Keeping the Vehicle on the Road – A Survey on On-Road Lane Detection Systems

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The development of wireless sensor networks, such as researchers Advanced Driver Assistance Systems (ADAS) requires the ability to analyze the road scene just like a human does. Road scene analysis is an essential, complex, and challenging task and it consists of: road detection (which includes the localization of the road, the determination of the relative position between vehicle and road, and the analysis of the vehicle's heading direction) and obstacle detection (which is mainly based on localizing possible obstacles on the vehicle's path). The detection of the road borders, the estimation of the road geometry, and the localization of the vehicle are essential tasks in this context since they are required for the lateral and longitudinal control of the vehicle. Within this field, on-board vision has been widely used since it has many advantages (higher resolution, low power consumption, low cost, easy aesthetic integration, and nonintrusive nature) over other active sensors such as RADAR or LIDAR. At first glance the problem of detecting the road geometry from visual information seems simple and early works in this field were quickly rewarded with promising results. However, the large variety of scenarios and the high rates of success demanded by the industry have kept the lane detection research work alive. In this article a comprehensive review of vision-based road detection systems vision is presented.

Categories and Subject Descriptors: I.2.10 [**Artificial Intelligence**]: Vision and Scene Understanding

General Terms: Algorithms, Experimentation, Performance, Reliability, Verification

Additional Key Words and Phrases: Computer vision, intelligent vehicles, lane detection, road detecetion, road following

ACM Reference Format:
Yenikaya, S., Yenikaya, G., and Düven, E. 2013. Keeping the vehicle on the road – A survey on on-road lane detection systems. ACM Comput. Surv. 46, 1, Article 2 (October 2013), 43 pages.
DOI: http://dx.doi.org/10.1145/2522968.2522970

1. INTRODUCTION

To an experienced human driver, driving may seem as a simple process in which two basic tasks are involved: keeping the vehicle on the road and avoiding collisions. But indeed, driving is not so trivial. In performing the driving tasks, automobile drivers have to analyze the road scene and continuously choose and execute appropriate maneuvers to deal with the current situation. In carrying out these activities, drivers rely mostly upon their visual systems.

The idea of assisting drivers in performing these activities led to Driving Assistance Systems (DAS). Such systems, which could work as extended eyes to help the driver to perceive the blind area in the road and as early warning to remind the driver of

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DOI: http://dx.doi.org/10.1145/2522968.2522970

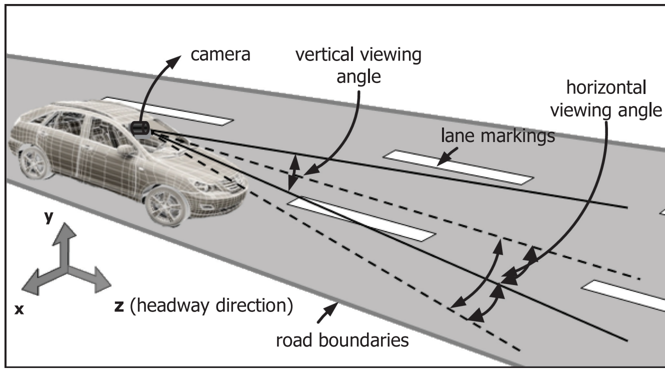

Fig. 1. Vision-based road detection system.

potential danger, had become a hot topic since 1990s. The next step, ADAS, has arisen as a contribution to traffic safety.

They require a system that can perform basic tasks, namely Lane Following (LF), Lane Keeping Assistance (LKA), Lane Departure Warning (LDW), Lateral Control (LC), Intelligent Cruise Control (ICC), Collision Warning (CW), and ultimately can lead to autonomous vehicle guidance.

This article presents a comprehensive survey on vision-based road detection systems where the camera is mounted on the vehicle. This work is organized as follows: First we review the problem. Then in Section 3, we examine the sensing technology. After that in Section 4 we present the detection techniques. Lastly we mention the hardware platforms that the detection algorithms are implemented on.

2. THE PROBLEM

As stated, road detection is a critical component in ADAS in order to provide meaningful and consistent road shape information for navigation purposes. The aim of road detection is to give information to on-board intelligent computing equipments as a major knowledge of driving environment. However, this is usually only one of several steps in the process of getting more complete information about the scene being analyzed (ego-speed, other traffic participants, characteristics of other participants, etc.). If we consider that we need a short response time and that we have limited computational resources, it becomes clear that this operation has to be done in a simple, yet effective way.

Vision-based road detection has been an active research topic in the past years and various methods have been presented in solving this problem. Road detection is not a very general problem in computer vision, nor a very general cognitive problem, since the target (the road) is typically prominent and fairly simple in the vision field. A basic vision-based road detection system can be seen in Figure 1.

Roads in the real world can be divided into two kinds, structured (Figure 2(a)) and unstructured roads (Figure 2(i)). Structured roads usually correspond to highways or some roads with clear markings, such as boundary lines. Thus, road detection can be carried out by detecting these road markings. Unstructured roads refer to roads which have no man-made markings or only a few road markings by which the road area cannot be segmented, such as rural roads. Although some systems have been designed to work on unstructured roads (without painted lane markings) or on unstructured terrain, generally road detection relies on the presence of painted road markings on the road surface.

The problem of detecting the road may seem very simple, especially in structured road scenarios, when the road markings are clear and the lane has a well-defined

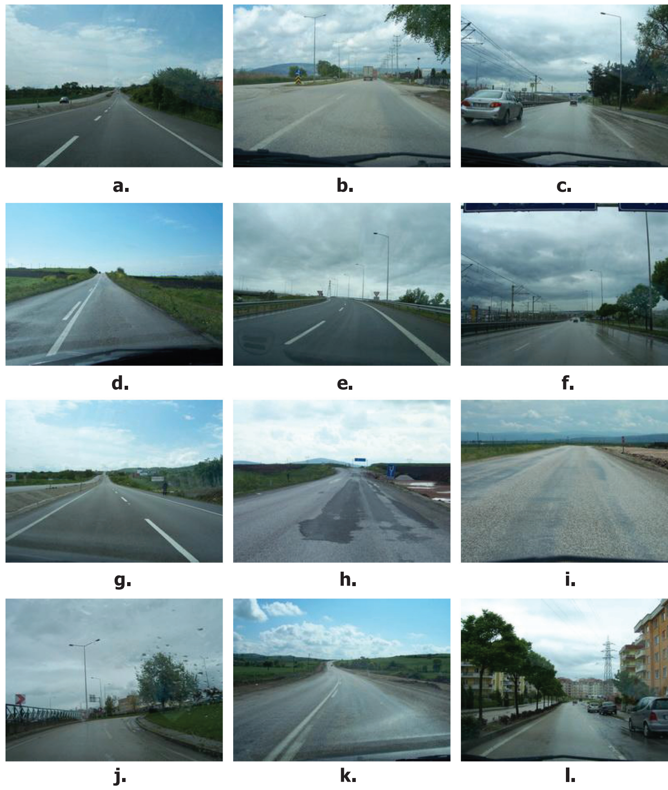

Fig. 2. Different road scenarios.

geometry. But despite the perceived simplicity, the great variety of road environments requires the use of complex vision algorithms that not only rely on fast hardware, but also on many adjustable parameters that are typically determined from experience.

—The main problems of road detection can be summarized into two categories: the high processing cost of detection and the unconstrained road environment. Unconstrained environments like the road pose serious problems to computer vision. Ego-motion, variable lighting, and other factors contribute to clutter the scenario and make it change frequently. Very few assumptions on scene appearance hold true for longer than 5–10 seconds [Lombardi et al. 2005]. To be acceptable, road detection systems should perform in various conditions: Roads may be structured or unstructured. Even in structured roads, sometimes lane markings are not always clearly visible due to their print quality and the changes in environmental conditions (Figure 2(b)).
—Lane markings may be degraded or occluded by the other traffic participants (Figure 2(c)).
—Various lane markings (continuous, dashed) may occur, and the geometry of the markings cannot be used as a discriminating factor as there is no governing standard. Further, road splitting or merging and the interference from roadside objects or shadows could worsen the detection.
—Road area may be significantly occluded by the other vehicles (Figure 2(c)).
—Road area may have road surface scars, may be degraded, and different road surfaces may appear on the same section (Figure 2(g)–(h)).

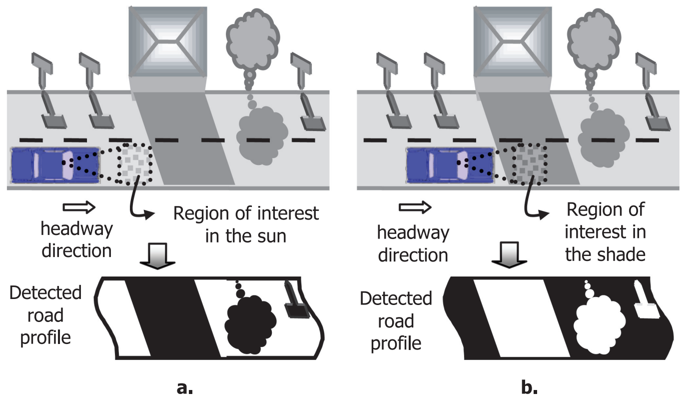

Fig. 3. Changing road conditions.

—The presence of shadows (projected by trees, buildings, bridges, or other vehicles) produces artifacts onto the road surface and thus alternates the road texture (Figure 2(l)).
—There may exist extraneous objects like security fences, trees, telephone poles, and power-line poles, shadows across the road, and mountain slopes in the distance (Figure 2(l)).
—The road/nonroad border may be spatially fuzzy and have low-intensity contrast, the overall road shape may not follow smooth curves, and the appearance of the road itself can change drastically; mud, clay, sand, gravel, and asphalt may all be encountered (Figure 2(i)).
—There may exist vehicles parked at the roadsides, which can cause confusion about the direction of the road (Figure 2(l)).
—Various meteorological conditions (sunny, rainy, snowy, foggy, etc.) may occur (Figure 2(d)–(f)).
—Various lighting conditions (sunny, cloudy, twilight, night, etc.) may occur (Figure 2(d)–(f)).
—Various road geometries (straight, curved, etc.) may occur (Figure 2(j)–(k)).
—There may exist intersections and roundabouts.

The urban scenario is, above all, complex. One may encounter highway-like portions of the road, but also one may encounter situations where the free look-ahead distance is very small, where the obstacles are all over the place, where roads have complex textures that produce edges, and so on. Moreover, the road may not always suit the model, no matter how complex this model. Besides, detection from a moving vehicle is notoriously difficult because of the combined effects of ego-motion and rapidly changing lighting conditions between shadowed and brightly lit areas (Figure 3).

To overcome such difficulties, many researchers based their methods on several assumptions, and this prevented the existence of a road detection system which can be acceptable under all of the conditions stated earlier.

3. SENSING THE ENVIRONMENT

The functionalities such as lane detection, obstacle detection, vehicle detection and classification, and road sign recognition can be performed by active sensors such as radio, acoustic, magnetic, and tactile sensors or passive sensors such as cameras. The active sensors measure quantities, such as distance, in a direct way and generate small amount of data.

Scanning Laser Radar (SLR) is often employed as an on-board sensor for headway distance measurement systems. This is because vehicles are generally equipped with reflectors at the rear that are suitable for reflecting laser radar beams. Furthermore, SLR, which scans one dimension horizontally, is suitable for installation on vehicles because of its high reliability, small size, and reasonable cost [Shimomura et al. 2002]. Grimmer and Lakshmanan [1994], working in the domain of locating pavement edges in millimeter wave radar imagery, used a deformable template approach to finding the best fit of a straight road model with unknown width and orientation to the radar data.

However, in an outdoor environment, the emitted signals from active sensors may interfere with each other and so decrease the reliability of these systems. In contrary to active sensors, passive sensors can acquire data in a noninvasive way. Probably video cameras are the most important type of passive sensors for Intelligent Transportation System (ITS) applications. In some applications such as lane detection, vision sensors play the basic role and can hardly be replaced with other sensors. And also, with the actual development of camera sensors, the cost of such devices is decreasing; furthermore, the information content of vision sensors is extremely rich. In addition, such devices have several other advantages, such as small sweep time, and are passive sensors that avoid interferences with other sensors and users in the environment.

However, it is clear that such systems are mainly affected by shadows, bad weather such as fog and rain, and by changing illumination. Indeed, the contrast of the objects contained in the camera scene is strongly related to illumination conditions and a variation of this value can result in the impossibility to detect the desired objects. As Shi et al. [2006] point out, the basic goal for on-board cameras is not to provide better images for human viewing, but to detect the lane markings in various luminance conditions for an on-board vision system. Pan and An [2008] proposed an approach to auto exposure control based on the content of the scene for on-board CMOS cameras. And another critical situation is the precise placement, configuration, and calibration of the vision sensors. There are several works which are focused on placement, configuration, and calibration aspects of the camera. Huh et al. [2004] proposed a lane detection system considering the configuration aspects of the visual sensors. Wu et al. [2009] applied a dynamic calibration algorithm to calibrate camera parameters and lane widths with the information of lane projection due to the possible changes of the parameters of the camera in a moving car by the vibration.

Furthermore, if a system is based on a single sensor and it suddenly breaks down, then the total system is completely unusable, which is not the case if the system uses several sensors. If the visual component is incorrect, the entire model will to some degree be compromised. Thus, the idea to develop a system that will fuse the data from different sensors is thought to achieve a better result. The key idea is to use a device when it has the best result, and to replace it with another device when its reliability decreases because of external conditions, as can occur in a foggy region. From this, many different solutions can be performed, such as when a camera, a Global Positioning System (GPS), and RADAR information will be fused together to build an internal map of the environmental situation of the real world in which the vehicle is evolving.

The type and number of sensors determines the data volume necessary for the processing and composition of the image from the environment. Nevertheless, the excess of information imposes a great computational cost in data processing. Besides, a system with a comprehensive view of the environment is likely to encounter more distractions than one with a dedicated setup.

4. DETECTION

Detecting and localizing lanes from a digital road image is an important component of many intelligent transportation system applications. Digital images are traditionally represented by a set of unrelated pixels. Valuable information is often buried in such unstructured data.

To make better use of images and image sequences, the visual information should be represented in a more structured form. One intuitive solution to the problem of visual information management is grouping the visually meaningful portions of the image data. The grouping of image regions into objects is driven by a semantic interpretation of the scene that depends on the specific application at hand. Region segmentation is automatic, generic, and application independent. In addition, the results can be improved by exploiting the domain-dependent information.

An interpretation algorithm for road detection may be composed of the following four basic steps: preprocessing, feature detection, fitting, and tracking, as shown in Figure 4.

4.1. Preprocess

By the term preprocessing, we understand two things: removing noise and preparing the image for the subsequent steps.

Many researchers considered noise or shadowy region removal as the first stage of their algorithms. Various tools have been used for this aim, such as thresholding the image with a predefined threshold [He et al. 2004; Sun et al. 2006; D'Cruz and Zou 2007; Shihavuddin et al. 2008] or using adaptive threshold segmentation [Li et al. 2004; Lu et al. 2007, 2008; Soquet et al. 2007; Saudi et al. 2008; Borkar et al. 2009; Wu et al. 2009] or Otsu [Neto and Rittner 2006; Wang et al. 2008b] to segment the region from jumbled backgrounds, applying steerable filters considering the lane orientation characteristics [Guo et al. 2006; McCall and Trivedi 2006], applying Median Filter [Foda and Dawoud 2001; Apostoloff and Zelinsky 2003; Jia et al. 2007; Nasirudin and Arshad 2007; Routray and Mohanty 2007; Shihavuddin et al. 2008; You et al. 2008; Zheng et al. 2008] or Gaussian filter [Liatsis et al. 2003; Huang et al. 2004; Hsiao et al. 2005; Yu et. al 2008a] or both [Birdal and Erçil 2007; Truong and Lee 2008; Truong et al. 2008] to blur the image to reduce random, pepper-and-salt noise, using the Finlayson-Hordley-Drew (FHD) algorithm to remove strong shadows from the RGB image [Assidiq et al. 2008], applying dilation and erosion filters to suppress inhomogenities in the images [He et al. 2004; Gamec and Urdzík 2008], using 2D high-pass filters to extract the lanes from the shadow effect in omnidirectional images [Ishikawa et al. 2003], and applying temporal blurring to extend the lane markers and give the appearance of a long and continuous line [Borkar et al. 2009].

The major problem with thresholding is that we consider only the intensity, not any relationships between the pixels. There is no guarantee that the pixels identified by the thresholding process are contiguous. We can easily include extraneous pixels that aren't part of the desired region, and we can just as easily miss isolated pixels within the region (especially near the boundaries of the region). These effects get worse as the noise gets worse, simply because it's more likely that pixels' intensity doesn't represent the normal intensity in the region. When we use thresholding, we typically have to play with it, sometimes losing too much of the region and sometimes getting too many extraneous background pixels. (Shadows of objects in the image are also a real pain—not just where they fall across another object but where they mistakenly get included as part of a dark object on a light background.) The methods proposed approximately provide similar performance in terms of removing noise. In removing shadowy regions, not for all scenarios, but with incorporation of clear road markings and road texture, Guo et al. [2006], McCall and Trivedi [2006], and Assidiq et al. [2008] gave better results.

Preprocessing is not limited with noise or shadowy region removal. In the literature, there are a lot of papers in which the structure of the image coming from the camera has been changed. To yield computational gains in terms of decreased pixel count, subsampling is used in prior studies. In many of the papers, the image size coming

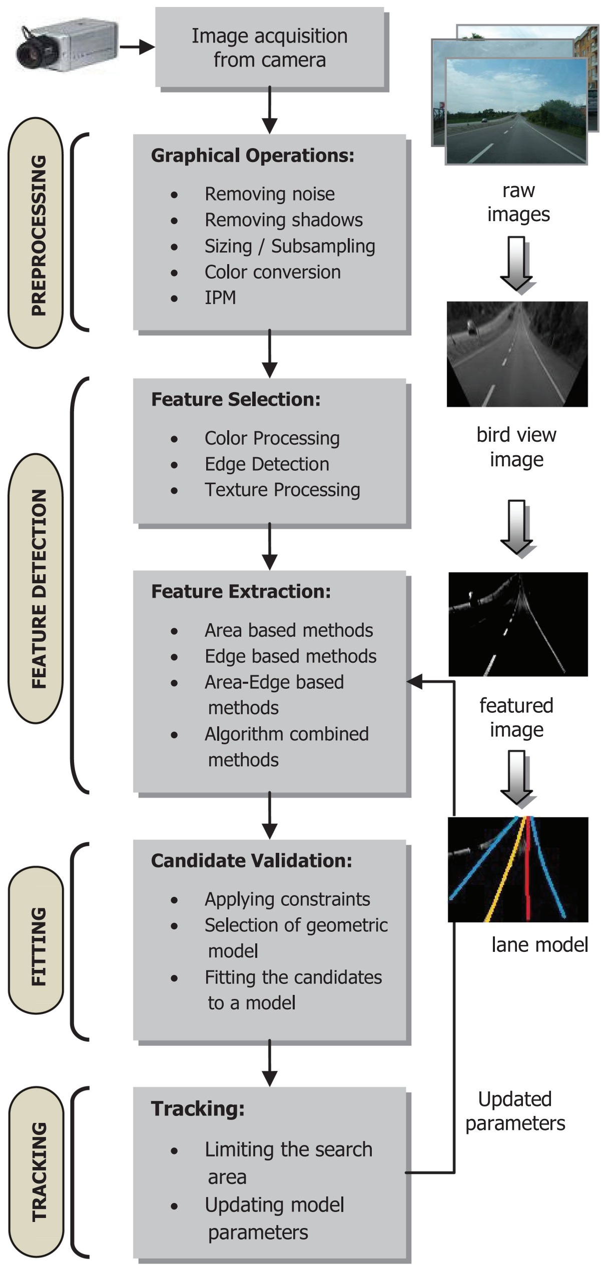

Fig. 4. Architecture of the vision-based road detection system.

from the camera has been reduced by subsampling due to high cost of high-resolution image processing [Crisman and Thorpe 1991, 1993; Jeong and Nedevschi 2003; Yim and Oh 2003; Li et al. 2004; Cheng et al. 2006; Nasirudin and Arshad 2007; Sehestedt et al. 2007a; Shihavuddin et al. 2008]. Most of the time monochrome images tend to be preferred over color for structured roads, due to better resolution and reduced data load. Therefore, gray-level conversion is carried out by many researchers [Li et al.

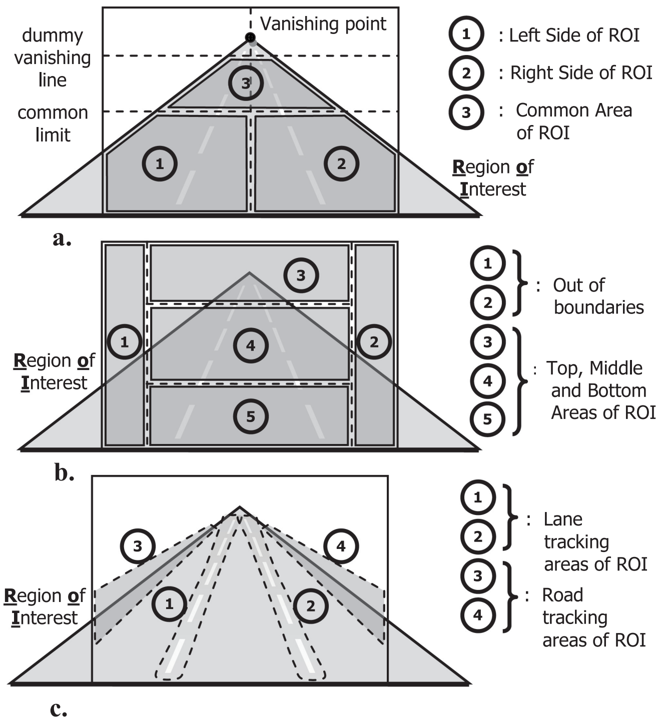

Fig. 5. Region of Interests (ROI): (a) Vanishing point based (detection mode); (b) area based (detection mode); (c) area based (tracking mode).

2004; D'Cruz and Zou 2007; Danescu et al. 2007; Assidiq et al. 2008; Gamec and Urdzík 2008; Shihavuddin et al. 2008]. As a different approach Li et al. [2004] used only R and B channels of color image to form the gray-level image. For color image approaches, some researchers used to change the color format. RGB to HIS [Rotaru et al. 2004; Samadzadegan et al. 2006; Sun et al. 2006] or RGB to HSV [Lipski et al. 2008] conversions are discussed. Sun et al. [2006] argued that advantages of loose threshold yields good detection results using an HSI model compared to RGB. But changing the format or size of the images frequently resulted in the loss of useful information, especially in complex situations.

Complex computational vision systems can lead to some problems due to the processing time. It is not practical to process all images completely in the time available, so focusing attention on important regions is required. These regions are commonly referred as Regions of Interest (ROI).

Splitting the images into ROIs can be mentioned separately for two phases: detecting phase and tracking phase. Lane detection is the problem of locating road lane boundaries without an a priori knowledge of the road geometry. For the lane detection mode, ROI determination is troublesome because on the one hand it is likely to eliminate a useful part of the image before the subsequent processes, and on the other hand to keep the ROI large will decrease its advantages. Some researchers preferred to split ROIs by a predefined percent of the image from bottom or top of the image as region of interest [Hu et al. 2004; Yu et al. 2008a], some took the part between the bottom of the image and vanishing point or vanishing line [Sun et al. 2006; Lu et al. 2007; Wen et al. 2008] as in Figure 5(a), some researchers divide the image horizontally [Bellino et al. 2004] or vertically [Kang et al. 1996] into several parts as in Figure 5(b), RALPH (Rapidly Adapting Lateral Position Handler) applied a trapezoid to eliminate the irrelevant part [Pomerleou 1995]. The lower and upper boundaries (according to the image) of the trapezoid vary with vehicle velocity. Jeong and Nedevschi followed distinct strategies in splitting rural ways and highways in Jeong and Nedevschi [2005], as predefined splitting for rural ways and adaptive splitting for highways.

Lane tracking is an easier problem than lane detection, as prior knowledge of the road geometry permits lane tracking algorithms to put fairly strong constraints on the likely location and orientation of the lane edges in a new image (Figure 5(c)). The pointed location by the previous detection would be the main cue in constructing the ROIs for the following steps.

Due to the perspective effect induced by the acquisition conditions, the road markings' width changes according to their distance from the camera and the parallel lane marks in the real world will intersect into one point (vanishing point) in the image plane. Thus, the correct detection of road markings by means of traditional pattern matching techniques should be based on matching with different sized patterns, according to the specific position within the image.

As an alternative to this approach, the Inverse Perspective Mapping (IPM) [Foedisch and Takeuchi 2004b] allows us to transform an image from a perspective view to a view from the sky by remapping each pixel toward a different position. Fitting specific lane models in the image given by the inverse perspective mapping proved an effective solution and used widely.

4.2. Feature Detection

Image features that are stable across varying scales, rotations, illuminations, or viewpoints are desirable for recognition and indexing tasks, since objects are likely to repeat these invariant features in varying real-world imaging conditions. A feature extraction process can be carried out in two steps: feature selection and extraction of selected features.

4.2.1. Feature Selection. Feature is one of the most important ingredients for building an acceptable recognition system. There are several features of the road environment that can be used for extraction.

Color. The human visual system processes three bands of the electromagnetic spectrum independently and so the system incorporates a type of multisensory fusion. However, studies by Colenbrender and De Laey [2006] have shown that abnormal color vision is not incompatible with safe driving. The problem of recognizing traffic lights has been overcome by the standardized position of the different lights, appropriately chosen colors, and in some countries by the differences in their sizes. But the difference between abnormal color vision and monochromatic vision should be distinguished. We did not encounter any research dealing with a human with monochromatic vision.

For machine vision, color processing is only useful as means of acquiring greater information beyond monochromatic imagery. Because of the information richness that color imaging can provide, we, and ultimately the machine, can distinguish more objects or regions in a color image than a monochromatic one. However, the restrictions on color processing due to increased computational demands suppress its usefulness. Using color to detect road or path regions in images for autonomous navigation has been deemed important since the 1980s. Color-based approaches extract the road color or road-marking colors for lane detection. They need to learn the color space of the lane and road surface and use the model to detect lane boundaries. If there are some vehicles whose colors are similar to the lane boundary colors, they will likely result in error results. In Section 4.2.2 color-based approaches are comprehensively reviewed.

Edge. An edge is mathematically defined by the gradient of the intensity function [Ma et al. 2001]. In structured roads, lane markings or road boundary markings constitute a strong cue in road detection because these markings usually have clear edges and relatively high intensities. However, the gradient magnitude can be misleadingly high due to the contrast between the asphalt and road elements (e.g., vehicles) or be low because of shadows, wearied marks, etc. Moreover, the gradient orientation tends to be noisy because of its very local nature. In fact, these usual circumstances are challenging, since for a road with low traffic, well-painted lane markings, shadow free, etc., a well-designed computer vision algorithm may succeed.

In unstructured roads, when there are no lane markings, the border between the road and its surroundings is often characterized by low and irregular (and in some places even fuzzy) road shoulders. If the images have uniform regions with good separation between them, the performance of the road detection algorithms using an edge feature increases. However, real road, lighting, and weather conditions seldom give rise to such clear and contrasting images. Difficulties arise as well from the fact that it is not always possible to choose a threshold that filters image noises from relevant edges. And also there may be lots of extraneous edges such as trees, telephone poles, and power-line poles, shadows across the road, and mountain slopes in the distance. In Section 4.2.2 edge-based approaches are comprehensively reviewed.

Texture. Texture plays an important role in human visual perception and provides vital information for recognition and interpretation [Chindaro et al. 2003]. Texture characterizes any visible surface such as plants, skin, terrains, etc., and this is the major reason that texture analysis methodologies are incorporated into the construction of image analysis systems. Apart from various other applications, the texture processing is an essential part of computer graphics, Content-Based Image Retrieval (CBIR), computer vision systems, medical imaging, and the Land-cover Classification (LcC) in Remote Sensing (RS) systems.

The texture characterization and recognition and the defect detection in textural sets are difficult problems in image processing, probably because it's not likely to give a precise definition of what a texture is [Huet and Mattioli 1996]. In general, people agree on the fact that a texture is a particular spatial arrangement of grey levels, with the property that grey-level variations have to be of a rather high frequency, and that it presents a pseudoperiodical character. According to this definition, classical techniques of texture analysis are divided into statistical methods and structural methods. The first category is more suitable for disordered textures, where the spatial distribution of grey levels is more random than structured. Structural methods are suitable for more ordered textures. We need only consider that a texture is more or less generated by primitive patterns, sometimes referred to as *"textons"* [Huet and Mattioli 1996] which are repeated and arranged in a certain way.

Since a real-world texture may, in general, be viewed from any angle and distance, and under a range of illumination conditions, contrast, scale, and affine invariance are natural requirements for texture description. The appearance of a texture depends hugely on the imaging geometry and illumination. It follows that any generally applicable texture description must be able to distinguish between intrinsic properties, those which are fundamental aspects of the texture, and extrinsic properties, those which are dependent on imaging conditions.

Texture segmentation is the task of identifying regions with similar patterns in an image. A common strategy is to extract features pixel-by-pixel and then classify the extracted features. To improve the overall quality of image texture segmentation, either the quality of the texture features or the quality of the classification algorithm must be improved. A number of approaches for texture classification and analysis

a. **b.**

Fig. 6. Area detection: (a) Original image; (b) area detected image (pure black fields).

have been developed and used in various applications such as scene analysis and industrial inspection [Chindaro et al. 2003; Hu et al. 2004]. In Section 4.2.2 texture-based approaches are comprehensively reviewed.

4.2.2. Feature Extraction. Feature extraction is a function that extracts image features of road areas, road markings, or road boundaries using various filters or statistical methods. In feature extraction, the approaches in the literature can be categorized basically into three classes: area-based methods, edge-based methods, area-edge-combined and algorithm-combined methods. In area-based methods the road detection problem is considered as a classification problem. The main idea of a classification algorithm is to classify the road image into road and nonroad areas and it is the most important portion of the road detection. It must overcome the presence of noise such as shadows, puddles, and tire skid marking, and the classification time must be reduced to use it in real-time applications. In edge-based methods at first an edge map of the road scene is obtained and then using a predefined geometric model a model matching procedure is carried out to detect the road. In area-edge-based methods, either an edge-based algorithm is supported by an area-based algorithm or vice versa. In algorithm-combined methods, several methods are carried on together in parallel to increase detection performance.

Area-based methods. Area-based methods extract road area candidates from the road image as in Figure 6. In Figure 6(a) we can see the original road image and in Figure 6(b), the extracted road areas are painted to black. There are several techniques used in area classification according to selected features.

Using RGB or HIS information in classifying the pixels or regions as road or nonroad is one of the most commonly used methods. Foda and Dawoud presented a detection process which involves classifying the input image pixels into road and nonroad using LVQ (Learning Vector Quantization) [Foda and Dawoud 2001]. Learning vector quantization employs a self-organizing network approach which uses the training vectors to recursively "tune" placement of competitive hidden units that represent categories of the inputs. Once the network is trained, an input vector is categorized as belonging to the class represented by the nearest hidden unit. For LVQ, it is required to be able to generate useful distance measures for all attributes and model accuracy is highly dependent on the initialisation of the model as well as the learning parameters used. Accuracy is also dependent on the class distribution in the training dataset: a good distribution of samples is needed to construct useful models and it is difficult to determine a good number of codebook vectors for the given problem. UNSCARF (Unsupervised Clustering Applied to Road Following) [Crisman and Thorpe 1991] collects similar pixels in the color image using a modified clustering technique (ISODATA) and then extracts the edges between groups of pixels. The ISODATA algorithm is similar to the k-means algorithm with the distinct difference that the ISODATA algorithm allows for different number of clusters while the k-means assumes that the number of clusters is known a priori. The general disadvantage of the ISODATA algorithm is that it works best for images with clusters that are spherical and that have the same variance.

SCARF (Supervised Classification Applied to Road Following) [Crisman and Thorpe 1993] uses Bayesian classification to determine road-surface likelihood for each pixel in a reduced color image. Road-surface likelihood is created where each pixel contains the likelihood that it belongs to the road surface according to the color model. The color model formulation module then uses the previous road or intersection descriptions projected onto the image to determine a set of Gaussian models for both road and off-road colors. The naive Bayes classifier is simple, fast, and of limited capability when it comes to anything but the most trivial cases of classification. Fortunately many real-world problems fall in exactly that category, so it shouldn't be ruled out.

Beucher and Bilodeau [1994] and Mu et al. [1992] proposed a technique based on a mathematical morphology tool called watershed transform. The segmentation is made up from temporal filtering, and an edge detector is used as preprocessing step and then watershed transformation. After transformation, it produces a marker of the current lane. The strength of watershed segmentation is that it produces a unique solution for a particular image, and it can be easily adapted to any kind of digital grid and extended to n-dimensional images and graphs. However, the noise in the image results in oversegmentation. Another disadvantage of watershed segmentation, again related to the image noise and the image's discrete nature, is that the final boundaries of the segmented region lack smoothness. So it is not an efficient idea to treat the watershed segmentation as the final segmentation.

Soquet et al. [2007] proposed a stereo-vision approach in which the road detection is carried out by color segmentation. The segmentation is performed by the ISODATA clustering algorithm on the hue and saturation distribution (2D histogram) of the given image. Dahlkamp et al. [2006] introduced an approach in which the system identifies a nearby patch of drivable surface first for detecting the drivable surface in desert terrain. The basic model for the road appearance is a mixture of Gaussians MOG (Modified Gravity) model in RGB space, with k-Gaussians to be found. The method classifies all the pixels in the training area using k-means then models each cluster by its average value, its covariance matrix, and mass. At this point, they score all pixels in the image according to the learned models. The weakness of the k-means is similar to the ISODATA.

Foedisch and Takeuchi used independent color histograms of the RGB images as features in Foedisch and Takeuchi [2004a, 2004b]. They used neural networks based on these features. In Foedisch and Takeuchi [2004b], as the continuation of Foedisch and Takeuchi [2004a], the system updates the neural network continuously based on the road image structure. Based on the estimated road location in the image, feature vectors are collected from predefined windows, which cover either road (road windows) or nonroad areas. Zhang et al. used a Support Vector Machine (SVM) in Zhang et al. [2005] to classify every pixel of road image into road surface and nonroad surface group based on R, G, and B values of the RGB image. SVMs can be a useful tool for insolvency analysis, in the case of nonregularity in the data, for example, when the data are not regularly distributed or have an unknown distribution. But in our case, the major disadvantage of the proposed method is the inability of SVM to deal with nonstatic data (dynamic data, sequences).

Prochazka [2008] tried to estimate the probability density function (pdf) of the road region appearing in sequential images and the problem of pdf estimation was formulated in terms of Bayesian filtering. Sequential Monte-Carlo method was adopted as a tool to solve the problem in the paper. The method is known also as particle filtering and the key idea is to represent the posterior density by a set of random particles with associated weights. The main drawback of the method is the high computational

Fig. 7. Texture analysis: (a) Original image; (b) refined image (white fields point to the road, blue fields point outside).

complexity and the difficulty of determining the optimal number of particles. Nevertheless, the method can deal with non-Gaussian noise and allows for including multiple models. It is one of the most promising approaches. Gao et al. [2007] proposed a Rough Set-based Unstructured Road Detection (RSURD) method which uses color as the main feature of the road surface. The main goal of the rough set analysis is induction of approximations of concepts. It can be used for feature selection, feature extraction, data reduction, decision rule generation, and pattern extraction (templates, association rules), etc. They used HSV color representation and thus the h, s, and v values of the samples are set as condition attributions. It is followed by the definition of the decision system. Jeong and Nedevschi [2003] proposed an approach which uses a local averaging classifier relying on decision trees, and in case of altered or noisy road regions, a special intelligent detection procedure. The main idea of this method is that a decision tree is constructed based on the averaging feature vector of the entire region and of the local regions of the resized input images. Among the major decision tree disadvantages is its complexity. Decision trees are easy to use compared to other decision-making models, but building decision trees, especially large ones with many branches, is complex and time consuming.

Son et al. [2008] presented a road identifier based on a supervised learning approach to estimate a "roadness" probability. A two-category classification is employed, and to produce a multiscale and hierarchical representation of the image a Segmentation by Weighted Aggregation (SWA) algorithm is used. The SWA algorithm finds the best partition from the constructed graph according to the saliency measure, which represents the segment's dissimilarity from its surroundings, divided by its internal homogeneity. As a study in gray-level domain Gonzalez and Ozguner [2000] performed a region growing segmentation based on histogram characteristics. This segmentation classifies the objects in the scene as road, lane-markers candidates, or obstacle candidates. They calculated the mean value of the gray-level distribution of the road, as well as the maximum and minimum values of such distribution.

For unstructured roads, texture is an important feature in extracting road area candidates as shown in Figure 7 and used commonly by several researchers. In Rasmussen [2004], Rasmussen used dominant orientation of the texture at each location in the image for locating the road's vanishing point. These dominant orientations which are computed with multiscale Gabor wavelet filters vote for a consensus road vanishing point location. Similarly, Zhang and Nagel proposed an approach for estimating the orientation and strength of oriented textures based on the covariance matrix of the gray-value changes in the image [Zhang and Nagel 1994].

As an image feature, the strength of texture anisotropy is used. ISODATA clustering is used in the initial phase and in subsequent phases a Bayesian classifier is used for supervised road segmentation. Fernandez-Maloigne and Bonnet used neural networks for road-nonroad classification using texture clusters [Fernandez-Maloigne and Bonnet 1995]. For each pixel, they set the 16×16 pixels' normalized neighborhood as the input of NN.

The question is: what will we prefer in classification, a single strong feature or a set of weaker features? This question resembles the question of Kearns [1988]: Can a set of weak learners create a single strong learner? Boosting arose as an answer to such a question. Boosting is a machine learning meta-algorithm for performing supervised learning. Sha et al. proposed a classification-based road detection algorithm by boosting [Sha et al. 2007, 2008] which utilizes the feature combination method in road detection. The image is segmented by the region growing technique and for each region, four kinds of features, namely the coordinate, the color, the luminance, and the size are used in classification. In Sha et al. [2008], a comparison is presented between boosting and a random forest algorithm for feature selection performance. To evaluate the boosting feature selection approach, the support vector machine is employed. Random forest algorithm is an ensemble classifier using many decision tree models. In this algorithm class assignment is made by the number of votes from all of the trees and for regression the average of the results is used. Several advantages of the random forest algorithm are: no need for pruning trees, the accuracy and variable importance are generated automatically, overfitting is not a problem, it is not very sensitive to outliers in training data, and is easy to set parameters. And its limitations are that regression can't predict beyond range in the training data and in regression extreme values are often not predicted accurately, that is, it underestimates highs and overestimates lows, so the random forest algorithm is suppported with boosting feature selection with an SVM. The result is promising. Gopalan et al. [2009] proposed a machine learning approach based on Real Adaboost, and trained linear classifiers for both the appearance and edge cues of the training exemplars. To utilize both channels of information, they trained two separate layers of Real Adaboost, with the first layer trained on a novel set of lines and curves (of different slopes and curvatures) to capture the edge patterns, and the second layer trained with the set of Haar-like features to capture the appearance variations in the training samples.

In our experiments, Sha et al. [2008] and Chindaro et al. [2003] gave the best results in the meaning of classification rate. As a conclusion, we can say that rather than using a single method, combining methods in an appropriate way is more preferable. But the computational cost and classification speed is considerable in these cases.

Most of the area-based methods have a simple and straightforward implementation, well suited for parallel implementations based on VLSI circuits or Digital Signal Processors (DSP), as well as their robustness against certain image transformations. Also using stereo vision they provide the dense disparity map, whereas in feature-based approaches an interpolation step is required if a dense map of the scene is desired. However, they have some drawbacks, the major one being the significant computational load associated to the computation of the dense matching field.

Edge-based methods. Edges are the most common feature used in road detection for structured roads. Edge-based methods use the edge information extracted from the road image to obtain road or lane boundary candidates or lane-marking candidates. In Figure 8, the original image and the edge images of the original image are shown. Frequently, a model matching process which tries to fit the candidates to a predefined geometric model follows the edge extraction. To date various methods have been proposed by researchers.

Certainly, we can say that to extract the edges the most common technique is following a sequence starting from well-known filter banks such as Canny or Sobel to the end of the Hough transform. In obtaining the edge map of the given image Canny filters

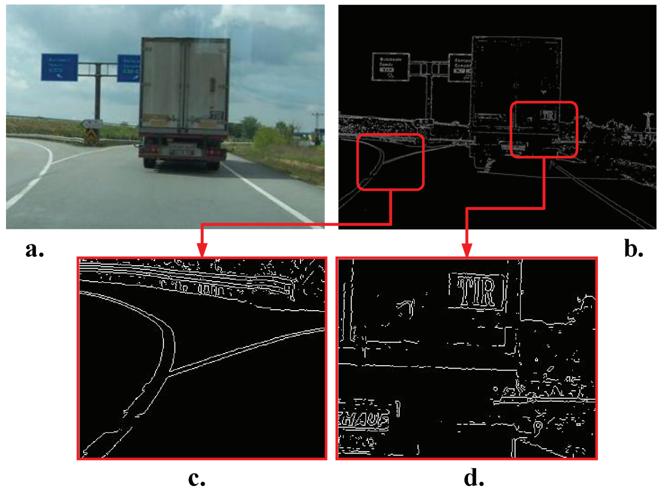

Fig. 8. Edge detection: (a) Original image; (b) edge detected image; (c) and (d) details of the edge detected image.

[Yu and Jain 1997; Wang et al. 1998, 2004; Schreiber et al. 2005; Tian et al. 2006b; Boumediene et al. 2007; He and Chu 2007; Assidiq et al. 2008; Isa 2008; Truong and Lee 2008; Truong et al. 2008], Sobel filters [Haga et al. 1995; Lai and Yung 2000; Jeong et al. 2001; Hong et al. 2002; Tang et al. 2002; Yim and Oh 2003; Li et al. 2004; Shu and Tan 2004; Liu et al. 2006; Samadzadegan et al. 2006; Nasirudin and Arshad 2007; Lu et al. 2008; Maeda et al. 2008; You et al. 2008; Zheng et al. 2008; Zhu et al. 2008; Wang et al. 2009], peak finding in scan-line [Chapuis et al. 2000; Park et al. 2000; Aufrère et al. 2001; Huang et al. 2004; Hsiao et al. 2005; Wang et al. 2005; Wang and Chen 2006; Benmansour et al. 2008; Döbert et al. 2009; Jiang et al. 2009; Yu and Zhang 2009] and thresholding [Chiu and Lin 2005; D'Cruz and Zou 2007; Lu et al. 2007, 2008, 2009; Benmansour et al. 2008; Maeda et al. 2008; Nieto et al. 2008; Yu et al. 2008a; Wen et al. 2008; Borkar et al. 2009; Watanabe et al. 2009; Xinyu and Zhongke 2009] are used. Subsequent steps of these operations are usually binarization [Ishikawa et al. 2003; Shu and Tan 2004; Mori et al. 2004; You et al. 2008; Yu et al. 2008a; Zheng et al. 2008; Borkar et al. 2009; Weigel and Wanielik 2009], thinning [Maeda et al. 2008; Truong and Lee 2008; Truong et al. 2008; Weigel and Wanielik 2009], and then applying Hough transform to get a line segment possibly representing the road or lane boundary. For each pixel and its neighborhood, the standard Hough transform algorithm determines if there is enough evidence of an edge at that pixel. Also, the standard Hough transform does not apply to grayscale, so the brightness changes must be first translated into solid lines by edge detection or thresholding. This step is usually followed by thinning. There are various forms of Hough transform such as standard Hough Transform (HT) [Kang et al. 1996; Ishikawa et al. 2003; Tsuji 2001; Wijesoma et al. 2001; Mori et al. 2004; Schreiber et al. 2005; Liu et al. 2006; Lin et al. 2007b; Nasirudin and Arshad 2007; Assidiq et al. 2008; Benmansour et al. 2008; Isa 2008; You et al. 2008; Borkar et al. 2009; Döbert et al. 2009; Weigel and Wanielik 2009], coarse Hough transform [Yu and Zhang 2009], segmented Hough transform [Mori et al. 2004], Randomized Hough Transform (RHT) [Samadzadegan et al. 2006; Maeda et al. 2008], Adaptive Randomized Hough Transform (ARHT) [Sehestedt et al. 2007b; Zhu et al. 2008], multiresolution Hough transform [Yu and Jain 1997] and spoke filter [Haga et al. 1995] have been proposed by several researchers. Hough transform is frequently used in vanishing point extraction [Wang et al. 2004] or as a preliminary stage of the model fitting phase.

For the use of parallel hardware platforms such as FPGA in real-time lane detection situations, some of the algorithms used in lane detection should be ready for parallel processing. There are several studies in implementing parallelism in these algorithms. One of them is Suchitra et al. [2009], in which the authors implement parallelism in Hough transform.

Bertozzi and Broggi enhanced the image by exploiting its vertical correlation, (since a simple threshold seldom gives a satisfactory binarization), then performed an adaptive binarization [Broggi 1995b; Bertozzi and Broggi 1998]. The enhancement of the filtered image is performed through a few iterations of a geodesic morphologic dilation.

For IPM images either lane markings or road boundaries provide gradients which can be approximated by quasi-vertical bright lines of constant width surrounded by a dark region [Broggi 1995b, 1995c; Bertozzi and Broggi 1998; Shu and Tan 2004; Sehestedt et al. 2007b]. With this definition the edge detection problem turns into a gradient-detection problem. To determine them Broggi [1995c] proposed a serial scanning of the image. Tarel and Guichard similarly used a gradient-based approach in Tarel and Guichard [2000] but to avoid missing low-contrast boundaries they defined "edgel" as a straight line embedded in level lines of the given image. Gradient-based feature detectors offer important advantages over their standard edge-only equivalents; however, gradient-based feature detection is more sensitive to noise. As the total gradient magnitude at a pixel decreases, the component of the gradient at that point that arises from image noise increases. Thus, when a pixel votes in its gradient direction out to an extended radius, its position is more likely to be inaccurate if the gradient magnitude is low. Lee proposed a method which uses edge information to define an Edge Distribution Function (EDF), the histogram of edge magnitudes with respect to edge orientation angle [Lee 2002] remaining the sensitivity to noise. The EDF enables the edge-related information and the lane-related information to be connected. Lee only determined the orientation of each lane boundary but did not compute these boundaries explicitly. Jung and Kelber used EDF as the feature extraction stage of detecting lane boundaries explicitly in Jung and Kelber [2004]. Risack et al. [1998] proposed a method in which on each scan-line, edge pixels are searched which are given by local maxima of gradient magnitude in gradient direction. Tian et al. proposed a method in which the blobs of road markings are extracted from low-high-low gradient and then cluster the blobs into several groups using a KNN function [Tian et al. 2006a]. All of these algorithms show similarity in both methodology and drawbacks. In complex road situations or images, they suffer misclassification. Broggi proposed an adaptive smoothing algorithm known also as anisotropic diffusion as clustering algorithm [Broggi 1995a]. Anisotropic diffusion filters usually apply spatial regularization strategies. Edge-enhancing anisotropic diffuison offers advantages at noisy edges. It substitutes a fixed threshold with a function of neighborhood, in order to enhance also weak and isolated discontinuities. Since the image obtained so far consists of a set of almost disjointed clusters with well-marked borders, an approximated version of a gradient-based filter, such as an extremely simple convolution with a 3×3 fixed kernel, is sufficient to determine the image edges. This step is followed by a binarization, and by a thinning or a nonmaximum-suppress algorithm to decrease line thickness. Sun et al. used the histogram of intensity difference based on HIS color model in lane-marking extraction [Sun et al. 2006]. To divide pixels with lane-marking-like intensity threshold Fuzzy C-Means clustering (FCM) is applied. To overcome the fixed threshold shortage, they used saturation value as a support. And by means of Connected Component Labeling (CCL) of the binary image, pixels connecting with one another are encoded to components along with labeling. Similarly, Lipski et al. [2008] used a histogram-based method based on the HIS color model. The basic idea of the proposed feature detection is to identify the local differences in lane-marking regions using 8×8 pixels neighborhood.

Some researchers handle the problem with state machine techniques. Wu et al. [2009] proposed Lane Marking Extraction (LME) Finite State Machine (FSM) in extracting features such as graylevel and lane width of lane markings. Sehestedt et al. [2007b] proposed an exhaustive search across each row of the image to produce potential lane-marking candidates where the match probability can be measured with the edge quality (difference of intensity). The method uses an Inverse Perspective Mapped image (IPM image) to run a particle set from the bottom to the top and observing the presence of lane markings in each line. For every incoming observation, the filter starts from the bottom of the image. In every timestep the particles are then moved to the next line of the image according to a defined Markov model, which incorporates general knowledge about the road design. Tsai et al. proposed a novel morphology-based method to find all possible lane segments [Tsai et al. 2008]. At first, they define proper structure elements to extract different lane-mark features from input frames using a novel morphology-based approach. Connected component analysis is executed for extracting all the lane-analogue segments from roads. To extract the real road lane, they model the direction of the lane line in each lane segment as a Markov random process. Without assuming any line models, they model the lane direction change as a state transition problem. Thus, the relationships between each lane segment can be embedded into a matrix of state transition probability. Then a linking technique can be proposed for finding the correct lane locations from this matrix.

The lane markings painted on the road have several color properties. Evaluating color properties led various researchers to the extraction of lane markings. Cheng et al. [2006] used three multivariate Gaussian distributions (for white, yellow, and red lane markings) to represent the three main classes of lane-marking colors. In the proposed method, first the color range possibly representing the lane markings is extracted using some loose constraints, which gives the mean values and standard deviation of the three color components. The lane-marking color extraction is completed by setting the binary mask, and highlighting possible regions of the lane markings in the image. Fardi et al. [2003] proposed an ad hoc approach like Boundary Pixel Extractor (BPE) in extracting pixels expected from lane boundaries. In the edge extraction first a Sobel edge operation provides edge features composed of gradients, magnitude, and orientation. Then BPE which is based on a priori knowledge that the lane marks painted in one of three colors of white, yellow, and even blue are brighter than road surface is implemented. After the BPE extracts pixels, the orientation and magnitude of lane boundaries are computed by means of the Hough Transform (HT). In addition, they constructed EDF using edge features also giving rise to orientations of lane boundaries.

McCall and Trivedi [2006] used steerable filters which can be convolved with the input image and provide features that allow them to be used to detect both dots and solid lines while providing robustness to cluttering and lighting changes. For detecting lanes, the response in the direction of the lanes should be near maximum. Lei et al. used steerable filters in image preprocessing and then applied a Hough transform in Guo et al. [2006].

Kreucher and Lakshmanan proposed to work in the frequency domain to discriminate between edges that are diagonally dominant and those that are randomly oriented [Kreucher and Lakshmanan 1999]. In their paper, a given image is divided into blocks and each of the blocks is then orthogonally composed in terms of Discrete Cosine Transform (DCT) basis elements. Despite the original image having features/edges of various strengths and orientations, the corresponding DCT feature images contain only information about those edges which are diagonally dominant. In the method proposed by Jamal et al. [2005] a road boundary detection technique brings the preprocessed image stream into the frequency domain for fast processing. Then the DC component was made zero to reduce the effect of nonuniform illumination. The original image is computed by inverse Fourier transform. Then edge detection is performed by a Sobel gradient operator. Morphological cleaning is applied. Then the image is closed by a small structuring element in the vertical direction to bridge the gaps which resulted from correct localization of road boundaries.

From a different point of view, López et al. propose ridgeness instead of the edge as the low-level image descriptor [Broggi 1995b; López et al. 2005a]. Ridgeness stands for a degree of how much a pixel resembles a ridge. They see a lane marking as an elongated mountain and, then, its ridge is the longitudinal center of the painted line in the lane detection case. Therefore, a ridgeness measure must have high values near this center and low far. According to them the proposed ridgeness measure is invariant under monotonic grey-level transforms of the input image, which, in practice, helps to the lane detection task in presence of shadows. Second, the process of obtaining the ridgeness measure also yields the dominant gradient orientation of the original image. In the next phase, Hough transform is applied.

In the literature some comparisons between the extraction techniques can be found. For example, Kim [2006, 2008] compared the classification performance and computational requirements of various classifiers such as Artificial Neural Networks (ANN), perceptron, Naive Bayesian Classifiers (NBC), and Support Vector Machines (SVM) for lane-markings extraction. According to the results ANN showed a good classification performance with small computational time. Veit et al. [2008] also performed a systematic approach to evaluate feature extractors. Using a natural road image database containing over 100 images as reference, they evaluated and compared extractors in a systematic way.

Edge-based methods have similar performance meaning that the dominant decision factor at this point becomes the computational times, and ease of parameter tuning. On the other hand, all of them have a more serious problem. Edge-based methods heavily rely on the existence of proper road markers or road indicators. In the absence of road markers, most of the algorithms failed to detect the edges. The performance of the edge-based methods is also affected seriously by the complexity of the image. For example, with the different illumination conditions or with the existence of dirt on the road, edge detection can be degraded, resulting in misperception of the environment. So, for a successful perception of the environment we believe that area-based methods and edge-based methods should be combined.

Area-Edge-based Methods. Area-edge-based methods use an area-based method as the core and in addition use an edge-based method as a support to the area-based results, or vice versa, in order to obtain a more reliable and robust detection system.

In the literature, there are various researchers who have used such an approach. He et al. [2004] proposed a method which combines edge detection based on the intensity of images with a road-area extraction process based on the color components of an image. Boundaries are first estimated based on the intensity image and road areas are subsequently detected based on the full-color image. They showed that their algorithms work well on structured and semistructured roads. Similarly Liu et al. [2008a] combined boundary recognition (with a Sobel operator) with road area recognition (with a region growing method). In contrast, Wen et al. [2008] presented an algorithm based on the color consistency of the road surface. They first compute the road surface color and its variance by assuming the road color follows a Gaussian distribution, and then extract the road surface using an improved region growing method with edge enhancement. Additionally, two kinds of edges are extracted: line and nonline edges. For line edges, the probabilistic Hough transform is used. For nonline edges, the first-order

Sobel operator is applied. Similarly Hu et al. [2004], Shihavuddin et al. [2008], and Wang et al. [2008b] presented an approach which first segments the images into road and nonroad and then uses a hypothesis verification strategy based on Canny edge detection. Shihavuddin et al. [2008] used Radon in the detection of the continuous straight lines and curves of the edges.

Tsai et al. [2006] analyzed the road scene structure by classifying the pixels into three different types, including road surface, lane markings, and nonroad objects, relying heavily on lane markers. Instead of detecting these three objects separately in traditional approaches, they integrate different ad hoc methods within a conditional random field framework. Three feature functions based on three cues, including smoothness, color, and lane-marking segmentation, are used for pixel classification. Besides, an optimization algorithm using graph cuts is applied to find the solutions efficiently. Rotaru et al. [2004] used HSI components and edge data to make a predetection for road areas and lane markings and to validate the inferred assumptions. This method requires knowledge about the environment that would not be feasible for many real-world applications. In this method the Prewitt operator is used for edge detection. The road area detection is applied to an HIS image. The lane detection is applied both to the HIS and edge image. Lombardi et al. [2005] used the TextureLess (TL) detection algorithm which extracts regions grouping connected components for nonedge pixels after an edge detection step. Edge detection is achieved by a SUSAN (Smallest Univalue Segment Assimilating Nucleus) 3×3 operator with a threshold. Morphological kernels are used to connect disconnected edges and to prolong edges that are close to the image border until they touch it. The difficulty of the method arises from the predefined model selection. Danescu et al. [2006] proposed a method in which the 3D points that belong to the road surface are selected using the road surface parameters inferred from the current lane detection, and that are used for detection of the side lane.

Area-edge-based methods have very high potential for being implemented in future autonomous vehicular motion systems and driver assistance systems, due to their accuracy. Also, with the development of new architectures that support more and more parallel computation, we believe that this approach can be seen as a viable solution of this class of computer vision problems.

Algorithm combined method. In Labayrade et al. [2005], the authors proposed the parallel use of the approaches in Aufrère et al. [2001] and Labayrade et al. [2004] implementing two low-level detection algorithms, namely lateral consistency detection and longitudinal consistency detection [Labayrade et al. 2006], while in Labayrade et al. [2004] they introduced redundancy by using two independent algorithms. By combining their outputs together, they obtain more reliable results as well as a confidence value. The first algorithm computes longitudinal-coherent results whereas the second algorithm computes lateral-coherent results. With three parallel algorithms working together, a reliability indicator is provided to avoid reporting false detection, which is crucial for the driver to be confident in the system and to be used safely for vehicle control. But the point is, for autonomous driving, rather than finding the mistake of the other algorithm, producing the right decision for a given situation is more important.

The system proposed by Cheng et al. [2008] classifies the environment before applying suitable algorithms for different types of roads. For environment classification, pixels with lane-marking colors are extracted as feature points to check the existence of the lane markings with the feature extraction method in Cheng et al. [2006]. Afterwards, for a structured road environment Eigenvalue Decomposition Regularized Analysis (EDRDA) is used with the previous lane-marking information, and for unstructured roads mean-shift segmentation is used for lane extraction. The selection of the suitable algorithm is cumbersome. In their promising method, Apostoloff and Zelinsky [2003] installed two different vision platforms, one for driver monitoring consisting of a passive set of cameras mounted on dashboard, and the other for active vision carrying two cameras that are used for dual near-field and far-field scene coverage. They introduced a system based on a distillation algorithm that attempts to dynamically allocate computational resources over a suite of cues to robustly track the road in a variety of situations. The basis of the distillation algorithm is that a suite of cues is calculated from image and state information and combined to provide evidence strengthening or attenuating the belief in each hypothesis of the particle filter. The cue fusion process involves lane-marker cues, road edge cues, road color cues, and nonroad color cues as image-based cues and road width cue, and elastic lane cue as state-based cues. Various techniques are used in extracting the relevant cues in their paper. The study is promising but has a relatively high computational complexity.

Danescu et al. [2007], Nedevschi et al. [2004], and Danescu and Nedevschi [2008] presented a lane detection method based on stereo vision. The detection starts with the estimation of the vertical road profile, using the stereo-provided 3D information and afterwards continues with horizontal profile detection. For vertical profile detection, using the side view of the 3D points, an angle histogram is built for each possible pitch angle, using the near 3D points, and then the histogram is searched from under the road upwards [Nedevschi et al. 2004]. The first angle having a considerable amount of points aligned to is taken as the pitch angle. The detection of curvature follows the same pattern. The pitch angle is considered known, and then a curvature histogram is built, for each possible curvature, but this time only the more distant 3D points are used, because the effect of curvature is significant only in more distant points. Horizontal profile road detection works on edges; the edge points are filtered, where only those edges that comply with the vertical road profile are extracted for further steps. Research in stereo imaging is a hot topic, because it offers a multilateral and robust way to reconstruct lost depth information. The few available state of the stereo-vision solutions have disadvantages such as cost, size, inflexibility, and high power consumption and are often incapable of making depth maps in real time.

Guo and Mita [2009] proposed an algorithm composed of three modules: a preliminary classification module, which selects the most appropriate classifier from the road appearance model to detect the preliminary road-like region; a feature-based detection module, which finds the correspondences of feature points on the road plane to estimate the homography for the first image pair, and then extracts the drivable road region; and an area-based detection module, a nonlinear optimization process which uses the results obtained in module 2 as the initial values for the homography estimation as well as drivable road region detection of the subsequent image pairs with the driving state model based on sequential information.

Jeong and Nedevschi [2005] proposed a method which uses two different lane detection procedures in accordance to input images for highways and rural ways. Tsai and Sun [2005] propose a flexible scenario that combines histogram-based color difference fuzzy cluster analysis (HCDFCM) with a shadow removing algorithm. According to the Histogram-based Color Difference Fuzzy Cluster Method (HCDFCM) Tsai and Sun [2005] used only one scan-line to find the lane boundary, thus can save the computing time and the amount of processing data. According to the road shadow removing algorithm developed in their previous works they can solve the HCDFCM problem in the case of a shadowy road. Lin et al. [2007a] presented a new road boundary detection algorithm based on double filtering. This approach employs two filters, namely the Edge Distribution Function (EDF) and Dynamic Programming (DP). In Lin et al. [2007b] they introduced a method combining DP and HT. Ko et al. [2006] also proposed

Table I. Domain Constraints and Related Works

Symmetry Constraint	Bertozzi and Broggi 1998; Lai and Yung 2000; Hu et al. 2004; Rotaru et al. 2004; Tsai and Sun 2005; Foedisch et al. 2006; Lin et al. 2007c; Wu and Lin 2007
Smoothness Constraint	Lai and Yung 2000; Rotaru et al. 2004
Continuity Constraint	Chiu and Lin 2005; Foedisch et al. 2006; Wu and Lin 2007; Liu et al. 2008a
Lane Marker Width Constraint	Rotaru et al. 2004; Tsai et al. 2006; Liu et al. 2008b
Lane or Road Width Constraint	Bertozzi and Broggi 1998; He et al. 2004; Tsai and Sun 2005; Cheng et al. 2006; Dahlkamp et al. 2006; Wu and Lin 2007; Borkar et al. 2009
Lane or Road Orientation Constraint	Tsai and Sun 2005; Cheng et al. 2006; Lin et al. 2007a
Vanishin Point Agreement Constraint	Rasmussen 2004; Schreiber et al. 2005; Wang et al. 2005; He and Chu 2007; Nieto et al. 2008; Yu et al. 2008b

a method that combines DP and HT. Finally, Michalke et al. [2009] proposed an architecture relying on four novel approaches that make such systems more generic by autonomously adapting important system parameters to the environment. The system detects the road based on six robust features that are evaluated and fused in a probabilistic way.

Still, the proposed methods suffer either from the computational complexity or from relying on the road markers or predefined models. The required model should evaluate all the cues on the road image, without predefined models, learning on the way, with minimum hardware requirements to be able to work in real time.

4.2.3. Candidates Validation. In order to achieve robust system performance, spatial and temporal domain constraints are widely used in validating the features and obtaining the correct road location. In fact, the lane model imposes some assumptions about the real lane in order to extract 3D information from 2D images. There are three basic approaches in validation: applying domain constraints to the extraction results, fitting the candidates to a geometric model, and applying both.

Applying domain constraints. Almost in all papers, lane detection is described as detecting the lane in a single image without a priori information about the road position. But this does not mean that we could not impose any spatial or temporal constraints to the road domain. The detection system should take the advantage of global scene constraints to improve its robustness in the presence of noise or occlusion in the images. There are several constraints that can be used in detection.

Definition 2.1 (*Symmetry Constraint*). A symmetry constraint has been used by several researchers as shown in Table I. Each road boundary segment on the left side has at least one right boundary segment that is locally parallel to the specified left-side segment. Line segments that satisfy these relations provide geometric support for each other. In addition, the distance between two supporting edge segments should be close to the road width.

Definition 2.2 (*Smoothness Constraint*). Both the left and right boundaries of a road change direction smoothly even on curved roads. Several researchers used this constraint (Table I).

Definition 2.3 (*Continuity Constraint*). A road spans continuously on ground planes; therefore continuity between road boundaries exists between two successive images. Several authors made use of this constraint as in Table I.

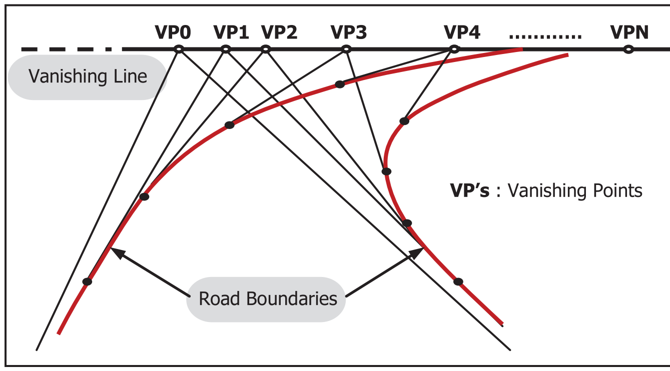

Fig. 9. Line segments in an image.

Definition 2.4 (*Lane-Marker Width Constraint*). A maximum and a minimum value about the lane-marker width can be defined in structured roads. The edges can be filtered out through these values and related works are in Table I.

Definition 2.1 (*Lane or Road Width Constraint*). A maximum and a minimum value about road or lane width can be defined for structured roads regarding the previous lane width information, and related works can be found in Table I. The edges can be filtered out through these values. For unstructured roads, especially for multilane roads where there are no lane markings or where the lane markings are degraded or occluded, these constraints would not be practical.

Definition 2.1 (*Lane or Road Orientation Constraint*). Lane or road orientation is handled as the angle of lane-related lines according to the camera view and is used by several researchers (Table I) as a constraint.

Definition 2.1 (*Vanishing Point Agreement Constraint*). Vanishing point is a point in the image plane to which a set of parallel lines in the 3D space will converge and is used to compute the homography between the image plane and the road plane.

The roadway is approximated from the combined information of the lanes and their vanishing point (Figure 9). Various researchers see the vanishing point's detection as a prerequisite in lane detection and started with vanishing point detection (Table I).

Selection of geometric model. Some authors created predefined models to fit the road in the image [Crisman and Thorpe 1991, 1993; Pomerleou 1995; You et al. 2008]. Each model represents the expected road appearance in a standard situation. In Shihavuddin et al. [2008] and Kim et al. [2007] the shape of lane is considered as a trapezoid. The vehicle then moves through the trapezium and reaches the next approximated trapezium having a tilt angle with the previous one.

The straight-line model is the most commonly used geometric model in validating the observation data as seen in Table II. Several constraints such as parallelism [Lu et al. 2002; Wang et al. 2002; López et al. 2005a; Adachi et al. 2007] or predefined road or lane width [Wang et al. 2002] are applied additionally. Huang et al. [2007] used a piecewise-linear model in their algorithms.

A conventional model for a lane is a circular arc (in Figure 10(a)) on a ground plane. Various algorithms are based on a model of road structure in the world which assumes that the markings and pavement boundaries defining the road and its lane structure

Table II. Geometric Models and Related Works

Straight Line	Lu et al. 2002; Wang et al. 2002; Ishikawa et al. 2003; Huang et al. 2004; Mori et al. 2004; Collado et al. 2005; López et al. 2005a; Adachi et al. 2007; Huang et al. 2007; Nasirudin and Arshad 2007; You et al. 2008; Borkar et al. 2009; Xinyu and Zhongke 2009
Circular Arc	Kluge 1994; Kluge and Lakshmanan 1995; Yu and Jain 1997; Kreucher et al. 1998; Kreucher and Lakshmanan 1999; Ma et al. 2001; He et al. 2004; Li et al. 2004; Samadzadegan et al. 2006
Spline (Various)	Wang et al. 1998, 2004; Kim 2006; Asif et al. 2007; Kim 2008; Truong and Lee 2008; Truong et al. 2008; Wen et al. 2008
Space Ribbon	Dementhon and Davis 1990
Polynomial (second degree, cubic or quadratic)	Chapuis et al. 2000; Gonzalez and Ozguner 2000; Park et al. 2000; Tarel and Guichard 2000; Aufrère et al. 2001; Hong et al. 2002; Jung and Kelber 2004, 2005; Labayrade et al. 2005; Boumediene et al. 2007; Lu et al. 2007, 2008; Benmansour et al. 2008; Yu et al. 2008a
Hyperbola Pair	Labayrade et al. 2004; Chen and Wang 2006; Wang and Chen 2006; Zhu et al. 2006; Ba et al. 2007; Assidiq et al. 2008; Wang et al. 2008a; Zhu et al. 2008
Snake (Active Contour)	Kang et al. 1996; Wijesoma et al. 2001; Tian et al. 2006b
Clothoid	Risack et al. 1998; Nedevschi et al. 2004; Danescu et al. 2006; Nedevschi et al. 2006; Tian et al. 2006a; Danescu et al. 2007
Transitional Models	Lombardi et al. 2005; Sehestedt et al. 2007a, 2007b; Prochazka 2008; Tsai et al. 2008

can be approximated by circular arcs on a flat ground plane over the length of the road visible in a single image. Related work can be found in Table II.

A spline (in Figure 10(b)) is a smooth piecewise polynomial function, which is widely used to represent a curve. Various spline representations have been proposed and used in lane-detection. Kim proposed to group the detected lane-markings pixels into cubic spline curves of five control points in Kim [2006] and to group into uniform cubic spline curves of two to four control points in Kim [2008]. Wang et al. [1998] used a Catmull-Rom spline, also called Overhauster spline, which is a local interpolating spline developed for computer graphics purposes. Wen et al. [2008] proposed the third-degree Bezier spline using Bernstein polynomials to fit the left and right edge of the road surface, which are supposed as the true road boundaries. Wang et al. [2004] argued that a more economical realization of snake can be reached by using far fewer state variables by cubic B-splines. The B-splines are piecewise polynomial functions that provide local approximations to contours using a small number of parameters (control points). They used B-splines in their algorithm [Wang et al. 2004]. Asif et al. [2007] used a second-order B-spline curve with three control points to define a road model and Truong and Lee [2008] and Truong et al. [2008] used a nonuniform B-spline (NUBS) interpolation to construct left and right lanes of the road.

DeMenthon and Davis [1990] modeled the road as a space ribbon generated by a centerline spine and horizontal cross-segments of constant length cutting the spine at their midpoints at a normal to the spine with the constant road width assumption.

Some researchers used polynomials of second degree [Hong et al. 2002; Aufrère et al. 2001; Chapuis et al. 2000; Labayrade et al. 2005], cubic or quadratic [Lu et al. 2007, 2008] or variable degree [Tarel and Guichard 2000] directly in modeling the road geometry assuming the road flat. For nonflat roads Benmansour et al. [2008] proposed using two cubic polynomials, first representing the horizontal profile and second vertical profile. In order to include nonflat and curved roads Gonzalez and Ozguner [2000] used a second-degree polynomial. Jung and Kelber [2005] divided the

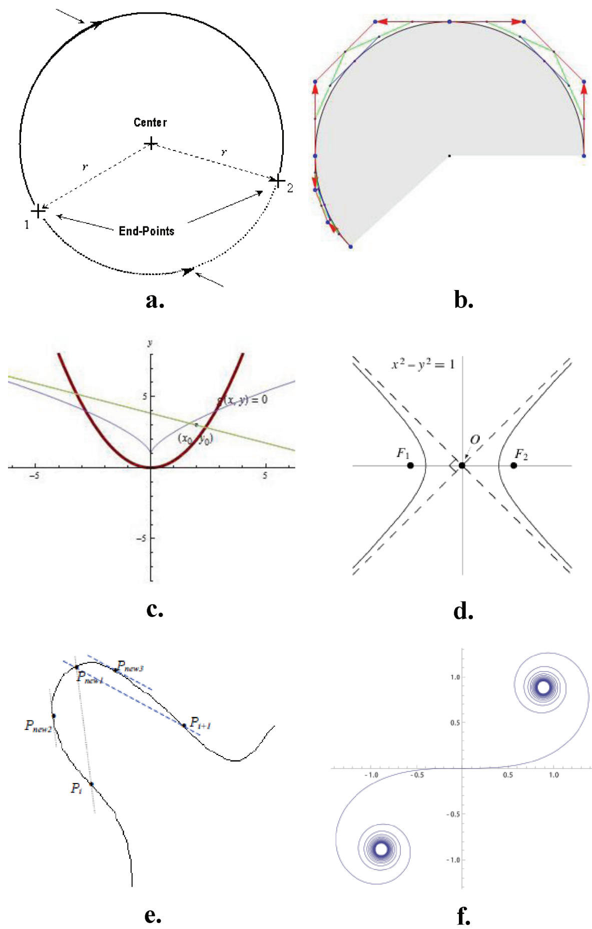

Fig. 10. Road geometry models: (a) Circular arc; (b) B-spline; (c) parabola; (d) hyperbola; (e) B-snake; (f) clothoide.

scene into two as near field and far field. In modeling the near field they proposed to use linear functions and in modeling far field they used parabolic functions (in Figure 10(c)). Similarly in Jung and Kelber [2004], the near field is composed by a linear function, and far field is composed by a parabolic function. In Boumediene et al. [2007], Yu et al. [2008a], and Park et al. [2000] a parabolic lane model is selected to represent the road boundary.

Hyperbola pair (in Figure 10(d)) is another geometric model widely used in lane detection and tracking (Table II).

Snakes or active contours (in Figure 10(e)), are curves defined within an image domain which can move under the influence of internal forces from the curve itself and external forces from the image data. Once internal and external forces have been defined, the snake can detect the desired object boundaries (or other object features) within an image. Several researchers used snakes in their algorithms as depicted in Table II.

Several researchers assumed the shape of the lane is as clothoide (in Figure 10(f)), which is approximated by a third-order polynomial in the world coordinate system (z-axis to the front, y-axis to the right, and x-axis upwards) which could be described by a state vector at discrete time. Without the flat road assumption, in Risack et al. [1998], Nedevschi et al. [2004, 2006], Danescu et al. [2006], and Tian et al. [2006a] the road is modeled as 3D surface defined by the horizontal and vertical clothoid curves determined by some important parameters. In Danescu et al. [2007], the authors proposed an algorithm which is segmented by distance intervals. For near-range detection a straight lane model and for far-range detection a clothoid lane model is applied. In addition free-form lane border detection is carried on based on a Catmull-Rom spline.

Some authors preferred transitional models rather than geometrical models for describing road state. In Lombardi et al. [2005] the class of road appearance is defined probabilistically by a road state vector. The *road state* is updated at every frame by probabilistic time dynamics in the form of a transition matrix. The transition matrix E is applied to the previous road state vector to obtain an estimation of the current road state. The described probabilistic Markov chain summarizes a prediction of road state, to which a measurement step must be added. In the process model proposed by Sehestedt et al. [2007a, 2007b], the authors define how the particles move in the image. For every incoming observation, the filter starts from the bottom of the image. In every timestep the particles are then moved to the next line of the image according to a defined Markov model, which incorporates general knowledge about road design. To extract the real road lane, Tsai et al. model the direction of the lane line in each local lane segment as Markov random process [Tsai et al. 2008]. Prochazka [2008] defined an importance function and a transition model to build up a prediction step.

Using complex shapes will increase the computational complexity in matching the shape to the detected items; on the other hand, with simple shapes accuracy will be degraded. Then, what will be the decision? The decision should rely on the methodology used to detect the lane. Selection of the ROI or selection of the range has great importance. If the method evaluates the whole scene, than a spline, snake, or a clothoide should be selected. Else if we have ROIs, then we can use a straight line, or perhaps an arc.

Fitting the candidates to a geometric model. Least Squares Method (LSM) may be interpreted as a method of fitting data. The best fit, between model and observed data, in its least squares sense, is an instance of the model for which the sum of squared residuals has its least value, where a residual is the difference between an observed value and the value provided by the model. Least squares method is applied to a linear parabolic model [Yu et al. 2008a], a pair of hyperbolas [Zhu et al. 2006; Assidiq et al. 2008], Bezier spline [Wen et al. 2008], and quadratic and cubic curves [Lu et al. 2007, 2008]. However, the crucial fact that the LS estimator is very sensitive to outlying observations may lead to unreliable results in the regression estimates and, hence, to a misleading interpretation of the data. Gonzalez and Ozguner performed least square fit and calculate the Mean Squared Error (MSE) in the model fitting [Gonzalez and Ozguner 2000].

Least Median Squares (LMS) is a robust fitting approach which attempts to minimize the median squared residual of the regression (equivalent to minimizing the median absolute residual). The algorithm in the lane detection domain works by exactly fitting lines to random subsets of observations. In Kluge [1994] and Jiang et al. [2009] LMS is used to estimate the parameters of the circular arcs on the flat ground plane.

RANSAC is an abbreviation for “RANdom SAmple Consensus”. It is an iterative method to estimate parameters of a mathematical model from a set of observed data which contains outliers. It is a nondeterministic algorithm in the sense that it produces a reasonable result only with a certain probability, with this probability increasing as more iterations are allowed. A basic assumption is that the data consists of “inliers”, that is, data whose distribution can be explained by some set of model parameters, and “outliers” which are data that do not fit the model. In addition to this, the data can be subject to noise. The outliers can come, for example, from extreme values of the noise or from erroneous measurements or incorrect hypotheses about the interpretation of data. RANSAC also assumes that, given a (usually small) set of inliers, there exists a procedure which can estimate the parameters of a model that optimally explains or fits this data. The LSM result will be of a great derivation from the ideal one when some outliers exist. RANSAC is capable in that case. Chen and Wang used a RANSAC paradigm in fitting the two straight lines for the first pair of lane markings in Chen and Wang [2006] and for estimating the parameters of the hyperbola-pair lane model in Wang and Chen [2006]. Kim applied the RANSAC algorithm to a cubic spline curve fitting in Kim [2006, 2008]. Lipski et al. [2008] performed a RANSAC algorithm to estimate the parameters of a global model with which straight streets, sharp curves, and a mixture of both can all be described.

A particle filtering theory for the filtering of nonGaussian nonlinear state space models will be used to calculate the likelihood between two images [Maček et al. 2004; Shu and Tan 2004; Danescu and Nedevschi 2008].

Lu et al. [2002] used a Kalman filter to find the four parameters of their linearly parameterized model. Behringer [1995] successfully applied the Kalman filter scheme to the estimation of horizontal road curvature. In Risack et al. [1998], world parameters of clothoide-shaped lane borders with horizontal and vertical curvature are estimated with a Kalman filter.

Park et al. [2000] used a Metropolis algorithm in fitting the model. Kluge and Lakshmanan [1995] used a Metropolis algorithm for optimizing the likelihood function which determines how well a hypothesized lane is matched with a road image. Samadzadegan et al. [2006] used a genetic algorithm to find the global maximum of the likelihood function.

In decision theory and estimation theory, a Bayes estimator is an estimator or decision rule that maximizes the posterior expected value of a utility function or minimizes the posterior expected value of a loss function. In Lombardi et al. [2005] model-based validation of candidate regions is based on Markov chains for temporal filtering and Bayesian classification. In Kreucher and Lakshmanan [1999], the authors reduced the lane detection problem to finding the global maximum of a four-dimensional posterior probability density function; exhaustive search is employed to find the global maximum. Bayesian estimation is used for circular shape models in Ma et al. [2000] and for clothoid or parabola model in Ma et al. [2005]. In Bayesian statistics, a Maximum a Posteriori (MAP) estimate is a mode of the posterior distribution. The MAP can be used to obtain a point estimate of an unobserved quantity on the basis of empirical data. It is closely related to Fisher's method of Maximum Likelihood (ML), but employs an augmented optimization objective which incorporates a prior distribution over the quantity one wants to estimate. MAP estimation can therefore be seen as a regularization of ML estimation. In Kreucher et al. [1998] and Ma et al. [2001] the prior (model) and likelihood models are combined in a Bayesian framework, resulting in the lane detection problem being posed as finding the MAP estimate of the lane shape parameters. Zhou et al. [2006] proposed a lane detection approach which makes use of a deformable template model to the expected lane boundaries in the image, a maximum a posteriori formulation of the lane detection problem, and a Tabu search algorithm to maximize the posterior density. The most common risk function used for Bayesian estimation is the Mean Square Error (MSE), also called squared error risk. Using the MSE as risk, the Bayes estimate of the unknown parameter is simply the mean of the posterior distribution. This is known as the Minimum Mean Square Error (MMSE) estimator. The Bayes risk, in this case, is the posterior variance. In the method of Wang et al. [2004], the B-snake would deform to lane boundaries more precisely by using the MMSE approach.

A Dynamic Programming (DP) algorithm is another technique used to reject the candidates which do not fit the geometric model applied. Several researchers used this technique in their works [Kang et al. 1996; Ko et al. 2006; Lin et al. 2007a, 2007b].

Some authors used the Hough transform in extracting model parameters. In Wijesoma et al. [2001], Nasirudin and Arshad [2007], You et al. [2008], Borkar et al. [2009], and Xinyu and Zhongke [2009], the Hough transform is used for extracting model parameters where the model is straight line. Zhu et al. [2008] used ARHT and a Tabu search algorithm to calculate the parameters of the model. Mori et al. [2004] used segmented Hough transform.

In statistics, M-estimators are a broad class of estimators which are obtained as the solution to the problem of minimizing certain functions of the data which exhibit certain robust properties. Many classical statistics can be shown to be M-estimators. In Labayrade et al. [2004] the road model is described by a hyperbolic polynomial basis and the road shape estimation is based on the M-estimators theory. In Wang et al. [2008a], the authors used M-estimators to fit a line to the vanishing points. In Truong and Lee [2008] and Truong et al. [2008], the authors proposed a new formulation that is called a vector-lane concept to extract control points for Non-Uniform B-Spline (NUBS) interpolation processing. To estimate stable road parameters and provide continual localization, Maeda et al. [2008] applied AMF (Approximated Median Filter) and PDF (Probability Density Function).

4.2.4. Tracking. Lane detection and lane tracking should be distinguished. Most of the researchers see lane detection as the initialization process and go on with the tracking process until initialization is required. Initially most of the algorithms will search the whole image area to extract the features. A lane tracking process refers to making use of previous information in detecting the new features on the incoming image area.

To this end the most direct approach would be use of the optical flow that reflects the magnitude and direction of the motion of the image regions. Based on that, the current position of a street segment detected in the past can be determined and used for a fusion with the current road detection results. However, the optical flow has certain drawbacks. For example, the optical flow cannot be calculated at the borders of an image and is error prone due to ambiguities resulting from the aperture problem, illumination change, and camera noise [Michalke et al. 2008]. And as a remark, it is difficult to get a reliable optical flow on a homogeneous road surface.

In Lieb et al. [2005], an application of optical flow techniques, paired with one-dimensional template matching, allows identification of regions in the current camera image that closely resemble the learned appearance of the road in the recent past. For each pair of consecutive images, a set of unique features are found in the first image and traced to their locations in the subsequent image, with the displacement vectors constituting the optical flow field. In their implementation, features are first identified using the Shi Tomasi algorithm, which selects unambiguous feature locations by finding regions in the image containing a significant spatial image gradient in two orthogonal directions. Feature tracking is then achieved using a pyramidal implementation of the Lucas-Kanade tracker.

Furthermore, some researchers proposed to limit the search area on the new image with the information obtained by the previous operations, while some researchers who use model-based extraction proposed updating model parameters continuously by well-known techniques.

Limiting the search area. Some authors argued that with the road constraints, the road edge location on the frame is similar to that on the next frame, so they can use the road information in the current frame to quickly locate the road edge in the next frame [Kang et al. 1996; Takahashi and Ninomiya 1996; Aufrère et al. 2001; Wang et al. 2002;

Foedisch and Takeuchi 2004; Huang et al. 2004; Nedevschi et al. 2004; Labayrade et al. 2005; Lu et al. 2007, 2008; Lin et al. 2007c; Wu and Lin 2007; Liu et al. 2008a].

In Aufrère et al. [2001] and Wang et al. [2002] they defined the road identification probability which decides the dimensions of ROI. If the road edge identification probability is high, the region of interest will be cut too small, while it should become bigger if the road identification probability is decreased. In Jung and Kelber [2004], the authors update the detection for the following frames after the initial segmentation in the first frame. To determine these parameters, they apply a minimum weighted square error approach, fitting the proposed model to the detected edges within the LBROI. This initial detection is used to find the Lane Boundary Region of Interest (LBROI), which will be the search space for lane boundaries in the subsequent frame of the video sequence.

Updating Model Parameters. In Wang et al. [2004], the authors regard the estimated parameters of the lane model in the previous frame as the initial parameters for the current frame. In Lu et al. [2002], Asif et al. [2007], Danescu et al. [2007], McCall and Trivedi [2006], Benmansour et al. [2008], You et al. [2008], and Zheng et al. [2008] a Kalman filter is used to track road model from frame to frame to provide more precise and more robust detection results. Although a Kalman filter can give real-time performance and reduces computation greatly, it has its own defects. The Kalman filter provides a recursive solution of the least square method, and it is not a robust estimator. It is incapable of detecting and rejecting outliers which may cause collapse of tracking. Besides, Kalman filter does not record the data ever measured but only combines states at time k-1, which means the final detection result is insensitive to the order of measurement. Sometimes such properties will worsen the accuracy of the detection result. To alleviate these problems, Lu et al. [2002] define a measurement describing the reliability of current Kalman tracking. In Tian et al. [2006a] the authors used an extended Kalman filter for road tracking. In Zhu et al. [2008] and Kim [2006, 2008] using strong temporal coherence of the lane boundaries in the consecutive frames, a tracking algorithm based on a particle filter is represented. Danescu and Nedevschi presented a solution for lane estimation in difficult scenarios based on the particle filtering framework [Danescu and Nedevschi 2009]. In their paper particle filtering for probability-based tracking allows multiple-hypothesis tracking, simple measurement, and faster handling of road discontinuities. In Sehestedt et al. [2007a] the authors proposed a motion model to carry information on to the next obtained image. This model will move particles to the following image. Furthermore, they also use the uncertainty measure from the previous timestep. In Apostoloff and Zelinsky [2003], the authors proposed to combine various cues through a cue fusion process which produces a robust solution to lane tracking. In Prochazka [2008] and Wang et al. [2008a] a condensation filter is used.

Proprioceptive and Exteroceptive Sensors. The autonomy of the system can be enhanced by merging data from proprioceptive (inertial measurement unit, gyrometer, odometer, etc.) and exteroceptive sensors (laser range finder, GPS sensor, etc.) into the tracking process, Then, localizing the vehicle consists in estimating its state by merging data from these sensors. In Labayrade et al. [2005, 2006], the authors used odometer data and steer angle data to predict the behavior of the vehicle attitude on the road between two successive images. They proposed a formulation to estimate the 3D localization of the next image due to the current image. In Kolski et al. [2006], the authors proposed an estimation method which uses wheel encoders and an inertial measurement unit through the CAN (Controller Area Network) bus of the vehicle as proprioceptive sensors and a laser range finder as an exteroceptive sensor. A wheel encoder is used to obtain the vehicle speed and steering angle, and IMU (Inertial Measurement Unit) provides all three dimensions of accelerations. A laser range finder is used to detect the obstacles. Tsogas et al. [2007] used GPS with digital maps to determine the position of the vehicle with respect to the road and extrapolate the lane-marker locations.

4.2.5. Multilane Detection. Most works identify only one lane; nevertheless, these models which were initially designed for single-lane detection can be extended to perform multilane detection. Usually, some additional assumptions are needed, such as the same lane width constraint for different lanes.

Luetzeler and Dickmanns [1998] defined a straight skeleton line centered on the road which describes the near-range model. On multilane roads lanes are described by an offset from the skeleton line and an individual predefined lane width. Similarly, Apostoloff and Zelinsky [2003] used the road width cue for multilane roads, where the cue returns a value from a Gaussian function centered at a desired road width, given the hypothesized road width. Huang et al. [2007] modeled the lane boundary configuration to expand the current lane to the extra left- and right-side boundaries. In Sun et al. [2006], identification of multiple lanes is done by first detecting the own lane and estimating its geometry under perspective distortion. Then adjacent lanes estimation takes place by forming hypotheses of adjacent lanes assuming the same width and curvature for all lanes. A confidence criterion is applied to verify the hypothesized lanes. Adachi et al. [2007] proposed a multiple-lane model which is constructed by straight lines, rather than handling only the running lane or detecting each lane boundary individually. For tracking a multiple-model particle filter, Vacek et al. [2007] proposed a rule-based system which handles the tracking of multiple lanes by deleting invalid lanes and creating new lanes if necessary. The lane model used for estimating each lane describes the lane in front of the car and assumes that it is straight and flat.

The main problem about the multilane approaches is that no validation process is done, which ensures that detected lanes are correct with some degree of confidence, and therefore, there is a lack of robustness, particularly in the presence of nonhomogeneous road color, shadows, vehicles, etc. [Nieto et al. 2008].

5. HARDWARE PLATFORM

Most of the works in this area use a standard PC platform as hardware platform and Matlab as the software development platform. However, the great variety of road environments necessitates the use of complex vision algorithms that not only require expensive hardware to implement but also rely on many adjustable parameters that are typically determined from experience. Due to this necessity various researchers developed ad hoc hardware platforms to carry on their algorithms. In Aufrère et al. [2001], a sequential code is implemented on an architecture dedicated to vision applications. Hsiao et al. [2005] designed a SoC integrated with a mixed signal mode CMOS image sensor to carry on the algorithm. Boumediene et al. used a DSP processor to perform their algorithm in Boumediene et al. [2007]. Haga et al. [1995] developed a hardware called a “spoke filter board” for high-speed detection of pairs of parallel line edges. On the other hand, several researchers preferred to use more powerful computer systems in implementing their software. UNSCARF [Crisman and Thorpe 1991], SCARF [Crisman and Thorpe 1993], and the algorithm proposed by Yu and Jain [1997] use a supercomputer for implementing the algorithm.

Vision applications generally require considering many pieces of information simultaneously. Computers, which are basically sequential machines, are not adequate for such tasks [Fang et al. 2003]. However, human brains with their extreme degree of parallelism seem to deal with these tasks effortlessly. The effectiveness of parallelism depends on knowledge representation schemes involved in information processing.

Table III. Performance of the Methodologies due to Challenges of Section 2

<table>
<tr><th>Challenge</th><th>Methodology</th></tr>
<tr><td>Well structured roads with no environmental variation (Figure 2.a)</td><td>Approximately all methodologies give similar results on well structured roads from the point of detection. In case of well structured roads, the choice should concern the computational complexity due to timing considerations. So an edge detection methodology such as Sobel or Canny combined with a suitable fitting geometry (due to the complexity of road shape from a predefined geometry to a complex shape) will satisfy the requirements. Most of the edge detection algorithms can deal with real time considerations but Sobel-Hough transform with circular arc using LMS gave the optimal results.</td></tr>
<tr><td>Unclear lane markings (Figure 2.b)</td><td>In case of unclear road markings, since they heavily rely on lane detection, edge detection methodologies are not suitable standalone. Area detection and ridgeness detection techniques provided satisfactory results in our experiments. Ridgeness detection failed in case of unclear road shoulders. We tested area based methods with/without color information. Without ROI, all of the techniques have serious problems in detection of the road area and especially meeting the real time considerations. LVQ suffers from long learning time and even can not learn, Region growing technique had better results unless the road degradation occurs, also well at timing. UNSCARF and SCARF provided good results in case of detecting road area, but just like the region growing technique, worked best at trivial road surface variations. SVM is a great tool for many applications but have shortcomings dealing with dynamic nature of the road following. RSURD, relying on HSV color map, uses the color as the main cue and followed by a decision system. The technique gave good results with a time-consuming profile. Local averaging classifier is not suitable due to its complexity and time-consuming structure. Particle filtering and boosting with Random forest algorithm combined with SVM gaves the best results in case of road area detection. Both suffer from high complexity and time-consumption.</td></tr>
<tr><td>Occlusion of lane markings (Figure 2.c)</td><td rowspan="6">When road indicators somehow disrupted by an object or a shadow or another disturbance source, edge-based detection failed to detect the road markers, and even worse, they produce false road models, with the tracking algorithm used, the wrong detection can easily be maintained in consecutive frames. On the other hand, while the disturbances are temporary it is not reasonable to give up using edge-based methodology due to their simplicity, high speed and also their accuracy. So without giving up using edge-based methodology, an area-based method can be employed to support the detection of edge-based techniques. Also this is true for supporting area-based techniques with edge-detection methodology. Except the unstructured or highly disrupted road scenario, combination of an edge detection technique with an area based technique give satisfactory results. We tried Sobel-Hough-Region Growing, Canny-Hough-UNSCARF combinations, as expected we had satisfactory results both in the manner of detection and real time considerations. But another important issue at this point is the fitting methodology used to fit the geometry used with the information obtained from the detection phase. For choosing the geometry, using predefined geometries will limit the detection techniques. Zelinsky's [2003] near field and far field concepts are substantially valueable concepts. For near field, indeed, even a straight line is acceptable, maybe a circular arc could be used. But for far fields a more complex shape like Bezier Spline, or clothoide or a snake is required. In our expreriments, we noticed that rather than geometry selection, fitting methodology selection is more significant, for accurately modeling the geometry. Under an accurate detection and simpler geometry scenario, an LMS like algorithm will perfectly fit our needs both in accuracy and timing considerations. But with the varying accuracy and more comlex shapes, according to our observations, RANSAC and Dynamic Programming outshined with regard to other methodologies.</td></tr>
<tr><td>Occlusion of the road area (Figure 2.c)</td></tr>
<tr><td>Various lighting conditions (Figure 2.d-f)</td></tr>
<tr><td>Presence of extraneous objects probably interfere with road objects (Figure 2.l)</td></tr>
<tr><td>Presence of parked vehicles (Figure 2.l)</td></tr>
<tr><td>Presence of shadows (Figure 2.l)</td></tr>
</table>

Table III. Continued

Challenge	Methodology
Unstructured roads (Figure 2.i)	In case of fully unstructured roads, no lane marking, no road shoulder and even the absence of the asphalt and probably with extraneous objects on the driving space, texture-based methodology seems and experienced to be the best methodology. But the texture based methodologies heavily rely on predefined textures and have some problems in learning (not all of them learns) the new road textures. Also another major problem, due to their high complexity they are not resistant to quick changes on the road environment. Nevertheless, the best technique in fully unstructured roads is still texture-based according to our experiments.
Highly disrupted roads	Stereovision is a great tool in road detection for all scenarios, but due to extra hardware requirements, high computational complexity and the time-consumption as the consequence of the high computational complexity, it's not a frequently used tool in road detection. In highly disrupted roads, stereovision can suggest most accurate results.
Various road geometries, round abouts and intersections (Figure 2.j-k)	We prefer to detect the road model variations in the far field region, not in the near field. Otherwise, in the fitting phase, we faced modeling problems for 5–10 consecutive frames while passing the variation.
As one can see none of these scenarios are isolated and can be seen individually. In a typical road scenario we can face all of the challenges at the same time, or a in a few seconds. Some methods have superiority over the others, and some are faster than the others. According to our observations, there is no single methodology (or a paper more generally) that can address all of the scenarios that can be encountered in a road environment. So it is reasonable to be able to use the methodologies or cue processing in parallel. Labayrade [2004, 2005] proposed to use two and three different algorithms in parallel, respectively. Apostoloff [2003] proposed to process multiple cues. These studies will probably lead the similar works in this area. In our opinion, a well structured algorithm should use all of the techniques in parallel. This parallelism will induce the different methodologies to support each other and increase the overall confidence. But moreover, the major need for such a system will be a semantic preprocessor which will give idea about the general road condition to the system and let a methodology to lead the others. The others will support the leader technique and probably increase its confidence. For various road scenarios and challenges, the leader technique should be changed. This will be valid for detection, geometry selection, fitting and even tracking.	

Some researchers implemented their algorithms on parallel architectures. For example, Suchitra et al. implement parallelism in a Hough transform [Suchitra et al. 2009]. In another study, Broggi performed removal of the perspective effect on a massively parallel architecture, namely PAPRICA [Broggi 1995a, 1995b, 1995c; Bertozzi and Broggi 1998].

Another platform for implementing lane detection is a mobile platform. There are several studies which implement lane detection algorithms in mobile devices such as iPhone, smart phones, or PDA. In Ren et al. [2009], the authors implemented their algorithm on an iPhone. In Chao-Jung et al. [2009], the authors used a Windows mobile OS-based smart phone to run their algorithm.

6. CONCLUSION

At first glance the problem of detecting the lane geometry from visual information seems simple, and early work in this field was quickly rewarded with promising results. However, the large variety of scenarios and the high rates of success demanded by the industry have kept lane detection research alive. To be accepted by drivers, such a system must have a high degree of robustness and reliability. It should be able to know its operating state, in order to automatically switch off when nothing is seen or when the confidence of the detection is too low. This point is very important in any assistance system. Moreover, the system must be able to deal with various road profiles (straight lines, longitudinal or lateral curvatures), different lines configurations (continuous,

Table IV. Works in the Literature

Work	Preprocess	Feature Extraction	Edge Detection	Fitting Geometry	Comments
Cheng et al. [2006]	Predefined Threshold, (IPM)	Multivariate Gaussian	Erosion and dilation	Predefined circular parallel arcs	Tests are carried out on roads with well-painted markers.
Hu et al. [2004]	Bottom of %60 of the whole image as ROI	Histogram based segmentation.	Canny edge detection	Two parallel lines.	Not robust in occluded roads.
Wang et al. [2002]	Median Filter, ROI extraction	Gray Intensity Values	Sobel operator then binarization	Straight line model with predefined width constraint	Not robust in unstructured roads.
Foedisch and Takeuchi [2004b]	NN training for road/non-road labels, IPM	Independent color histograms from RGB Images.	No edge detection	No Model	Not robust in occlusions.
Rasmussen [2002]	No preprocess	Height, Smoothness, Color histogram and texture Gabor filters.	No edge detection	No Model	Not robust to quickly changing conditions.
Rasmussen [2004]	No preprocess	multi-scale Gabor wavelet filters	No edge detection	Tracking of vanishing point.	Not robust to quickly changing conditions.
Zhang and Nagel [1994]	No preprocess	Texture anisotropy	No edge detection	No Model	Not robust to quickly changing conditions
Crisman and Thorpe [1991]	Image size reduction.	ISODATA	The edges between groups of pixels are extracted.	Predefined curves	Best for images with clusters that are spherical and that have the same variance
Lombardi et al. [2005]	No preprocess	Textureless detection algorithm.	SUSAN 3×3 edge detection operator is used.	Predefined candidate models	Limited to predefined models
Rotaru et al. [2004]	RGB to HIS conversion	HSI component	Prewitt operator	No Model	Not robust in occlusions
Labayrade et al. [2004]	No preprocess	Intensity threshold.	No Edge Detection	Dynamic Transition Model	Not robust in several lighting and shadow conditions also in occlusions
Dahlkamp et al. [2006]	No preprocess	mixture of Gaussians MOG – training area using k-means	Mahalonobis distance	No Model	Focused on rural roads. Show some robustness
Kim [2006]	No preprocess	ANN, Naïve Bayesian Network and SVM	No edge detection	cubic spline curves. RANSAC for curve fitting	Focused on structured roads

Table IV. Continued

Work	Preprocess	Feature Extraction	Edge Detection	Fitting Geometry	Comments
Hong et al. [2002]	No preprocess	Color information	3×3 Sobel operator is used	World model	Focused on well-painted
Jeong et al. [2003]	Subsampling	Predefined intensity vectors	No edge detection	No Model	Not robust to quickly changing conditions
Chapuis et al. [2000]	No preprocess	No Feature Extraction	The point of maximum gradient.	Probabilistic Model	Not robust to shadows and occlusions
Lai and Yung [2000]	Feature preserving filtering	No Feature Extraction	Sobel edge detector	Locally flat, defined by parallel road markings or curbs and roundabouts.	Limited by predefined models
Assidiq et al. [2008]	GrayScaling F.H.D. algorithm.	No Feature Extraction	Canny - Hough	A pair of hyperbolas – deformable template. Least squares technique in fitting	Not robust to shadows and occlusions
Yim and Oh [2003]	Windowing and resampling. Sobel enhancement, IPM	No Feature Extraction	Hough transform	Previous lane data as model	Lane model increases the error.
Cheng et al. [2008]		Multi-variable Gaussian	No Edge Detection	Predefined lane boundaries	Limited by predefined models
Labayrade et al. [2005]	No preprocess	Lateral consistent detection, Longitudinal consistent detection,	Gradient thresholding	No Model	Tested for well-painted roads.
Huang et al. [2004]	Gaussian Filter	Peak-finding algorithm	No Edge Detection	Symmetry property	Not robust to shadows, occlusions and degraded roads
Chiu and Lin [2005]	No preprocess	Color segmentation	Hough Transform	Parabolic	Do not robust to extraneous objects
Gonzalez and Ozguner [2000]	No preprocess	Histogram based segmentation	No Edge Detection	A second order model with least squares fitting.	Not robust occlusions
Wen et al. [2008]	ROI extraction	Region growing method.	Probabilistic Hough and first-order Sobel operator.	No Model	Not robust to occlusions
Apostoloff and Zelinsky [2003]	Median filtering	Lane tracking cues.	Particle filter	No Model	May fail under cue contradiction. Show strong robustness.

(Continued)

Table IV. Continued

Work	Preprocess	Feature Extraction	Edge Detection	Fitting Geometry	Comments
Bellino et al. [2004]	Predefined ROIs	Gradient of the edges	No Edge Detection	Line color, line width, lane width are constraints.	Rely on strong edges
Sun et al. [2006]	RGB – HIS Conversion, predefined ROIs	FCM (Fuzzy C-Means) for lane marking color	Thresholding, adaptive saturation and stage 3 filtering	No Model	Rely on well-painted lane markings
He and Chu [2007]	No preprocess	No Feature Extraction	Canny	Straight lines	Heavily rely on lane markings' quality
López et al. [2005b]	No preprocess	Ridgeness and IPM	Hough Transform	No Model	Not robust to occlusions, rely on strong edges or shoulders
Nieto et al. [2008]	No preprocess	Lane Color and IPM	Hough transform	No Model	Rely on strong edges and distinct color info
Maček et al. [2004]	No preprocess	Color difference	Canny – Hough and LoG edge detection	No model	Not robust to occlusions, shadows.
Danescu et al. [2007]	Grayscaling	No Feature Extraction	DLD and Hough transform	3D lane model with Kalman filtering	Show some robustness with high computational time
Zhu et al. [2008]	No preprocess	No Feature Extraction	RHT (Random Hough transform) and ARHT (Adaptive Random Hough transform)	Circular arcs with TABU search algorithm based on MAP estimate for fitting	Heavily rely on strong edges.
Nedevschi et al. [2004]	No preprocess	No Feature Extraction	Vertical profile through stereovision	Clothoid	Not robust to shadows, occlusions and degraded roads
Ishikawa et al. [2003]	Omni-image to ground image conversion. 2D high pass filter.	No Feature Extraction	Edge Detection, binarization and Hough transform	Two parallel straight lines.	No tests for occlusions and extraneous objects
Hsiao et al. [2005]	Gaussian filter	Peak finding algorithm	Line segment filter	Predefined lane boundaries	Good example as a dedicated hardware.
Wang et al. [2005]	No preprocess	Peak-finding algorithm	Canny - Hough	Parallel lines	Show robustness on night conditions with different illumination. Rely on strong edges.

Table IV. Continued

Work	Preprocess	Feature Extraction	Edge Detection	Fitting Geometry	Comments
Nedevschi et al. [2006]	No preprocess	No Feature Extraction	2^{nd} numerical approximation of the Canny optimal operator.	Clothoid model.	Not robust to shadows, occlusions and degraded roads
Son et al. [2008]	No preprocess	SWA algorithm	No Edge Detection	No Model	Robust to lighting
Prochazka [2008]	No preprocess	Constructing PDF from consecutive frames	No Edge Detection	Previous image	Not robust to shadows, occlusions and degraded roads
Soquet et al. [2007]	No preprocess		Hough transform on V-disparity image from stereovision images	No Model	Not robust in most situations, high computational load
Wu et al. [2007]	No preprocess	Finite State Machine (FSM)		B-spline	Not robust to illumination, shadows and degradation.
Guo et al. [2006]	Steerable filter		Hough transform		Good at occlusion, Limited to strong edges
Tsai et al. [2008]	No preprocess	Morphology based method	No Edge Detection	No Model	Show some robustness to degradation and illumination conditions.
Lu et al. [2008]	No preprocess	Region connectivity analysis	Sobel	Cubic and quadratic road model	Focused on structured roads with strong cues.
Foda and Dawoud [2001]	No preprocess	LVQ (Learning Vector Quantization). And BPN (Back-propagation network)	No Edge Detection	No Model	Designed for structured roads. BPN training is cumbersome.
Ma et al. [2001]	No preprocess	Edge gradient feature for optical images.	ad hoc weighting scheme carried on the two likelihood functions	concentric circular models.	Good at elevated or bordered rural roads.

dashed), and occluded or degraded road markings and under various meteorological conditions (day, night, sunny, rainy).

We set up a test platform both in a computer environment and an FPGA platform and tested the mentioned techniques. Our computer platform is Intel Core i7-3520M CPU with 16GB of RAM, and as FPGS platform we used Xilinx Spartan®-3A DSP 1800A FPGA kit. We implemented the techniques in Matlab®. We performed all of the experiments with same video sequences of various scenarios as summarized in

Table III. According to our observations, there is no single methodology (or a paper more generally) that can address all of the scenarios that can be encountered in a road environment. To handle all of the scenarios the research should go on.

One can also find some details about the relevant work in the literature in Table IV. We tried to investigate the relevant publication on the lane detection subject. We dealt with mostly recently published literature, but we could not skip the milestones of the area. So we gave place to some older publications. We believe that we covered almost all of the work related with this subject and light the way of the researchers who will work on this area. Also a similar but briefer survey on this area could be found in Hillel et al. [2012].

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Received October 2011; revised September 2012; accepted October 2012