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A CLASSIFICATION OF ON-ROAD OBSTACLES ACCORDING TO THEIR RELATIVE VELOCITIES

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Abstract

The systems is based on image processing have various applications in the domain of motion control of robots and the autonomous vehicles. The current paper is oriented to solution of the problem that precedes to the implementation of automatic avoidance of on-road obstacle—and how to detect them, to tracking the sequence of images, and to identify which of the mare stationary, incoming, or outgoing from the camera. The overall algorithm of obstacles classification is presented in this paper consists of three different basic phases:(1) image segmentation in order to extraction of the pixels belonging to the image of a road and also the objects over it; (2) extraction of characteristic points inside the area of the obstacles, their description and also the tracking in following frames; and (3) estimation of distances between the camera, the obstacles and their rates of changing relative velocities. The verifications of a particular steps of the proposed algorithm are described using real road-traffic images, while the overall algorithm is tested using both the synthesized sequences of images and also the ones acquired in real driving.

Index Terms: Machine vision, Image processing, Image segmentation, Pattern recognition, Support vector machines, Feature extraction, Tracking, SURF, Pose estimation.

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1. INTRODUCTION

In recent years, self-anti-collision systems that have been developed for preventing the traffic accidents and achieving safe driving. This system should have alert drivers of the presence of any obstacles and help them to react in advance. In these systems, the ability of detecting obstacles is very essential. The safe operation of the vehicle depends heavily on only the vision. The vision of a driver or a person driving can be improved by the systems that provide information about the environment around the vehicle which cannot be seen or barely seen by human eyes. Therefore, any obstacle detection system based on machine vision is the topic of current research in the smart vehicle technology. The particular

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objective of this work is to allow the classification of the on-road obstacles on the basis to the irrelative velocities, on to the categories as incoming, outgoing, and stationary, as a prerequisite for their avoidance into the context of autonomously guided cars. This existing techniques used in the on-road obstacle detection may differentiate according to the definition of the obstacles. This might be classified into two categories and they are [1]. The first one is related to the obstacles reduced to a specific object that is vehicle, pedestrian, etc. In this case, detection can be based on search for specific patterns, which is possibly supported by features such as texture, shape [2, 3], symmetry [4, 5], or by the use of an approximate contour. The second category which is used when the definition of the obstacles is much more general. In this case, two methods are being generally used. (1) The usage of a monocular camera which is generally based on an analysis of the optical flow [6–9]. This method require a rather huge calculations, and it is very sensitive to the vehicle movement. Also, it detects only the obstacles that are moving and fails when obstacle has small speed or null speed (2)The method is based on stereo vision [10–13]. Images are captured by using two or more cameras at the same time from various angles, and then obstacles are to be detected by matching. This method generally require more time to do the necessary calculations, and it is very sensitive to the local motion of each camera caused by vehicles movement.

Usually, a method for detecting both the moving and static objects are simultaneously required because of the static objects such as boxes which may fall on the road in the front of car and they are very dangerous too.

Actually, an algorithm of on-road obstacles detection which should provide that: 1. The objects which are outside the road are eliminated. 2. Irregularities on to the road surfaces which are not affected by the driving that are not to be considered. 3. Static obstacles that are on the road are properly recognized in order to be ignored. 4. Vehicles that are on the road are detected in order to adjust the own motion according to the irrelative distances and their velocities.

We proposed in this paper that an obstacle detecting method used into the monocular camera mounted on a vehicle receiving the light variations into the scene on road ahead and calculating the captured images to know out the obstacle detection. The output of the proposed algorithm is a classification on to classes of moving obstacles and s tatic obstacles. After getting the information of obstacles, drivers can quickly react and precisely to take actions to prevent car accidents. Moreover, the systems of autonomous car driving may react appropriately in order to keep the car motion along the nominal trajectory relative to the road borders, simultaneously avoiding incoming cars and outgoing cars. Here, obstacles are explained as actual arbitrary objects protruding from the ground plane in the area of road, both static ones and moving ones. Road markers in the area of road (e.g., pedestrian crossing) as also a number of objects outside the road region are considered as obstacles of no interest.

2.THE METHODS

In order to know the obstacles on road, to track them, and to know their positions and relative velocities, the following operations are performed (asillustratedonFig.1).

First, the region of road is detected using the SVM(support vector machine) classification method in order to differentiate class “road” from the class “non-road”. Secondly, the non-road region as the result of this detection are classified into two categories :“obstacles” and “road environment.”After classification, one has three types of region: environmental area, road region, and obstacles. The real obstacles of the road like cars, pedestrians, boxes, etc. Are all belonging to the class called “obstacles.” Monitoring each of these obstacles are done by the use of SURF matching algorithm. The final step that is conclusion consists in calculating the obstacles’ positions in the field of its view and also the calculation of their relative velocities in order to distinguish as the static obstacles and dynamic obstacles (inside range of 200 m ahead).

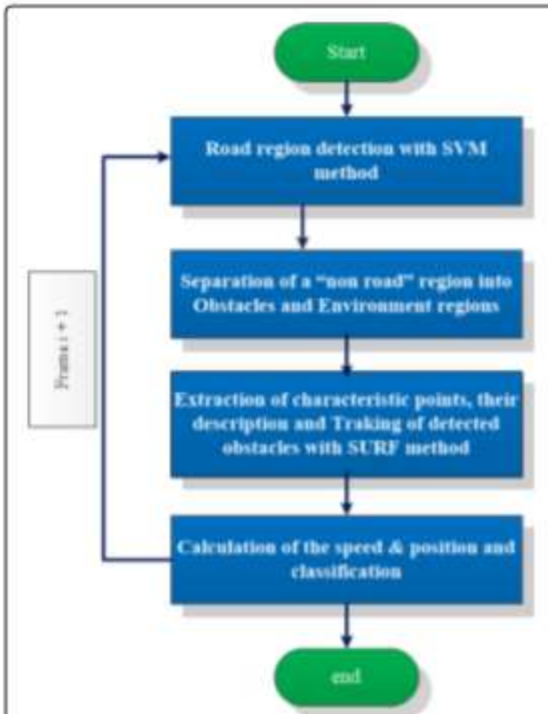

Fig. 1 Flowchart of the proposed method

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2.1 Road region extraction

The initial step in the algorithm that consists in segmentation of an images into the region of roads and the other region that includes the remaining image parts(“non-road”).In order to differentiate one pixel as a member of a class “road,” there is a number of possible segmentation methods which based on color, texture descriptors that are based on statistic parameters, structure, or frequency spectrums, etc. While some are acceptable results that have been obtained when the color components have been utilized only, even three decade ago [14] or are used by the best candidates among texture statistics and also structured descriptors [15], our reasoning here was

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oriented toward more complexed approach where the color and texture are considered simultaneously [16].

The proposed algorithm is composed of the five components. In the first feature of extraction component ,a feature vector is extracted from every pixel of the input image. Secondly, the components of the dynamic training database(DTD) is filled with the training set labelled by a human supervision or in initialization and are updated by the new training set that is online. Thirdly, the component of Classifier Parameters Computing is utilized to estimate the parameters in the SVM classifier. Fourthly the SVM classifier component are in charge of training and classifications that utilizes the training data and the classifier parameters to train the SVM classifier and to utilize the trained SVM classifier in order to classify image in to road/non-road classes. The last component contains two stages: morphological operations and online learning operations. The former implements connects region growing and also hole filling on the basis of classification result to determine the road regions. The latter compares the morphological result and classification result to know the quality of the current classification, then choose new training set from that comparison and updated DTD. The flowchart is shown on Fig.2 illustrates the algorithm.

As an initial operation, the populations of "road" pixels and "non-road" pixels are indicated by an operators (driver) action, via marking appropriate rectangular regions on the images as shown in Fig. 3. The same initialization can be made by the automatic designation of rectangular windows in the central lower part of image, a priory guaranteeing that the contents is typical for the road area. This way, an initialisation content of a Dynamic Training Database (DTD)is specified. In order to reduce the calculations, also the number of pixels inside the region of rectangle is limited to that of 1000. If the total of encompassed pixels is larger, one thousands of them will be selected in random way. This DTD will be continually updated in order to follow the changes of the road scene. The selected set of classification parameters is calculated for each subsequent images. The process of differentiation is based on the SVM method. The final step of the classification consists in morphological processing of any binarized images. After the final segmentation is completed, the upgrade consisting in the online updating of DTD is the finishing step prior the acquisition of a new images. Featured vector is of eight-dimensional:

$$F_{ij} = [f_{t1(i,j)}, f_{t2(i,j)}, f_{t3(i,j)}, f_{t4(i,j)}, f_{t5(i,j)}, f_{c1(i,j)}, f_{c2(i,j)}, f_{c3(i,j)}] \quad (1)$$

where $i = 1..H$ and $j = 1..W$

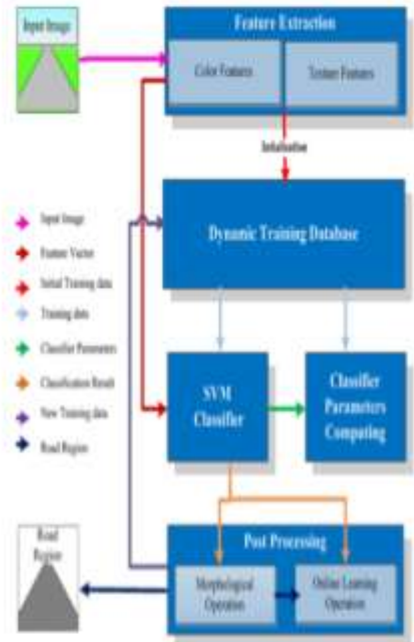

Fig. 2 Flowchart of the road region extraction algorithm

The first five elements of Haralick's statistical features are:

$$\text{Energy} = \sum_u \sum_v \{p(u,v)\}^2 \quad (2)$$

$$\text{Enthropy} = \sum_u \sum_v p(u,v) \log\{p(u,v)\} \quad (3)$$

$$\text{Contrast} = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{u=1}^{N_g} \sum_{v=1}^{N_g} p(u,v) \right\} \quad (4)$$

$$\text{IMD} = \sum_u \sum_v \frac{1}{1+(u-v)^2} p(u,v) \quad (5)$$

$$\text{Correlation} = \frac{\sum_u \sum_v (u.v) p(u,v) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (6)$$

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Fig. 3 Initialization of DTD. Red rectangles are used for "positive" training (road class), and blue ones for "negative" training (non-road class)

where the IMD is the inverse moment of the differences, p(u,v) is element of the gray level co-occurrences matrix (GLCM), (μx,μy) and (σx,σy) are the mean values and covariances which are calculated by using this matrix. The remaining three elements of the feature vector are pixels, USV color, and the components. It is very natural to suppose that the feature space of "road" classes and "non-road" classes are in non-linear relation and that is not expected to be obtain some linear hyper-plane which distinguish these two classes in original feature of space. Following the outcome given in [17], a Gaussian radial basis function (RBF) kernel is being used as the SVM kernel function. There are two types of classification parameters: complexity parameter C and the γ parameter. It should be found that which one is more appropriate for this discrimination. In order to do this, the parallel validation relative to these two parameters are done on the image belonging to DTD. Due to the continuous changes in dynamic of the road contents as a outcome of camera motion, DTD should be updated from time to time. It was selected that after every ten frames, the training databases for both the classes are refreshed by replacing hundred of stochastically selected old members by hundred of new ones, among population of pixels that is already classified in the particular class. The larger numbers of updated elements denotes to excessive impact of the incorrectly classified pixels, while for too low numbers of replaced sampled pixels, one can also expect low adaptation abilities of it.

After the step of classification, it is very usual that there would be number of small unconnected groups of pixels around the road, classified as the "road", as well as the number of "holes" over the road region. In order to eliminate this type of small aggregations of the pixels, the algorithms include morphological operations that are "opening" and "filling the holes". Online training upgrades of the SVM method[16] is optional but it is very useful in the context of this applications. Besides the already mentioned update in the DTD, it includes the evaluation of the performances of the current classifications. This process which is based on the basic assumption that the road region is consisted from connected pixels. As a result to this, "road" pixels are detected outside the main region of road and as well as the "non-road" pixels that are located over the road region are the sources of the information on how the classifier should be evolved.

2.2 Obstacles extraction

In order to the extraction of shape of obstacles in the foreground images, we have to delete two kinds of different things: road marking and the noise or unwanted marks on the road or outside of it. For the road marks, the result of the road region is being used. And the result of road region detection is used to mark the unwanted obstacles or noice. In order to solve the problem of detection of obstacle the road region is to be divided into the road region and as well as the noice or unwanted region.

2.3 Region classification

As the non-road region is to be grouped into the obstacle and the noise that is everything outside the road. Figure 4 shows that the result of detection of region of road (a) and the template image of this region of road (b) where the black pixels are representing the road region. After evaluation of a particular row in the images, obtains a profile as shown in Fig.5. Based on that of line profile, white line segments that have the two adjacent black segments on both its left side and right sides are the line segments that are belonging to the on-road obstacles. By checking each of the row in the template images of the road, this classification can be obtained. Figure4c shows the results of this classification obtained. The overall classes of obstacles on the road is shown by gray pixels on fig(d).

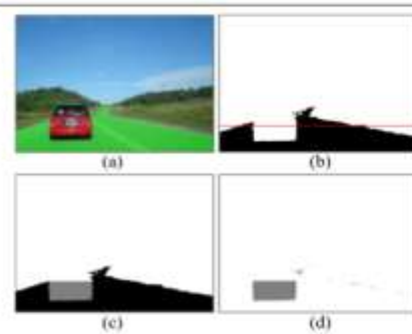

Fig. 4 Phases of classification inside the "non-road" region. a The result of road region detection. b Road region template image c The result of region classification d Obstacle region

3. OBSTACLE DETECTION AND MARKING

After the classification phase, three regions (that is classes of pixels) are extracted: road region, obstacles on the road, and environment region, while the on-road obstacles class is needed only. This region contains the various objects of different sizes (Fig.4d).As a first step, the small objects which are less than 50 pixels are eliminated because they are considered as the false obstacles or obstacles of no use.

The extracted obstacles should be monitored continuously in the sequence of coming frames. In order to prepare this monitoring phase, some areas of interest should be specified—to the detected obstacles should be marked by specifying some of the tracking windows for encompassing each of them. Even at the last step in the relative velocities estimation it is strictly affected by the choices of this regular geometrical shape

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corresponding to the particular obstacles. Figure 6 shows the various steps of marking the obstacles on the road region. Figure 6 as shows the region of the obstacle after filtering unwanted objects that is noice. The red colored rectangle around this region is shown in the b which will be replaced in the other step by the green colored square of the width which is equal to the base of red rectangle as shown in c. The final representation of this search area superimposed to the original image is shown in the block d.

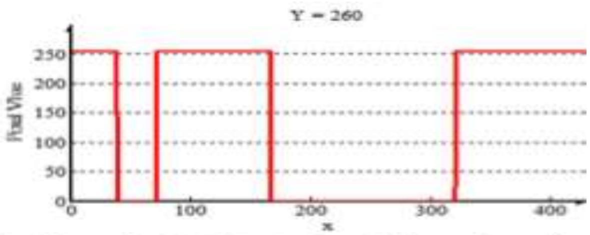

Fig. 5 Line profile of pixel intensity values (260th row in the road region image)

On-road obstacles extraction

3.1 Experimental result of the on road obstacle extraction

Figure given above shows the different steps of the on-road obstacles that is detected in a sequence of digital images. The first row illustrates the final classification outputs of the road region using the SVM method. The second row shows the result of the real obstacle extraction of it. The third row shows the final representation of a search area which is superimposed onto the original image. Some of which the tall vehicles, like the trucks, are not going to be completely encompassed by this type of tracking window, some low-profile cars would not be filled in the tracking window completely, but the choice of a square-shaped tracking window used seemed as a reasonable compromise to that of others used.

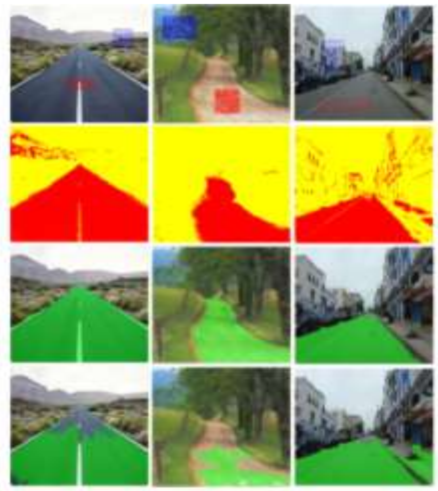

fig- The process of basic road detection algorithm and comparison of results obtained by SVM method and color only method. 1st row: the original image and sampling windows. 2nd row: the classification results (Red is road class, Yellow is non-road class). 3rd row: the results of morphological filtration of SVM method. 4th row: the results obtained by the color only method

4. CONCLUSION

The algorithm of an automatic classification of obstacles into the on-road obstacles on the basis of their relative velocities. The on-road obstacles has to be detected firstly, then explained properly in order to enable their tracking from frame to frame. Our choice on specially these two steps have been oriented toward rather the complex methods: SVM based on eight component vector (color + texture) for the purpose of recognition of a road area and SURF is based on 64 component vector for the description and also for the tracking of characteristic points inside the windows of tracking. These steps are verified using the realistic images of road-traffic. The effects of choices of these complex methods onto the accuracy of detection and tracking that have been given partially, comparing them with that of the simpler approaches in road detection and obstacle's characteristics, and showing the superiority. Consequently, higher computational cost should be paid and the ability to implement this algorithm in real time might be compromised.

The final step of verification which was related to the estimation of distances of the obstacles and their rates of change was made by the use of the synthesized sequences representing the simulated motion of the cameras involved, and multiple vehicles as well as on the basis of sequences from the driving.

These results have been shown has highly acceptable accuracy of an estimated relative velocities of the obstacles. A number of practically important algorithms parameters have been analyzed. They are regarding to the part of the field of view not able for basic orientation on the road, minimal size of tracked vehicles, minimum correspondence of the characteristic points which is required for the reliable tracking of obstacles, the size of an average filter used in estimation of relative velocity, etc. The future work will be more oriented towards the further verifications of the algorithm using controlled experiments in the real road-traffic situations.

ACKNOWLEDGEMENT

The automatism of this given algorithm is reduced by the very first requirement that the operator should always point onto the regions in the image which are typical representatives of road and non-road that is unwanted, but from that point on, nothing is necessary as a human intervention. A priory knowledge of some road measures, as the lane-width, could be easily provided from the vehicle global positioning system and that of the digital map of the road. A number of practically important algorithms parameters that have been analyzed and specified. They are regarding to the part of the field of view which is usable for basic orientation on the road, minimal size of tracked vehicles, minimum correspondence of the characteristic points that is required for the reliable tracking of obstacles, the size of an averaging filter which is used in estimation of relative velocity, etc. The future work will be oriented toward the further verification of the algorithm using controlled experiments in the real road-traffic situations.

REFERENCES

[1]. CDemonceaux, DKachi-Akkouche, in Proceedings of the IEEE Intelligent Vehicles Symposium 2004.Robust obstacle detection with monocular vision based on motion analysis(IEEE,Parme,2004),pp.527–532. doi:10.1109/IVS.2004.1336439

[2]. ABroggi, MBertozzi, AFascioli, MSechi, in Proceedings of the IEEE Intelligent Vehicles Symposium 2000(Cat.No.00TH8511).Shape-based pedestrian detection(IEEE,Dearbon,2000),pp.215–220. doi:10.1109/IVS.2000.898344

[3].MLützeler,EDickmanns, in Proceedings of the IEEE Intelligent Vehicles Symposium 98. Robust road recognition with marv eye(IEEE,Stuttgart,1998),pp.341–346

[4].AKuehnle,inProc.SPIE,TransportationSensorsandControls: CollisionAvoidance,TrafficManagement,andITS.Symmetry-basedvehiclelocationforAHS,vol.2902(SPIE,Orlando,1997),pp.19–27.doi:10.1117/12.267158

[5].SSTeoh,TBräunl,Symmetrybasedmonocularvehicledetectionsystem.Mach.Vis.Appl.23(5),831–842(2012)

[6].WKruger,WEnkelmann,SRossle,inProceedingsoftheIntelligentVehicles'95Symposium.Realtimeestimationandtrackingofopticalflowvectorsforobstacledetection(IEEE,Detroit,1995),pp.304–309.doi:10.1109/IVS.1995.528298

[7].CBraillon,CPradalier,JLCrowley,CLaugier,inIEEEIntelligentVehiclesSymposium2006.Realtimemovingobstacledetectionusingopticalflowmodels(IEEE,Tokyo,2006),pp.466471.doi:10.1109/IVS.2006.1689672

[8].SAMahmoudi,MKierzynka,PManneback,KKurowski,Real-timemotiontrackingusingopticalflowonmultiplegpus.Bull.Pol. Acad.Sci.Tech.Sci.62(1),139–150(2014)

[9].GLefaix,TMarchand,PBouthemy,inObjectrecognitionsupportedbyuserinteractionforservicerobots.Motionbasedobstacledetectionandtrackingforcardrivingassistance,vol.4(IEEE,Quebec, 2002),pp.74–77.doi:10.1109/ICPR.2002.1047403

[10.]MBertozzi,ABroggi,Gold:Aparallelrealtimestereovisionsystemforgenericobstacleandlanedetection.IEEETrans.ImageProcess.7(1),62–81(1998)

[11].QYu,HAraújo,HWang,Astereovisionmethodforobstacledetectionandtrackinginnonflaturbanenvironments.Auton.Robot.19(2),141–157(2005)

[12.]NBernini,MBertozzi,LCastangia,MPatander,MSabbatelli, in17thInternationalIEEEConferenceonIntelligentTransportationSystems(ITSC).Realtimeobstacledetectionusingstereovisionforautonomousgroundvehicles:asurvey(IEEE,Qingdao,2014),pp.873–878.doi:10.1109/ITSC.2014.6957799

[13].RLabayrade,DAubert,Robustandfaststereovisionbasedobstaclesdetectionfordrivingsafetyassistance.IEICETrans.Inf.Syst. 87(1),80–88 (2004)

[14].DKuan,GPhipps,ACHsueh,Autonomousroboticvehicleroad following.IEEETrans.PatternAnal.Mach.Intell.10(5),648–658(1988)

[15].SGraovac,AGoma,Detectionofroadimagebordersbasedontexture classification.Int.J.Adv.Robot.Syst.9,1–12(2012)

[16].SZhou,JGong,GXiong,HChen,KIagnemma,inIntelligentVehiclesSymposium(IV),2010IEEE.Roaddetectionusingsupportvectormachinebasedononlinelearningandevaluation(IEEE,San Diego,2010), pp.256–261.doi:10.1109/IVS.2010.5548086

[17.]CCChang,CJLin,Libsvm:alibraryforsupportvectormachines.ACMTrans.Intell.Syst.Technol.(TIST).2(3),27(2011).doi:10.1145/1961189.1961199

[18.]SKrig,inComputerVisionMetrics:Survey,Taxonomy,andAnalysis.Interestpointdetectorandfeaturedescriptorsurvey(Apress,Berkeley,2014),pp.217–282.doi:10.1007/978-1-4302-5930-5_6

[19].CHarris,MStephens,inProceedingsoftheAlveyVisionConference.Acombinedcornerandedgedetector(CiteSeerX,Manchester,1988),pp.147–152.doi:10.1.1.231.1604

[20]DGLowe,inTheproceedingsoftheseventhIEEEinternational conferenceonComputervision,1999.Objectrecognitionfromlocalscale-invariant features,vol.2(IEEE,Kerkyra,1999),pp.1150–1157.doi:10.1109/ICCV.1999.790410

[21].DGLowe,Distinctiveimagefeaturesfromscaleinvariantkeypoints.Int.J.Comput.Vis.60(2),91–110(2004)

[22.]HBay,AEss,TTuytelaars,LVanGool,Speededuprobustfeatures(surf).Comp.VisionImageUnderst.110(3),346–359(2008)

[23].DHellyM,GVaibhav,Realtimemovingobjectdetectionusingsurf.IOSRJournalofComputerEngineering(IOSRJCE).17(3),75–78(2015)

[24].KKanatani,Geometriccomputationformachinevision.(OxfordUniversityPress,Inc,NewYork,1993)

[25.]CYan,YZhang,JXu,FDai,LLi,QDai,FWu,Ahighlyparallel frame work for HEVC coding unit partitioning tree decision on m any-core processors.IEEESignalProc.Lett.21(5),573–576(2014)

[26].CYan,YZhang,JXu,FDai,JZhang,QDai,FWu,EfficientparallelframeworkforHEVCmotionestimationonmanycoreprocessors.IEEETrans.Circ.Syst.VideoTechnol.24(12),2077–2089(2014)

[27.]CYan,YZhang,FDai,XWang,LLi,QDai,ParalleldeblockingfilterforHEVConmany-coreprocessor.Electron. Lett.50(5),367–368(2014)

[28.]CYan,YZhang,FDai,JZhang,LLi,QDai,EfficientparallelHEVCintrapredictiononmanycoreprocessor.Electron.Lett.50(11),805–806 (2014)