Statistical Modelling of Multi-Sensor Data Fusion

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***Abstract*— Increasing the reliability of sensor data, especially in collision avoidance applications, is of great importance and involves the development of different sensor fusion methods. To reduce the limitations and disadvantages of common fusion methods and their challenges with respect to highly automated driving, this paper proposes a statistical model of sensor data distribution and a new algorithm for multi-sensor data fusion according to specific detected driving situations. To this end, a scene catalogue consisting of four different traffic scenarios is modeled in a specific ADAS simulator. The analysis showed that, considering a specific road situation, the combination of sensor data as well as its training resulted in an increase in detection performance and position accuracy.**

I. Introduction

As stated by the Eurostat website, total fatalities due to road traffic accidents in the EU saw a 45 % decrease between 2004 and 2014, but even considering this decrease, slightly over 25 thousand persons lost their lives in road accidents in 2014 [1] (see also [2]). Therefore, increasing road-related safety is a very pressing issue that concerns not only the European Commission, but also car manufactures and researchers in the field. In this regard, sensor technologies have been used actively and/or passively to perceive surrounding vehicles' for Advanced Driver Assistance Systems (ADAS) in the ITS domain, and more particularly in collision avoidance applications [3-5].

In vehicle engineering in general, and in active safety in particular, the reliability of sensor data is critically important. To have a real picture of a vehicle's environment and in order to make the system more robust, multi-sensor data fusion (MSDF) is used frequently [6], [7]. To increase accuracy and reliability of the active safety systems, it is necessary to know the distribution probabilities of the sensor data. To address the limitations, disadvantages and challenges with respect to highly automated driving of the common fusion methods, this paper proposes a new algorithm for multi-sensor data fusion based on a statistical model of sensor data distribution.

In the term multi-sensor data fusion, "multi-sensor" reflects that the data fusion integrates multiple sensors. The second part involves combining data or information in order to estimate or predict the state of a considered object [8]. There are other terms for multi-sensor data fusion, such as data fusion, sensor fusion, multi-source integration and information fusion [9], [10]. The origin of sensor fusion technology lies in the field of military technology, but recently, multi-sensor data fusion techniques have been successfully applied to non-military fields like maintenance engineering, robotics, pattern recognition, radar tracking, remote sensing, traffic control, aerospace systems, law enforcement, medicine, finance, metrology, and geo-science [11], [12].

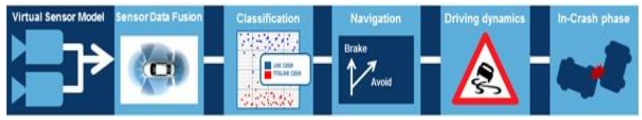

Figure 1. This simulation chain shows the steps that should be considered to develop an autonomous system for decision making. It consists of 6 phases: Simulation, Sensor Data Fusion, Classification, Navigation, Driving dynamics, and In-crash phase.

To approach decision making for an autonomous system using sensors the first step is simulation, where the exact values from all sensors are known. Then it is possible to develop several scenes with different sensor sets and the probability distribution of sensor output can be obtained. Sensor data fusion helps to classify a potentially unsafe situation more precisely by using the virtual sensor model output, so that the system is able to take the appropriate measure, for example by warning the driver. As shown in Fig. 1, more precise sensor data fusion increases the accuracy of the classification of the situation and consequently improves safety by guiding the driver accordingly.

In order to provide a methodology to improve road safety detection-related applications, we define the following hypotheses:

- A mathematical relationship can be determined from the combination of different sensor data and related performance.
- The result of the sensor data fusion algorithm is always closer to reality than the single sensor output.

The first hypothesis means we can find a mathematical relationship between measured distance deviation and real data, depending on the respective driving situation. And the second one states that the distance data obtained by the sensor data fusion algorithm is always closer to reality than the measurements of each single sensor.

This paper is organized as follows: section II presents related works in the field; section III presents the implemented methodology; evaluation results are shown in section IV; section V concludes the paper by summarizing and discussing the work and suggesting future work in this field.

II. Related Work

Numerous projects have been dedicated to the study of MSDF for active safety applications [13-16]. In all of the proposed systems, a limited number of sensors were used and

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 DOI: 10.1109/ICVES.2017.7991925

the focus was on only one specific algorithm. Although the number of sensors in this work is also limited, it can be used in any active safety application.

Some of the algorithms used for MSDF are Dempster-Shafer Theory [17-21], Kalman filter [22-26], Clustering [27], Bayesian rules [28-30], and Fuzzy logic [31]. Most of the works are based on the Kalman filter algorithm due to its noise filtering capabilities and good performance. Authors in [23] compared 3 different algorithms based on the Kalman Filter showing that the state vector fusion performed the best compared to measurement fusion and gain fusion. In [22] continuous-time decentralized Kalman filters (DKF) are used as data fusion devices on local subsystems. In [32] the authors defined the first sensor as the detection sensor and the second as the validation sensor, and then used the algorithms defined in [33] for fusion. The proposed fusion system provided three types of services:

- "Time alignment: to compensate for the individual time delays from several asynchronous sensors and the motion of both the targets and the ego vehicle during these delays".
- "Object state fusion: the combination of several single sensor estimates or measurements into a single estimate".
- "Virtual sensors: the creation of specific estimates that either are not available from a single sensor or cannot be measured at a reasonable cost".

As the authors in [32] stated, the focus of their work was a flexible fusion system that makes it possible to add new sensors to the sensor set. The main task of the proposed fusion method is increasing the accuracy of sensor output, specifically the position of detected objects.

In a further work the authors in [34] used laser and camera sensor combination in order to boost the advantage of laser scanners and mitigate the weakness of camera sensors. To this end, they relied on the counter detection algorithm for camera and clustering for laser scanner.

The work described in this paper also focuses on fusion algorithms based on a laser and camera sensor combination, but considers diverse traffic scenarios and situations. The fusion function is explained in the following section.

III. Methodology

There are usually two steps to develop a new system before putting it into practice in the automotive industry; simulation analyses and estimates of the proposed system's technical developments. Simulation enables developers to overcome possible faults in an early stage [35]. To this end we first generated the scenes through a scenario catalogue simulated on the Scene Suite simulation by IAV GmbH [36]. Then we developed the MSDF algorithm. Before these two stages, sensor selection took place in order to make the simulation as realistic as possible.

A. Sensors Selection

In this study, we focused on laser scanner (lidar) and camera. If a camera is available in 80-90 percent of road situations, adding a laser scanner can cover the remaining percentage, in situations such as dense fog or heavy rain [37].

The decision to use a laser scanner was influenced by its being considered an important sensor for use in future Advanced Driving Assistant Systems (ADAS), as well as the fact that its benefits with respect to realistic simulation have been already investigated [38]. The laser scanner has a variable viewing angle. As its measurements are taken many times with a rotating sensor in all directions, the result is a scanned planar slice. This process can be done many times within one second (5-50Hz). As a consequence it is possible create a real time view of the surroundings [39].

The laser scanner that we modelled in the Scene Suite simulation was based on the specific, real Ibeo Lux sensor that was specifically designed for ADAS applications, which has the following characteristics [39]:

- Range up to 120m
- Up to 3 distance measurements per shot
- Embedded object tracking
- Wide horizontal field of view: 2 layers: 110° (50° to -60°), 4 layers: 85° (35° to -50°)
- Vertical field of view: 3.2°
- Multi-layer: 4 parallel scanning layers
- Data update rate: 12.5/ 25.0/ 50.0 Hz
- Operating temperature range: -40 to 85 ºC
- Accuracy (distance independent): 10 cm

Angular resolution:

- Horizontal: up to 0.125°
- Vertical: 0.8°
- Distance Resolution: 4 cm

Cameras are the most precise mechanisms used to capture data at high resolution. Like human eyes, cameras capture the scene with details that other sensors like radar, ultrasonic and lasers cannot detect.

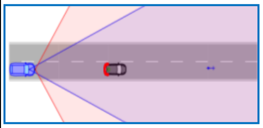
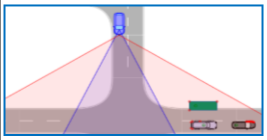
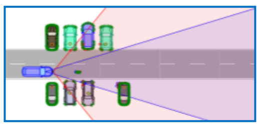
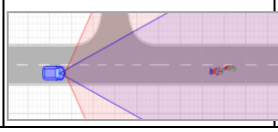
To keep the simulation as simple as possible, as the vision- based device we selected the monocular camera model Magna EYERIS Gen 2.5 (characteristics listed below). The system and analytics of this type of camera can identify lanes, pedestrians, many traffic signs and other vehicles in the path with good accuracy [40].

- Field of View 46 °
- Initial Vehicle Detection(max) 70-90 m
- Vehicle Tracking(max) 130 m
- Pedestrian Detection Day 45 m

B. Scenario Catalogue

Modelling and simulation has proven to be very important in evaluating systems, and are considered the first steps in introducing and developing a new system [35]. To this end, we simulated four different complex scenarios in the ADAS catalogue (via IAV Scene Suite), which we then

TABLE I. SCENARIO CATALOGUE

No.	Scenario	Illustration	Description
1.	Overtaking		Ego vehicle is following a car. Car is following a motorbike. Motorbike breaks heavily. Car overtakes the motorbike.
2.	Turning		Ego is turning left. Two cars are in the lane. There is an object beside the road.
3.	Parking Area		Ego is driving with constant speed in a parking area. All cars are parked. A pedestrian runs into the street.
4.	Merged Objects		Ego is following to motorbikes with different speeds.

analyzed and evaluated (Table 1). The color code of the ego vehicle is blue. Two sensors (laser scanner and camera mono) are mounted on the vehicle. The detected area of the laser scanner is red and the detection range of the camera is shown in blue.

C. *Proposed Fusion Method*

There are two main variables to resolve when designing MSDF: the representation of sensor output and the fusion method of multiple sensors [17]. To deal with the first issue, IAV Scene Suite is used, where the sensor outputs are available as an .xml file. The proposed fusion method is based on a statistical analysis of sensor data and can be summarized as follows (Fig. 2).

- For each scenario in all timestamps the mean value of sensors' output for each detected object is calculated.
- The difference between the mean value and the exact position of each detected object is considered. (An example for overtaking scenario is illustrated in Fig. 3.)
- To reduce the deviation from the exact position a deviation function is calculated. (An example for overtaking scenario is illustrated in Fig. 4.)
- The deviation function is added to the mean value.
- The calculated function(s) is/are saved in a library for each specific situation. Running again the simulation calls the related function to fuse the sensor's data accordingly.

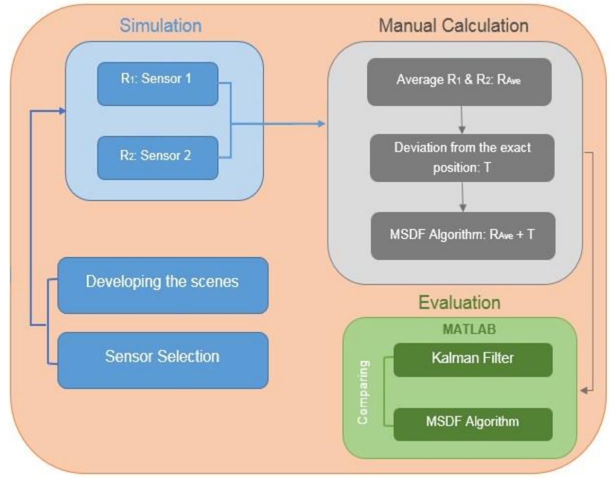


Figure 2. Overview of the proposed fusion method

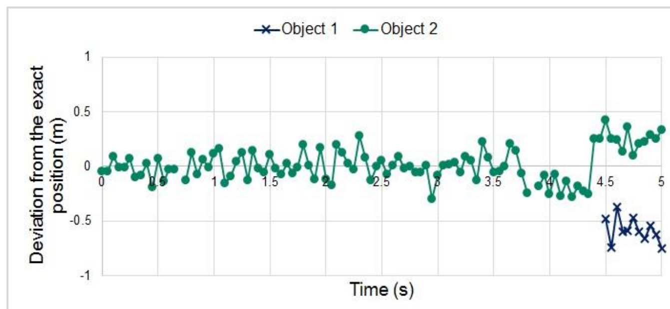


Figure 3. Overtaking scenario. Differences between the exact positions of random points detected by the laser scanner. Blue points are related to the object 1 (motorcycle), which can be detected after overtaking the car. The change in vehicle points (shifting up) and motorcycle (shifting down) are related to their speed. Both the vehicle and the motorcycle are decelerating.

D. *Evaluation*

We evaluated the fusion model for accuracy and reliability of the fusion algorithm comparing it with single sensors and the most common fusion algorithm, the Kalman Filter. To determine accuracy, the sensor output from the simulation is compared with the exact position of the related object by plotting them on a chart. The resulting calculated fusion is also plotted on the same chart. The Kalman filter was applied on the sensor output from the simulation for data fusion using MATLAB software. First, the Kalman filter code was developed and then Kalman filter fusion results were obtained by using the sensors output as the MATLAB code input.

E. *Mathematical Model for MSDF*

To mathematically represent the behavior of the MSDF system and determine the structure of the fusion model through equations, we analyzed the information obtained from the four mentioned scenarios (Table 1). The resulting specification is described in the next section.

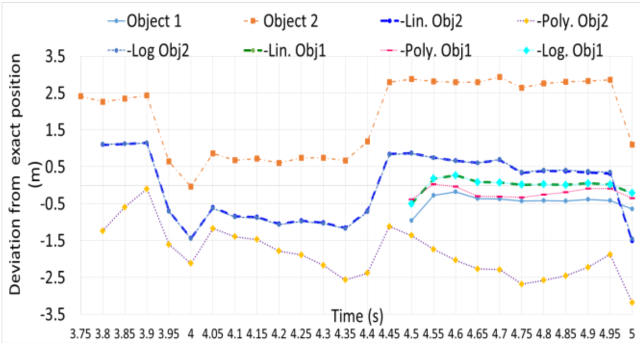


Figure 4. Overtaking scenario. Deviation of the object 1, the motorcycle (blue) and object 2, the vehicle (orange), are shown and compared with different T functions. For both objects, polynomial equation caused a high deviation. However, linear and logarithmic equations caused a deviation decrease.

IV. RESULTS

A. *MSDF Algorithm*

After detecting the specified scenario, following equations (1) and (2) were used to find the most reliable position;

$$P = R(ave.) + T \quad (1)$$

P is the exact position of each object (average of all detected points by the perfect sensor related to each object). T is the deviation function.

$$R(ave.) = Ave.(R1,R2) \quad (2)$$

Where, R1 (laser scanner) and R2 (camera) are the average of all points that sensor 1 and 2 detect in each time step (t). This means that instead of having many points illustrating an object, we have an average point to show that object.

$$R1 = Ave.(R1)t \quad (3)$$

$$R2 = Ave.(R2)t \quad (4)$$

Each scenario might be divided into different situations. Therefore a different fusion function (T function) should be taken into account for each situation:

1) *Overtaking Scenario*

a) *Before overtaking (ego is following a car that has constant speed)*

$$T = 0.0083\tau + 2.509 \quad (5)$$

b) *During overtaking*

- Object with positive acceleration

$$T = -18.559t3 + 248.56t2 - 1103.5t + 1625.3 \quad (6)$$

- Object with negative acceleration

$$T = -5.0418t2 + 47.871t - 114.22 \quad (7)$$

2) *Turning Scenario*

Due to lack of information from the camera, there is no need for fusion. Only a deviation function can be used to reach a better result.

3) *Parking Area Scenario*

$$T = -0.20827t - 1.0368 \quad (8)$$

4) *Merging Scenario*

At first, object 1, the occluded object that has more distance from the ego vehicle at the beginning, is occluded by the object 2. Then some points from object 1 become detectable, and by increasing the distance between the two objects and the ego vehicle, both objects 1 and 2 are merged, being detected as one vehicle.

a) *Occlusion situation:*

$$\text{Object 1: } T = 0.4332t + 0.0323 \quad (9)$$

$$\text{Object 2: } T = 0.105t + 0.9433 \quad (10)$$

b) *Without occlusion:*

$$T = 0.01025t + 0.96745 \quad (11)$$

c) *Merged objects*

$$\text{Object 1: } T = -0.58t3 + 7.1481t2 - 29.077t + 39.914 \quad (12)$$

$$\text{Object2: } T = -0.6122t4 + 9.9818t3 - 60.563t2 + 161.88t - 159.79 \quad (13)$$

B. *Evaluation Results*

Following the approach described in section III D, results regarding the accuracy and reliability of the developed fusion algorithm compared to single sensors and the Kalman filter are shown in Table 2. The values were calculated as the average of the absolute distance between the detected/estimated position and the exact position over the time for each object in each scenario individually. Results show a considerable gain in precision achieved by the proposed sensor fusion model compared to single-sensor(s). Furthermore, our model performed better than the Kalman filter in 6 out of 7 cases. Fig. 5 and Fig. 6 depict as showcase the overtaking scenario for individual sensors and Kalman filter respectively.

V. CONCLUSION AND FUTURE WORK

The methodology described in this paper provided the results to answer the hypotheses defined in the introduction and determine which sensor data fusion algorithm provides the best accuracy and reliability, considering the properties of different sensor technologies and relevant situations for automotive systems in road traffic.

For each scenario there is a specific relationship between sensor output and the exact position that was calculated by the functions used. Results showed that the sensor data fusion algorithm is always closer to reality than the single sensor input (Fig. 5).

TABLE II. NUMERICAL RESULTS; COMPARING ACCURACY OF THE PROPOSED MSDF ALGORITHM AND KALMAN FILTER.

		Average of absolute distance from the exact position (m)			
Scenario	*Object*	*Laser Scanner*	*Mono Camera*	*MSDF Algorithm*	*Kalman Filter*
Overtaking	1	0.45	0.99	0.14	0.12
	2	2.37	2.34	0.15	0.36
Parking Area	3	0.75	1.76	0.24	0.82
	7	0.72	1.71	0.32	0.77
	P	0.93	1.95	0.17	0.40
Merged Objects	1	0.59	0.98	0.12	0.87
	2	0.72	1.26	0.09	1.04

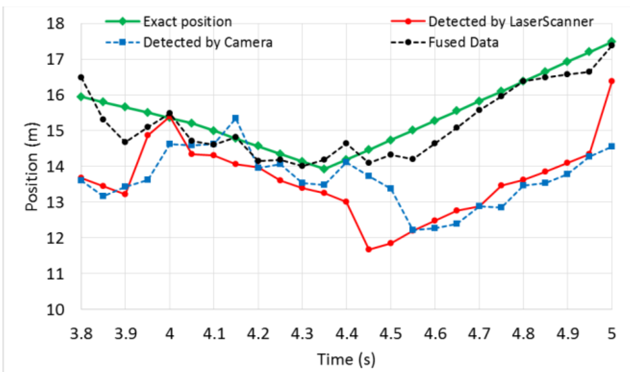


Figure 5. Comparing results of individual sensors and the fused data by MSDF algorithm with the exact position for the vehicle object 2 when it is overtaking (from 3.7 to 5 s).

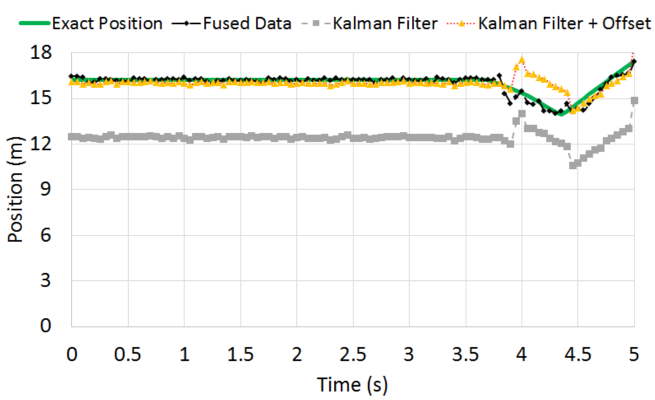


Figure 6. Overtaking Scenario; Comparing fusion results of using Kalman filter and the proposed MSDF algorithm for vehicle objet 2.

As it is shown in the picture, the sensors' outputs (blue and red points) have more than 2m deviation from the exact position shown as the green points. In contrast, the proposed fusion algorithm, which is explained in III C (black points), provides less deviation from the exact position (<1m). We also showed that the proposed fusion algorithm depending on a currently detected driving situation reveals a better performance than other algorithms like the Kalman filter (Fig. 6). Comparing yellow points (Kalman filter result) with the green ones (the exact position) shows more than 2m deviation, where there is only some cm difference between the exact position and our proposed algorithm result (black points).

In contrast to the single sensors, the accurate outcome is the result of reducing sensor shortcomings like delay, short range, etc. and increasing their strength, such as larger field of view (FOV). However, when compared with the Kalman filter, the results are similar or better in specific situations where the vehicle object is accelerating.

Future work will focus on the extension of detection sensors and the addition of V2X communication in further traffic scenarios.

ACKNOWLEDGMENT

This work was supported by IAV GmbH (Ingenieurgesellschaft Auto und Verkehr).

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