VEHICLE DETECTION AND TRACKING METHODS

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Abstract - *This paper presents a scheme for vehicle detection and tracking and categorization from pavement CCTV in traffic surveillance. The system counts vehicles and separate them into four categories: car, van, bus and motorbike. A new backdrop Gaussian Mixture Model and dark elimination method have been used to deal with sudden enlightenment changes and camera shaking. A Kalman filter tracks a vehicle to enable categorization by majority voting over more than a few successive frames, and a level set method has been used to purify the foreground blob. Wide-ranging experiments with real world data have been undertaken to assess system concert. The best routine results from training a SVM (Support Vector Machine) using a combination of a vehicle outline and intensity-based HOG features extracted next background subtraction, classifying forefront blobs with mass voting. The vehicle monitoring system is evaluated on a new dataset together on Italian motorways which is provided with fairly accurate ground truth obtained from laser scans. For a broad assortment of distances, the remember and exactitude of detection for cars are outstanding. Information for vehicles are also informed. The dataset with the ground truth is through communal.*

Keywords: Traffic surveillance; Gaussian Mixture Model; Vehicle detection; Support Vector Machine

1. INTRODUCTION

We present a structure for vehicle detection and tracking using a single camera mounted on a stirring or inactive vehicle. The scheme is repeatedly in real-time on a single CPU center. A large variety of sensors, e.g. lidar, radar, ultrasound and stereo based intensity sensors, is available to driver support system designers. We opted for a single camera-based system seeing as it is contemptible, consumes minimum energy, is brightness and vigorous. It can effortlessly by mounted on a motorcycle or yet, forward or rear facing, on a bike. In a car, multiple single camera systems with dissimilar viewing instructions, angles and distance ranges can be deployed. Visual in order is composite to procedure, but it provides rich in turn about the surroundings. Vision as a sensing apparatus has restrictions but these are fine understood since they are analogous to difficulties qualified by human drivers. As the main role of the paper we in presence a description scheme for detection and tracking of vehicles that integrates high-performance vision algorithms. We have the evidence for how to control the WB detector and the TLD tracker to get real-time concert through process setting up. As a second giving, a new dataset intentional for estimate of on-board systems for motor vehicle monitoring is accessible. The dataset was serene on Italian motorways and includes a multiplicity of illumination and traffic setting, For the dataset, an estimated ground reality was considered from laser scans together with the illustration data. The dataset and the fairly accurate position truth will be made municipal.

2. RELATED WORK

2.1 Vehicle Detection

Object detection in motionless images is a glowing deliberate problem. In processor apparition research, cars are common objects of attention due to their inflexible structure, low exterior variations and ordinary presence in everyday scenes [3], [4], [5], [6], [7], [8]. Untimely approaches were aiming typically at high exactness and remember rather than real-time act and were based on numerical methods like SVM [4], [5], PCA [6], Neural Networks [7] or Bayesian decision-making [8]. A penetrate in application of statistical knowledge techniques to real-time entity detection was brought by the cascaded classifier[9] who planned a method for preparation a sequential classifier working on simpleton-evaluate like features and confirmed its real-time presentation on the face detection problem. Hundreds of related papers have been available focusing on civilizing different aspects of the come near and applying it to various errands, including car detection [10]. Of the track up work on the scrupulous interest to this paper are methods focusing on routine cascaded classifier preparation with respect to both classification accuracy and the average arrangement time [1], [11]. They permit guidance a time-precision optimized cascaded classifier without the dreary manual intrusion needed in the unique. An alternative come up to stimulate by the success of part based detectors in Pascal VOC Challenge [3] is taken in [12]. However, in spite of the good detection recital, the difficulty of the method allows the scheme to run at only 1-2 frames per second. Driving assistance systems for inner-city environment require relatively composite algorithms and the problem is immobile considered to be very testing [13]. In less challenging scenarios like motorway driving, a range of quite simple heuristic-based vehicle detectors have been planned in the reporting. Some authors develop the shadow radiate on the road by cars which are classically darker than the rest of the way [14], some use the fact that car external edges could be approximated by a U-shape curve [15]. Others rely on vehicle equilibrium as the main cue [16], [17]. At the identical time, methods that diminish the range of probable vehicle positions to be tested by constraining to viable on-road locations are often functional [18]. The advantage of these systems is their real-time performance, but their assumptions regarding the real-world scenes are crude and do not grasp in general. Indeed, such papers often not have meticulous quantitative assessment on some openly available dataset and contrast to other methods.

2.2 Vehicle Tracking

In the prose, the Particle Filter (PF) algorithm [23] is most likely the accepted approach for vehicle tracking. It has been useful both to single object tracking [12], [21] as well as in an absolute form which is clever to path an indefinite and uneven number of objects [10], [20]. The advantage of the PF approach is that it can model composite thing dynamics throughout non-parametric, particle based, multi-modal motion allocation inference. In the [13] it has been used in its position of PF. Instead of modeling the allocation of possible states as it keeps only a tiny set of the most possible motion explanations. The intrinsic problem of the higher than approaches is their sympathy to flow from the factual object position, specially in long sequences. They offer no correcting mechanisms and finally fail when the object changes exterior drastically due to occlusion, change in illumination conditions or facade change. Recently, discriminative methods have turn into accepted in tracking writing posing the tracking as a foreground background classification mission [24], [25]. In these approaches, the problem of multipart motion modeling is avoided by exhaustively searching the neighborhood of the predicted situation. The methods also tender means for permanent exterior model updating through on-line erudition algorithms.

3. THE SYSTEM

The organization of the vehicle detection and tracking system is depicted. The position of the Wald Boost (WB) detector, the detection of new cars and trucks in the grassland of view. The new detections are tracked by a Flock of Trackers (FoT) which is thorough. The become skilled at and re-Detect component uses on-line unsubstantiated learning to construct a explicit detector for all monitored vehicles; it allows long-term vehicle individuality preservation even in case of tracking crash. The in sequence from the tracker, explicit and common vehicle detectors is included and passed on to the 3D pose assessment and neighboring vehicle continuation module; these two modules are not described here due to not have of space.

3.1 The Detector

The rear view vehicle detector is a Wald Boost [1] trained chronological classifier functional within a descending window scaffold. Wald Boost is an AdaBoost-based algorithm which routinely builds a fine-grained detection pour [9]. Wald's chronological chance ratio test (SPRT) performs early refusal of negative samples after valuation of a single weak classifier. Speedy rejection of negative samples is momentous for detection velocity, as a gigantic greater part of tested windows do not have a vehicle. Wald Boost training is iterative, increasingly building a more multifarious sequential classifier. In the first iteration, a average AdaBoost culture search for the finest weak classifier is performed. Then the denial porch for Wald's SPRT is expected on a large puddle of data. Finally, the puddle is pruned and a bootstrap approach is employed to amass supplementary non-object examples. To speed up the AdaBoost culture, the weak classifier variety relies only on a detachment of the puddle sub-sampled using the QWS+ strategy [30]. The weak classifiers are select from an extensive set of multi-block local binary model features [31] and their assistance to the final conclusion are a utility of the weighted blunder for each double code as in the confidence-rated cataloging method [32].

3.2 The Tracker

Tracking is performed by an modified Flock of Trackers (FoT) [29]. The advantages of the FoT are its pace, regarding 5 milliseconds on a ordinary notebook for every tracked object, and its sturdiness to fractional occlusion and unclear initialized. It can be estimates object motion from the dislocation of local trackers which are multiply uniformly within a section casing the object. Local trackers estimation displacements by the Lucas-Kanade (LK) method [33].Motor vehicle tracking strategy Multi-object tracking and data relationship have received substantial attention in the computer vision and a great deal of the setting work has been in non-transportation applications. From the computer vision writing, the deferent tracking approaches for cartridge data can be confidential as follows.

3.3 Model Based Tracking

Three-dimensional model-based motor vehicle tracking systems have beforehand been investigated by quite a few explore groups, the most well-known being the groups at the University of appraisal (Baker and Sullivan, 1992; Sullivan, 1992). The importance is on getting better trajectories and models with high exactness for a small amount of vehicles. The most stern Achilles' heel of this approach is the dependence on detailed arithmetical object models. It is improbable to expect to be gifted to have detailed models for all vehicles that can be found on the thoroughfare.

3.4 Region Based Tracking

In this come near, the VIPS identifies a related province in the image, allied with each vehicle and then tracks it over time using a cross-correlation calculate. Typically, the process is initialized by the background subtraction method. A Kalman filter-based adaptive background model allows the environment estimation to grow as the endure and time of day illumination situation. Foreground objects are detected by subtracting the inward bound image from the existing background educated guess, looking for pixels where this dissimilarity image is above a quantity of threshold and then sentence allied components. This approach works reasonably well traffic.

However, beneath heaving traffic situation, vehicles partly occlude one another in its place of being spatially lonely, which makes the task of segmenting personage vehicles not easy. Such vehicles will turn into grouped mutually as one huge splash in the foreground image. This phenomenon on a imaginary one dimensional thoroughfare viewed from the camera's point of view, from now on referred to as the image airplane. The vehicles have restricted duration, hence the trajectories are shown as `wide bands in the time space plane. By time t3, vehicle 2 incompletely occludes vehicle. Region based tracking would speciously combine the two `blobs' mutually at this summit.

3.5 Active Curve based Tracking

A double to the section based approach is tracking based on energetic line models, or snakes. The fundamental idea is to have a illustration of the bounding outline of the object and remain vigorously updating it. The earlier system for vehicle tracking urbanized in our group was based on this approach. computational involvedness. However, the incapacity to sector vehicles that are moderately occluded relics. If one could initialize a take apart form for each vehicle, then one can path even in the incidence of partial occlusion. However, initialization is the thorny part of the dilemma if the vehicles cross the threshold the detection province moderately occluded, the coordination will collection two vehicles into a lone article and this will outcome in noteworthy amount errors.

3.6 Feature Based Tracking

A substitute approach to tracking abandons the plan of tracking matter as a complete and as an alternative, tracks sub-features such as discernible points or appearance on the object. The advantage of this come up to is that even in the being there of partial occlusion, some of the features of the touching object stay behind noticeable. in addition, the same algorithm can be used for tracking in brightness, nightfall or night-time environment; it is autonomous because it selects the nearly all outstanding features under the given situation, feature tracking for the identical two vehicles in the prior model. Personality features are tinted at three instants in time and the position point out their individual tracks. For design, the features from poles apart vehicles are shown with different cryptogram, but, in carry out, the features would be identical at the tracking level. By t3, some of the features beginning the first vehicle are occluded and vanished, however, other features from this vehicle continue behind and prolong to be tracked. While detecting and tracking vehicle features makes the classification more tough to limited occlusion, a vehicle will have various features. This introduces a new predicament of grouping. To deal with this problem we use a frequent motion limitation; features that are seen inflexibly affecting together are grouped reciprocally. Numerous to the simple illustration once more, applying a general motion restriction to the features and collecting the feature tracks into disconnected vehicles yields. The open circles signify features that were misplaced to occlusion at a little summit in their path, and thus, not built-in in the final grouping.

4. METHOD VEHICLE DETECTION

This segment particulars the main steps of the projected technique. We take out the border points and corners of the successive descriptions. We remain only the border points belonging to curves containing corners. The involvement is performed linking successive images. We investigate the involvement results to perceive obstacles. Finally, Adaboost is used to choose if a detected object is a vehicle or not.

4.1 Detecting Corner

We use turn detector that is customized from the Harris corner detector. Shi and Tomasi corner detector is based on the Harris corner detector. After devious the point's corners entrance was performed to get rid of small secure point's corners, in a vehicle are a large amount more compared to foliage or features of the road.

4.2 Detecting Edge and Filtering

Canny operator is used to detect edge points of the uninterrupted images. The edge curves are twisted by alliance edge points using morphological operations. Among the ensuing curves, we maintain only the ones passage at slightest one of the corners premeditated in subsection.

4.3 Association

The put your feet up of this clause describes the method we use to find involvement between edges of following frames. Let be a curve in the image and Ck be its analogous one in the image IK. Consider two to the curves and their corresponding edges Pk-1 and Qk-1 belonging ones Pk and Qk belonging to the curve Ck. We define the associate point belonging to the curve Ck which has the same y synchronize as Pk-1. Note that the connection is not communication neither activity.

4.4 Detection of Objects

Let us reflect on the image connection and M and N be the image width and height, in that order. At each pixel (x,y) in the present image, (x,y) is the detachment between the pixel (x,y) and its connect one in the earlier image. The obstacles can be detected by with the next functions. The principles of the function F1 and F2 should be utmost at the areas where present are obstacles. The function F1 allows to conclude the straight boundaries of obstacles. The function F2 allows to resolve the erect bounds of obstacles. The segmentation of the two functions helps to establish the horizontal and vertical limits of obstacles

4.5 Validation using Adaboost

In the rung of detecting and locating faces, we recommend an draw near for vigorous and rapid algorithm based on the mass of images, AdaBoost, which combines uncomplicated descriptors for a muscular classifier.

5. CONCLUSION

A arrangement able to constantly perceive and track vehicle rears in images from a sole camera was accessible. The collection showed good recital in terms of recollect, exactness and false constructive rates even in bad illumination situation. The estimate was accepted out on a new dataset that will be at large to the scientific neighborhood. Recent evaluations of profit-making VIPS found the obtainable systems have troubles with blockage, occlusion, lighting transitions between night/day and day/night, camera tremor due to wind, and long darkness linking vehicles mutually. We have accessible a vehicle detection and tracking structure that is considered to control under these difficult conditions. in its place of tracking complete vehicles, vehicle features are tracked, which makes the arrangement less perceptive to the dilemma of partial occlusion. The similar algorithm is used for tracking in daylight, twilight and nighttime surroundings, it is autonomous by selecting the majority important features for the given situation. Common action over entire attribute tracks is used to group features from being vehicles and diminish the chance that long darkness will link vehicles in concert. Finally, camera motion through elevated storm is accounted for by tracking a small number of fiducial points.

REFERENCES

[1] J. Sochman and J. Matas, "WaldBoost - Learning for Time Constrained Sequential Detection," in CVPR, vol. 2, 2005, pp. 150–157.

[2] Z. Kalal, J. Matas, and K. Mikolajczyk, "P-N Learning: Bootstrapping Binary Classifiers by Structural Constraints," in Conference on Computer Vision and Pattern Recognition (CVPR), 2010.

[3] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, "The Pascal Visual Object Classes (VOC) Challenge," International Journal of Computer Vision, vol. 88, no. 2, Jun. 2010.

[4] C. Papageorgiou and T. Poggio, "A Trainable System for Object Detection," Int. J. Comp. Vision, vol. 38, no. 1, pp. 15–33, Jun. 2000.

[5] Z. Sun, G. Bebis, and R. Miller, "On-road Vehicle Detection using Gabor Filters and Support Vector Machines," in 14th Intern. Conf. on Digital Signal Processing (DSP), vol. 2, 2002, pp. 1019–1022 vol.2.

[6] J. Wu and X. Zhang, "A PCA Classifier and its Application in Vehicle Detection," in Neural Networks, Proceedings. IJCNN '01. International Joint Conference on, vol. 1, 2001, pp. 600–604 vol.1.

[7] N. Matthews, P. An, D. Charnley, and C. Harris, "Vehicle Detection and Recognition in Grayscale Imagery," Control Engineering Practice, vol. 4, no. 4, pp. 473–479, 1996.

[8] H. Schneiderman and T. Kanade, "A Statistical Method for 3D Object Detection applied to Faces and Cars," in IEEE Conf. on Computer Vision and Pattern Recognition, vol. 1, 2000, pp. 746–751 vol.1.

[9] P. Viola and M. Jones, "Rapid Object Detection using a Boosted Cascade of Simple Features," in Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on, vol. 1, 2001, pp. I–511–I–518 vol.1.

[10] S. Sivaraman and M. Trivedi, "A General Active-Learning Framework for On-road Vehicle Recognition and Tracking," IEEE Trans. on ITS, vol. 11, no. 2, pp. 267–276, June 2010.

[11] L. Bourdev and J. Brandt, "Robust Object Detection via Soft Cascade," in CVPR, 2005, pp. 236–243.

[12] A. Takeuchi, S. Mita, and D. McAllester, "On-road Vehicle Tracking using Deformable Object Model and Particle Filter with Integrated Likelihoods," in Intelligent Vehicles Symp., june 2010, pp. 1014–1021.

[13] A. Ess, K. Schindler, B. Leibe, and L. Van Gool, "Object Detection and Tracking for Autonomous Navigation in Dynamic Environments," The International Journal of Robotics Research, vol. 29, 2010.

[14] C. Tzomakas and W. von Seelen, "Vehicle Detection in Traffic Scenes Using Shadows," IR-INI, INSTITUT FUR NEUROINFORMATIK, RUHR-UNIVERSITAT, Tech. Rep., 1998.

[15] E. Richter, R. Schubert, and G. Wanielik, "Radar and Vision-based Data Fusion - Advanced Filtering Techniques for a Multi-object Vehicle Tracking System," in Intelligent Vehicles Symposium, 2008 IEEE, june 2008, pp. 120–125.

[16] A. Broggi, P. Cerri, and P. Antonello, "Multi-resolution Vehicle Detection using Artificial Vision," in Intelligent Vehicles Symposium, 2004 IEEE, june 2004, pp. 310–314.

[17] A. Khammari, F. Nashashibi, Y. Abramson, and C. Laurgeau, "Vehicle Detection Combining Gradient Analysis and AdaBoost Classification," in Intelligent Transportation Systems Conf., sept. 2005, pp. 66–71.

[18] T. Kowsari, S. Beauchemin, and J. Cho, "Real-time Vehicle Detection and Tracking using Stereo Vision and Multi-view AdaBoost," in Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on, oct. 2011, pp. 1255–1260.

[19] Z. Sun, G. Bebis, and R. Miller, "On-road Vehicle Detection: a Review," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 28, no. 5, pp. 694–711, may 2006.

[20] J. Arrospide, L. Salgado, and M. Nieto, "Vehicle Detection and ´ Tracking using Homography-based Plane Rectification and Particle Filtering," in Intelligent Vehicles Symposium (IV), 2010 IEEE, june 2010, pp. 150–155.

[21] L. Juan and O. Gwun, "A Comparison of SIFT, PCA-SIFT and SURF", International Journal of Image Processing (IJIP), (2008) September 10.

[22] M. Chaple and S. S. Paygude, "Vehicle Detection and Tracking from Video frame Sequence", International Journal of Scientific & Engineering Research, vol. 4, no. 3, (2013), March, ISSN 2229-5518.

[23] S. P. Hoogendoorn and P. H. L. Bovy, "State-of-the-art of vehicular traffic flow modeling", Journal of Systems and Control Engineering, vol. 215, no. 4, (2001), pp. 283, 303.

[24] Video based Vehicle Detection and Classification in Heterogeneous Traffic Conditions using a Novel Kernel Classifier (IETE JOURNAL OF RESEARCH | VOL 59 | ISSUE 5 | SEP-OCT 2013).

[25] Signal & Image Processing: An International Journal (SIPIJ), vol. 5, no. 1, (2014) February.

[26] L. Vasu, "An effective step to real-time implementation of accident detection system using image processing", Master of Science, Oklahoma State University, USA, (2010).

[27] T. E. Boult, "Frame-rate Omni directional surveillance and tracking of camouflaged and occluded targets", in Visual Surveillance, (1999), Second IEEE Workshop on, (VS'99), 1999, pp. 48-55.

[28] G. Xiang, "Error analysis of background adaption", in Computer Vision and Pattern Recognition, (2000), Proceedings, IEEE Conference on, 2000, vol. 1, pp. 503-510.

[29] I. Haritaoglu, "W4: Real-Time Surveillance of People and Their Activities", Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 22, (2000), pp. 809-830.

[30] G. C. De Silva, “Automation of Traffic Flow Measurement Using Video Images”, Master of Engineering, University of Moratuwa, Sri Lanka, (2001).

[31] D. Koller, “Towards robust automatic traffic scene analysis in real-time”, in Decision and Control, Proceedings of the 33rd IEEE Conference on, vol. 4, (1994), pp. 3776-3781.

[32] W. Zhang, “Moving vehicles detection based on adaptive motion histogram”, Digit. Signal Process, vol. 20, (2010), pp. 793-805.

[33] F. Porikli and A. Yilmaz, “Object Detection and Tracking”, in Video Analytics for Business Intelligence. vol. 409, C. Shan, Eds., ed: Springer Berlin Heidelberg, (2012), pp. 3-41.

[34] S. Rhee, “Vehicle Tracking Using Image Processing Techniques”, in Rough Sets and Current Trends in Computing. vol. 3066, S. Tsumoto, et al., Eds., Ed: Springer Berlin Heidelberg, (2004), pp. 671-678.

[35] L. Li, S. Ranganath, H. Weimin and K. Sengupta, “Framework for Real-Time Behavior Interpretation from Traffic Video”, IEEE Tran. On Intelligent Transportation Systems, vol. 6, no. 1, (2005) pp. 43-53.

[36] K. H. Lim, “Lane-Vehicle Detection and Tracking”, Proceedings of the International Multi-Conference of Engineers and Computer Scientists (IMECS 2009), vol. 2, (2009), pp. 5–10.

[37] D. Koller, N. Heinze and H. Nagel, “Algorithmic Characterization of Vehicle Trajectories from Image Sequence by Motion Verbs”, Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, (1991), pp. 90-95.

[38] A. Giachetti, M. Campani, and V. Torre, “The Use of Optical Flow for Road Navigation,” IEEE Trans. Robotics and Automation, vol. 14, no. 1, (1998), pp. 34-48.