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Multi-Mode Surround View for ADAS Vehicles

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***Abstract*—Advanced driver's assist systems for optional self-driving vehicles require highly reliable navigation capabilities to ensure dependable autonomous function of vehicle safety and driver assistance. Radars, lidars and cameras have found widespread application in nearly all vehicle brands for this purpose. In this paper we present the implementation of these sensors for constructing a 360-degree field of view of the vehicle surrounding. A stereo vision system is complemented by several long, mid and short- range radar sensors. The data gathered from the advanced sensors is prioritized and fused to create a model of the surrounding. The system is being tested on an autonomous car vehicle. In particular, this paper discusses three clustering algorithms that were tested.**

I. Introduction

An autonomous car is a self-driving vehicle that has the capability of perceiving the surrounding environment and navigate itself without human intervention. For accomplishing autonomous driving, complex autonomous driving algorithms, including perception, localization, planning and control, there are required many heterogeneous sensors, actuators, and computers [1]. For the development of these autonomous driving technologies, the Defensive Advanced Research Projects Agency opened the Grand Challenge and Urban Challenge competitions in the U.S. The Grand Challenge competition focused on the development of autonomous cars that traverse off road terrain by themselves [2]. Based on the results of the Grand Challenge, the Urban Challenge competition aimed at the advancement of autonomous cars with urban driving technology [3]. Ahead of the 2020 Olympic Games in Tokyo, Japanese vehicle manufactures are also amongst the automotive companies that are pushing the development of innovations in Advanced Driver Assistance Systems (ADAS) and automated driving. There are different levels of autonomy, one must continue to research, develop, engineer, test and evaluate the technology.

II. Intelligent Ground Vehicle Competition – Spec2

Continental Corporation began research on driver assistance systems 20 years ago and today the company is very well-positioned thanks to its core skills in assisted and automated driving, such as cameras, radar systems, high resolution laser sensors, electronic control units and software [4]. The Autonomous Car Spec2 at Oakland University in Rochester, Michigan, US presents a good case of application and integration of new sensor technologies for the autonomous cars purposes. The overall goals for Spec2 focus on the radar surround sensing that has been installed in the electric vehicle Polaris Gem3 [5]. See Figure 1. While sensor fusion was our main goal, the second objective is to train our future engineers in utilizing the latest sensors and mastering the sensor fusion algorithms. The Spec 2 will be demonstrated at the 2016 IGVC international robotic competition [5]

Figure 1. Autonomous Car Spec2.

III. Technologies

A. Radars

Automotive radar sensors are used to alert/notify the driver or a higher level of automation of vehicle interferes with braking and other vehicle controls to prevent an accident.

B. Lidar

Lidar uses a combination of reflected laser/light and radar to create a 3D profile of the surroundings of the car. Lidar technically does not detect


Figure 2. High flash resolution Lidar

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a moving object but creates a rapid series of 360° profiles, compares them with each other and maintains a database to detect changes (i.e., movement).

C. Cameras

Consisting of four cameras – in front, in the rear and on the outside rearview mirrors – it can only monitor the area all around the vehicle, but also recognize pedestrians, warn the drive or even stop the vehicle in critical situations.

Figure 3. Cameras

D. On-Board Sensors

Several sensors are used for Blind Spot Detection (BSD), Rear Cross Traffic Alert (RCTA), Rear Cross Assist (RCA), Safer Lane Changes and Overtaking. Their aim is also to avoid accident-conductive situations, enable more relaxing driving and significantly reduce the driver's workload, increase safety when revising out of a parking space, distinguish easily between static and moving objects, and realize high spatial resolution in a narrow bandwidth.

Another type of sensor is used for broad field of view realized by two independent scans. Is supports ACC + Stop & Go with one single sensor, distinguishes easily between static and moving objects, auto alignment in both directions (horizontal + vertical), Adaptive Cruise Control (ACC) Stop & Go up to 200 km/h, Traffic Jam Assist, Forward Collision Warning, Emergency Steering & Intersection Assist.

A GPS is widely used for localization systems because it provides a direct global position and speed of the self-driving vehicle. However, the position of the Global Position System (GPS) raw data cannot be used for an autonomous driving system that the quality of the GPS position is significantly affected by the satellite signal conditions. Accurately, reliability and continuity of measured GPS position data will deteriorate quickly when the GPS satellite signal is weak. A lot of previous research focused on the fusion of a GPS with additional information such as motion sensors to vehicles (sensor wheel-speed, gyroscope, acceleration, and magnetic sensors) perception of environmental data and digital maps to compensate for weaknesses GPS

Figure 4. Multiple purpose sensors.

E. Methods

To drive themselves, autonomous vehicles must be equipped with such devices as Lidar, cameras, sensors and GPS, forming a buffer around the car, as shown in Figure 5. Sensors were placed in strategic locations in order to obtain 360-degree field of view.

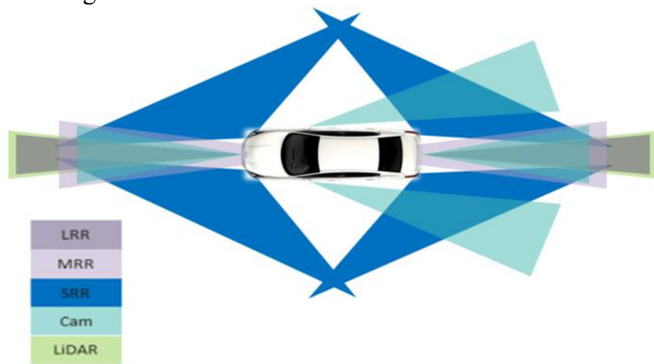


Figure 5. Sensors set-up of autonomous car Spec2.

Figure 6 depicts the objective of our current project and the vision where we are heading. The data gathered from the advanced sensors is utilized to create the environmental model. Furthermore, the data is then fused together and is available for utilization. The United States and European Union car manufacturers have been working to include Cooperative Intelligent Transport Systems (C-ITS) in their new vehicles in the 2016-2020 timeframe, while Japan has already deployed vehicles with Vehicle-to Infrastructure (V2I) and Infrastructure to-Vehicle (I2V) C-ITS capability [6].

IV. Active Safety Capabilities

The following are some of the typical applications implemented into our system: Adaptive Cruise Control (ACC). Brake Assistant (BA). Traffic Sign Recognition (TSR). Lane Keeping Assistant (LKA). Parking Assistance (PA) [7].

Adaptive Cruise Control (ACC). ACC automatically adjusts vehicle speed to maintain safe distance from vehicles ahead. ACC uses on board sensors being lasers, radar or a combination of them..

Brake Assistant (BA). If the driver can no longer take corrective action, that is, brake or turn away safely, then emergency brake assistant occurs.

Traffic Sign Recognition (TSR). Another fairly straight forward use of computer vision is TSR that it is deliberately structured to aid human drivers. TSR uses a set of well-defined shapes, colors, and patterns. The signs are placed at consistent heights and positions in relation to the road.

Lane Keeping Assistant (LKA). LKA warns the driver and if no action is taken automatically to keep vehicle in its lane. Blind Spot Detection (BSD) is a sensor device that detects other vehicles located to the driver's side and rear. Warnings can be visual, audible, vibrating or tactile.

Parking Assistance (PA). PA is also a low-speed aid. In a typical scenario, the driver initiates the system by pushing a button when driving past an empty parking space. The system measures the length of the space using odometry, measures the positions of the cars in front and in back using short-range sensors, and infers the position of the curb by assuming that the surrounding cars are standard sized cars parked near the curb [7].

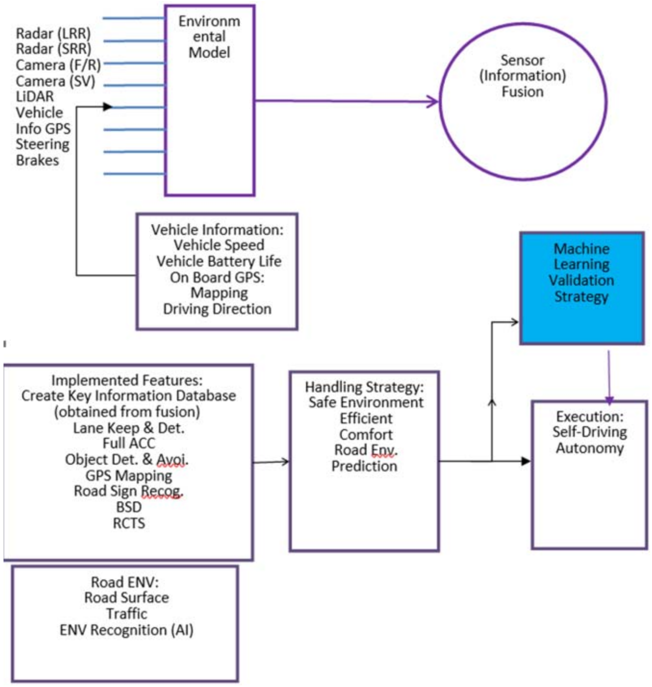


Figure 6. Structural overview of the autonomous driving algorithm.

A. *Inputs and Outputs*

Given proper implementation and fusion, our project can execute the above applications seamlessly. The following radar characteristics are utilized in the target design:

- Range, Range Accuracy, Range Resolution
- Azimuth Accuracy, Resolution & Beam Width
- Elevation Beam Width
- Velocity , Point Target Velocity

Input:

- Lane Departure Mode Switch
- Warning Parameters
- Vibration Parameters
- Vehicle Kinematics Information
- Vehicle Status Information
- Alert Sensitivity

Output

- Indicator Display Request
- Warning Buzzer Operation Request
- Lane Marker Status Display
- Object Existence
- Unavailable Vehicle Speed Display
- Camera Adjustment
- Temporary Unavailable State Display Request.

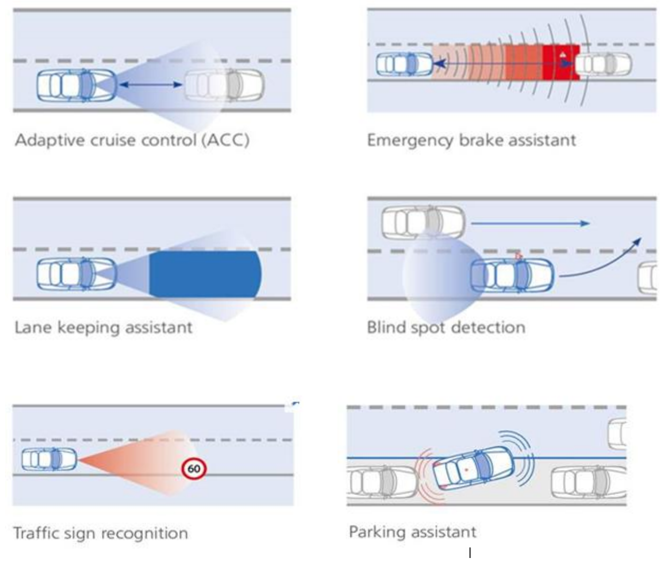


Figure 7: ADAS Applications implemented into Spec2 autonomous car.

V. SAMPLE SCREEN SHOT

Data obtained from Long Range Radar (LRR), Mid Range Radar (MRR) and Short Range Radar (SRR) is utilized to give us a 360 degree view of our surrounding by utilizing only Radar data. Processed data is further analyzed and proper objects are classified, such as: vehicle, semi-truck, bicycle, motor cycle, people, curb, etc. Each object is tagged with an ID, location, distance and velocity (reference Figure 8).

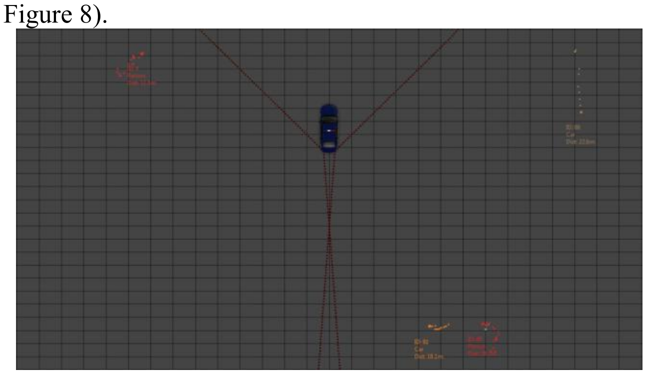


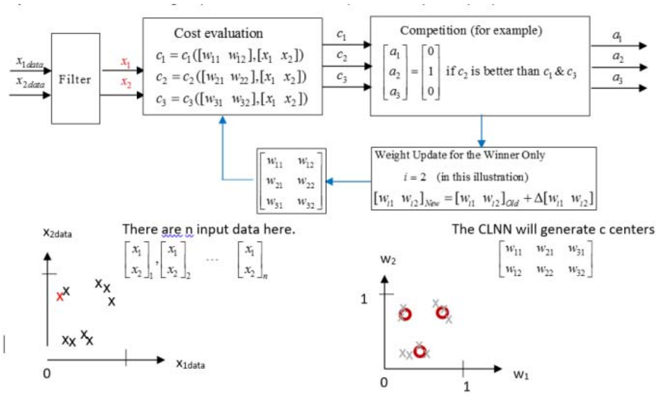
Figure 8. Top view (rear of the vehicle) of the 360 degree view window.

VI. CLUSTERING ALGORITHMS

Among the many emphases in this research, we explored three clustering algorithms.

A. *Competitive Learning Neural Network algorithm*

A CLNN takes the form of cost evaluation, competition and weight update as illustrated below. It adjusts itself so that its weights point to cluster centers presented by the input pattern.



B. K-mean algorithm

Given date points $x_k, k=1,\cdots,n$, the K-mean algorithm seeks to find the centers v_i, $i=1,\cdots,c$ and *crisp* membership values $u_{i,k}=0$ or 1 that optimizes the distance-to-center cost function:

$$J(U,V)=\sum_{k=1}^{n}\sum_{i=1}^{c}u_{i,k}\left\|x_k-v_i\right\|^2 \quad u_{i,k}=\begin{cases}1, & x_k\in A_i\\ 0, & x_k\notin A_i\end{cases}$$

Step 1: Fix centers to c, $2\le c\le n$. Initialize

$$U^{(0)}=\left\{u_{i,k}^{(0)}\right\}=\begin{bmatrix}u_{1,1}^{(0)} & u_{1,2}^{(0)} & \cdots & u_{1,n}^{(0)}\\ \vdots & & & \vdots\\ u_{c,1}^{(0)} & u_{c,2}^{(0)} & \dots & u_{c,n}^{(0)}\end{bmatrix} \quad u_{i,k}^{(0)}=0 \text{ or } 1$$

Step 2: Set l = 0, 1, 2, …, compute the c-mean vectors for i = 1,…, c,

$$v_i^{(l)}=\left(\sum_{k=1}^{n}u_{i,k}^{(l)}x_k\right)\Bigg/\sum_{k=1}^{n}u_{i,k}^{(l)}$$

Step 3: Update $U^{(l)}$ to $U^{(l+1)}$ using

$$u_{i,k}^{(l+1)}=\begin{cases}1 & \left\|x_k-v_i^{(l)}\right\|=\min\left(\left\|x_k-v_j^{(l)}\right\|,\ 1\le j\le c\right)\\ 0 & \text{otherwise}\end{cases}$$

Step 4: Compare $U^{(l)}$ with $U^{(l+1)}$: if $\left\|U^{(l+1)}-U^{(l)}\right\|<\varepsilon$ for small constant ε, stop; otherwise set $l=l+1$ and go to Step 2.

C. Fuzzy C-Mean (FCM) algorithm

Given date points $x_k, k=1,\cdots,n$, the fuzzy C-mean algorithm seeks to find the centers v_i, $i=1,\cdots,c$ and *soft* membership values $u_{i,k}\in[0,1]$ that optimizes the distance-to-center cost function:

$$J_m(U,V)=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m\left\|\mathbf{x}_k-\mathbf{v}_i\right\|^2,$$

where $m\in[2,3,\cdots\infty)=$ a weighting constant

Step 1: Fix centers to c, $2\le c\le n$. Initialize

$$U^{(0)}=\left\{u_{i,k}^{(0)}\right\}=\begin{bmatrix}u_{1,1}^{(0)} & u_{1,2}^{(0)} & \cdots & u_{1,n}^{(0)}\\ \vdots & & & \vdots\\ u_{c,1}^{(0)} & u_{c,2}^{(0)} & \dots & u_{c,n}^{(0)}\end{bmatrix} \quad u_{i,k}^{(0)}\in[0,\ 1]$$

Step 2: Set l = 0, 1, 2, …, compute the c-mean vectors for i = 1,…, c,

$$v_i^{(l)}=\left(\sum_{k=1}^{n}\left(u_{i,k}^{(l)}\right)^m x_k\right)\Bigg/\left(\sum_{k=1}^{n}\left(u_{i,k}^{(l)}\right)^m\right)$$

Step 3: Update $U^{(l)}$ to $U^{(l+1)}$ using

$$u_{ik}=1\Bigg/\sum_{j=1}^{c}\left(\frac{\left\|\mathbf{x}_k-\mathbf{v}_i\right\|}{\left\|\mathbf{x}_k-\mathbf{v}_j\right\|}\right)^{\frac{2}{m-1}}, \quad i=1,\ldots,c, \quad k=1,\ldots,n$$

Step 4: Compare $U^{(l)}$ with $U^{(l+1)}$: if $\left\|U^{(l+1)}-U^{(l)}\right\|<\varepsilon$ for small constant ε, stop; otherwise set $l=l+1$ and go to Step 2.

All the three algorithms produce the comparable same results; that is the centers produced are approximately the same. *It was found that the fuzzy C-mean converges approximately 10 faster than the K-mean and 100 times faster than the CLNN.*

VII. Conclusion

Fusion of other sensors is necessary and the work required to fully incorporate all the sensors will be very difficult, yet very educational. We have a lot of work ahead of us and lots to learn. We look forward to seeing our work flourish and more importantly to be part of a team which takes engineering students and prepares them for the future of automotive industry.

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