ICSG İstanbul 2017
5. Uluslararası İstanbul Akıllı Şebekeler ve Şehirler Kongre ve Fuarı
5th International Istanbul Smart Grids and Cities Congress and Fair

Smart Driving in Smart City

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***Abstract*—Smart cities have been drawing attention of researchers as seen in recent intensive studies. In associated with this fact, this situation is expected to continue in future works. In other side, smart vehicles are an indispensable part of smart cities. Scientists have been researching vehicles and transportation in order to reach safe and comfortable mobility. Among these vehicles, cars are the first ones that affect human life. In this study, smart cars and their drivers are elaborated in behavioral aspect. Existing works have been discussed to figure out futuristic driving behavior in smart city environment. In order to understand human thought system, additional studies have been given and recommendations have been provided. As seen in the researches conducted in recent years, researchers have been tried to interpret behavior of drivers by examining data taken by smart phones and vehicle OBD output. Evaluations are conducted by result of the specified methods. In recent decade, it has been observed that these behaviors are not only estimations; but also systems mounted on vehicles learn overall driving behavior. Hence, developed systems should work online while drivers on steering wheel. Consequently, this study will enlighten existing trends for different types of learning schemes. Future studies are expected to combine car, driver's biologic, psychological, and environmental data. Thus, in the near future, systems that understand the human thought will be developed.**

***Index Terms*-- Smart driving, incremental learning, driver behavior, online learning, smartphone sensors.**

I. INTRODUCTION

In smart cities, it is desirable to be formed a system that can be integrated into many associated systems. This system includes smart houses, intelligent vehicles, intelligent energy systems, intelligent roads, some technological devices, and spaces that can be added to them.

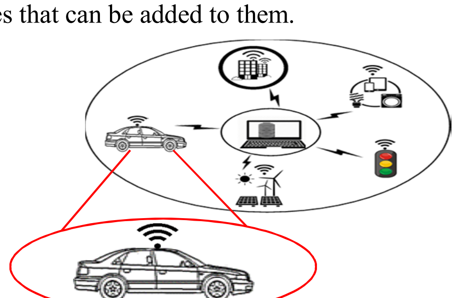

Figure 1. A smart car on smart city structure.

Today, smart cars have already been brought in to the testing stage by many companies. For example; Google and Tesla have put test versions of their driverless smart cars on the market. First one focuses on the software portion, and the second one is still on mass production.

In fact, intelligent systems are being developed to simulate human brain structure. Each division in the brain has a separate task. The parts of the brain and their tasks are shown in Figure 2. Each part can take place in intelligent automobile systems, and we can determine the tasks corresponding to them.

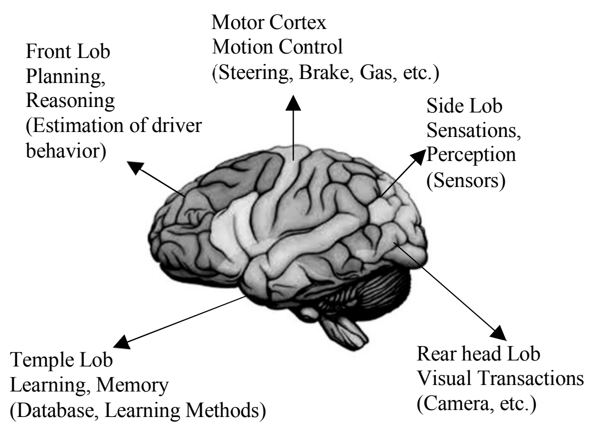

Figure 2. Brain regions corresponding to intelligent automobile system.

In order to develop driverless systems, we initially need to collect the data associated with drivers and vehicles. Collection of these data is realized by sensors. The parts performing this task in the brain are known as the parietal lobe and occipital lobe. Then, the obtained data is stored somewhere to work on it. The region achieving this task in the brain is called the temporal lobe. The classification of the recorded data and extracted events should be determined. This process is done as a function of the temporal lobe of the brain. It needs to analyze, plan, evaluate, and predict the subsequent situations related to these detected events. This is performed in the brain part called front lobe. After detected events are processed by the associated regions of the brain, the movement organs should be instructed and acted upon. This process is done with the motor cortex section. In this way, an event can be detected, recorded, learned, interpreted, and next one is predicted.

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A. Problem Statement

Driving assistant systems have an important place in smart car systems. Development of new driving assistant systems is possible by means of driving behavior. Thus, the recognition of the driver characteristics should be obtained. Also, the tactics, maneuvers, and overall behavior on steering wheel should be estimated. Before the action, some preliminary work is needed to build driver assistant systems having next generation artificial intelligence. To reach the main goal, the following problems should be solved:

a. During driving, environmental factors and driver biological data should be taken by sensors; and they should be properly stored.
b. Events should be identified by means of receiving data.
c. These events should be classified.
d. The behavior of drivers need to be understood by using new generation learning methods.
e. An overall system should be developed to estimate the behavior on steering wheel.
f. The system should be updated online to improve the right driving behavior.
g. A characteristic profile for the driver should be defined.

B. Proposed Approach

In order to recognize driver profile and to enable understanding by the vehicle, information about the driver, vehicle and environmental conditions should initially be obtained by appropriate equipment while driving. They will be stored in suitable format. Figure 3 sketches the ongoing process for receiving and storing data.

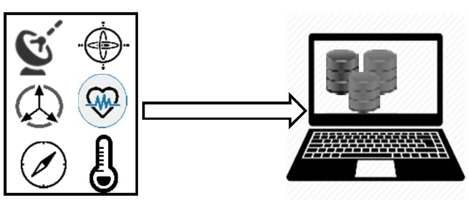

Figure 3. Capturing and storing sensor data.

By analyzing obtained data, we can determine possible events occurring on steering wheel. In this regard, labeling should be performed to correctly validate end-points of these events. The labeling could be accomplished as seen in Figure 4.

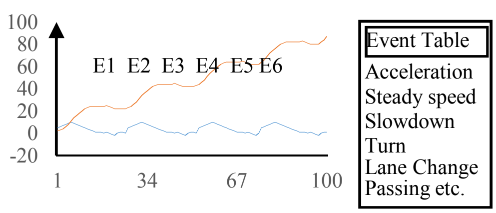

Figure 4. Event detection from data (E is Event).

The events detected by the obtained data during driving are classified. The class of an event can be determined by using estimation methods. The behavior of the driver is determined as a result of the classification of events for the sake of the analysis of long driving data. In this manner, it can be predicted overall behavior type and actual behavior on steering wheel. It can be predicted persistent behaviors and transition points while passing to another actual driving behavior. This estimation system is constructed using probabilistic methods such as Markov Chain. An estimation example is given in Figure 5.

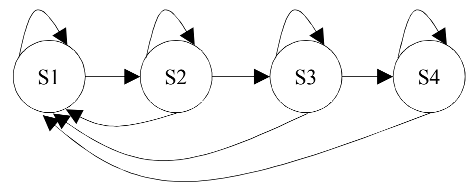

Figure 5. Markov model for state transitions.

Once the system is established, then it should be transformed into a system that continuously can update itself with actual feedback. This is possible by blending instant data with past data. Taking account of former experiences, new events and driver behaviors are detected by feeding new streaming data. This allows driver to be alerted on steering wheel, and it leads to improve driving comfort. Proposed system is shown in Figure 6.

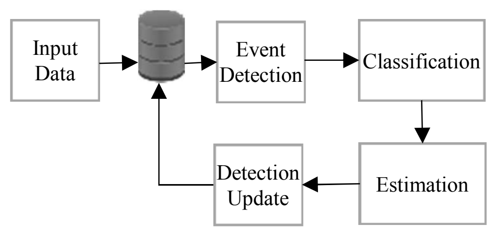

Figure 6. Online data analysis system.

The system, which is put into practice is represented by multiple factors including previous experiences of driver, his characteristic features, and combination of biological and vehicle data. By combining all these data, the profile of driver is obtained, and resultant decision about driving profile can be made. Such examples to these decisions could be given as safe, drowsy, aggressive, cool, or unsafe. Figure 7 depicts aforementioned decision mechanism.

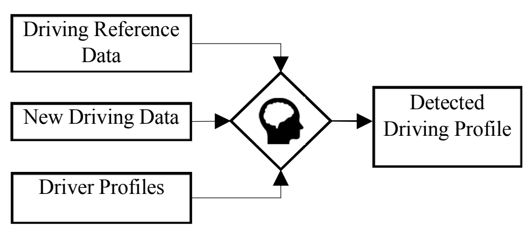

Figure 7. Driver profile decision system.

C. Related Work

Development of driver assistant systems is important for safe and comfortable driving. Researchers have been constantly working on new approaches to develop similar systems, and introducing new developments. Existing studies are generally classified as offline and online running systems [2-37]. Besides, there are many studies gathering data and detected events [2, 6-8]. The studies carried out in the early stages of intelligent vehicle systems were based on detecting driver behavior [10, 13, 14, 16, 24, 25, 34]. Current studies are mostly based on learning driver behavior and forming driving profiles [17, 19-23, 26-29, 31-33, 35-37]. In particular, analysis of data received from smartphones and automobiles is an indispensable element of intelligent vehicle system. By recent years, most of the data were taken from cars [3, 13, 17, 18]. In the subsequent period, with worldwide usage of smartphone based studies, the data received from smartphone sensors are widely employed [13-16, 19, 21-23, 25, 26, 30].

In addition to all these systems, one more component could also be taken account, which is biological data for driver. Today, smart phones and cars extensively collect related data. Moreover, it will be possible to combine three different data, which are traffic, weather, and driver biological data. Consequently, it is not far to develop online intelligent driving systems that can predict how driver will behave under what conditions, updating road experiences feedback driving on steering wheel, leading to comfortable travelling and safe driving.

D. Outline of the Paper

In the next part of this work, the previous studies are examined. The advancements from past to present, including methods, devices and properties, are introduced in tables. Also, systematic evolutions in the recent studies are given in plots. In the end part of the paper, the results obtained are discussed, and suggestions are provided for future work.

II. MAINFRAME OF THE SYSTEM

The studies on intelligent driving system are classified according to the methods they are addressed, the motions they are tested, types of sensors to use, and the types of learning approaches on which they are performed. Understanding of the recent developments and trends will introduce new sensor types and approaches along with the progress of futuristic technologies.

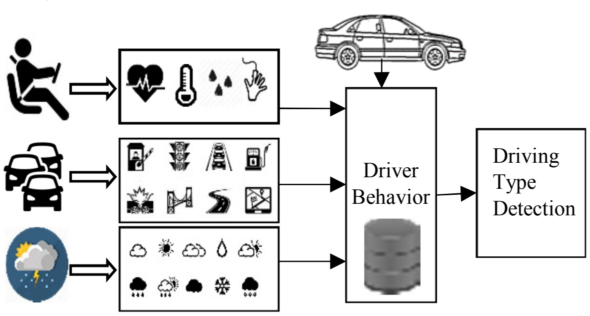

Figure 8. System design for future studies.

In the past, the vast majority of studies were done offline. Nowadays, the number of online studies is getting increase. Previous studies were mostly based on collecting data and determining events from them, but today, classification of detected events, determination of driver behavior, and prediction of future situations are added. With development of online studies, learning systems have started to be developed on steering wheel driving.

Especially, development of smart phones and the technology of sensors in smartphones make possible new generation artificial intelligence based driving studies easier. Low cost learning systems can be developed by analyzing the data received by sensors in cars and sensors in smartphones. Table I shows which driving behaviors have been detected by literature studies. As driving, the driver's accelerations, decelerations, and rotations of the car are detected from the received data.

Performance function for previous studies can be calculated by

$$\mathcal{P} = \frac{\sum \mathcal{B}}{100} + \frac{\sum \mathcal{S}}{100} + \frac{\sum \mathcal{M}}{100} + \frac{\sum \mathcal{H}}{100} \quad (1)$$

where $\mathcal{P}$ is performance rate for each study, $\mathcal{B}$ is number of detected maneuvers forming tactical behavior such as acceleration, breaking etc. as seen in Table I, $\mathcal{S}$ is total number of sensors employed, $\mathcal{M}$ refers to method, and $\mathcal{H}$ is number of biological data types obtained by drivers.

Performance result $\mathcal{P}$ for each study is in between 0-1. The influence of each component on the performance function is intuitively taken as 0.25. Impact of each maneuver is 3.125 (25/8) as seen in Table I; the impact of each sensor is 3.125 (25/8) as seen in Table II; and the impact of each method is 25 out of 100 as seen in Table III; and also impact of each biological data is 6.25 (25/4).

Biological data include pulse, moisture rate, amount of oxygen, and temperature. Ambulatory data are of great importance for realistic determination of driver's behavior. We examined several studies none of which involves in biological data.

TABLE I. STUDIES CLASSIFICATION BY DETECTED BEHAVIORS.

Behavior Type	References
Acceleration	[3, 6, 8, 10, 11, 13-21, 23-30, 32, 36, 37]
Breaking	[3, 8, 13, 15-18, 21, 24, 26, 27, 34]
Turn (Left, Right)	[3, 8, 12-14, 16, 18, 21, 23, 24, 28, 31, 32, 34-36]
Stopping	[3, 24]
Lane Change	[2, 3, 7, 13, 14, 21, 31, 36]
Lane Keep	[2, 28, 31, 35, 36]
Slowdown	[3, 14-17, 24]
Passing	[3]

Various methods have been employed by existing studies. The classification of studies in the literature according to different data acquisition methods and sensors is shown in Table II. Particularly, smartphone sensors and car sensors have been investigated in many studies.

TABLE II. STUDIES CLASSIFICATION BY SENSOR.

Sensor Type	References
Accelerometer	[8, 11, 13-16, 19, 21-23, 25, 26, 30]
Gyroscope	[8, 13, 14, 21, 23, 25]
Magenometer	[13, 14, 25]
Camera	[2, 3, 5, 10, 12, 13, 15, 17, 21, 22, 24, 28, 31, 33, 35, 37]
Laser Scanner	[12, 15, 22]
Can Bus	[3, 13, 17, 18, 20, 22, 24, 26, 29, 30, 32, 34, 37]
GPS	[8, 13, 16, 17, 19, 21, 24-27, 29-32, 36]
Other	[4-6]

TABLE III. CLASSIFICATION OF STUDIES BY METHODS.

Method	References
Hidden Markov Model	[2, 3, 8-10, 12, 31]
Bayes	[5-7, 14, 23]
Neural Network	[11, 30-33, 35, 36]
Support Vector Machine	[18, 29]
Fuzzy	[20]
Other (DTW, GMM ect.)	[13, 15-17, 19, 21, 22, 24-28, 34, 37]

The methods in the studies are shown in Table III. Studies have been classificated according to methods.

In terms of smart cars' features, the classification of low-to-high level works has been provided. In this classification, the studies only collecting data are regarded as low level, while studies performing incremental learning and online updating are accepted as high level. The studies categorized in this way are given in Table IV. Here, it can be resulted that the number of high level studies are getting increase. It can be expected that this number will rise to higher rates in the future.

TABLE IV. CLASSIFICATION OF STUDIES FROM LOW TO HIGH LEVEL.

High		References
	High Level Learning (Incremental, Deep, Online, Experience)	[17, 19-23, 26-29, 31-33, 35-37]
	Unsupervised and Supervised Learning	[5, 18, 30]
	Recognition	[7, 8, 10, 13, 14, 16, 24, 25, 34]
	Classification	[2, 6],
Low	Low Level (Data Collection)	[1]

Variation of existing online and offline studies over the years, and their future estimates are given in Figure 9.

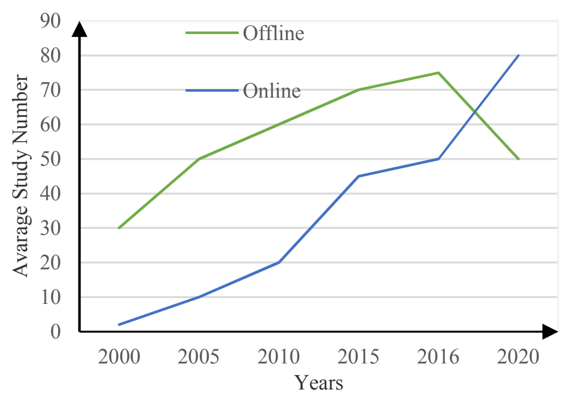

Figure 9. Number of online and offline studies versus years.

Figure 10 depicts the number of methods in the studies according to years.

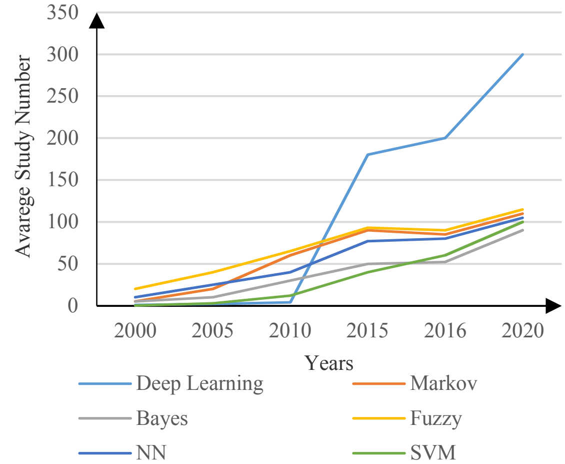

Figure 10. Number of methods versus years.

The results calculated by the performance function of the studies are provided in Figure 11. Since biological data doesn't exist in our sample studies, none of which exposes full performance.

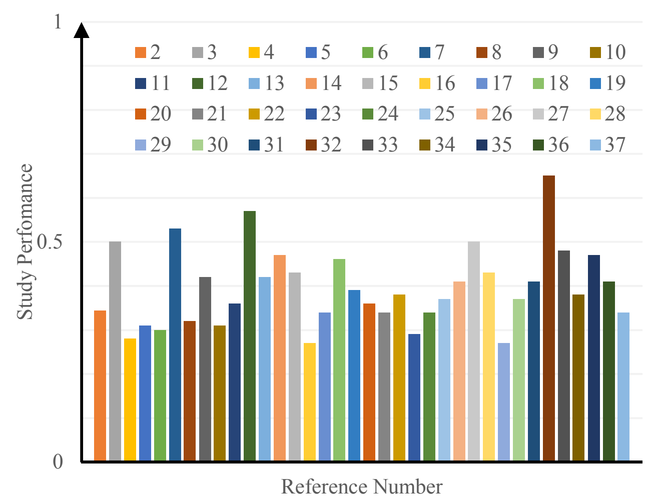

Figure 11. Study performance graphics.

III. EVALUATIONS AND RESULTS

Today and in the future, smart cities will continue to be on the focus of researchers. The desire for a more comfortable and safe environment draws continuous attention of stakeholders in this area. Smart car systems will also be designed and developed according to citizen needs as a part of intelligent cities. Therefore, it can be understood that smart phones are indispensable parts for these types of systems. With development of wearable intelligent technologies, human biological data can also be integrated into the intelligent system. In this way, systems can be developed so that it can better recognize drivers in the future, and are more likely to predict possible driving behaviors. Thus, intelligent driver assistant systems and driverless cars can be built to exhibit similar behavior to an actual driver. Further, it reduces the possibility of accidents enabling comfortable travel.

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