Web Driving Performance Monitoring System

Ahmad Aljaafreh

Abstract—Safer driver behavior promoting is the main goal of this paper. It is a fact that drivers behavior is relatively safer when being monitored. Thus, in this paper, we propose a monitoring system to report specific driving event as well as the potentially aggressive events for estimation of the driving performance. Our driving monitoring system is composed of two parts. The first part is the in-vehicle embedded system which is composed of a GPS receiver, a two-axis accelerometer, radar sensor, OBD interface, and GPRS modem. The design considerations that led to this architecture is described in this paper. The second part is a web server where an adaptive hierarchical fuzzy system is proposed to classify the driving performance based on the data that is sent by the in-vehicle embedded system and the data that is provided by the geographical information system (GIS). Our system is robust, inexpensive and small enough to fit inside a vehicle without distracting the driver.

Keywords—Driving monitoring system, In-vehicle embedded system, Hierarchical fuzzy system.

I. Introduction

MOTOR vehicle accidents are one of the leading causes of death. More than 90 percent of these accidents involve drivers behavior, like suddenly change lanes, drivers tailgate, and driver distraction. The risk of the accident increases with the speed of the vehicle. Excessive speed, Frequent or unsafe lane changes, Tailgating, Impaired driving are some characteristics of aggressive driving. Aggressive driving is a major concern. It is ranked at or near the top of traffic safety issues. It includes driving above speed limit, changing vehicle speed suddenly, changing vehicle lateral position quickly, abrupt acceleration or deceleration, etc. There are different reasons for abnormal driving such as alcohol drinking, sleepiness, bad attitude, and driving fatigue. Driving style can characteristically be categorized to: normal (typical) and aggressive[1]. Driving monitoring system significance comes from its need in many applications like; Improving driver behavior, driving performance estimation in the elderly, insurance company, intelligent transportation systems, and fleet management. A tremendous benefits can be offered by technologies to promote safer driving behaviors [2]. Close and continuous monitoring is a key factor in improving driver behavior [3]. This paper presents a vehicular data acquisition and analysis system for driving performance monitoring and estimation. It exploits On-Board Diagnostic (OBD), GPS, 2-D accelerometer, RF radar, and GPRS technologies. This paper describes a vehicle embedded data acquisition system places in vehicle as well as a web inference system for driving performance monitoring and estimation as in Fig. 1. Data collected in a database forms the basis for decision making, performance monitoring, and vehicle and driver performance optimization. The main parts of this system are in-vehicle embedded system, and vehicle monitor server and database. The in-vehicle embedded system obtains the location of the vehicle from GPS receiver, the vehicle parameters from OBD interface, longitudinal and lateral acceleration from the 2-D accelerometer, and following distance indication (FDI) from the RF medium range radar. Then the in-vehicle embedded system transmit the collected data via GPRS to the web server. Besides the reliability and cost effectiveness of this system, it also can be exploited for driving pattern learning and forward collision avoidance and warning.

A. Aljaafreh is with the Department of Electrical Engineering, Tafila Technical University, Tafila, 66110 Jordan, e-mail: (a.aljaafreh@ttu.edu.jo).

II. Background

The methods of detecting the abnormal driving behaviors can be divided into two major categories; monitoring of drivers and vehicle-human interactions. Driver monitoring includes the visual observation of drivers. For example, Zhu et al. [4] used cameras to capture eyelid movement, head movement, and facial expression to predict driver fatigue based on probabilistic model. Lee et al. [5] used cameras to capture the driver's sight line and the driving path and calculated the correlation between them to monitor the driving status and patterns. Also, abnormal driving can be detected using physiological signals. For example, the sleepiness signs can be detected by analyzing the signals of brain activity which obtained through electroencephalography [6]. Moreover, driver's fatigue and drowsiness can be detected by using electrocardiogram, electromyogram, skin conductance, etc. [7]. In addition to driver monitoring, vehicle-human interactions monitoring provides valuable information about abnormal driving. For example, Krajewski et al. [8] estimated driver's fatigue from steering behavior. They collected the steering data and used signal processing to capture fatigue impaired patterns. Dai et al. [9] utilized mobile phone as the platform for drunken driving detection. They measured the lateral and longitudinal acceleration of a vehicle of interest by using accelerometers which are integrated in a mobile. Then, they compared them with typical drunk driving patterns extracted from real driving tests. When any evidence of drunk driving is present, the mobile phone will automatically alert the driver or call the police for help. Mohamad et al. [10] proposed abnormal driving detection based on real time GPS data. In-vehicle transponders send the GPS data to a monitoring station for processing and detecting the abnormal situation automatically. Their detection algorithm was based on vehicle position and velocity. They used the maximum speed, maximum acceleration and deceleration as the threshold values in the developed algorithm. Also, they took in consideration the unsmooth vehicle direction movements. Based on fuzzy logic, Imkamon et al. [11] proposed a method for detecting unsafe driving behaviors. They used a 3-axis accelerometer to detect sudden

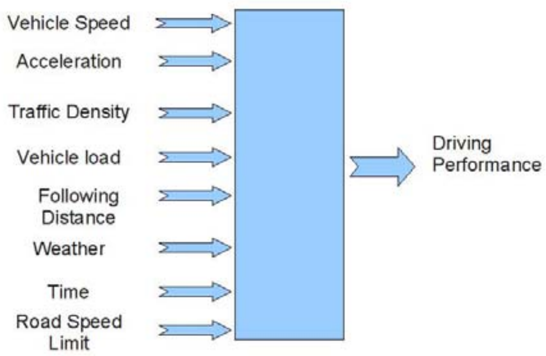

Fig. 1. Framework for the driving performance monitoring system

turns or brakes, a camera to emulate the driver's vision, and an On-Board Diagnosis (OBD) reader to obtain both the speed of the vehicle and the engine from the Engine Control Unit (ECU). Then, a fuzzy logic system combined the measured data to classify different levels of hazardous driving. Hailin et al. [9] designed a system to detect fatigue driving. They a acquired the signals from pedals, steering wheel, gear shift and driver's grip. Then, they analyzed these signals by a fuzzy recognition model to judge whether the driver is fatigue or not. A system for automating fleet management is described in [12], where a microprocessor based embedded system sends the GPS to a remote software that keeps track of the position of the vehicle and prepares reports. A fleet management system is proposed in [13] which incorporates GPS, Global Systems for Mobile Communication (GSM), and web-based management software. This software enables user to monitor the fleet and perform some fleet management tasks. OBD, GPS, 3G techniques are integrated in [14] as a remote on-line diagnostic system. Ref. [15] presents two prototype remote fleet management softwares based on connection over 802.11 as well as private radio networks. Ref. [16] measures the latency, throughput, and packet loss from vehicle to the base station using WiFi and WiMAX. A web information system for fleet management is described in Ref. [17].

III. Driving Monitoring System

The proposed system consists of two main parts as in Fig. 2. The first one is the in-vehicle embedded system that installed in the vehicle and the second is the web based information system. The in-vehicle embedded system is composed of a GPS receiver, a two-axis accelerometer, radar sensor, OBD interface, and GPRS modem. The firmware of this unit is divided into two parts. The first part is responsible for communicating with the OBD, 2-D accelerometer, radar sensor, and GPS receiver to get the data, compress it and store it in the memory. The second part is responsible for establishing communication with the web server, getting the data from memory, framing it and sending it to the web server. On the server side, an adaptive hierarchical fuzzy logic inference system is used to detect abnormal driving behaviors.

IV. In-vehicle Embedded System

The embedded system integrates the OBD, 2-D accelerometer, radar sensor, GPS receiver, and GPRS modem in one device to be installed in the vehicle as in Fig.3.

A. GPS, GPRS Module

GPS has many advantages that make it spreads in many life applications. The spread of the satellites all over world services the GPS data free. GPS hardware modules are available with cheap prices. It also can be integrated on electronic easily. Tracking and Fleet Management Platform Enfora's GSM2418 MT2500 is used in this research. The MT2500 is a certified quad-band integrated device with 3-axis accelerometer Providing complete GSM/GPRS communications and GPS.

B. 2-Axis Accelerometer

acceleration data is useful in assessing sudden movements [18]. Accelerations parallel and perpendicular to the automobile were measured by a single sensor. longitudinal accelerations are associated with the use of the automobile accelerator and brakes. Lateral accelerations are produced by steering maneuvers. A 2-axis accelerometer is used in this paper to measure the g-force that is caused by longitudinal and lateral acceleration. The norm of the longitudinal accelerations and the lateral accelerations is calculated as in equ. 1. Then the norm is using a moving average filter with window size (N) equals 40 as in equ. 2. The output is used as input in our system as an indication of the dynamics of the vehicle.

$$Norm(n) = \sqrt{Accel^2_{Lan}(n) + Accel^2_{Lat}(n)} \tag{1}$$

$$Norm(i) = \frac{1}{N}\sum_{n=1}^{N} Norm(n) \tag{2}$$

C. OBD Interface

OBD devices is incorporated into vehicles as early as 1994 [15]. OBD system turns on the Malfunction Indicator Lamp (MIL) in the car when there is any malfunction in the engine. The engine control unit also store the malfunction code to be accessed through the OBD connection by the OBD scan tool [14]. The system in this paper reads the Revolution Per Minutes (RPM) to deduce the vehicle load which is one of the inputs of the fuzzy system to infer the driving performance.

D. Radar Technology

A TRW's AC100 24 GHz radar is used in this system for following distance indication. This radar technology senses the distance and relative speed of the nearest vehicle in front. It is also capable of operating under all weather conditions. It achieves outstanding speed resolution and very high detection range of more than 250 meters. The radar sensor is installed in the front bumper to be used for distance detection between the vehicle and the vehicle in front.

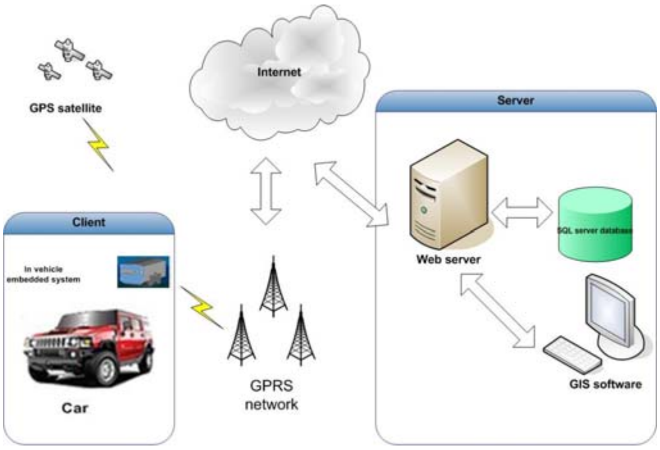

Fig. 2. Driving performance monitoring system layout

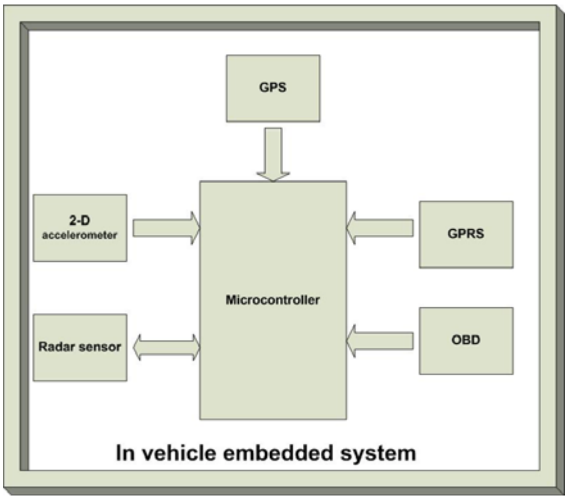

Fig. 3. In-Vehicle Embedded System Apparatuses

V. Web Information System

On the server side, a fuzzy logic inference system is used to detect abnormal driving behaviors.

A. FUZZY LOGIC

Fuzzy inference system can be considered as an inference system that maps, by means of combination rules, input to output using fuzzy logic. The Fuzzy Inference System (FIS) determines the level of abnormality in driving to report, notify or warn the driver so that he can pay back his/her full concentration in driving. Fuzzy logic inference is a simple approach to solving problem rather than attempting to model it mathematically. Empirically, the fuzzy logic inference depends on humans experience more than the technical understanding of the problem. Fuzzy logic inference consists of three stages: 1) Fuzzifcation: map any input to a degree of membership in one or more membership functions, the input variable is evaluated in term of the linguistic condition. 2) Fuzzy inference: fuzzy inference is the calculation of the fuzzy output. 3) Defuzzifcation: defuzzifcation is to convert the fuzzy output to a crisp output.

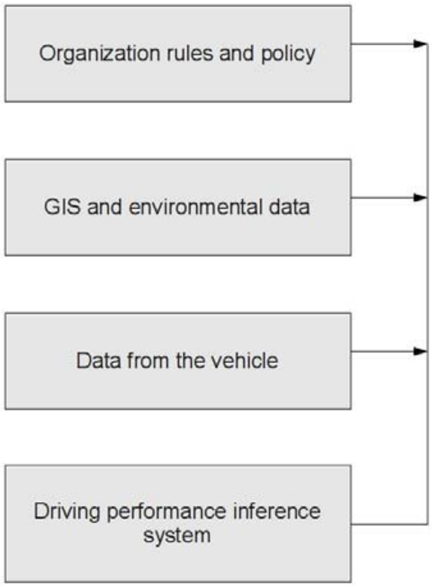

Fig. 4. Framework for the driving performance monitoring system

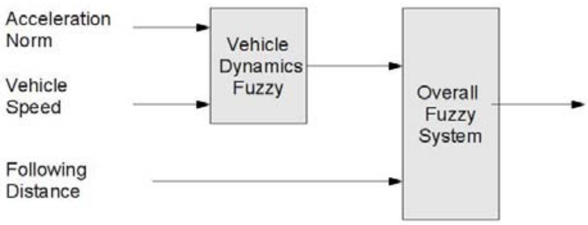

Fig. 5. The hierarchical fuzzy system

1) Fuzzy Classification System: Vehicle speed, following distance between vehicles, load of the vehicle, average of the Euclidean norm of longitudinal acceleration and lateral acceleration are all used as inputs to the fuzzy inference system to infer the driving performance. In this paper, the selection and formulation of the input and output fuzzy sets and their membership functions are based on expert driver knowledge.

2) Following Distance Input: Based on the calculation of the stopping distance, it is recommended to keep a distance

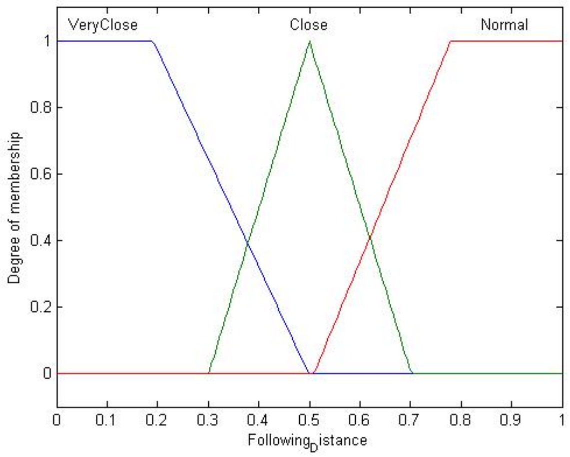

Fig. 6. The membership functions for the following distance inputs

of three seconds between vehicles for typical dry road. The stopping distance increases for wet and icy roads. Following distance should be increased to six seconds in traffic or at night. It also increases to nine seconds in heavy rain or in ice or snow. The corresponding fuzzy values are defined to be Very Close (VC), Close (C), and Normal (N) as shown in Fig 6. The parameters of each of these fuzzy membership function is adaptive to the road weather condition, time, and traffic density. In this paper, a decision tree is used to provide the parameters of each of these membership function based on weather, traffic and time variables. These variables are provided from the GIS system. The main idea of the decision tree is to reduce the dimension of the rules to a linear function of system input variables and to make it easy for expert to set the rules with less input fuzzy variables. The following distance critical value (FDCV) is determined according to the decision tree. The membership function of the Very Close (VC) fuzzy set is a trapezoidal function with the following parameters [0 0.7*FDCV 0.9*FDCV]. The membership function of the Close (C) fuzzy set is a triangular function with the following parameters [0.7*FDCV 0.9*FDCV 1.1*FDCV]. The membership function of the Normal (N) fuzzy set is a trapezoidal function with the following parameters [0.9*FDCV 1.1*FDCV]. FDCV is calculated by the decision.

3) Speed Input: To determine weather the speed is low, normal, or high depends on the following factors: speed limit of the street, weather, traffic, and time. These input variables are speed limit of the street and the other inputs for the decision tree in the previous section. Thus, we get use of the decision tree decision to determine the parameters for the fuzzy sets of the speed input variables.

4) 2D Acceleration Norm Input: The norm at any point is calculated as in equ. 1. Then the norm signal is averaged using a moving average filter with window size (N) equals 40 as in equ. 2.

5) Overall Fuzzy System: The first input is the norm of the acceleration on longitudinal (forward and backwards) and lateral (side to side) directions of the vehicle. The corresponding fuzzy values are defined to be Low (L), Medium (M) and

TABLE I
FUZZY RULES FOR FUZZY VEHICLE DYNAMICS INPUT

Acceleration \ Speed	Low	Medium	High	Very High
Low	Low	Medium	High	High
Medium	Medium	Medium	High	Very High
High	Medium	High	Very High	Very High

TABLE II
FUZZY RULES FOR FUZZY DRIVING PERFORMANCE OUTPUT

Following Distance \ Vehicle Dynamics	Low	Medium	High	Very High
Very Close	Normal	Aggressive	Very Aggressive	Very Aggressive
Close	Normal	Normal	Aggressive	Very Aggressive
Normal	Normal	Normal	Aggressive	Aggressive

High (H). The second input is the speed of the vehicle. The corresponding fuzzy values are defined to be Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH). Finally the output of the system is the driving behavior, which is defined by four fuzzy values Below Normal (BN), Normal (N), Aggressive (A) and Very Aggressive (VA). The whole process mapping is shown in Fig. 5. The inputs and output membership functions and the fuzzy rules were tuned manually based the real test data and three expert drivers. The fuzzy rules are summarized in table I and table II.

VI. CONCLUSION

A driving monitoring system for safety promotion and fleet management based on GPS, OBD, 2-D accelerometer, radar system, and GPRS modem is implemented and evaluated successfully in this paper. We focus on the server-side software where an intelligent inference system is designed based on an adaptive hierarchical fuzzy system to classify the driving performance based on the data that is sent by the in-vehicle embedded system and the data that is provided by the geographical information system (GIS).

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