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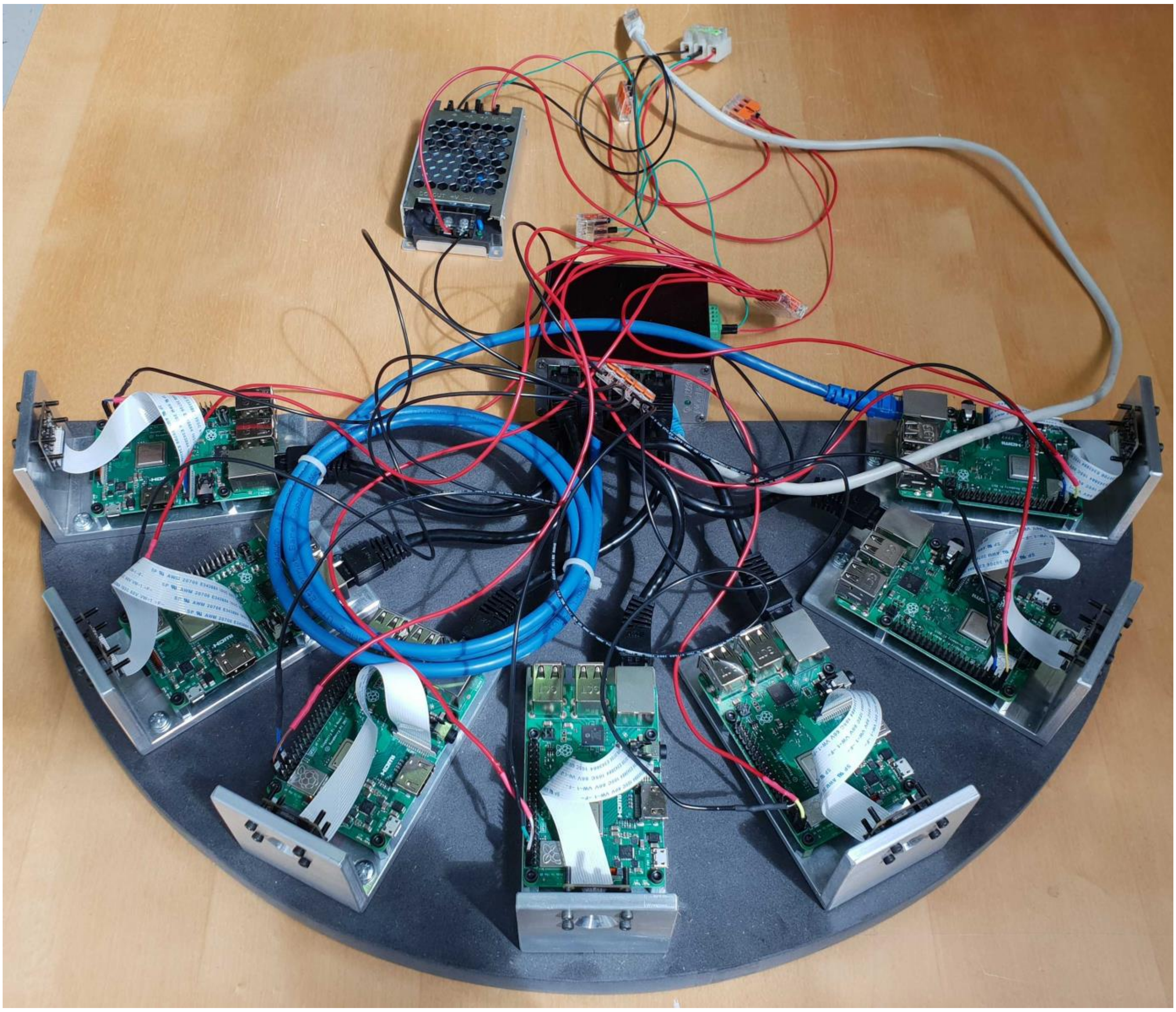

HISCAOD: a high-speed camera array for obstacle detection

Bachelor of Science Thesis in Software Engineering and Management

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{HISCAOD system description}
[This document contains description of HISCAOD – an obstacle detection system for autonomous vehicles, developed using high-speed cameras, including process of its development and testing results]

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[Front view of the device]

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HISCAOD: a high-speed camera array for obstacle detection

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Abstract – this document contains description of HISCAOD – an obstacle detection system for autonomous vehicles, developed using high-speed cameras. Using image processing data from seven cameras the device is able to detect potential obstacles both during the movement and on a still position. Extensive testing was performed to access its functionality, effectiveness and accuracy. Such approach to feature tracking and obstacle detection may be of use for both autonomous and manual cars and may greatly improve driving safety, reliability and comfort.

I. Introduction

Starting in 1950s, cars were preferred means of travelling between and within cities (Howard & Dai (2014)). Although they are very useful and enable comfortable travel, cars also create numerous problems such as pollution and traffic jams. One of possible solutions for mentioned problems is driverless car. Although first prototypes of this type of vehicle were developed in 1920s, significant advancements and progress in true self-driving car occurred only at the beginning of 21st century. This kind of vehicle uses variety of positioning and proximity sensors enabling it to drive without human control. One possible variant of proximity sensor is a camera which provides obstacle recognition and avoidance. Current implementations of such variant use standard cameras which although proved to be reasonably effective do not provide very fast framerate, which together with motion blur leads to decrease of their efficiency (Lalonde, Laganiere & Martel (2012)). Furthermore, image noise induced by vehicle movement can also adversely affect camera feature tracking performance (Bertozzi & Broggi (1998)). In this research, a proximity sensor system will be developed using an array of seven high-speed cameras providing approximately *250 frames per second* and enabling very accurate and rapidly reacting obstacle detection which is not affected by sharp movements of vehicle or its high speed. The aim of the research is to study the functionality of this system, its performance in realistic scenario and consequently its advantages and potential relatively to existing similar systems. As autonomous cars are becoming more prevalent and popular in the world, improvements of their sensor systems become highly important as they will potentially allow to merge all autonomous cars into a single efficient network ("Internet of vehicles"), enabling smooth traffic flow with lower or no pollution and increased comfort for both passengers and drivers (Gerla, Lee, Pau & Lee (2014)).

The purpose of this study is to access the effectiveness of high-speed camera array in obstacle detection. The system was developed as a result of study using OpenCV ("Open Source Computer Vision Library", n.d.) library and Raspiraw application ("Example app directly receiving raw data from CSI2 sensors", n.d.) and subsequently tested in a realistic scenario with road cones. Testing results were used in its evaluation to determine the effectiveness of the system both on its own and compared to already existing solutions. The ultimate goal of this study is to develop a new more effective method of obstacle detection for autonomous racing car with the possibility of its implementation for production of other types of driverless vehicles.

Car manufacturers who produce autonomous vehicles can hugely benefit from the results obtained during this study as more effective obstacle detection with the application of high-speed cameras may enable driverless cars to operate more safely and accurately, potentially increasing their popularity and consequently leading to higher sales. Increased numbers of autonomous cars can in turn improve the traffic situation, lead to decreased emissions and less accidents (Litman (2017)).

Arising from purpose of the study are following research questions:

RQ1: What is the design of a high-speed, low-cost, multi-camera cluster to be used on an autonomous racing car?

RQ2: What is the best performance achievable in a robust way for object detection of colored cones compared to existing approaches for autonomous racing cars?

Successful solution of these research questions can potentially increase usability and effectiveness of autonomous cars (by improving their obstacle avoidance and perfecting the system of driving navigation), leading to increase of their numbers and improvements in worlds' traffic situation.

II. Literature review

Bertozzi & Broggi (1998) described a real-time Stereo vision obstacle and lane detection system in their research. The GOLD (Generic Obstacle and Lane Detection) device used pattern matching for lane detection and processing of stereo image pairs for obstacle detection. Both of those methods used image warping, which bases on a flat surface assumption. Inverse perspective mapping was applied to images obtained from camera to create their 2D representation for lane and obstacle detection. The system was mounted on experimental mobile laboratory for testing purposes. It was deemed effective during the testing, being reliable, sufficiently accurate and resistant to mechanical distortions. However, authors noted that image noise induced by sharp vehicle movements on some types of surface (for example paved roads) could lead to erroneous obstacle detection. Furthermore, far (more than 45 meters away) and partially visible obstacles could cause errors in detection process.

Lalonde, Laganiere & Martel (2012) described usage of rear-view camera as a backup system for driver assist, motivated by its low cost and sufficient spatial resolution compared to radar and ultrasonic range finders. Their approach involved usage of triangulation to create a model of the scene visible through camera and find 3D locations of objects. Additionally, the system was able to filter out features which were clustered together and erratic motion objects. It was proven to be reliable and efficient through testing conducted during the research, but according to the authors, a number of factors such as small framerate of used camera and motion blur decreased efficiency of feature tracking process.

Zeilinger, Hauk, Bader & Hofmann (2017) described an autonomous car design for Formula Student competition, providing complete analysis of its obstacle avoidance features. Cameras and lidar were used for the detection of traffic cones, using two approaches – a processing of a camera image using block-matching algorithm for cone position estimation, and usage of algorithm to compute z-depth and disparity of cone, allowing to determine its 3D position. Resulting system was unreliable, achieving 30 to 90% detection rate depending on the fragment of a race track. Authors noted that difference in lighting conditions could have severe negative impact on the reliability of an object detection camera, although its algorithm had at least 75% accuracy no matter the lighting in image.

III. Methodology

Design science research (DSR) method was chosen for the study because of several important reasons. Firstly, this method allows a real problem (drawback of camera obstacle detection) via applied research. Secondly, this method enables creation of artifacts for real problem solving (the obstacle detection system in this case). Design science research process model (DSRP) proposed by Peffers, Tuunanen, Rothenberger & Chatterjee (2007) was used in the study, as it allows effective application of DSR. It has six stages (Figure 1).

1) Problem identification and motivation, when specific study problem is defined, and its solution value is justified. In this case, defining the problem enables creation of the artifact to solve it, while justification of the solution value motivates both the study audience and researcher(s) to follow solution and then to accept outcome of its application. Low frame rate of feature tracking cameras (which led to substantial image noise and object detection issues) was identified as a problem in this research.

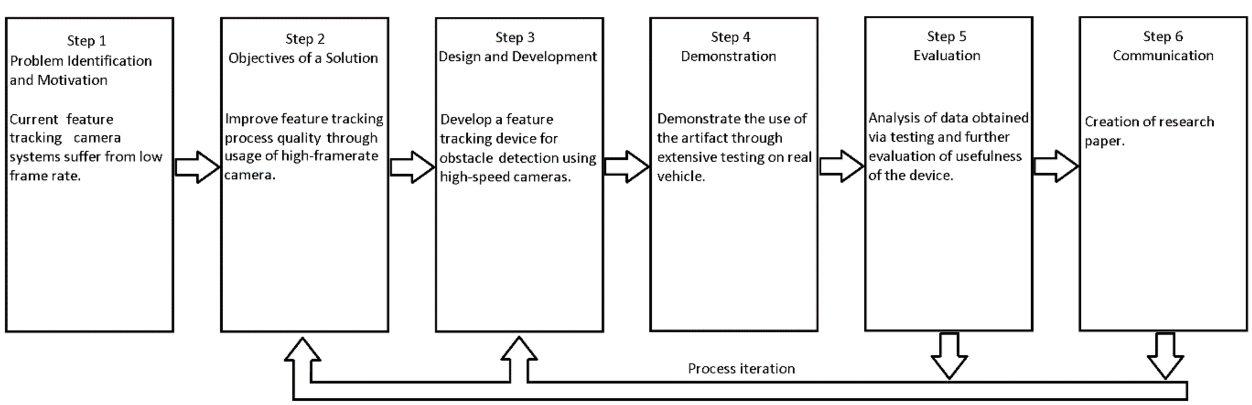

Figure 1 - DSR used in study

2) Definition of objectives for a solution. During this step, objectives of a solution are inferred rationally in accordance with problem definition, with feasibility and realism of the solution in mind. Improvement of the obstacle detection was defined as an objective in this study.

3) Design and development. The artifact is created during this stage. It may be a construct, method, instantiation or model. Generally, any designed item can be DSR artifact, if its design has research contribution embedded in it. Both planning of artifact's functionality and desired properties, and creation of it are executed during this step. The feature tracking device that used high-speed cameras was firstly designed in 3D modelling software, then implemented both software and hardware-wise.

4) Demonstration, where artifact is used to solve instance(s) of problem. This step may be composed of a case study, proof, experimentation, simulation or other similar method. During the development of the device both unit and system testing were used to test its components separately (camera, Raspberry PI and main computer) and together respectively. After the device was completed, it underwent extensive testing with road cone detection. Three types of testing were executed in order to gather quantitative performance data – detection of road cones at variable distance, detection at 2 meters during the movement of the device, and detection at 5 meters under the different lighting conditions. Stationary testing was performed by placing a road cone at distances of 5, 10, 15 and 20 meters away from the camera array and measuring percentage of successful detections during 8-second device run, 5 times for each distance. Movement testing was executed by mounting one of the device's cameras on rotating stand, placing road cone at 2 meters away in front of it, and then manually turning the stand in 30-degree sector (field of view of hi-speed camera) to determine if image noise or blur occurred. Testing for influence of lightning conditions was conducted during partially cloudy day. The measurements were conducted when sun was in and out of clouds (5 times during each condition, 10 in total) to assess its influence on device's accuracy. 30 cm high traffic cones were used in all tests (Figure 2).

Figure 2 – Example of a traffic cone used in testing

Testing was used to obtain data to determine if HISCAOD gives the best performance in comparison to existing similar systems (camera obstacle detectors).

5) Evaluation. This stage consists of measurements and observation of artifact's efficiency as solution to the researched problem. Results of artifact usage obtained during Demonstration stage are compared against objectives of a solution with usage of analysis technics and relevant metrics. In general, this stage can contain a logical proof or factual evidence of usefulness of developed artifact. In this study, the data obtained from testing (quantitative) was used to evaluate the performance of the experimental device. Testing data was used to create graphs (in case of stationary testing) or by itself (in case of movement and lighting testing) to assess accuracy of the system's feature detection depending on a distance to obstacles, device's movement and lighting level. HISCAOD was evaluated both by itself and compared to existing similar systems to determine if it achieves the best performance compared to existing road cone detection cameras.

6) Communication. During this last stage, the researched problem (and its significance) together with artifact (and its effectiveness, novelty, rigorous design etc.) are communicated to relevant audiences such as for example business practitioners and scientists. This process' structure can be used to format the research document itself. The study will be communicated by means of this document.

Steps 2,3,5 and 6 would be repeated 2 to 5 times (depending on testing results at the end of each iteration cycle) in order to improve the system and fix its possible drawbacks.

IV. RESULTS

The obstacle detection system consists of seven camera-Raspberry Pi pairs mounted on the metal platforms with openings for camera lenses, which are in turn fixed onto reinforced wood platform in semi-circular pattern to cover 180-degree field of view (Figure 3). Each Raspberry PI is connected to ethernet switch, which routes their messages to car's onboard computer.

Figure 3 - Front view of the assembled device

Each Raspberry PI is powered through 5V and ground pins using DC/DC converter, which lowers high voltage from the vehicle to 5 volts (which is acceptable for Raspberry PI). Power connections of converter and ethernet switch are joined together via cable connectors to create one power input which can allows connection to the vehicle equipped with the device (Figure 4).

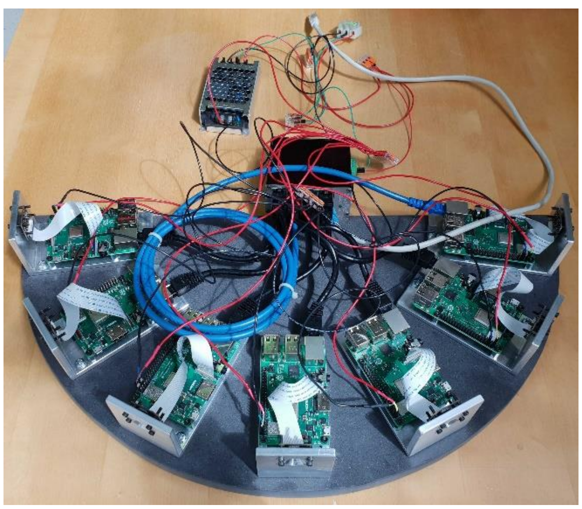

Figure 4 – Device with power wires and main ethernet cable attached

Each camera is connected to Raspberry PI computer, which handles image processing (feature tracking). The detections process is conducted as follows. Firstly, modified Raspiraw (with added function of sending frames to other program) is used to provide high-speed video input for the feature extraction algorithm. During the development, initial framerate was set at 360 fps, but following extensive testing it was decided to reduce it to 300 and then to 250 fps to increase feature tracking accuracy and minimize system load. Initial communication between Raspiraw and cone detection algorithm was implemented using UDP sender and receiver with built-in conversion from raw Bayer data (unprocessed image) to .ppm file recognizable by the algorithm. However, practically it resulted in very slow image processing (3-4 frames per second), and it was decided to replace it with communication through Fifo pipe, which allows Raspiraw to send frames to the algorithm for latter to read them asynchronously. Due to the absence of a conversion during this process, Raspiraw was reconfigured to output .pgm (Portable Grey Map) greyscale frames, which are recognizable by OpenCV used in cone detection algorithm (Figure 5).

Figure 5 – Example of .pgm frame produced by Raspiraw

The latter was extremely simplified to maximize its processing speed. The algorithm used adaptive thresholding and contour finding functions of OpenCV library in order to find and isolate cone-shaped objects in each frame (Figure 6).

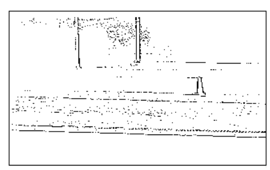

Figure 6 – Frame after application of adaptive treshold method

As cone height is already known (30 cm cones were used in testing), distance to it was calculated via multiplying it by camera's focal length and then dividing the result by detected object's height in pixels. After this, an angle to the cone was calculated, using its position in the frame relatively to camera's orientation and the field of view. Resulting information was used to determine cone's coordinates in relation to the device, which then were sent to central computer. It received the data from all connected components in 50-millisecond increments and converted it into a spline (Bezier curve) via converter algorithm (Figure 7), as splines can be effectively used to model the shape of 3D objects (Sullivan & Ponce (1998)). In this scenario, a curve was used to model a line of cones at the side of the road and allows to filter out erroneous readings, in turn increasing the accuracy of the device.

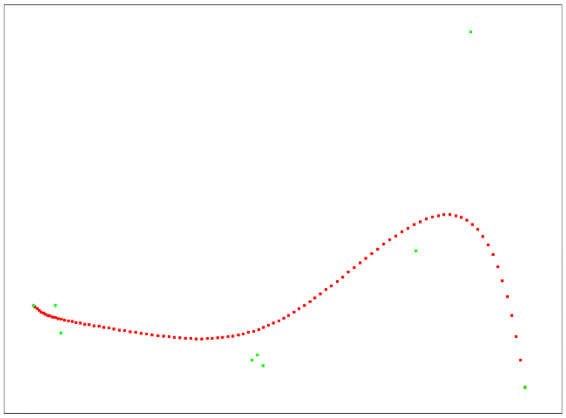

Figure 7 – An example of Bezier curve generated by the device from cone detection data (green points).

During the movement testing, the device's camera showed very little accuracy decrease (96% down from 99% when camera was in a still position) when detecting single cone 2 meters away. Additionally, the frames recorded by the Raspiraw (which was set to not only send them to cone detection algorithm, but to save them to Raspberry PI's memory in this test) showed no signs of motion blur and very little image noise.

Stationary testing demonstrated that the device had accuracy range from 99% at 2 meters to 4.8% at 20 meters (Figure 8). It was performed when clouds covered the sun for consistent lighting levels.

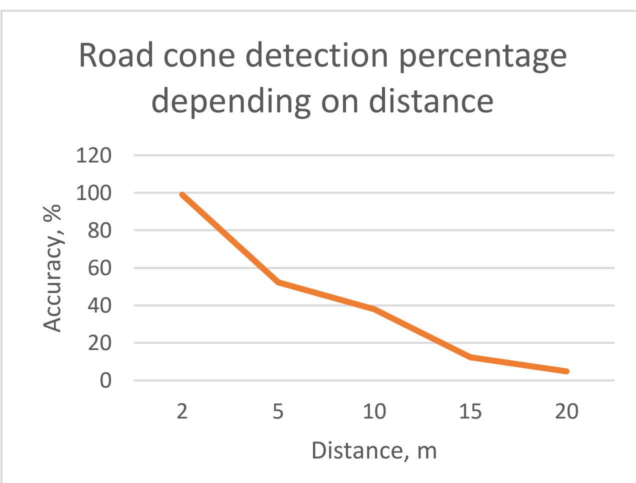

Figure 8 – Cone detection accuracy depending on distance.

During the lighting test, the device demonstrated varying detection accuracy, which was lower in bright lighting (from the sun), ranging from 15 to 38% (29% average), and higher under less bright lighting conditions (when clouds covered the sun), ranging from 48 to 59% (56 % average).

V. DISCUSSION

The HISCAOD device proved to be compact and durable, which allows its easy mounting on any sufficiently flat surface on the car and allows it to resist mechanical damage and strain. Tightly mounted components ensure total absence of camera movements caused by car's vibration, therefore providing high stability even while driving at a high speed. Additionally, usage of accessible, low-cost components and open-source software makes the system affordable and allows to install it even on inexpensive cars (total estimated cost is less than 700 €, which is significantly less than production high-speed cameras, and can be even lower if HISCAOD will be mass-produced). The system also demonstrated very high reliability during testing, with all components (hi-speed camera, detection algorithm and Bezier curve converter) never failing, as their bugs were fixed during the development process. Additionally, the system has necessary connections (power and Ethernet) to be connected to an autonomous car. Therefore, the system represents a very efficient design of a high-speed, low-cost, multi-camera cluster to be used on an autonomous racing car.

Performance data shows that the device has considerable advantages over existing camera obstacle detection approaches (such as low image noise and absence of motion blur during movement). However, its accuracy appeared lower. For example, device described by Zeilinger, Hauk, Bader & Hofmann (2017) had minimum accuracy of 30 and maximum of 90% compared to HISCAOD's 4.8 and 52% at similar distances (except for 99% at 2 meters) and its algorithm detected at least 75% of cones at any lighting, while HISCAOD's algorithm achieved 29% to 56% detection rate depending on a lighting level (meaning approximately 51% accuracy decrease when exposed to bright lighting). As such, the HISCAOD failed to achieve the best performance in a robust way for object detection of colored cones when compared to existing approaches for autonomous racing cars. However, such mediocre performance was caused to overwhelming extent by extremely simplified cone detection algorithm (which practically sacrificed cone detection accuracy for increased processing speed). Thus, replacing current feature tracking software with the more accurate and effective option may drastically increase HISCAOD's accuracy, potentially allowing it to achieve the best performance among existing cone detection system approaches.

VI. Conclusion

The findings of the study can be of great use for autonomous vehicle software engineers, providing them with practically useful information on how to implement an affordable and potentially effective (if used with more accurate detection algorithm) proximity sensor for driverless car both hardware and software-wise. The study will also be useful for researchers, as it represents a radically new extension of existing technology (camera obstacle detection), offering significant potential improvements and a base for further research in this area (usage of high-speed cameras for feature tracking).

Additionally, the results of the study can be used by camera software engineers to improve objects detection and tracking process in areas such as security and military surveillance systems, robotics and manufacturing industry (for example, quality control on production lines), using inexpensive high-speed cameras.

In a long run, the information contained in this research can potentially assist in improving the obstacle detection methods of autonomous vehicles, improving their driving quality, resulting in their popularity rising (and consequently increase of their production). The proposed system can potentially improve existing traffic situation, help to lower pollution and protect environment, computerize traffic network, therefore ensuring safety on the roads.

VII. References

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