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M2M Telematics for Vehicle Detection Using Computer Vision

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Contents

1 Abstract

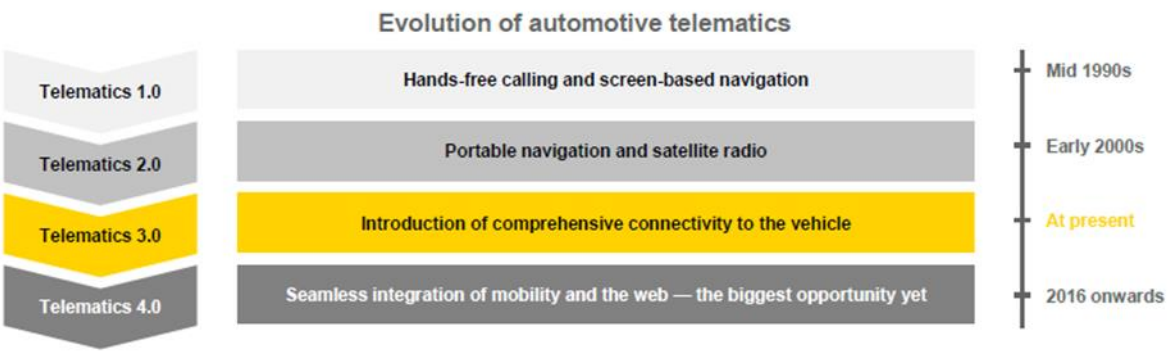
This paper after a brief survey of computer vision in telematics, describes the various steps involved in vehicle detection through image processing. The paper also covers Monocular and stereo based vision for image detection and also discuss about how the system can work under various lighting conditions (day and night) and different approaches adopted to achieve it. And finally end with the recent development and implications of computer vision in telematics.

2 Introduction

Increasing collaboration between vehicle manufacturing companies and telematics vendors is one of the major reasons contributing to the growth of telematics services industry. Next generation vehicle telematics application such as automatic vehicle identifier systems, fleet operation management systems, remote vehicle diagnostics, incident detection systems, and in-vehicle terminal assistance are expected to increase the demand of telematics services in vehicle manufacturing industry.

Rising awareness amongst consumers over the need and importance of telematics services will drive the market demand in upcoming years. Need of effective vehicle tracking systems is further expected to drive the demand of telematics services in diverse application areas such as emergency service vehicles, public transport (taxis), cargo delivery, and others. Growing consumer demand for electric vehicles will lead to investment in telematics.

Growing popularity of GPS enabled smart phones can pose a challenge to the growth of this industry. Smart phones are consuming an important share in world telematics market and these phones provide multiple functionalities of telematics systems. Currently, the U.S. and Europe accounts for the majority of global telematics services market due to stringent regulations from government to have vehicles equipped with emergency services. Further growth of this industry is expected to be driven by widespread use of this technology in emerging economies and extended support from governments to promote vehicular telematics.



3 Services in Telematics

At its core, automotive telematics deals with services provided to vehicles over a telecommunications device. Some of the key services presently available in the domain of automotive telematics include:

- Automatic Crash Notification
- Roadside Assistance Services
- Vehicle Tracking
- Remote Door Services
- Navigation Assistance
- Traffic Assistance
- Concierge Services
- Infotainment Services
- Fleet Management
- Diagnostics

The future of the Telematics would be affected by the increased availability of bandwidth and the penetration of the wireless network infrastructure.

4 Road Safety and Vehicle Detection

Road safety is of major concern today. This is particularly true of two major groups: motor insurers and the drivers they insure, especially the youth and employers and their work force who drive to work. In-vehicle monitoring and road safety needs have become increasingly critical driving the use of vehicle telematics and/or driver telematics. The research and development of advanced sensing, environmental perception, and intelligent driver assistance systems presents an opportunity to help save lives and reduce the number of on-road injuries [1]. A variety of sensing modalities have become available for on-road vehicle detection, including radar, lidar(illuminating a target with laser and analyzing the reflected light), and computer vision. Imaging technology has progressed immensely in recent years. Cameras are cheaper, smaller, and of higher quality than ever before. Concurrently, computing power has increased dramatically [1]. Consequently, developing on-board automotive driver assistance systems aiming to alert a driver about driving environments, and possible collision with other vehicles has attracted a lot of attention. In these systems, robust and reliable vehicle detection is the first step — a successful vehicle detection algorithm will pave the way for vehicle recognition, vehicle tracking, and collision avoidance [2].Vehicle detection can be classified into various categories, one of them being Monocular and Stereo vision .The following table depicts the work done in the recent years in vehicle detection using computer vision (Monocular and Stereo) [1].

TABLE I
REPRESENTATIVE WORKS VISION-BASED VEHICLE DETECTION

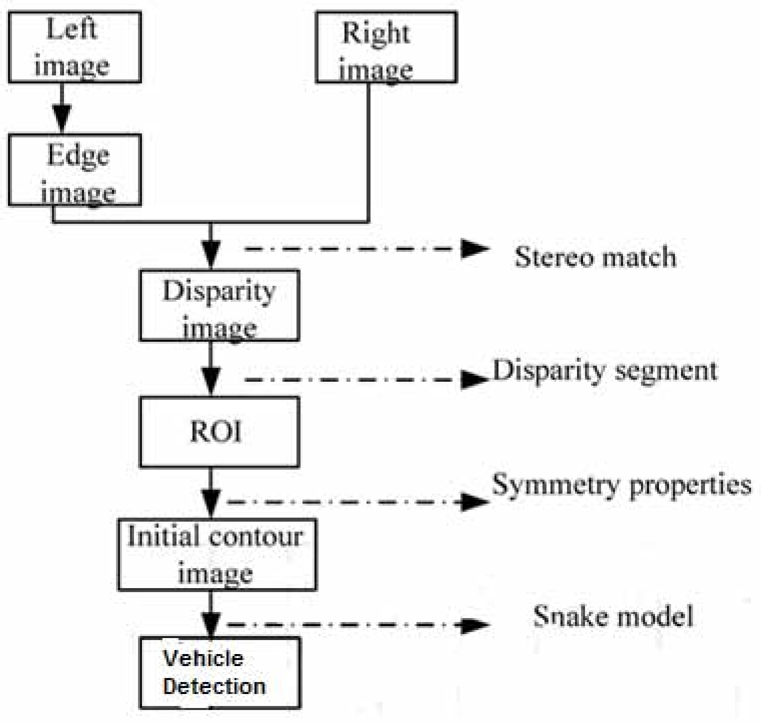
Monocular Vision			
Research Study	**Motion/ Appearance**	**Description**	**Comments**
Sun et al., 2006 [7]	Appearance	HOG and Gabor features, SVM and neural network classification	Feature and classifier evaluation. Evaluation on static images.
Zhu et al., 2006 [8]	Motion	Dynamic background modeling of overtake area	Validation on real-world video, with ego-motion compensation.
Wang and Lien, 2008 [9]	Appearance	Statistical modeling of local features	Detection of sedans in statics image. Evaluation is performed on static images.
Diaz-Alonso et al., 2008 [10]	Motion	Optical flow for blind spot detection	Detection results were validated with lidar for ground truth, and TTC validation.
Chang and Cho, 2010 [11]	Appearance	Haar-like features, boosted classification, online learning	Online learning allows for adaptation to new environments.
Sivaraman and Trivedi, 2010 [12]	Appearance	Haar-like features, Adaboost classification, active learning	Active learning shown to improve detection and false alarm rates, evaluated on highway video.
Yuan et al., 2011 [13]	Appearance	HOG features, SVM classification. Orientation determined using multiplicative kernel learning	Vehicles are oriented using matched detectors. The same framework was shown to work for hand gestures and head rotation.
Jazayeri et al., 2011 [14]	Motion	Optical flow, hidden Markov model classification	Modeling the position and motion of preceding vehicles in the image plane.
Niknejad et al., 2012 [15]	Appearance	HOG features, deformable parts-based model	Adaptive threshold for detection in urban environments.
Lin et al. 2012 [16]	Appearance	SURF and edge features, probabilistic classification, blind spot detection	Front and side car models were evaluated to accommodate different views of blind-spot vehicles.

Stereo Vision			
Research Study	**Motion/ Appearance**	**Description**	**Comments**
Chang et al. 2005 [17]	Appearance	Size, width, height, image intensity features, Bayesian classification	A combination of object geometry, template-matching, image features, and depth map features were used for vehicle detection from single stereo pair. Evaluation in parking lot.
Cabani et al. 2005 [18]	Appearance	Color, 3D vertical edges	Sparse stereo matching using L*a*b* color image pairs, and vertical edges, in order to detect vehicles and obstacles.
Franke et al., 2005 [19]	Motion	Optical flow	Optical flow interest points are tracked in the image plane, and their corresponding 3D positions and velocities are tracked using Kalman filtering.
Badino et al., 2007 [20]	Motion	Occupancy grid, free space computation	6D vision points are tracked. Stochastic occupancy grids are solved using dynamic programming, and free space is computed.
Barrois et al., 2009	Appearance	Clustering of 3D points, vehicle orientation estimation	Clustering of points in 3D using polar iterative closest point algorithm. Points are fit to a cuboid model, and pose is inferred.
Barth and Franke, 2009 [21]	Motion	Optical flow, clustering 6D points	6D vision points are tracked over time, with objects formed by clustering using the Mahalanobis distance.
Broggi et al., 2010 [22]	Appearance	V-disparity, clustering in the disparity space	Detection in the disparity space image.
Danescu et al., 2011 [23]	Motion	Optical flow, particle-based occupancy grid	Occupancy grid cells are represented by particles that serve a dual purpose. In a conventional particle filtering framework, each cell as a position and velocity. Particles also carry a probability of the cell's occupancy.
Erbs et al., 2011 [24]	Motion	Tracking stixels, fitting probabilistic cuboid model	Stixels, vertical intermediate representations of 3D points, are tracked using Kalman filtering. Stixels with similar motion are fit to a cuboid model for vehicle detection and tracking.
Perrollaz et al., 2012 [25]	Motion	Optical flow, spatio-temporally smoothed occupancy grid	The occupancy grid is also smoothed in the time and spatial domains to account for noise and outliers.

There are three kinds of methods for locating potential vehicles: 1) knowledge-based methods; 2) motion-based methods; and 3) vision based methods. Knowledge-based methods make use of prior knowledge to locate candidate vehicles in an image. Such prior knowledge includes symmetry, colour, shadow, geometrical features and texture, etc. As one of the main signatures of man-made objects, symmetry has been used for object detection and recognition in computer vision. In general, knowledge-based methods are effective in relatively simple environments but cannot work in complex environments because the prior knowledge is susceptible to illumination, image quality and the complexity of background. Motion-based methods commonly use optical flow to estimate the relative motion of vehicles. The disadvantages of this method are time-consuming and cannot detect static obstacles. Vision-based vehicle recognition methods normally follow two basic steps: 1) hypothesis generation (HG), which hypothesizes the regions in an image where possible vehicles are; and 2) hypothesis verification (HV), which verifies the correctness of the hypothesis in step 1) by using certain algorithms. In general, HG is based on some simple features.

4.1 Vehicle detection using Stereo Vision

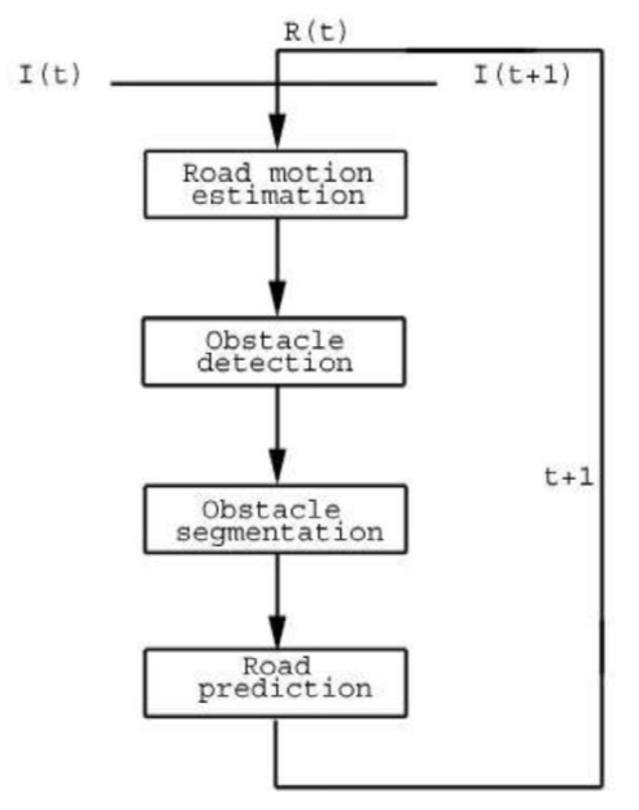
This method basically uses 2 cameras, set up in different angle to get a disparity map and then calculate the depth i.e distance of the obstacle in front. The schematic diagram of the system is illustrated in Fig. 1. Firstly, a stereovision rig corroborated with an edge-indexed stereo matching algorithm is employed to produce an edge-based disparity map. The regions of interest (ROIs) in the left image are created according to disparities between the objects and they comprise the potential vehicle objects in the scene. Secondly, symmetry properties are applied to eliminate the non-boundary points so that an initial object contour can be extracted. Subject to noise, the initial contour obtained can be discontinuous and incomplete, containing some noise points within the vehicle body. Therefore, the initial contour is refined with the snake model so that a closed and complete object contour curve is generated. Thirdly, two parameters including an object aspect ratio and an area ratio are calculated from the contour curve and accordingly the objects within the ROIs are classified into two classes - vehicles or other objects.



[Source: "On-Road Vehicle Recognition Using the Symmetry Property and Snake Models", International Journal of Advanced Robotic Systems, 2013]

4.2 Vehicle Detection using Monocular vision

Here a single camera mounted on a vehicle is used to detect an obstacle. The Previous image obtained by the camera is compared with the current image and the movement of an obstacle (Vehicle) is calculated based on the change in position of the obstacle in the images and the location of the vehicle is predicted. The method is roughly divided into four principal steps: road motion estimation, obstacle detection, obstacle motion estimation, obstacle segmentation and prediction as shown in the figure below.



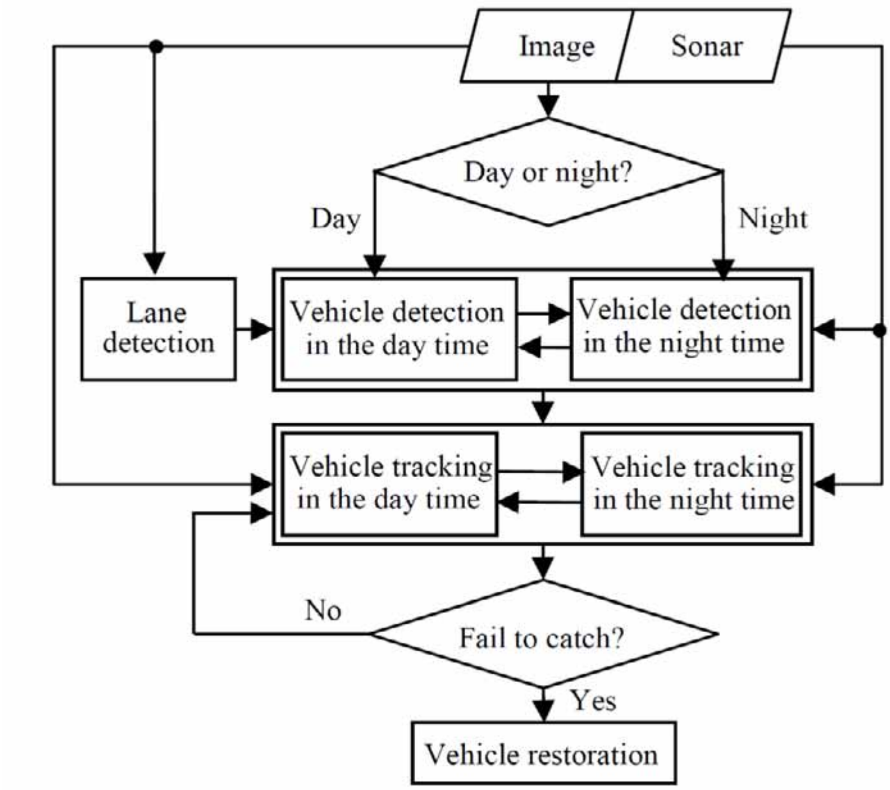
[Reference: C. Demonceaux , D.Kachi-Akkouche, "Robust obstacle detection with monocular vision based on motion analysis", Intelligent Vehicles Symposium, 2004 IEEE.]

4.3 Vehicle Detection during Day and Night

Most of the previous vehicle detection and tracking method assumed favorable light conditions where one can easily acquire the vehicle template in the image and cannot apply the dead zone at a close range. In the night time, we cannot acquire favorable clear images of the headlight pair, taillight pair and turn lights of other vehicles around the ego-vehicle. Thus, a robust algorithm must be developed to handle these difficult situations.

The two cameras that can detect vehicles in the medium and far range are installed by the side of a rear-view mirror and at the ceiling above the back seat and the two sonar sensors (its' beam angle is 15°) that can measure the distance in the near range are installed at the front and rear bumpers.

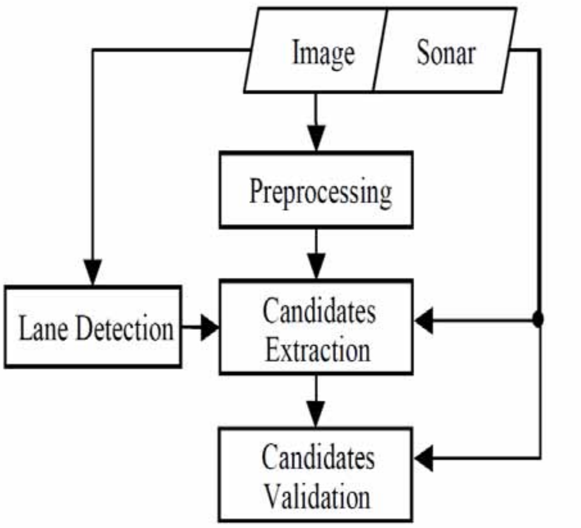
Because the environment of the vehicle changes relatively fast as the speed of an ego-vehicle is high, we acquire 2 images of 1 field and acquire 2 signals of sonar sensors successively. The overall block diagram is shown below [5].



[Source: "Front and Rear Vehicle Detection and Tracking in the Day and Night Times Using Vision and Sonar Sensor Fusion", Intelligent Robots and Systems, 2005 (IROS 2005)]

Vehicle Detection in the Day Time

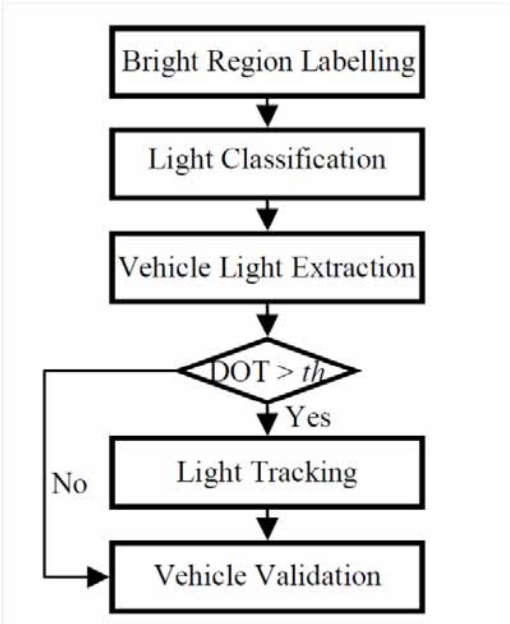
The detection system in the day time consists of 4 parts that is, the preprocessing module working on the input raw image, the vehicle candidate extraction module by a shadow region and a template, the validation module by a prior knowledge, and the fusion module for fusing sonar and image data.



[Source: "Front and Rear Vehicle Detection and Tracking in the Day and Night Times Using Vision and Sonar Sensor Fusion", Intelligent Robots and Systems, 2005 (IROS 2005)]

Vehicle Detection in the Night Time

The bright regions generated by headlights, taillights, brake lights and reflected lights around light sources are used as the vehicle feature in the night time. Overall system is shown



[Source: "Front and Rear Vehicle Detection and Tracking in the Day and Night Times Using Vision and Sonar Sensor Fusion", Intelligent Robots and Systems, 2005 (IROS 2005)]

By extracting the pairs of lights, filtering the noise region, and reducing the size according to the size and shape of the bright region by light classification and light extraction, we extract vehicle candidates.

For pairing by light shape, we use the light classification step. First, we calculate possible vehicle pixel width (PW: 1.5*m* is used) at the center of gravity (COG) points of each bright region clusters by IPT. Vehicle light shape that can be appeared in the night time image is divided into 3 shapes.

- Small light: Light source by tail lights and brake lights without spreading.

- Large light: Reflected light appeared in a vehicle by other light sources

- Huge light: Light source by headlight

These lights are classified by the ratio of a vehicle size using PW to a light size.

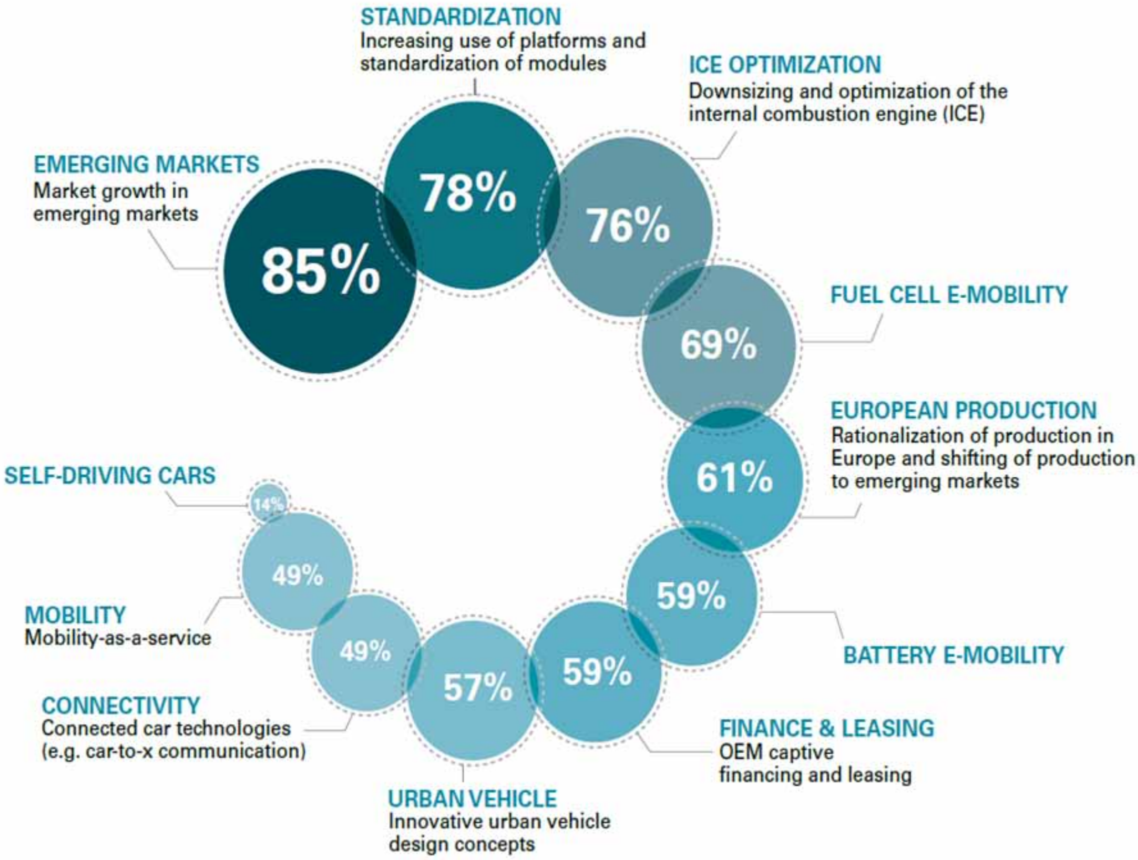
- Small light: light size ≤ (PW/5) × (PW/5)

- Large light: small light *th* ≤ light size ≤ (PW/2) × (PW/2)

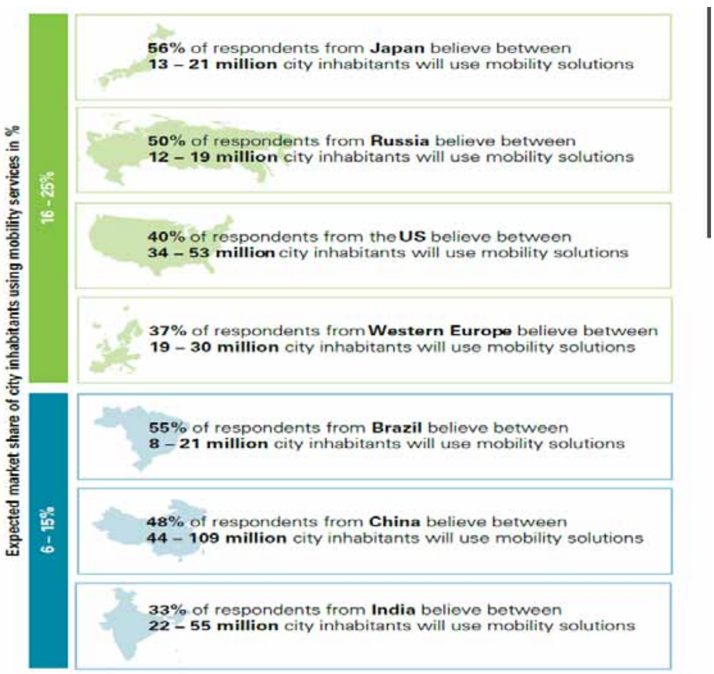
- Huge light: otherwise case

5 Conclusion:

The computer vision and image processing can be applied in many aspects for the traffic parameter extraction (Vehicle counting, speed measurement etc.). While vehicle detection has been an active research area for quite some time, open challenges still remain. In this paper I have discussed briefly the various techniques used in vehicle detection. Almost all the major Automobiles Giants like BMW, Ferrari, and Toyota are working to build advanced vehicle and driver telematics that aims to significantly improve road safety and lead the innovations towards making driverless cars a future reality. Even though the Idea of Autonomous cars existed way back, it is only been in the past decade that this field has evolved tremendously. Respondents to this year's survey feel that emerging nations offer the best hope for expansion. Eighty-five percent say that growth in the BRICs (Brazil, Russia, India and China) and other up-and coming nations is the biggest single industry trend up to 2025, which is consistent with the 2013 survey. The following shows the key Automotive trend up to 2025 by a survey conducted by KPMG Global Automotive.



Source: KPMG's Global Automotive Executive Survey 2014.



Source: KPMG's Global Automotive Executive Survey 2014, United Nations World Urbanization Prospects.

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About the author

Navya Manoj is a consultant with the Happiest Minds Technologies Product Engineering Services business and is very passionate about telematics. As part of this team, she is involved with telematics design framework development for M2M / IoT solutions. She holds a Masters' Degree in Mechatronics, a very specialized field of engineering

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