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An Efficient Mechanism For Sensor Fusion And Road Boundary Detection Using Intersection Of Co-Variances-DST

Ningappa Uppal[1], Dr Vijaya Kumar C N[2], Dr Ravikumar T[3]
[1]*Research Scholar, Dept. of ECE EWIT Bangalore, India*
[2]*Professor, Dept. ofECE EWIT Bangalore, India*
[3]*Medical officer Denso kirloskar Ltd Bangalore, India*

ABSTRACT
The physical hardware of the ADAS cars are supported by number of sensors like radar, lidar, camera, imu , gps etc. however , in addition to these enormous structure each sensor has its own limitation. Various adas sense functions fuse the input from various sensors to subsidize each other and to achieve better functionality of autonomous driving which include cross traffic scenario, obstacle avoidance, tracking etc. ADAS systems are made to take critical decisions, one among critical decision functionality is sensor fusion. Sensor Fusion applications should be designed to mark with highest standard requirements with exceptional performance. Autonomous cars have increasingly on demand research for the safety vehicles.State-of-the-art ADASs are primarily vision based, but light detection and ranging (lidar), radio detection and ranging (radar), and other advanced-sensing technologies are also becoming popular. In this paper, we present the three adas functionalities and their capabilities along with results. We discussour approaches used for vision-based recognition (OEDR) and sensor fusion in ADAS solutions using radars. We also highlight challenges for the next generation of ADASsand experimental results are shown.This function component currently researched is a key component for the fused static environment perception information, like static obstacles, free space or road boundaries. Based on the provided radar sensor models, it transforms the specific sensor output into a generic and area-based Dempster Shafer Theory (DST) grid map along with that we presented our research work considering sensoring with radars and cameras and estimated results have be showed . Estimating the shape of objects is crucial for vision-based advanced driver assistance and safety systems. However, conventional radar processing is unable to resolve the different parts of a vehicle as required for this task. To address this issue a two-stage approach is considered which employs high-resolution camera techniques in combination with conventional Fourier-based methods. Single- and two-dimensional high-resolution pedestrian detctionis discussed, which includes range and range-rate estimation in the temporal dimensions considering the camera data.

Keywords:- sensor fusion, tracking, discrete time fourier signals, object event detection and responsce(oedr), vision based systems, static environment, road boundaries, traffic signs, ADAS(Advanced driver assistance systems), Association, kalman filter, intersection of co-variances, mahalanobis distance.

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I. INTRODUCTION

Driver safety in cars has become a major significance since the early days of on-road vehicles. Since years prominent thinkers and original equipment's manufacturers have put their best efforts to address the issues by originating with various safety systems however they failed in assisting to highest standard in other sense to a ideal scenario. In recent years ADAS systems have gained a lot of attention by developing various safety systems of highest standard to protect the occupants and prevent deaths of the occupants. The ADAS systems are broadly classified into two types: reactive or passive systems and proactive systems.Passive systems provide their support during the crash with the help of seat belts, air bags, and padded dashboards.

Active systems are broadly one of the core subject of interest which have seen a demand growth in recent vehicles such systems include lane assist using third degree polynomial, automatic braking, and adaptive cruise control. These systems are commonly known as *driver assistance systems, Advanced*and are subjective to the broad area of interest.As a way for automotive manufacturers to differentiate their offerings while promoting consumer safety. Ongoing investigations from the World Health Organization demonstrate that 1.25

million passings happen each year because of streetcar crashes [1]. Additionally, such mishaps as of late have a yearly worldwide expense of US$518 billion, which removes roughly 1–2% of total national output from the entirety of the nations on the planet [2]. These high casualty rates, money related misfortunes, and expanding client interest for keen wellbeing frameworks are a portion of the key explanations behind OEMs to create ADASs. Besides, with the expanding number of electronic control units and combination of different kinds of sensors, there are currently adequate registering abilities in vehicles to help ADAS arrangements. The various sorts of sensors, for example, cameras, lidar, radar, and ultrasonic sensors, empower a wide range of ADAS arrangements. Among them, the vision-based ADAS, which fundamentally utilizes cameras as vision sensors, is famous in most advanced vehicles. Figure 1 shows a portion of the best in class ADAS highlights and the sensors used to execute them. Present day ADASs are likewise key advancements to acknowledge independent vehicles [3].In any case, a few difficulties with the structure, execution, and activity of ADASs stay to be survived. A portion of these difficulties incorporate limiting vitality utilization, lessening reaction inactivity, adjusting to changing climate conditions, and security. Right now, give a summary of the scene of ADAS innovative work to address these difficulties.

Sensor combination alludes to joining data from different homogenous or heterogeneous sensors to locate a solitary best estimation of the condition of the earth. Combination helps sensors

Supplement each other's confinements and offers more prominent influence to the framework contrasted with a framework with singular sensors. Sensor combination offers high exactness, dependability, strength to vulnerability, expanded spatial and fleeting inclusion, and improved goals, which are urgent in wellbeing basic frameworks, for example, vehicles. In spite of the fact that this comes at a higher calculation cost, the calculation power accessible in innovative vehicles and the diminishing expense of the sensors are encouraging the boundless reconciliation of these frameworks. The order of various degrees of sensor combination alongside the most generally utilized procedures for intertwining information are talked about in [2]. The developing enthusiasm for profound learning and other ML strategies as of late has driven specialists toward investigating progressively proficient and clever systems that improve ADASs with sensor combination capacities.

Another ADAS include utilized in a couple of creation vehicles is the capacity to keep the vehicle inside the path lines out and about However, path lines are one of the hardest street highlights to identify on account of their irregularities, for example, being various hues, blurred, and in some cases not by any means present. Current techniques to distinguish path lines frequently utilize a canny change to discover the edges in the picture. When the edges are discovered, a Hough change is utilized to contrast the lines with a solitary slant to decide whether they are for sure path lines [2]. The utilization of CNNs is likewise getting famous for path line recognition.

II. CURRENT RESEARCH WORK

a. Static environment

This document describes the processing steps of Dempster Shafer grid mapper. Most steps are sensor independent only the sensor model is different. The GridMapperRadar is a new Runtask. It requires a vehicle pose and requires the SensorModelServer to run, which is dependent on the VehicleConfigServer. Both server tasks provide the parameters of the sensor models. Including the sensor extrinsic, key parameters like detection ranges or resolutions and the probability modulation description.

The general idea of such DST grid maps is to subdivide the area around the vehicle in tiles. Each tile contains information about the corresponding amount of free, occupied and unknown probability that is estimated from the sensor signal. The size of the tile itself and the overall map size is dependent on the use case, while for highway scenarios resolution is less important, compared to parking functions, while the overall map size needs to be much larger. In general, those grids transform a sensor specific signal into a generic sensor independent representation based on a sensor model that assigns free and occupied probabilities to sensor detections. Also, the temporal accumulation of sensor signals is a key component of the chosen approach to increase the robustness to sensor noise and also increasing the accuracy of the static obstacle description. Furthermore, it provides static environmental information close to the ego vehicle that is currently outside of the sensor detection range of the mounted sensors.

Based on the DST grid maps a variety of high-level signals about the static environment can be extracted. The most common ones are road boundaries, drivable free space around the vehicle and static obstacles. Due to the generic principle ofthis representation fusion algorithms can be used to increase the overall availability and accuracy of such data.

As most probability-based methods also the DST grid maps assume statistical independence of the provided input data. Although the overall algorithm is robust, it should be guaranteed as good as possible. This basic assumption is e.g. violated at stand still or based on the processing stages done on the sensor itself.

The current implementation of the DST grid map is designed for the static environment only. To avoid artefacts in the representation (moving objects will produce obstacle tails) all dynamic obstacles should be removed from the input data.

For the accumulation of sensor data over several measurements, the module requires with respect to the used map size a precise and consistent vehicle position. Otherwise obstacles may get larger than in reality or in worst case are erased by implicit free space. finally a common time basis is assumed to relate the individual sensor measurements to the vehicle position. This is especially important due to the asynchronous operation of sensors and processing units.If this assumption is violated the accumulation of data over time is strongly impaired.

Each measurement point needs to be assigned to an obstacle and/or free confidence. This confidence is interpreted as probability of existence and is provided by this probability assignment framework. Beside the directly measured information, also implicit ones (mostly free space) can be inferred. Inside this framework it is handled by different matrices of probabilities. Basically, those probabilities are heavily influencing the performance that can be achieved, with respect to achievable detection ranges and potential errors (false positive and negative).

The general idea behind the probability assignment framework is to modulate the sensor degradation with respect to distance and angle of the objects. Additionally, a complex modulation was needed based on a low number of parameters. For efficiency reasons the probability distributions for direct (mainly obstacles, because many sensors provide only coarse height information) and indirect information are calculated once during the initialization.

All explicit and implicit probabilities of a single sensor scan is inserted into a polar (radial and azimuthal coordinate, instead of Cartesian x,y) sensor map. If the original sensor data provides also height information it might be used to distinguish between explicit free and obstacle points, but per definition those polar maps are just 2-dimensional.

b. Sensor fusion

Sensor fusion is a cumulative approach, Error in sensor measurements when fused will give an inaccurate state.

Probability of loss of track is more as error accumulates and track smoothness is not maintained.

Kalman filter helps us in giving the best estimate by minimizing the mean squared error.

State prediction

$$\hat{x}_{t|t-1} = \hat{x}_{t-1|t-1} F_t \quad (1.1)$$

$$P_{t|t-1} = F_t^T P_{t-1|t-1} F_t + Q_t \quad (1.2)$$

State updating

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t (z_t - H_t \hat{x}_{t|t-1}) \quad (1.3)$$

$$P_{t|t} = P_{t|t-1} - K_t H_t P_{t|t-1} \quad (1.4)$$

$$K_t = P_{t|t-1} H_t^T (H_t P_{t|t-1} H_t^T + R_t)^{-1} \quad (1.5)$$

Here,$\hat{x}_{t|t}$ which is the posterior estimate is our final result.

$\hat{x}_{t|t}$is also a fused posterior estimate i.e. the error of the fused

Traffic Participant vector is minimized to give a better estimate.

The joint Probability data association is a measure of the **distance** between a point P and a distribution D.

Measuring how much standard deviations away measurement is from the mean. It indicates the fit of the distribution. i.e how well the measurement fits with the mean. this is the mahalanobis distance.

$$\boldsymbol{dij} = \sqrt{(\boldsymbol{z_i} - \square)\boldsymbol{S^{-1}}(\boldsymbol{z_i} - \square)^{\boldsymbol{T}}} \quad (1.6)$$

The deterministic distance value itself cannot say the degree of association. Hence degree of association is evaluated be its probability given by

$$P_{ij} = \frac{dij}{A_{ij} + A_{ji} - dij} \quad (1.7)$$

The covariance intersection filter is given by the convex combination

$$x = \sum_{n=1}^{N} \omega_n S_n^{-1} x_n \quad (1.8)$$

The ω_n is unknown which indicates the weight of each measurement

while fusing

$$tr(S_1)\omega_1 - tr(S_2)\omega_2 = 0 \quad (1.9)$$
$$\omega_1 + \omega_2 = 1$$

The lower hessenberg form

$$\begin{bmatrix} tr(S_1) & -tr(S_2) \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad (1.10)$$

Two measurements weight constraint

$$\omega_1 = \frac{tr(S_1)}{tr(S_1) + tr(S_2)}, \quad (1.10.1)$$

$$\omega_2 = \frac{tr\,(S_1)}{tr\,(S_1)+tr\,(S_2)} \quad (1.10.2)$$

c. Object detection and event response(OEDR)

OEDR takes entirely its support with vision systems like camera where the image needs to be preprocessed. This includes cross road detection, traffic sign detection, pedestrian detection, lane detection etc. This is done once per frame. In this step, the integral histogram of the whole image is calculated and stored to the external memory. The DSP is used for this calculation step.

Next, the cells, blocks, and matching are to be calculated, once for every patch. The cells are loaded from the already preprocessed integral histogram. From the cells, the blocks can be calculated and normalized. These steps are done on the DSP. However, the following matching itself (SVM) is done on the EVE coprocessor, as it mainly consists of a lot of parallel MACs. This way, the DSP can prepare the blocks for the next patch, while the EVE is processing the SVM from the previous patch in parallel.

After all patches have been processed, the post-processing step follows. In this step, all matching hypotheses are sorted out and prepared for the following LRF algorithm. This post-processing essentially needs almost no processing power compared to the other parts. Therefore, it is performed on the DSP, after the whole patch processing is complete.

As a first step, the input image has to be pre-calculated to build the integral histogram. This is done by the DSP once after the start of every new frame. The input image is typically loaded from the external memory, and the integrated histogram stored back to the external memory. However, the memory locations can be chosen arbitrarily by the user.

The histogram consists of eight different directional bins, where the length of the gradients of every pixel is added to the corresponding directional bin. The three different steps, consisting of Sobel filtering, binning, and integration, are described in detail in the following sections

To get the horizontal and vertical gradient of the pixels, a Sobel filter is applied to every pixel of the image. A simple filter operator of the form [1 0 -1] is used to calculate the gradients. As there is not enough data available to calculate the gradient for the border pixels, the gradient calculation is omitted for those pixels.

As the pixel values are stored as 12-bit unsigned values, the resulting gradients are 13 bits wide. The calculated gradients are stored line-wise left to right from top to bottom, starting with the pixel (1,1). Four bytes are needed for every pixel, two for each gradient direction.

Using the horizontal and vertical gradients, the length of the gradient is calculated. This could be done using the L2-norm. However, the following approximation is used for the gradient length calculation:

$$\|\vec{x}\|_2 = \sqrt{\sum_{i=1}^{2} \vec{x}_i^2} \approx \frac{3}{8}\cdot(|x_1|+|x_2|)+\frac{5}{8}\cdot\max(|x_1|,|x_2|)$$
(1.11)

Then, the direction is calculated and the length of the gradient is added to the corresponding directional bin. In total, eight different bins are used. The eight bins are spanned over the upper hemisphere and expanded to the lower one. Therefore, each bin covers an angle of $\pi/8$:

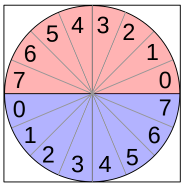


Figure 1: Distribution of the bins

To assign a pixel to a bin, the absolute value of the two gradient values is calculated first. Then, those values are used to assign the gradients direction to a bin of the first quadrant (0-3). Depending of the sign of the two gradient values, the final bin can be assigned by expanding from the first quadrant to all four quadrants.

The result of the binning process is the length of the gradient (12 bits) and the bin number (ranges from 0-7) where the gradient corresponds to.

The support vector machine is used to match every hypothesis of the patch against a given set of coefficients. The coefficients have the same dimensions as a hypothesis. Matching is performed by calculating the dot product of the hypothesis values and the coefficients. The coefficients are determined by training of the algorithm against known pedestrians and therefore known at compile time. The coefficient values are stored in exactly the same order as the block values. But as the coefficients are represented by 9bit values, 2 bytes are used for every coefficient value:

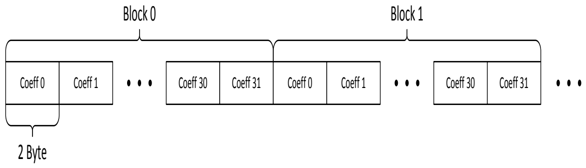


Figure2: Coefficient values in memory

The hypotheses are built by stepping by the block width and height through the patch. This means that the same block is used by several hypotheses, each time as a different relative position, and therefore matched agains a different coefficient block. In the current implementation, a hypothesis size of 5 blocks in width and 11 blocks in height is used. Therefore, a single block can be used by up to 55 different hypotheses. The hypotheses are stepped line-wise from top-left to bottom-right through the patch. The following figure assumes a patch width of n hypotheses, which would equal to a hypothesis width of n+4 blocks:

Evaluated results

In fig 3 the longitudinal and in fig 4 the lateral position of the radar sensors and the fused track is plotted over time. The good consistency of radar data and fusion result can also be seen here.

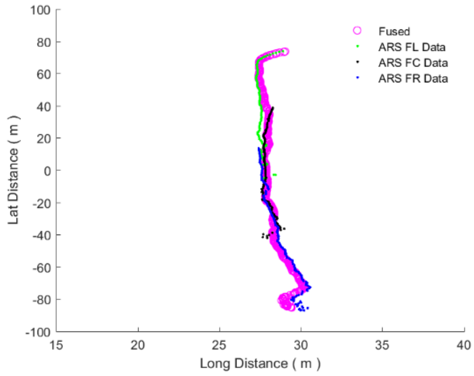


***Figure3**: lateral vehicle scenario estimate*

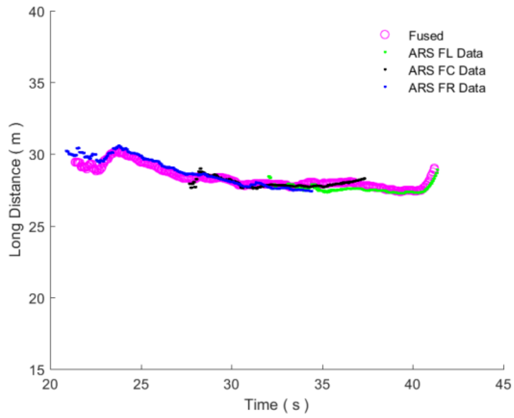


***Figure4:** longitudinal vehicle scenario estimate*

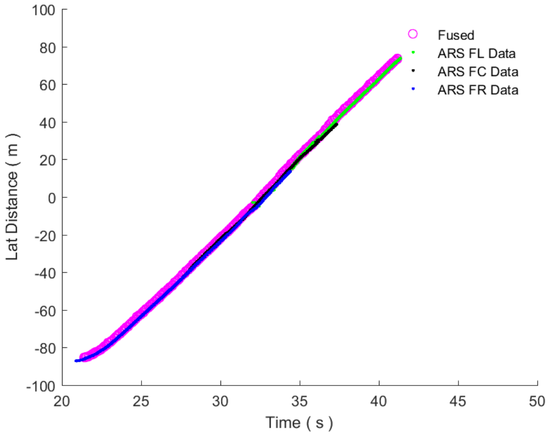


***Figure5**: position vehicle scenario estimate*

In 6the longitudinal and lateral position of the three ARS4xx radar sensors, the Mono Camera and the corresponding result of the CEM fusion can be seen.

It is visible that the frontal radar delivers a constant track from a distance of more than 150m. The two side-mounted radars deliver a constant track from 60m on, almost at the same distance as the Mono Camera.slight differences between the lateral position measurements of the radar sensors can be seen, which is to explain by different mounting positions and orientations.The result from the CEM fusion covers and smoothens the sensor data very well.

In fig 7 the longitudinal position and in 6the lateral position is shown over time. Differences between the sensors (radar and camera) can also be seen here, as expected especially in longitudinal direction. Nevertheless, the fusion result describes the sensor data quite well.

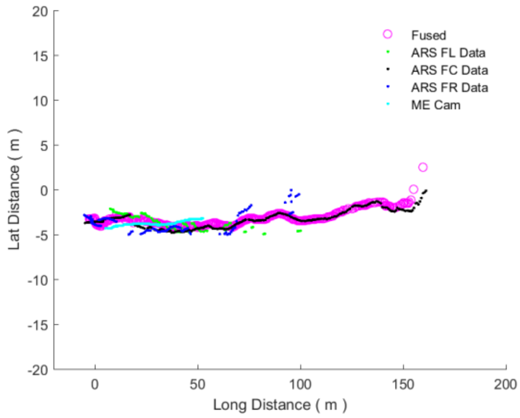


***Figure6:** lateral vehicle scenario estimate with radar,camera*

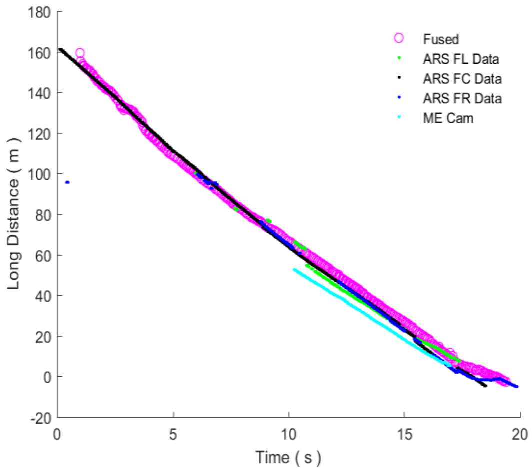


Figure7: *longitudinal vehicle scenario estimate with radar,camera*

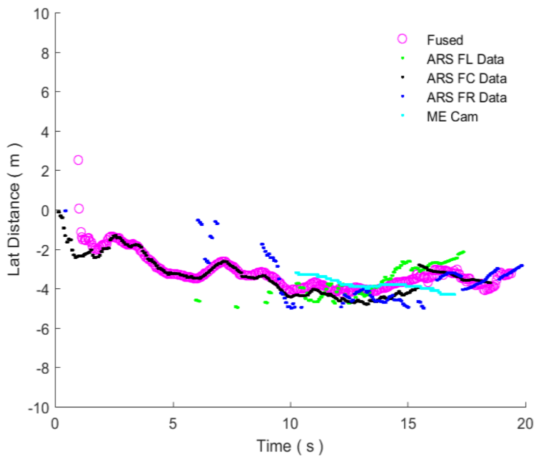
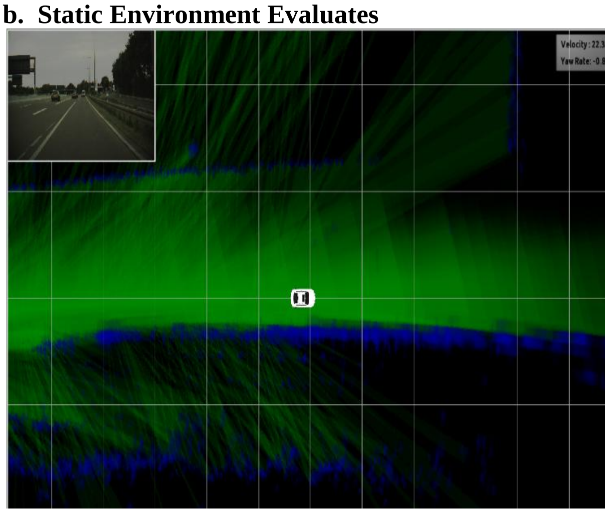


Figure8: *positional vehicle scenario estimate with radar,camera*

b. Static Environment Evaluates



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III. CONCLUSION

In this paper we presented the results of two prominent areas ofADAS variants. Sensor fusion (radar and camera) kalman filter and covariance intersection have yielded the best results for the longitudinal scenarios thus maintaining the track consistency. However, an improvement can be made with the lateral scenarioswhere camera and radar inputs are random by using particle filters.

Road boundary detection using dempster Shaffer grid is a innovative attempt we made to eliminate derivative complexity and thus use Bayesian technique for accurate boundary detections and is robust under all-weather conditions.

Future work

Sensor fusion can be implemented by combing particle filter and intersection of covariance's to yield more accuracy. road boundary can be extended by combining third order polynomial with spline to detect lane equally as well.

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