in the current frame. Then, adjacent vehicle rear lamps were added into the graph if they were closing adequate to the license plate. We will bring up that tracking results are used to recover the detection results by adding prediction of vehicle spot into the graph. Graph G = {V, E} was constructed with one license plate and multiple rear-lamp candidates, where V = {v1, v2... vn} are nodes denoting vehicle parts and E = {e1, e2,..., em} are edges denote the relationships with nearest nodes. G is a complete graph and each pair of nodes is connected by an edge. Each node in G corresponds to a arbitrary variable Fi. Order f = {f1, f2,..., fn} is a relationship of F. fi belongs to Q = {1, 2, 3, 0}. In our MRF graph, there are four types of nodes:

- *q = 1, license plate node;*
- *q = 2, left rear-lamp node;*
- *q = 3, right rear-lamp node;*
- *q = 0, false detection node.*

Pre-processing

The capture is recorded using mobile camera having pixels. In pre-processing the video has changed into the frames. The assorted parameters such as number of frames, frame rate, color format, frame size are extract. There are whole 372 frame in this cartridge. It has frame rate 30 frame per second. The frame size is of 640x480 pixels. Also at this stage the frames are renewed into double data format i.e. required for future action.

Moving Vehicle Detection

Detecting Moving vehicle from cartridge exactly is difficult task. To detect moving object there are mixed approaches such as sequential differencing method, optical flow algorithm, background subtraction algorithm. Temporal differencing method uses two adjacent frames only to search out background image. This method has one disadvantage that it cannot detect slow changes correctly. Visual flow algorithm detects object separately using camera motion. Optical flow algorithm is computationally composite and it is not fitting for real time purpose. In background subtraction utter difference between background model and each immediate frame is *taken to detect moving object. Background model is an image with no touching thing.*

In this effort, background subtraction algorithm is used to perceive moving vehicle. The background subtraction algorithm mostly consist in three stages Background Extraction, Thresholding, Morphological Operations.

1) *Background Extraction:*
   The spirit of Background Subtraction is background extraction. While footage video on highway; it is very tricky to get the image devoid of any moving vehicle. For receiving such picture which is called as background or background facsimile background extraction is used. In this work, typical of all frames pixel values,
2) *Thresholding: Thresholding is one of the customs for image segmentation. It convert grey scale image to binary image.*

Feature Extraction

Feature extraction is the type portion in moving vehicle tracking. The more inscriptions is available on various methods of feature extraction. Features are naught but some of the distinctiveness of detected vehicle such as location, speed, color, shape, censored, edges etc. By using result of connected module scrutiny bounding box has drawn about vehicle. In this work the centroid and histogram of vehicles delimited by bound box are selected as features.

Morphological Operations:

They are normally worn to obtain clear of bang as of imperfect segmentation. Morphological operations are specially matched for binary images. They are performing on output image of thresholding. Here opening, closing and dilation are performed. Opening and closing is used to eliminate holes in the detected center. Dilation is interface of structuring part and foreground pixels. The structuring element is nil but a small binary image. In the process of dilation the size and shape resolve of structuring element is very imperative.

Speed Determination

The detected vehicle has been match id is tracked more than frame. The total number of frames in which same object is present has designed. Vehicle tracking.

Detected vehicles are track to acquire vehicle trajectories. A simple detection-by-tracking approach was used to improve vehicle detection exactness. A. sketch of the Tracking Process Vehicle tracking is used to envisage vehicle positions in successive frames, match vehicles between adjacent frames, and eventually obtain the trajectory of the vehicle. In our system, we used the KF to pathway vehicles. In information, the KF [30] is a minimum variance inference of linear association. Each KF correspond to a tracked object, which is called a tracker. It estimates the true values of annotations with noise. B. KF In our system, we treated the hub of the vehicle license plate and the speed of the vehicle as the state vector, which is shown as $x = [px, py, sx, sy]\ t$ where px and py are x and y coordinates of the vehicle, respectively. sx and sy are the speeds of the x-axis and y-axis directions. KF is a recursive estimation method and can be crack into two steps, i.e., prediction and update.

1) Prediction: In the prediction step, we predicted state vector x and state blunder covariance matrix P at the current time k, as in $\hat{x}k = F\ xk-1$ $\hat{P}k = F\ Pk-1Ft + Q$ where $xk-1$ is the state of previous time $k-1$; F is the state transition matrix; xk is the state of current time; $Pk-1$ and Pk are error covariance matrices of the previous time $k-1$ and current time k, respectively; and Q is the process flare covariance matrix.

2) Update: We selected the closest vehicle around the guess location. If the distance between them was below the porch, it was considered the observation yk. If an observation was occupied, the inform step would be skip, and multiple forecast steps were performed. To perform the update, the Kalman gain Kk is computed in $Kk = PkHt\ (HPkHt + R)\ -1$.

C. Improved Detection by Tracking

The camera vision is for rear-facing vehicles. When the vehicle enters the camera pasture of view, the vehicle parts can be seen without any occlusion. With the vehicle moving forward, the camera outlook is lower, which may cause cruel occlusion of the license plate. Coupled with lower pledge in the distance, the plate is easily lost. However, the rear lamps are regularly localized. We wish to detect the vehicle vigorously in this case.

Conclusion

In this paper, we have proposed a rear-view vehicle detection and tracking method based on a high-resolution camera and using SVM technique. First, we localized the main parts of the vehicle, including the license plate and rear lamps. Then, we construct an MRF model by treat the vehicle parts as graph nodes. LBP was used to infer the MRF graph to get the vehicle locations. After vehicle detection, we *implement the vehicle tracking using KF. We realized a detection-by-tracking technique in which the calculation locations of KF were added into the MRF model as graph nodes. We carried out experiments in practical urban scenarios. Our method could adapt to limited occlusion and various weather conditions. The experiments showed that the proposed method could achieve real-time concert. This method could provide good results even in complex scenarios such as in a busy traffic connection.*

References

[1] F.-Y. Wang, "Parallel control and management for intelligent transportation systems: Concepts, architectures, and applications," IEEE Trans. Intell. Transp. Syst., vol. 11, no. 3, Sep. 2010.
[2] W. Wang, Y. Wang, F. Chen, and A. Sowmya, "A weakly supervised Approach for object detection based on soft-label boosting," in Proc. IEEE Workshop Appl. Comput. Vis., 2013.
[3] C. Stauffer and W. E. L. Grimson, "Adaptive background mixture models for real-time tracking," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 1999, vol. 2.
[4] R. Cucchiara, M. Piccardi, and P. Mello, "Image analysis and rule-based reasoning for a traffic monitoring system," IEEE Trans. Intell. Transp. Syst., vol. 1, no. 2, Jun. 2000.
[5] Z. Sun, G. Bebis, and R. Miller, "On-road vehicle detection using gabor filters and support vector machines," in Proc. IEEE Conf. Digital Signal Process. 2002, vol. 2.
[6] H.-Y. Cheng, C.-C. Weng and Y.-Y. Chen, "Vehicle detection in aerial Surveillance using dynamic bayesian networks," IEEE Trans. Image Process, vol. 21, no. 4, Apr. 2012.
[7] M. Cheon, W. Lee, C. Yoon, and. Park, "Vision-based vehicle detection system with consideration of the detecting location," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 3, Sep. 2012.
[8] W. W. L. Lam, C. C. C. Pang, and N. H. C. Yung, "Vehicle-component identification based on multiscale textural couriers," IEEE Trans. Intell. Transp. Syst., vol. 8, no. 4, Dec. 2007.
[9] L. Lin, T. Wu, J. Porway, and Z. Xu, "A stochastic graph grammar for compositional object representation and recognition," Pattern Recogn., vol. 42, no. 7, Jul. 2009.
[10] B.-F. Lin, Y.-M. Chan, L.-C. Fu, P.-Y. Hsiao, L.-A. Chuang, S.-S. Huang, and.-F. Lo, "Integrating appearance and edge features for sedan vehicle detection in the blind-spot area," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 2, Jun. 2012.
[11] J. Winn and J. Shotton, "The layout consistent random field for recognizing and segmenting partially occluded objects," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2006, vol. 1.
[12] D. Hoiem, C. Rother, and J. Winn, "3d layoutcrf for multi-view object class recognition and segmentation," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2007.
[13] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan, "Object detection with discriminatively trained part-based models," IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, sep-2010.
[14] H. T. Niknejad, A. Takeuchi, S. Mita, and D. McAllester, "On-road multivehicle tracking using deformable object model and particle filter with improved likelihood estimation," IEEE Trans. Intell. Transp. Syst., vol. 13, Jun. 2012.
[15] Z. Xu and S. Sun, "Part-based transfer learning," in Proc. Int. Conf. Adv. Neural Netw., 2011, ser. ISNN'11.
[16] S. Sun, Z. Xu, and M. Yang, "Transfer learning with part-based ensembles," in Proc. Multiple Classifier Syst., 2013.
[17] S. Sun, "A review of deterministic approximate inference techniques for Bayesian machine learning," Neur. Comput. Appl..
[18] K. Robert, "Night-time traffic surveillance: A robust framework for multivehicle detection, classification and tracking," in Proc. IEEE Conf. Adv. Video Signal Based Surv. 2009.
[19] W. Wang, C. Shen, J. Zhang, and S. Paisitkriangkrai, "A two-layer nighttime vehicle detector," in Proc. Digit. Image Comput., Tech. Appl., 2009.
[20] W. Zhang, Q. M. J. Wu, G. Wang, and X. You, "Tracking and pairing vehicle headlight in night scenes," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 1, Mar. 2012.
[21] R. O'Malley, E. Jones, and M. Glavin, "Rear-lamp vehicle detection and Tracking in low-exposure color video for night conditions," IEEE Trans. Intell. Transp. Syst., vol. 11, no. 2, Jun. 2010.
[22] D.-Y. Chen, Y.-H. Lin, and Y.-J. Peng, "Nighttime brake-light detection by nakagami imaging," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 4, pp. 1627–1637, Dec. 2012.
[23] A. Yilmaz, O. Javed, and M. Shah, "Object tracking: A survey," ACM Comput. Surv., vol. 38, no. 4, 2006.
[24] D. Comaniciu, V. Ramesh, and P. Meer, "Kernel-based object tracking," IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 5, May 2003.

[25] P. L. M. Bouttefroy, A. Bouzerdoum, S. L. Phung, and A. Beghdadi, "Vehicle tracking by non-drifting mean-shift using projective kalman filter," in Proc. Int. IEEE Conf. Intell. Transp. Syst., 2008.

[26] A. B. Chan, Z.-S. J. Liang, and N. Vasconcelos, "Privacy preserving crowd monitoring: Counting people without people models or tracking," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2008,

[27] P. Kilambi, E. Ribnick, A. J. Joshi, O. Masoud, and N. Papanikolopoulos, "Estimating pedestrian counts in groups," Comput. Vis. Image Understand., vol. 110, no. 1, 2008.

[28] A. B. Chan and N. Vasconcelos, "Bayesian Poisson regression for crowd counting," in Proc. IEEE Int. Conf. Comput. Vis., Sep./Oct. 2009,

[29] V. Lempitsky and A. Zisserman, "Learning to count objects in images," in Advances in Neural Information Processing Systems. Red Hook, NY, USA: Curran Associates, Inc., 2010.

[30] Y.-L. Hou and G. K. H. Pang, "People counting and human detection in a challenging situation," IEEE Trans. Syst., Man, Cybern. A, Syst., Humans, vol. 41, no. 1, Jan. 2011.

[31] T.-Y. Lin, Y.-Y. Lin, M.-F. Weng, Y.-C. Wang, Y.-F. Hsu, and H.-Y. M. Liao, "Cross camera people counting with perspective estimation and occlusion handling," in Proc. IEEE Int. Workshop Inf. Forensics Security, Nov./Dec. 2011.

[32] H. Ma, C. Zeng, and C. X. Ling, "A reliable people counting system via multiple cameras," ACM Trans. Intell. Syst. Technol., vol. 3, no. 2, Feb. 2012, Art. ID 31.

[33] Y. Zhou and J. Luo, "A practical method for counting arbitrary target objects in arbitrary scenes," in Proc. Int. Conf. Multimedia Expo, Jul. 2013.

[34] S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE Trans. Knowl. Data Eng., vol. 22, no. 10, Oct. 2010.

[35] B. Zhan, D. Monekosso, P. Remagnino, S. Velastin, and L.-Q. Xu, "Crowd analysis: A survey," Mach. Vis. Appl., vol. 19, nos. 5–6, 2008.

[36] J. C. S. Jacques, Jr., S. R. Musse, and C. R. Jung, "Crowd analysis using computer vision techniques," IEEE Signal Process. Mag., vol. 27, no. 5, Sep. 2010.

[37] S.-F. Lin, J.-Y. Chen, and H.-X. Chao, "Estimation of number of people in crowded scenes using perspective transformation," IEEE Trans.