Introducing a Sensor Network for Advanced Driver Assistance Systems Using Fuzzy Logic and Sensor Data Fusion Techniques

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Driving, one of our daily activities is a complex task involving a great amount of interaction between the driver, vehicle and environment. Drivers regularly share their attention among operating the vehicle, monitoring traffic and nearby obstacles, and performing secondary tasks such as conversing, adjusting comfort settings (e.g. temperature, radio). The complexity of the task and uncertainty of the driving environment points up the growing demand on automotive safety systems, which aim for a significant contribution to the overall road safety. In this paper we implement an applicable framework for advanced driver assistance systems based on fuzzy logic and multi-sensor data fusion techniques to reduce the driver's workload and to help lessen the danger of road incidence. Therefore we introduced a novel deployment for a network of multi-sensors such as Radar, Laser, Ultrasound and Vision which are mounted on a host vehicle with a specific tendency to degree of driver's vigilance. The proposed method is applied on some real driving tasks such as following and overtaking a vehicle with a safe speed and distance. The results are improved by a moving window filter and enriched by some MATLAB and *Fuzzy*TECH simulations.

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1 INTRODUCTION

As humans and animals have evolved, they have developed the ability to use multiple senses to help them survive. For example, assessing the quality of an edible substance may not be possible using only the sense of vision; the combination of sight, touch, smell, and taste is far more effective. Similarly, when vision is limited by structures and vegetation, the sense of hearing can provide advanced warning of impending dangers. Thus, multisensory data fusion is naturally performed by animals and humans to assess more accurately the surrounding environment and to identify threats, thereby improving their chances of survival [1], [2]. That's why in recent years, significant attention has focused on multisensor data fusion in a wide filed of sciences.

Multisensor data fusion is a rapidly evolving research area that requires interdisciplinary knowledge in control theory, signal processing, artificial intelligence, probability and statistics, etc. Multisensor data fusion refers to the synergistic combination of sensory data from multiple sensors and related information to provide more reliable and accurate information than could be achieved by using a single, independent sensor [3]. Actually Multisensor data fusion is a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data from single and multiple information sources. The results of a data fusion process help users make decisions in complicated scenarios.

Although, data fusion methods were developed primarily for military applications, however, nowadays, these methods have been applied to civilian applications, medical, robotics and intelligent transportation systems, etc. [4]. In Vehicle Navigations, the goal is to support the human operator in critical decision making situations or even eliminate the human operator altogether. Such systems are only desirable if they are able to perform at least as good as the human operator. For example fusing various sensors such as $3D$ cameras, sonar sensors and millimeter wave radar has the advantage of maintaining “higher reliability even in inclement weather or dusty conditions”[5], [6].

The complexity of the driving task and uncertainty of the driving environment make driving a very dangerous task, as according to a study in the European member states, there are more than $1,200,000$ traffic accidents a year with over $40,000$ fatalities. This fact points up the growing demand for automotive safety systems, which aim for a significant contribution to the overall road safety. For this reason, recently, there are an increased number of research activities focusing on the Driver Assistance System (DAS) development in order to reduce the driver's workload and prevent accident driving and several types of safety systems have therefore been proposed to help lessen the danger and assist the driver [7]. Current technology field of the automotive industry focuses on the development of active safety applications and advanced driver assistance systems (ADAS) instead of passive safety systems. Passive safety systems such as seatbelts and airbags provide protection in the case of collision; more recently however, active safety systems have been introduced to help the driver avoid collisions in the first place. We can name some new active safety systems such as lane departure warning and rear-end collision avoidance systems that have been introduced, recently [8][9]. These active safety systems are required to interact much more with the driver than passive safety systems, creating a closed loop between driver, vehicle, and the environment. Examples of such systems could be found in the Laboratory for Intelligent and Safe Automobiles (LISA) [10].

Generally speaking, an Advanced Driver Assistance system (ADAS) shall support the driver in his/her task to drive the vehicle providing additional information or warning when encountering any dangerous situation. The system should be equipped with various types of sensors to observer the environment around the vehicle. For example, radar and laser scanners are sensors used to measure distance and velocity of objects, and video cameras are used to detect the road surface and lane markings or to provide additional visual information [11].

2 STATE OF THE ART SENSORS APPLICABLE FOR ADAS

Competing and complementing technologies in vehicular surround sensing and surveillance that are integrated in our fusion approach in the host vehicle are: LIDAR (Laser Intensity Direction And Ranging), RADAR (RAdio Detection And Ranging), Ultrasonic, and Video cameras (based on CCD or CMOS chips including near-infrared sensitivity)[8][21]. In order to become more familiar with our final architecture of our proposed ADAS system, let's have a short description on current state of the art sensors in real world. An intelligent system most has a multi-sensor data fusion system designed to detect objects in front of the host car. This multi-sensor data fusion system consists of a set of internal and external sensors from where information is fused within a single data fusion unit.

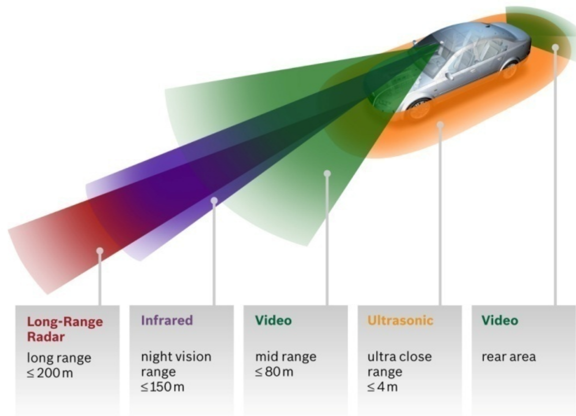

FIGURE 1
Wide sensing area around the host vehicle, thanks to multi sensory

Internal sensors give information about the host vehicle state, such as its velocity and steering angle information while external sensors (Laser, Radar, and image sensors) sense information external to the vehicle, such as the detection of obstacles. The ultimate objective is to provide a safe detecting area around the vehicle with a high degree of certainty. Figure 1 shows a typical covering area around the host vehicle with some overlapping area for better decision making (More details in section 4). All the sensors and the data fusion unit could be connected via CAN buses. A system specification of CAN messages has been built according to external sensors constraints. [12].

3 FUSION METHODOLOGY

In this research we provide a fuzzy logic algorithm to fuse and manage the gathered data both from driver scenes (human's sensors) and from vehicle-mounted sensors (physical sensors). The Fuzzy Logic Supervisor (FLS) is a steering algorithm for managing the overall direction, speed and acceleration of a vehicle during a traveling in a road [13]. Despite of public image that may think the driver is the supervisor of the vehicle, we would like to show by managing and fusing both the driver commands (as primary data) and physical sensors (as auxiliary data) a well-trained FLS can be the main supervisor.

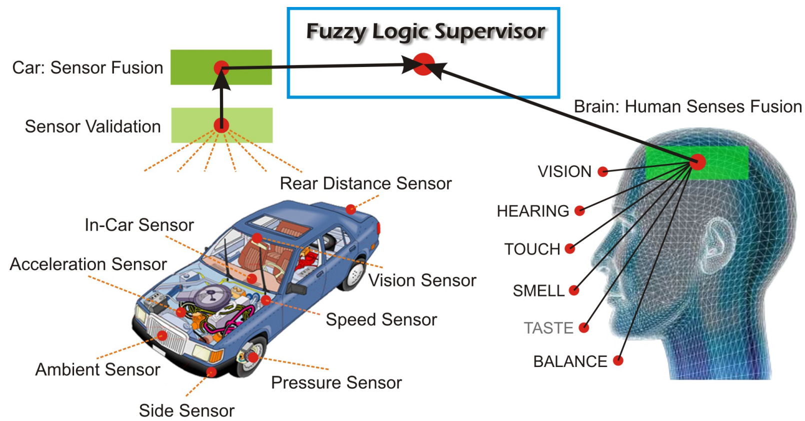

FIGURE 2
Hybrid multi data fusion (Human Sensors Fusion + Physical Sensors Fusion)

Keep in mind that the FLS action is different from autopilot and autonomous driving. This is a new approach and a hybrid data fusion algorithm which make better and safer performance in a vehicle driving. That means the FLS will intervene to actuators in case of driver's drowsiness or dangerous situations. Figure 2 shows a graphical image for our approach. Here we describe the FLS action in detail.

Step1 : The proposed architecture performs both the tasks of sensor validation and sensor fusion. As depicted in figure 2, left inputs to this architecture are the raw data from sensor readings and the output is a corrected value after sensor validation, time alignment and sensor fusion. This value can be used for the FLS along with driver decisions as “brain fusion”.

Step2 : After time alignment and sensor validation we have a real value from car sensor fusion and a real value from human senses fusion by brain. But which of them are more important for next departure decision of the vehicle? In this section we use a simple but more efficient weighted average fusion method with the following formula:

$$\hat{x}(k+1) = \lambda\hat{x}(k) + \alpha x_1(k+1) + \beta x_2(k+1) \tag{1}$$

where $\hat{x}(k+1)$ is the new determined value of hybrid sensor fusion to command the vehicle, $\hat{x}(k)$ is the previous value, $x_1(k+1)$ is value from driver side and $x_2(k+1)$ is the value from car sensor side. λ , α , β are the importance factor for each term respectively, while $\alpha + \beta + \lambda = 1$. After 5 hours driving and recording more than 5000 speed samples in time intervals of 3 seconds, it is found that mean deviation of speed at time $t+1$ cannot exceed more than $\%60$ than the speed at time t. In other word $MAX(v_{t+1}) = \pm 1.6 v_t$ and at least $\%40$ of vehicle's speed at time $t{+}1$ depends on its previous speed at time t. So we considered the constant value of 0.4 for lambda and a flexible value for α and β; so the final equation is as:

$$\hat{x}(k+1) = 0.4\hat{x}(k) + \alpha x_1(k+1) + (0.6-\alpha)x_2(k+1) \qquad (2)$$

This means the FLS as a predictor make determines the next value and decision based on the degree of driver's awareness and sensors output similarity. On the other word any perturbation in each of them, will lowers α or β respectively. So we define 20 sub rules and 4 essential fuzzy rules as below:

- IF driver is High-aware then α is high
- IF driver is Low-aware then α is low
- IF driver is Medium-aware then α and β are medium
- IF both driver and car sensors are High-aware then $\alpha = 0.4$ and $\beta = 0.2$.

We used a standard Gaussian function to form the input membership and triangular functions for output membership function of fuzzy logic supervisor block.

Step3 : Now, we are going for more detail. All sensor values are assigned a confidence value. According to our need (e.g. determining next speed, direction, or braking pressure) this confidence value depends on the specific sensor characteristics, the predicted value, and the physical limitations of the sensor value. The assignment takes place in a validation gate which is bound by the physically possible changes of the system [14]. Elapsing the time and according to last overall value determined by the FLS, the confidence value of each sensor changes from 0.0 to 1.0. That means if a specific sensor value is more similar to FLS value scope, then the confidence value increases to the limit of 1.0 and if value gathered by a specific sensor is less similar to FLS value scope, then it decreases to minimum confidence value of 0.0 and in this case this sensor may be eliminated in next evolution.

The confidence value changes in a feedback system like figure 3.

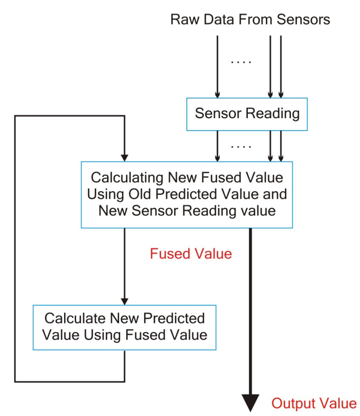

FIGURE 3
Algorithm of fuzzy sensor validation and fusion

Step4 : In the case of multisensor feature-level fusion, features are extracted from multiple sensor observations and combined into a single concatenated feature vector that is input to FLS. Finally fusion is performed through a weighted average of confidence values and distance measured as

$$X_f = \frac{\sum_{i=1}^{n} y_i \sigma(y_i)}{\sum_{i=1}^{n} \sigma(y_i)} \tag{3}$$

where X_f is fused value, y_i are Measurements and $\sigma(y_i)$ are Confidence values.

Considering all mentioned relations, we have:

$$\hat{x}(k+1) = 0.4\hat{x}(k) + \alpha x_1(k+1) + (0.6-\alpha)\frac{\sum_{i=1}^{n} y_i \sigma(y_i)}{\sum_{i=1}^{n} \sigma(y_i)} \tag{4}$$

Our approach has condensed two main benefits:

- Giving 40% importance degree to previous state in order to preventing sudden changes for the next state of the vehicle
- Possibility to change importance degree of gathered data from the driver and car sensors.

That means if the driver command is more similar to the predicted value by the FLS, so α limits to its maximum value (0.6) and if the driver commands are illegal or not mindfully, so the control switches to sensors and β or $(0.6 - \alpha)$ limits to its maximum value; all of these, direct the vehicle to a smooth and safe driving. In next section, we provide a simulation for our method. The above methodology is a general approach capable of adapting with any vehicle and any sensor assembly configuration.

4 OPTIMUM SENSOR SELECTION /ASSEMBLY

Image sensors have some drawback and advantages, such as low ability of sensing depth and higher ability of discrimination than LIDAR and radar. Radar shows limited lateral spatial information because it is not available at all, the field of view is narrow, or the resolution is reduced at large distances. Although LIDAR has a wide view field that solves part of the previous problems, there are other problems such as low ability of discrimination, clustering error, and recognition latency. These restrictions of the different types of sensors cause more attention to sensor fusion for object detection and tracking [15]. Several researchers, has been performed various type of sensors as well as various assembly configuration for better performance [8][7][11]. By consideration of advantages and drawback of each sensor in different weathers and situations, here we offer an optimal sensor selection and sensor deployment as figure 4.

In this scenario, 16 object detecting sensors in 4 main types of state of the art sensors are considered:

- One Long Range Radar (2nd generation long range radar by Bosch) mounted for front monitoring (R_L) and five Short Range Radar sensors (from M/A-COM / Tyco Electronics) four of them in both sides and one in the front (R_S); Radar sensor are appropriate for both direct ranging and relative speed measuring and low sensitivity to environmental condition.

- Four Laser scanners from IBEO with broad range and wide viewing angle and high angular accuracy, two of them in front and the others for rear side (L).

- Three CMOS cameras INKA-NSC640PG by Aglaia GmbH two in the side mirrors for rear and blind spot coverage and one in the middle of

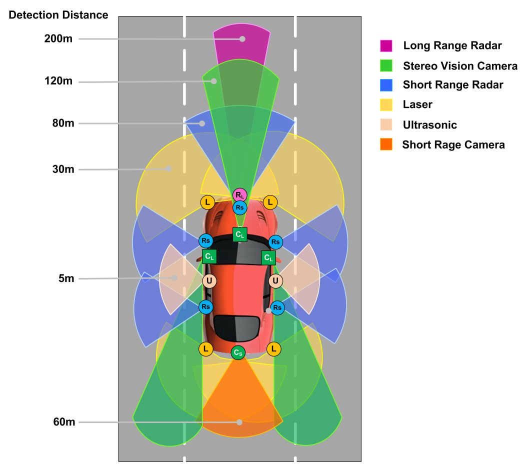

FIGURE 4
Optimal sensor selection and placement with full coverage, redundancy and sufficient overlapping area

the front windscreen to face forward (C_L), and a short range monocular camera for backside (C_S).

- Finally two ultrasonic sensors on both sides (U) which are inexpensive and suitable for near area around the vehicle.

The placement of these 16 object-detecting sensors is based on the following six main functionalities required in any ADAS:

1. Adaptive cruise control (ACC): a system which measures distance and relative velocity to objects ahead of the own vehicle by means of radar or laser sensors [11]

2. Lane departure warning (LDW): In LDW when the vehicle starts drifting off the lane without blinker , because of e.g. “micro sleep”, an adequate warning signal is issued to the driver enabling him to prevent an accident by steering back into the lane.

3. Lane change assistant (LCA): is a system that helps the driver to change the lane while turning right, left or overtaking, in a safe manner.

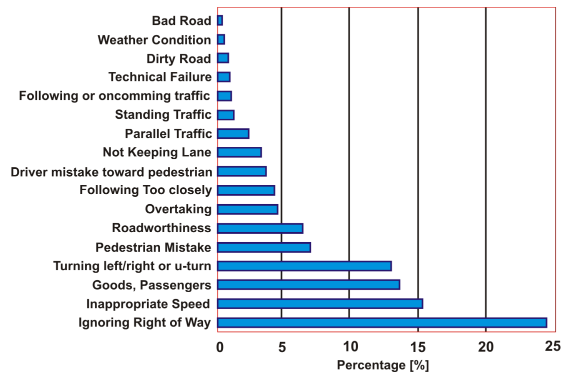

FIGURE 5
Distribution of main accident causes at intersections

4. Rear view (RV): used for backward driving
5. Lane keeping assistance (LKA): is used for driving straight without deviation of current lane
6. Emergency Braking System (EBS): reduces the speed with a logical deceleration in order to eliminate an unexpected obstacle or a collision.

Besides, according to a statistical study by GIDAS German In-Depth Accident Study, “*ignoring right of the way*”and “*inappropriate speed*”are two major factors of all road accidents and leading the ranking. That means ACC with safe speed and overtaking by keeping right of the way may be two of most needed driver assistance systems. Figure 5 is the summarization of this study that can help to determine the main causes of intersection accidents [16]

Therefore “Overtaking”and “ACC”are the most important driver assistance systems must be designed. Figure 6 shows active sensors needed for “Overtaking”and “ACC and Following”schemes among the whole 16 sensors.

5 FUZZY LOGIC SUPERVISOR (FLS)

In this section, we perform ACC as one of the most important driver assistance systems through FLS. Our approach is to determine suitable speed in following a vehicle (ACC) according to the data reading from various sensors

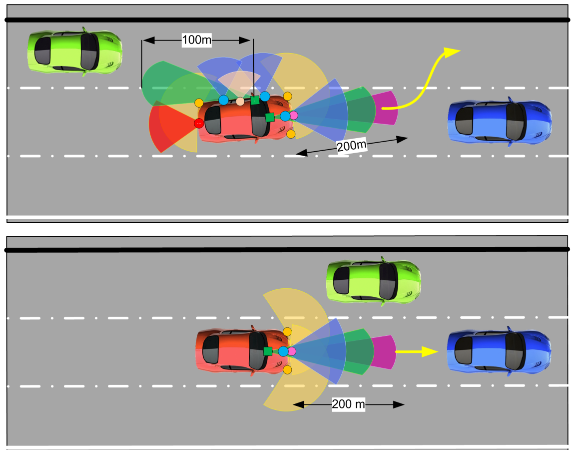

FIGURE 6
Eleven active sensors for lane change and overtaking (Top) and five active sensors for vehicle following (ACC) with safe distance and safe speed (Bottom)

such as Long range radar (LRR), Short range radar (SRR), Vision and Laser in addition to previous speed, driver's command and degree of his/her alertness. In this simulation the driver forces the pedal to change the speed of vehicle according to his/her brain decision; but the FLS checks the drivers command with auxiliary mounted sensors data in order to have a safe action. So it may change the final command something different to the initial driver command. Figure 7 and 8 show membership function and the $3D$ output graph for speed of the vehicle in different situations based on brain and sensor fusion.

Note: In case of noticeable difference in driver commands (Brain Fusion) versus the sensor fusion data, we use McCall and Bergasa facial processing methods [17][18][19] and in case of positive answer for tiredness or drowsiness of the driver, the importance factor of the driver will decrease significantly, especially in higher speeds. This is visible in figure 8.

Now we continue to check the accuracy of the host vehicle in keep following a vehicle. As mentioned before and can be seen in figure 6 we need to fuse five front sensors like Figure 9

The initial system structure is defined by input and output variables with their linguistic terms. Linguistic variables are components of fuzzy logic

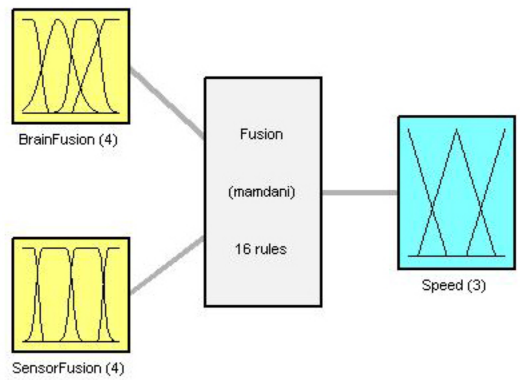

FIGURE 7
Input and output membership functions of FLS system

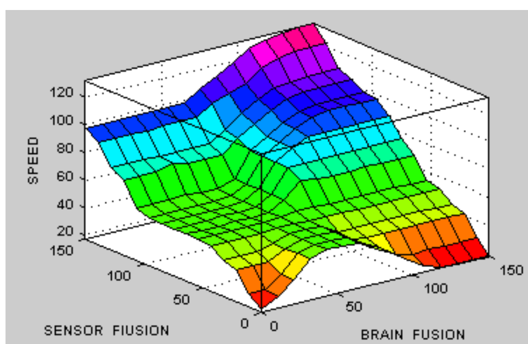

FIGURE 8
Proposed speed by FLS according to commands from “Driver”and “Car Sensors Fusion”.

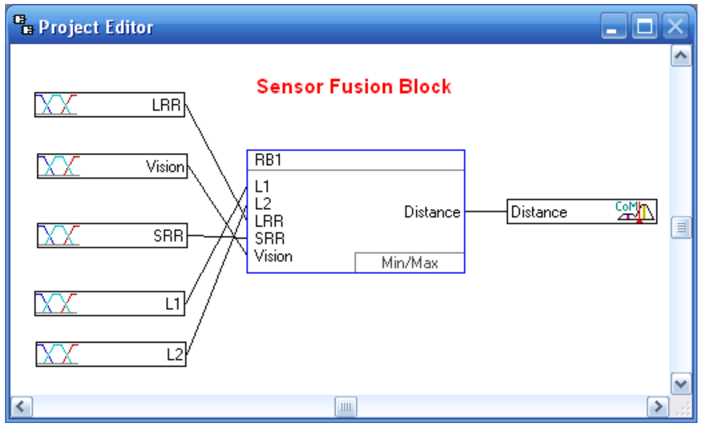

FIGURE 9
Sensor fusion scheme for ACC using fuzzy logic method

systems that “transform”real, crisp values, here from sensors, into linguistic values. The output also defined by some linguistic variables but finally should be defuzzified in to real output value, here distance (Figure 10).

In this step we divided each sensor range to some linguistic terms such as near, far, close, etc. and based on overall sate of the sensors the output value is determined.

After defining membership function of fuzzy fusion system, Rule block of the system is defined. Here are two sample rules according to figure 10:

- IF (LRR=Medium Far AND Vision, SRR, L1, L2 = Far) THEN Distance = Far

- IF (LRR=Close AND Vision=Medium Close AND SRR=Medium AND L1, L2=Far) THEN Distance = Above Medium

Then a sample input data set is entered as the distance of the front vehicle with various speed and acceleration to examine the robustness of the system. The results was very interesting, after several modification and improvement of membership functions with Min-Max Aggregation operator of *Fuzzy*TECH simulator, finally we obtained a satisfactory following by the host vehicle. As it can be seen in figure 11 in the area with more detecting

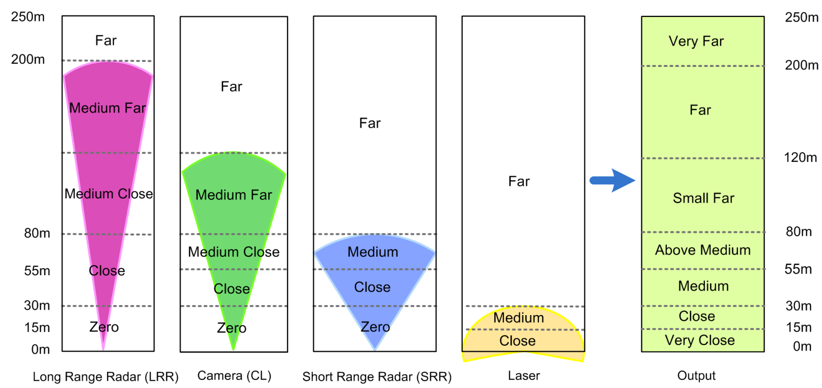

FIGURE 10
Linguistic variable definition for sensors (inputs) and fused data (output)

sensors, (e.g. in $distances < 50m$) we saw more fluctuations, But in far distance ($distance > 100m$) with just one LRR sensor coverage, we saw better following! The reason is very simple, because the nature of different sensors (in lower distances) they feed the system a little bit different measurements, which will cause some fluctuations. But despite to a little fluctuation, the result is more reliable than a single sensor in far distance. The worst deviation found in this stage was about ± 5.26 meters.

Now we try to keep reliability of multi sensory in lower distance and reduce the deviation and fluctuations. In this stage a filtering method is applied as it follows.

A slight improvement in computational efficiency can be achieved if we perform the calculation of the mean in a recursive fashion. A recursive solution is one which depends on a previously calculated value. To illustrate this, consider the following development:

Suppose that at any instant k, the average of the latest n samples of a data sequence, x_i, is given by:

$$\bar{x}_k = \frac{1}{n} \sum_{i=k-n+1}^{k} x_i \tag{5}$$

Similarly, at the previous time instant, $k-1$, the average of the latest n samples is:

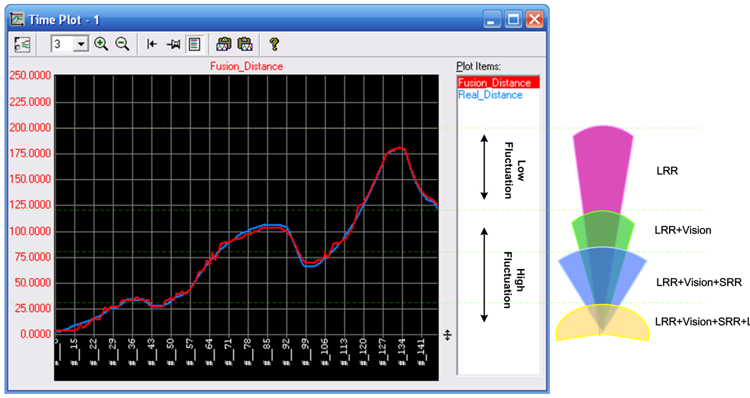

FIGURE 11
Host vehicle following based on sensor data fusion

$$\bar{x}_{k-1} = \frac{1}{n} \sum_{i=k-n}^{k-1} x_i \tag{6}$$

Therefore,

$$\bar{x}_k - \bar{x}_{k-1} = \frac{1}{n} \left[\sum_{i=k-n+1}^{k} x_i - \sum_{i=k-n}^{k-1} x_i \right] = \frac{1}{n} \left[x_k - x_{k-n} \right] \tag{7}$$

which on rearrangement gives:

$$\bar{x}_k = \bar{x}_{k-1} + \frac{1}{n} \left[x_k - x_{k-n} \right] \tag{8}$$

This is known as a **moving average** because the average at each k^{th} instant is based on the most recent set of n values. In other words, at any instant, a **moving window** of n values is used to calculate the average of the data sequence (see Figure 12).

When used as a filter, the value of $\bar{x}_k$ is taken as the filtered value of x_k. The expression is a recursive one, because the value of $\bar{x}_k$ is calculated using its previous value, $\bar{x}_{k-1}$, as reference. This is always the case, regardless of the number of data points (n) we consider, calculating the current filtered value requires the use of $\bar{x}_{k-n}$, i.e. the measurement n time-steps in the past.

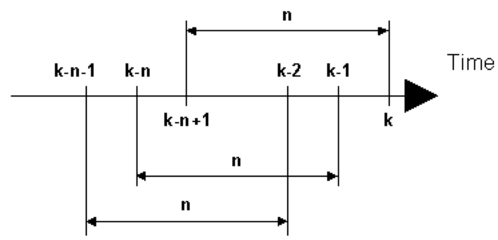

FIGURE 12
Moving Window of n Data Points

This means that:

1. the filtering cannot be initiated reliably until n measurements have been made, and

2. We need to store the value of $\bar{x}_{k-n}$ which, depending on the way the algorithm is coded, may require up to n storage locations.

Additionally, the technique places equal emphasis on all data points. Thus a value in the past will have the same influence as a more current measurement when calculating the filtered signal. This may be a desirable feature when the mean value of the measurement is almost constant, but not when the vehicle moves at various acceleration rates. These problems can however, be reduced by generating the filtered value in a slightly different manner.

Actually, in dynamic systems, such as forward vehicle monitoring, the most current values tend to reflect better the state of the process. A filter that places more emphasis on the most recent data would therefore be more useful. Such a filter can be designed by following the procedure used in developing the moving average filter. As before, the starting point is the mean expressed as:

$$\bar{x}_k = \frac{1}{n} \sum_{i=k-n+1}^{k} x_i \tag{9}$$

But in this case, consider also the mean with one additional point

$$\bar{x}_{k+1} = \frac{1}{n+1} \sum_{i=k-n+1}^{k+1} x_i = \frac{1}{n+1} \left[x_{k+1} + \sum_{i=k-n+1}^{k} x_i \right] \tag{10}$$

since $\sum_{i=k-n+1}^{k} x_i = n\bar{x}_k$ therefore,

$$\bar{x}_{k+1} = \frac{1}{n+1} \left[x_{k+1} + n\bar{x}_k \right] = \left(\frac{1}{n+1} \right) x_{k+1} + \left(\frac{n}{n+1} \right) \bar{x}_k \tag{11}$$

By shifting the time index back one time-step, we obtain the corresponding expression for $\bar{x}_k$ as:

$$\bar{x}_k = \left(\frac{1}{n+1} \right) x_k + \left(\frac{n}{n+1} \right) \bar{x}_{k-1} \tag{12}$$

To simplify the notation, let $\alpha = \frac{n}{n+1}$, which implies that $(1-\alpha) = \frac{1}{n+1}$.We can write the filter as:

$$\bar{x}_k = \alpha \bar{x}_{k-1} + (1-\alpha)\, x_k \tag{13}$$

This expression is Exponentially Weighted Moving Average Filter. When used as a filter, the value of $\bar{x}_k$ is again taken as the filtered value of x_k. Notice that now, calculation of $\bar{x}_k$ does not require storage of past values of x, and that only 1 addition, 1 subtraction, and 2 multiplication operations are required.

The value of the **filter constant**, α, dictates the **degree of filtering**, i.e. how strong the filtering action will be. Since $n \succeq 0$, this means that $0 \preceq \alpha \prec 1$. When a large number of points are being considered, $\alpha \to 1$, and $\bar{x}_k \to \bar{x}_{k-1}$. This means that the degree of filtering is so great that the measurement does not play a part in the calculation of the average! On the other extreme, if $n \to 0$, then $\bar{x}_k \to x_k$ which means that virtually no filtering is being performed.

The Exponentially Weighted Moving Average filter places more importance to more recent data by discounting older data in an exponential manner (hence the name). This characteristic can be illustrated simply by describing the current average value in terms of past data.

For example, since $\bar{x}_k = \alpha \bar{x}_{k-1} + (1-\alpha)\, x_k$, then

$$\bar{x}_{k-1} = \alpha \bar{x}_{k-2} + (1-\alpha)\, x_{k-1} \tag{14}$$

Therefore,

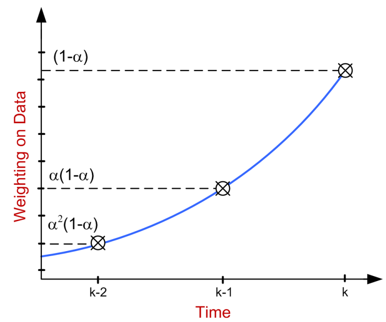

FIGURE 13
Exponential weighting effect

$$\bar{x}_k = \alpha\bar{x}_{k-1} + (1-\alpha)\,x_k = \alpha\left[\alpha\bar{x}_{k-2} + (1-\alpha)\,x_{k-1}\right] + (1-\alpha)\,x_k \quad (15)$$

i.e.

$$\bar{x}_k = \alpha^2\bar{x}_{k-2} + \alpha\,(1-\alpha)\,x_{k-1} + (1-\alpha)\,x_k \quad (16)$$

But $\bar{x}_{k-2} = \alpha\bar{x}_{k-3} + (1-\alpha)\,x_{k-2}$
Therefore,

$$\bar{x}_k = \alpha^3\bar{x}_{k-3} + \alpha^2\,(1-\alpha)\,x_{k-1} + \alpha\,(1-\alpha)\,x_{k-1} + (1-\alpha)\,x_k \quad (17)$$

If we keep on expanding x terms on the right hand side, we will see that the contribution of older values of x_i are weighted by increasing powers of α. Since α is less than 1, the contribution of older values of x_i becomes progressively smaller. The weighting on x_i may be represented graphically in a plot as depicted in Figure 13.

What this means is that in calculating the filtered value, more emphasis is given to more recent measurements. By applying this approach to figure 11 (Sensor Fusion Output) using MATLAB, we obtain more satisfactory results than before in overall fusion system. According to several experiments we obtained that windows size of 5 met better following and more smoothing on our fusion graph. Figure 14 shows Fusion graph before and after applying the filtering approach.

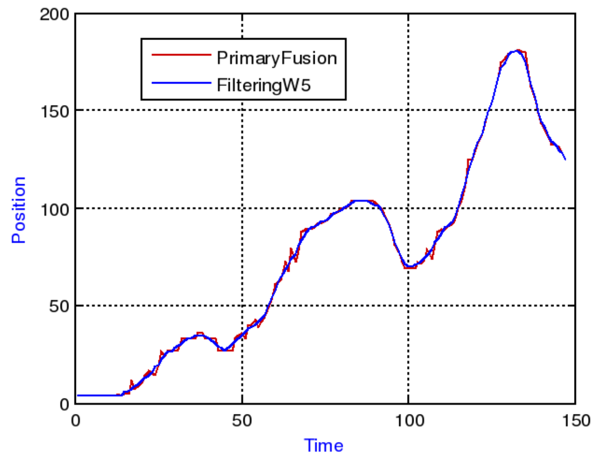

FIGURE 14
Sensor Data Fusion before and after applying moving average filter

6 DECELERATION AND STEER ANGLE CHANGES IN DANGEROUS AREA

In previous steps we determined the appropriate and safe speed according to driver request through human brain fusion and then environmental sensor fusion. Now as the next experiment we would like to determine the deceleration rate (Km/h) as well as determining a safe distance according to current speed of the vehicle and angular distance from an unexpected obstacle or vehicle. In fact we are going to fuse data one level more than previous. The sensor suite for this application consists of six readily available state-of-the-art sensors from Bosch, Tyco Electronics and Smart Microwave Sensors (SMS). One type of sensors is long range radar used for detecting vehicles and another type is a video lane detection system [20]. Of the five radar sensors two LRR operate at $77GHz$ (with $150m$ coverage and search area of $12°$) and three at $24GHz$ with coverage range of $80m$. The $77GHz$ sensors are radars based on the TRW production ACC unit [21]. One of these is being installed forward facing and the other is rear facing. One of the $24GHz$ radars used for forward facing and other two $24GHz$ radars are side facing (and whose data are combined). Figure 15 shows the radar sensor configuration and approximate areas of coverage.

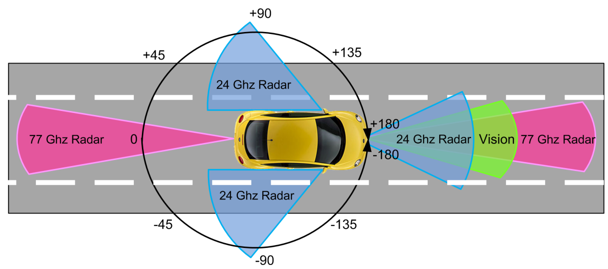

FIGURE 15
Radar sensor configuration

We use a simple but heuristic method; we fuse resultant of any overtaking vehicle or any obstacle around the vehicle by two parameters, θ or its angle (positive or negative) and d_1 its distance to vehicle. Whatever $|\theta|$ is greater and d_1 is smaller, the danger of collision is more probable and so the vehicle should be decelerated more quickly. This is essential to keep a safe distance without diverting from its path.

Figure 16 shows an overtaking vehicle beside the host vehicle. In figure 17, the blue sections show small deviation in current speed and more red areas shows more probability of collision detection according to obstacle angle and distance. (In our system, Deceleration% is percentage of speed decrement in each 3 seconds). Looking exactly to the symmetric graph provided by FLS proves a logical decision making like a perfect driver.

Simultaneously, it is also necessary to make correction in side distance by correction in steer angle to avoid from unexpected obstacle or overtaking vehicle. In this section our goal is to determine the steer angle change in order to define an immune margins (d_1, d_2) whiles other vehicles antecedence from the host vehicle. In this fuzzy based method, there are 3 input variables and 1 output. We have defined 27 optimal and corrected rules according to an expert driver experience.

The inputs for determining next action are distance from closest overtaking vehicle, its angle and distance of vehicle from the verge of the road. The output is some correction to the steering angle and directs the vehicle to a safe distance to the overtaking vehicle or an unexpected obstacle. This change should be done in a manner that do not deviate the vehicle from lane of the road.

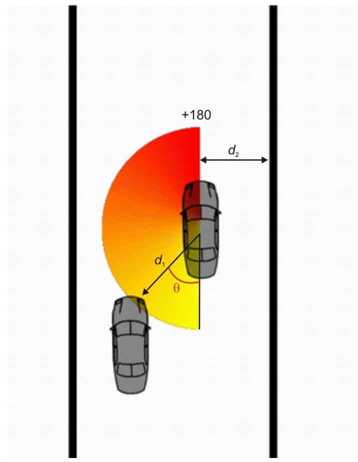

FIGURE 16
θ and d_1, Important factors to determining deceleration rate and preventing collisions

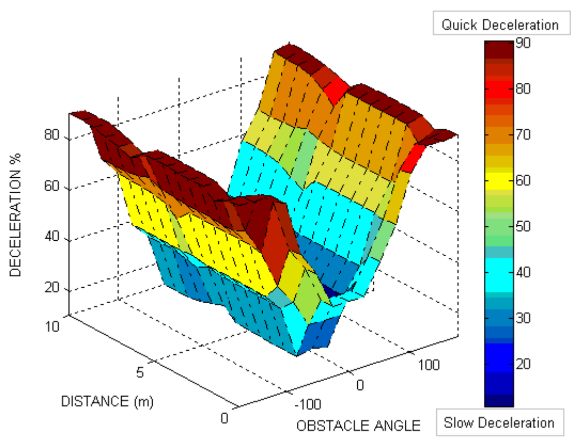

FIGURE 17
Deceleration rate commanded by FLS

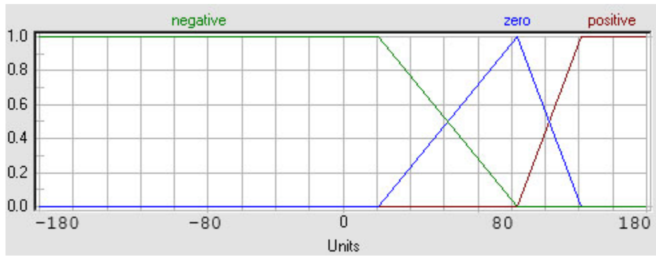

FIGURE 18
MBF of θ or Angle to Object

As depicted in figure 16, d_1 is distance of overtaking vehicle from our vehicle, d_2 is the distance of vehicle to the verge of the road, and θ shows the angle of side vehicle from our vehicle. The importance degree of the angle increases from 0 to $+180$ asymmetrically as the Membership Function (MBF) defined in figure 18.

Figures 19, 20 show distance inputs membership functions, figure 21 shows structure of fuzzy logic system and figure 22 shows the necessary change in steer angle of the vehicle as output.

7 CONCLUSION AND FUTURE WORKS

This paper, proposed a network of sensors for advance driver assistance systems with a specific deployment on a host vehicle integrated with a logical, effective and practical hybrid sensor fusion technique using fuzzy method which is applicable in various depth of fusion for high speed vehicles in roads and highways. We used some important intuitive and linguistic experiences of an expert driver as our fusion rules and on the other hand gave the driver to control the vehicle in conjunction with sensor fusion. The control section (FLS) played an acceptable rule, much better than an individual driver, to control the vehicle safely and observant in encountering unexpected obstacles. The results improved with exponentially moving average window filter and as the future works it is recommended to test this algorithm with more sophisticated mathematical approaches and filters for better performance.

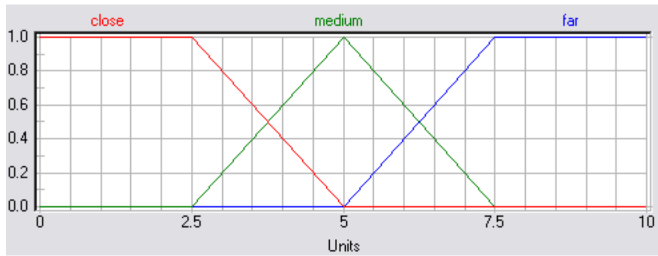

FIGURE 19
MBF of d_2 or “Distance to Right”

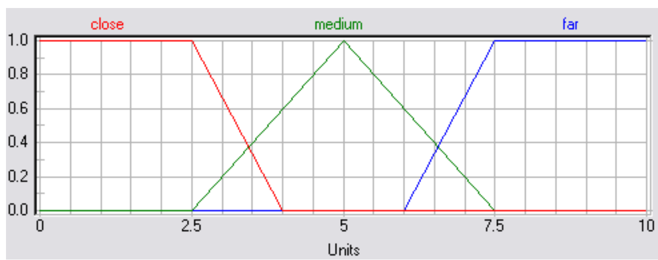

FIGURE 20
MBF of d_1 or “Minimum Distance”

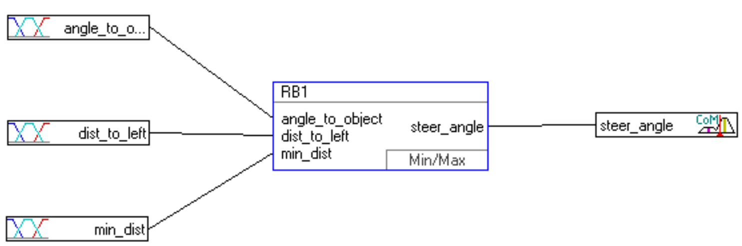

FIGURE 21
Structure of the Fuzzy Logic System

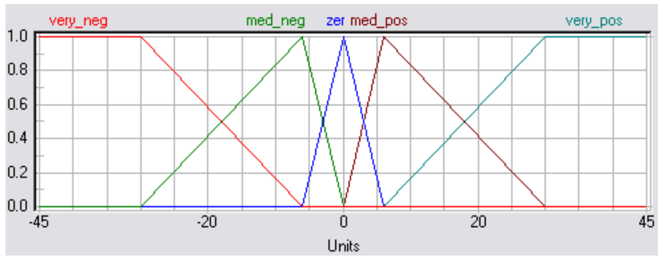

FIGURE 22
MBF of Output or "Steer Angle"

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