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# MACHINE VISION FOR AUTONOMOUS VEHICLES - POTENTIAL AND LIMITATIONS. A LITERATURE REVIEW

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Abstract: This paper is a brief review of the recent literature regarding the applications of machine vision in autonomous vehicles. We emphasize the main achievements as well as some challenges and limitations of these technologies, and also propose a simple taxonomy of the research directions in this field. The main contribution of this work is to provide a quick introduction and a bird's eye view of the extremely vast literature on this topic, and to identify some useful resources for starters.

Keywords: Machine vision, autonomous vehicles, advanced driver assistance systems

## 1. INTRODUCTION

According to recent statistics (STATISA, 2015) there are over 1.3 billion road vehicles in use. They account for 1.25 million deaths every year in road crashes (WHO, 2015). The associated material losses are in the trillions.

Since human errors are responsible for 90% of the total car crashes (Fagnant & Kockelman, 2015), developping intelligent autonomous vehicles (AVs) appears to be a very efficient way to reduce the death toll and the exorbitant insurance costs resulting from traffic accidents.

Additional benefits of driverless cars include: increased independent mobility for the elderly, and for people with various disabilities, reduced traffic congestion, less pollution, and energy conservation.

Considering these promises, a series of major technological players and stakeholders in the automotive industry, like Google, Tesla, Uber, General Motors, Mercedes, Volvo, Toyota invest hundreds of millions Euros in research for the development of (semi)autonomous cars.

The results recorded so far include the famous Google self-driving car project (Waymo, 2017) and a variety of commercialy available "Advanced Driver Assistance Systems" (ADAS) that address specific safety enhancement issues. For example, the Volvo "City Stop" system (Volvo, 2014) is a forward collision prevention system designed for low speed traffic in crowded metropolitan areas, based on low cost LIDAR sensors.

According to Krasniqi & Hajrizi (2016) the market for ADAS was $15.0 billion in 2016, and estimated to increase to $23.6 billion in 2022.

In the same time, the prototypes of the Google/Waymo self-driving cars autonomously travelled over 10,000,000 miles without major incidents since 2009, when the project started.

All this work is also reflected in a vast scientific literature. For example, a search in the Web of Science (WoS) with the keyword "autonomous vehicles" in the "topic" field returns over 14,000 results for the past 10 years. The same search in Google Scholar returns 34,000 results. Even much narrower searches like "autonomous vehicles" AND ("computer vision" OR "machine vision") return over 1000 results in WoS.

Under these circumstances, it is next to impossible (and far beyond the scope of this study) to perform an exhaustive review of the literature on this topic. We only aimed to draw a big picture of this area of research, emphasizing some notable results (and failures), and to identify useful resources for readers interested in this field.

## 2. A WORD ABOUT THE METHODOLOGY

Starting from the works of Bengler et al. (2014), Finn & Scheding (2010), and Schaub (2018) we derived a general sensing and control structure of an autonomous vehicle. It is shown in figure 1. See also (Behere, 2015).

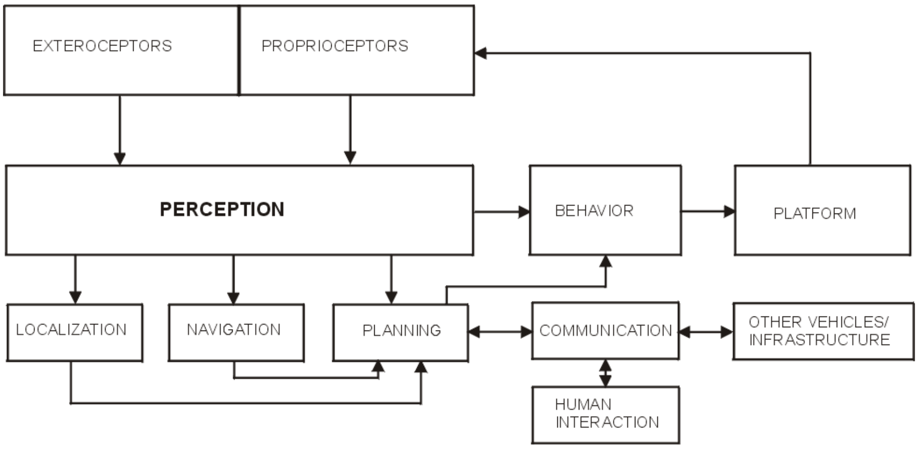


Fig.1. The general sensing and control structure of an autonomous vehicle (AV)

Furthermore, we searched the survey articles dedicated to the subsystems of the AV, with a focus on the "Perception" block, which includes dedicated modules for road detection, lane detection, vehicle detection, pedestrian detection, traffic light and traffic signs detection.

To this purpose, we conducted searches in WoS and Google Scholar for articles containing the keyword "survey" in the title AND "road detection"/"pedestrian detection" etc. in the topic. We filtered out the articles about aerial and underwater vehicles. When multiple choices were available, we selected the articles with a higher number of citations. The short list is presented in Table 1.

Table 1. The short list of articles considered for analysis

| Nr. | Publication | Topic |
|---|---|---|
| [1] | Hilel et al. (2014) | Road and lane detection |
| [2] | Sivaraman & Trivedi, (2013). | Vehicle detection |
| [3] | Bonin-Font et al. (2008) | General issues of visual navigation of autonomous vehicles |
| [4] | Geronimo et al. (2010) | Pedestrian detection |
| [5] | Bernini et al. (2014) | Obstacle detection |
| [6] | Kastrinaki et al (2003) | Video processing techniques for traffic applications |
| [7] | Diaz et al (2015) | Traffic light detection |
| [8] | Fu & Huang, (2010) | Traffic sign recognition |
| [9] | Xue et al. (2018) | Scene understanding |
| [10] | Janai et al. (2017) | State of the art in computer vision for AV |
| [11] | Shi et al. (2017) | Algorithms and hardware implementation for visual perception in autonomous vehicles |
| [12] | Horgan et al. (2015) | Taxonomy of vision based driver assistance systems |

## 3. LITERATURE REVIEW

### *3.1. General Issues of Machine Vision for Autonomous vehicles*

A very comprehensive and up to date survey of the general research topics related to machine vision for autonomous vehicles is available in (Janai et al., 2017). They also offer a valuable interactive web tool that provides quick access to the summaries of the reviewed articles. (http://www.cvlibs.net/projects/autonomous_vision_survey/ Accessed December, 2018).

The following presentation is structured according to an implicit taxonomy that divides the existing literature in two major classes, according to the level of data processing reported. Low level data processing include data acquisition, preprocessing, lane/road detection, vehicle detection and tracking, pedestrian detection, traffic lights and traffic signs detection. High level data processing include "scene understanding" and, in a larger view, prediction of human behavior in traffic.

### *3.2. Low Level Data Processing in Machine Vision for Autonomous Vehicles*

*Data acquisition*

Monocular vision cameras are the most common modality used for data acquisition in machine vision applications. The minimum resolution of the camera can be computed (Hilel, 2014) with (1)

$$(1)\quad Np = C\frac{d}{W}$$

where:

*Np* is the horizontal resolution of the camera (in pixels) , C is the Field of View (in radians), *d* is the distance at which the system is required to recognize lane marks, and *W* is the width of the lane marks.

Obviously, the 2D images provided by monocular cameras lack depth information. Therefore, it is mandatory either to use additional sensors (e.g. LIDAR), or use stereo vision camera and more complex algorithms (see Bernini et al., 2014) to process the visual data in 3D. However, it is worth to note that processing the stereo vision data is considerably more difficult than processing LIDAR data, and the results are less accurate.

*Image pre-processing*

Typical pre-processing operations include camera calibration, shadow reduction, exposure time (dynamic) adjustment. Though these operations are relatively simple when working with static images, they become a challenge when real-time adjustments are required (think of the variations of pixel intensity when passing through a short tunnel or when driving on very narrow streets in historical urban areas).

Excellent sources of information on algorithms for preprocessing visual data are in (Corke, 2017) and (Nixon & Aguado, 2012).

*Lane Detection*

Lane marks can only be detected visually - therefore all lane detection solutions must rely on machine vision. Since the problem of lane detection is central in any AV perception system, it results that such system must contain a mandatory machine vision module.

Since lanes are delimited with relatively uniform marks, the lane detection is typically treated as a feature extraction problem. Complete and up to date information about the research on road and lane detection solutions is available in (Hillel, 2014), (Sivaraman, 2013) and (Zhu et al., 2017).

The problem of road detection is more complicated than lane detection mainly because there are no standard marks for the boundaries of the roads. Therefore, many of the existing solutions (see Zhu et al., 2017) are based on detecting an elevation gap between the road and its surroundings, or by assuming that the road surface has an uniform appearance or color.

*Vehicle Detection*

Vehicle detection usually requires some active sensors (LIDAR or Radar) besides a camera. These active sensors detect "objects" that are subsequently classified as vehicles or non vehicles by processing the visual data from a camera.

Detected vehicles need further *tracking* in order to *predict* their future position and maneuvers.

While the actual detection relies on technologies like HOG (Histogram of Oriented Gradients) features (see Dalal & Triggs, 2005), or Haar-like features (Wijnhoven & de With, 2011), tracking is performed by means of Kalman filters (Alonso et al, 2008) and particle filter (Niknejad, 2012).

A comprehensive survey of the literature on vehicle detection is available in (Sivaraman & Trivedi, 2013).

*Pedestrian Detection*

Vision based pedestrian detection is a demanding task for several reasons (as shown in Geronimo et al., 2010):

- They must be detected in outdoor urban environments, usually on very cluttered backgrounds (see figure 2), and under variable illumination.

- Their appearance can be very variable, due to clothing, height, viewing angle, or the objects they carry. Moreover, they can be partly occluded by parked vehicles, advertising panels, or other elements of the urban landscape.

- It is virtually impossible to predict the behavior of pedestrians, therefore the detection system should have a very good reaction time.


Fig.2. Image of pedestrians waiting at a crossing in India (Image source Wikipedia)

Typical data processing involved in pedestrian detection include (Geronimo et al., 2010):

- Foreground segmentation
- Object classification
- Verification
- Tracking

More recent research propose solutions based on deep convolutional neural networks (Tome et al., 2016), combinations of sensors: LIDAR + camera (El Ansari et al., 2018), or FIR (Far Infrared) cameras (Gonzales et al., 2016).

See also (Dollar et al., 2012) for a good review of the state of the art in pedestrian detection.

*Traffic Light Detection*

This is a much simpler task compared to pedestrian detection: traffic lights are designed to visible, they are static, have known colors and predictable shapes. A survey of the research in this field is available in (Diaz, 2015).

*Traffic Sign Detection*

Having standardized colors and shapes, traffic signs are relatively easy to detect and classify in static images. However, in practice, this task must be executed in real-time along with many other machine vision tasks starting from a dynamic visual data stream. Therefore, we are still far from having definitive results in this field. A survey of the research on automatic traffic sign recognition is available in (Fu & Huang, 2010).

*3.3. High Level Data Processing*

*Scene Understanding*

It is pretty obvious that the completion of the low level vision tasks described above are not enough to build a comprehensive scene understanding. Moreover, vision alone appears to be insufficient for scene understanding, and Xue et al. (2017) argue in favor of vision based fusion of multiple sensors.

Xue et al. (2018) describe an event-based reasoning approach for scene understanding (see figure 3).

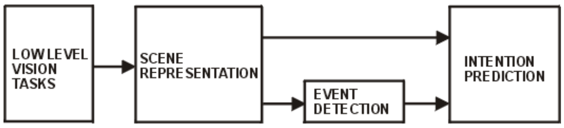


Fig.3. Scene understanding through event reasoning (adapted from Xue et al, 2018)

In this view, the concept of "event" (vehicle event or pedestrian event) is defined starting from the "traffic saliency" - a particular region of the scene representation that should draw the attention of the (automatic) driver.

If detecting vehicle events (e.g. lane change, overtaking) may seem easier to approach, pedestrian events - such as sudden road crossing - are much more difficult to detect, mainly because their higher mobility, unpredictable start-stop behavior, and trajectory changes.

Prediction of pedestrian intentions is usually based on detecting variations of the velocity or orientation, by comparing the past behavior (or average behavior patterns) with current visual data.

Despite the multiple contributions cited in the survey signed by Xue et al. (2018), we believe that the research on traffic scene understanding is still in its infancy.

*Predicting human behavior in traffic*

There are not just pedestrians in traffic: humans are also present in and around the ego-vehicle, in and around other vehicles, or they may be present as cyclists and traffic Police officers.

Ohn-Bar & Trivedi (2016) provide an analysis of the existing literature on automatic detection of human behavior in traffic.

The topic is complex and interdisciplinary. The existing solutions are context-specific (e.g. distracted driver or pedestrian, Police officer present, abnormal driving behavior etc.) and rely on detecting head orientation, gaze target, hand position and gestures, unexpected motion and other clues.

### *3.4. Benchmarks and Datasets*

Two of the most popular datasets & benchmarks for machine vision for autonomous vehicles are the CALTECH-USA dataset (described in Dollar et al., 2012) and KITTI (Geiger et al., 2012).

CALTECH-USA dataset is designed for pedestrian detection, and consists in about 10 hours video recorded from a car in traffic through urban roads. Additional files and utilities and details about the structure of the dataset are available on the dedicated web site (CALTECH, 2012).

The dataset created by the Institute of Technology from Karlsruhe, Germany (available online, KITTI, 2012) is a multi purpose dataset and benchmark tool, containing - besides the raw data collected with two high resolution grayscale and color cameras - ground truth information from a Velodyne laser scanner and a GPS localization system.

More information about other existing datasets and benchmarking tools is available in (Xue et al, 2018), and (Zhu et al, 2017).

### *3.5. Hardware Platforms*

The main issue with the machine vision tasks for autonomous vehicles is that they involve large computational loads, very difficult to be executed in real-time. Among the proposed solutions for this problem, hardware acceleration techniques seem to be promising. Karalot & Morris (2010) compared GPU and FPGA implementations for analyzing real-time stereo vision video and concluded that FPGA seems superior because it is much cheaper and slightly faster than a nVIDIA GeForce 280 GPU card. An additional advantage is that it is easier to connect a camera to a FPGA.

In a more recent work, (Luo & Lin, 2018), FPGA was successfully used for a complex pedestrian detection task based on HOG.

## 4. DIRECTIONS FOR FUTURE WORK

After reviewing the recent literature on machine vision for ADAS and AV, we notice that, despite the significant progress reported in the past years, the existing solutions seem excessively complex and costly, and therefore they have little chances to be included in commercial devices applicable on a large scale.

In our opinion, the main reason for this is the so-called "anthropomorphic bias" (Dacey, 2017) - the persistent belief that the various machines we design must follow the human model in what concerns perception, appearance, or behavior.

Human driving in 90% visual, therefore we assume that automatic driving should also rely mainly on machine vision.

In fact, as shown in (Macadam, 2003), the human driver model we try to imitate is far from being perfect, and we know that 90% of the accidents are caused by human errors. Creating rudimentary copies of an imperfect model is not the best strategy to solve the complex problems of the autonomous vehicles.

Therefore, we believe that exploring alternative solutions based - for example - on certain types of "cooperative perception" (Kim et al., 2015; Susnea, 2015; Susnea & Axenie, 2015) or "platooning" (Bergenhem et al., 2012) might lead to faster progress of the research in this field.

After reading a lot of studies on autonomous vehicles, we tend to agree with Litman (2017), who writes: "During the 2020s and perhaps the 2030s, autonomous vehicles will be expensive novelties, unable to operate in conditions such as heavy rain and snow, unpaved roads and mixed urban traffic.... It will probably be the late 2030s or 2040s before they become affordable to middle-income households."

## 5. CONCLUSION

We presented a systematic overview of the extremely vast and diverse literature regarding machine vision techniques for autonomous vehicles. Our objective was to provide a quick introduction and a bird's eye view of the main topics of this research field. To this purpose, we identified reviewed a relatively small number of comprehensive surveys of the state of the art in the main research directions. We also proposed a simple taxonomy of the existing literature, and identified some of the best resources available for starters.

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