

Body Sensor Networks for Driver Distraction Identification

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Abstract—Cars have become a part of almost everyone’s life taking people from one place to another. In such a fast paced mode of transport, there are a variety of ways in which drivers can get distracted while driving. Getting stuck in a traffic jam, doing other tasks simultaneously while driving- for example drinking, reading, talking over the mobile phone are various forms of distractions. Early detection of driver distraction can reduce the number of accidents. This paper describes the initial analysis of a system for detecting driver distractions using data from the Controller Area Network (CAN) and motion sensor (accelerometer and gyroscope). The paper mainly focuses on distractions perceivable with leg and head movements of the driver. The data from these expressive parts of the driver yield a high accuracy of distraction detection of over 90%. With such high accuracies, reliable systems could be built to have early warning or corrective mechanisms which would avoid or reduce the intensity of accidents caused due to driver distractions.

I. INTRODUCTION

TODAY we live in a fast paced world and the need for effective working environment, demands a fast mode of transport. There are more number of cars on road today than ever before and still the safety concerns remain the same. Safety features, for example, seat belts, air bags, antilock braking systems, traction control systems are a few to name. Along with safety, another important aspect which has grown very quickly in the recent past is the area of entertainment and multi tasking for drivers in the car. Voice interactive systems, navigation systems, hands-free mobile communications, and music players are a few examples. These new gadgets no doubt give the driver the ability of multi tasking but divert the driver’s attention from his primary task of driving. These diversions are collectively termed as distractions [1]. Distraction is formally defined as anything that diverts the driver’s attention from the primary task of navigating the vehicle and responding to critical events. Causes of distraction can be broadly classified into visual, cognitive, biomechanical and auditory [1]. National Highway Traffic Safety Administration (NHTSA) estimates

that about 1.2 million accidents are caused due to driver distractions [6].

There have been many attempts by researchers all over the world to detect distractions. Some of the key research topics in this area have been in pedestrian detection [5], lane tracking system, obstacle avoidance etc. Also from the control system’s side there have been some error correction and stability systems like traction control, anti-lock braking, adaptive steering systems etc which help the driver maneuver the vehicle in an efficient manner. While the above research areas concentrate on avoiding distractions from the environment using Image Processing techniques and stabilizing the system using control system techniques, not much has been done in the area of body sensor networks. Distraction detection using body sensor networks focuses on the driver and his body language. This has a wealth of information about his current state of mind which directly correlates to driver distractions.

In this study, attempts have been made to detect such distractions and classify them by using motion sensors on the leg and head and fusing them with CAN signals. The idea driving this paper is that every driver has a habit behind the wheels. He might be hitting the brake and gas gracefully or might take on the curves smoothly. However, when he is distracted, these normal driving patterns change and they directly reflect in his body movements. This study intends to detect these abnormal body movements using body sensors (e.g., accelerometers and gyroscopes) and hence arrive at the driver’s current mental status.

A subset of the UTDrive database is used for this paper along with data collected from the sensor nodes placed on the leg and head. UTDrive project is part of an on-going international collaboration to collect and research rich multi-modal data recorded for modeling driver behavior for in-vehicle environments [3].

The rest of the paper is organized as follows- Section II describes the data analysis in which the motion sensors and Controller Area Network (CAN) are briefly introduced to the readers. Section III explains the data collection process and the protocol followed to collect data. Section IV describes the various methods followed to detect distractions and the nature of the data used for the analysis. Section V gives the experimental results. The last Section summarizes the paper with future work.

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Fig. 1. UTDrive data collection equipments [2]

II. DATA ANALYSIS

Body movements reveal significant information about the distraction levels of a driver. An abrupt brake or a sharp turn or response to a phone call can be easily detected using sensors on the leg and head.

A sensor on the leg will indicate transitions between the accelerator and brake. A sensor on the head will indicate the movement of the head from left to right or a tilt to answer a phone call. The leg and the head movements are measured using a tri-axial accelerometer and bi-axial gyroscope mounted on the sensor node. Accelerometers are used to detect motion of the object as a result of change in the velocity of the body [5]. Gyroscope measures the degree of orientation of the body.

To obtain the vehicular dynamics, Controller Area Network (CAN) signals from the vehicle are tapped out from the On-Board Diagnostics (OBD2) port [1]. The vehicles manufactured these days have a number of embedded systems with sensors and actuators which work as replacements for most of the mechanical couples found in earlier cars. The sensor and actuator information are communicated between embedded systems via a network known as Controller Area Network (CAN). The CAN bus carries information about the current status of the vehicle such as speed, brake, acceleration, steering angle etc in binary format. Since the paper focuses on driver distractions, only the signals which are directly related to driver actions like vehicle speed, brake, acceleration and steering angle are extracted from the CAN bus. These signals directly relate the driver's actions and the vehicle's response to these actions and they are ideal indicators to the driver's behavior behind the wheels.

III. DATA COLLECTION

The UTDrive vehicle and the data acquisition system Dewetron DA-121 [3] as shown in Fig. 1 are used along with

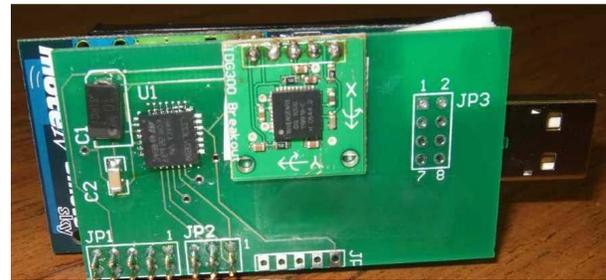


Fig. 2. Data collection using motion sensors

the motion sensor as shown in Fig. 2 for conducting experiments and collecting data. Since data is collected on two different acquisition systems, time synchronization of the data is very important. This is achieved by initially setting both the systems to the same global time and marking every trial data with a start time stamp. Both the systems are started and stopped at almost the same time. Once the data is taken offline, both the CAN and motion sensor data are resampled to the same value of 20Hz and realigned to the same start and end points. Cameras are also used in the data collection process to capture the head and leg movements and they also show the road ahead as shown in Fig. 3. The cameras are later used to segment data and to perform subjective analysis for labeling the segmented data as normal or distracted.



Fig. 3. Video data with motes placed on head and leg

A. Route Description

The route as shown in Fig 4 is used to conduct the experiments. The route includes intersections, turns and parking. The average time to complete this route is about 3 minutes. Each driver is asked to drive twice. The first trial is the normal driving where the person drives in the way he normally does. In the second trial, the driver is asked to perform some tasks while driving. The driver has to talk to the co-passenger, talk on the mobile phone, make some turns which are confusing, abruptly stop when asked to do so. The assumption behind following such a protocol for conducting

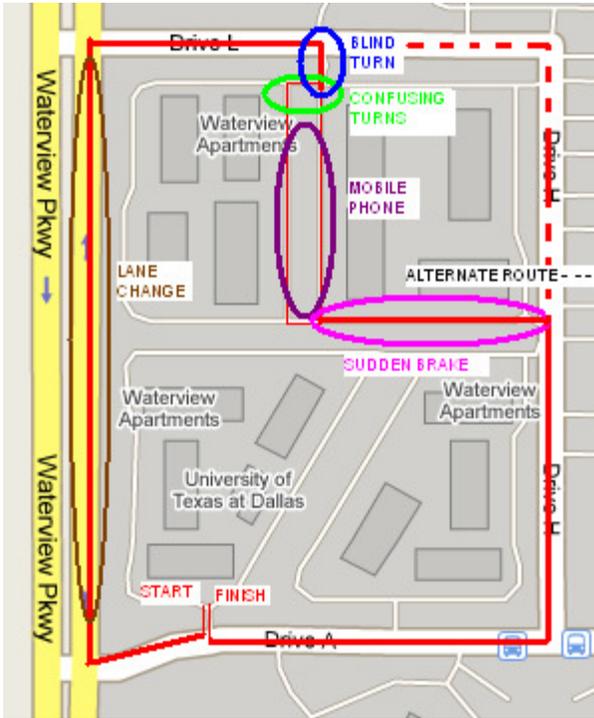


Fig. 4. Route map with task descriptions

experiments is that the driver could be distracted while performing the above mentioned tasks.

IV. EXPERIMENTS

The data collected is analyzed for distraction detection. Observing the video, specific regions of leg movements are marked and segmented either manually or automatically and labeled as normal or distracted data. The segmented data is classified using K-NN (K-Nearest Neighbors) to obtain classification accuracy.

A. Leg data, manual segmentation

Manual segmentation is performed by observing the video data collected focusing the leg. The CAN and sensor data are resampled and aligned to have the same start and end points. The transitions between the accelerator and brake are considered for the leg data segments. This process involves looking at the data collected and visually marking the points of interest as shown in Fig. 5. The regions are manually labeled as normal and distracted using the visual cues and the camera. From the segmented data, features such as time on task, variance of the signal etc are extracted and the system is trained with varied percentage (30%, 50%, 70%) of the data using K-Nearest Neighbors classifier (K=1 in our case). Once the training phase is over, the rest of the data is used to test the system and verify the accuracy by comparing the results with the manual labels. The ratios of the train and the test data are varied. A total of 35 features are used for classification. Principal component analysis (PCA) and Linear Discriminant Analysis (LDA) are used separately for

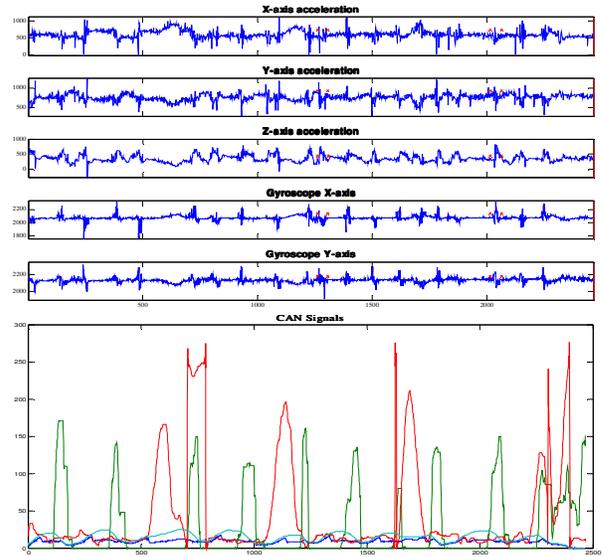


Fig. 5. Raw signals from leg motes and CAN

feature conditioning and to reduce the features to 5 and 1 respectively before applying the classifier. The accuracy of the system after the classification process is shown in the Section VA.

B. Leg data, automatic segmentation

The classification procedure is the same as manual segmentation. Instead of manual segmentation, the system is made to automatically segment the regions of interest.

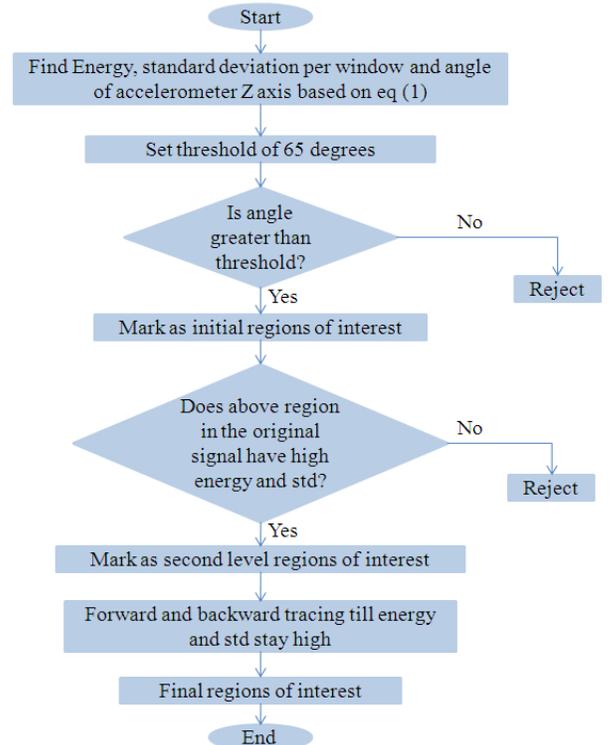


Fig. 6. Flow chart for Automatic segmentation

However, the labeling of normal and distracted regions is done on a manual basis using visual cues. For training the system to segment, a multiple decision tree structure is used as shown in Fig. 6.

On observation, it can be noted that the movement between the accelerator and brake is a maximum of 60 degrees. The accelerometer z-axis traces this angular path. A safer threshold of 65 degrees is used.

$$\theta_z = \arctan \left(\frac{\sqrt{a_x^2 + a_y^2}}{a_z} \right) \dots(1)$$

The forward and backward tracing method is used as a final step in segmentation as distraction is not a discrete point but a continuous event. The entire process is shown in Fig. 7. The segmented regions from this step are used for classification and results are tabulated in Section VB.

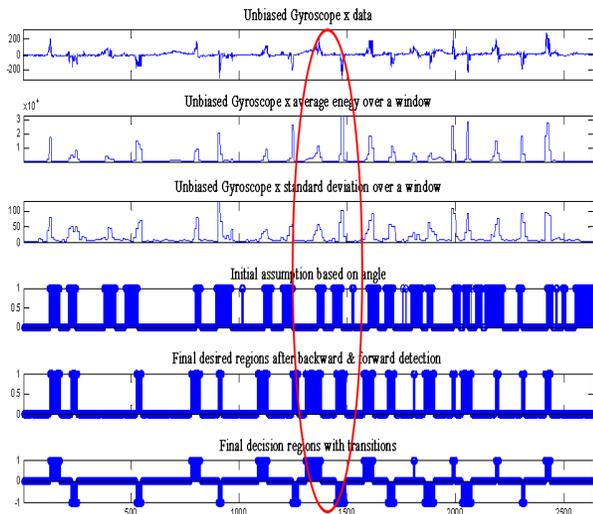


Fig. 7. Decision structure for automatic segmentation

V. RESULTS

Results for the two different approaches which have been described in the previous section are listed below. The entire set of features for the experiments is tabulated with their corresponding descriptions in Table I. A subset of Table I has been used for the classification of each experiment based on the nature of the segmented signals. The K-Nearest Neighbors classification results for each of the experiments are tabulated below along with the classification results after feature reduction using PCA and LDA. The dominant features after feature reduction using both the methods are also listed.

A. Leg data, manual segmentation

The motion sensor and CAN data are manually segmented as described in the previous section. They are labeled as

normal or distracted by observing the video and taking the maximum of the subjective response from four people. Eighteen datasets are used to train the system for classification and the classification accuracy is obtained by testing the system with another set of eighteen data samples. A set of thirty-five features is used to train and test the data samples using K-NN classifier. Different features are selected for motion sensor data and CAN data based on the nature of the signals.

TABLE I
FEATURES CONSIDERED AND THEIR DESCRIPTION

FEATURE	DESCRIPTION
amp	Difference between the maximum and mean value of the signal
maxvalue	Maximum value of the signal
minvalue	Minimum value of the signal
s2e	Amplitude of the difference between the first value and the last value
time	Duration of the signal
maxvalue2	Maximum difference between any two consecutive values
med	Median of the signal
mnvalue	Mean of the signal
p2p	Difference between the maximum and minimum value of the signal
stdvalue	Standard deviation of the signal
rms	Root mean square value of the signal
p2pd	Difference between the maximum and minimum value of the differential of signal

These features are listed in Table II. For each of the feature listed, there are five signals from the motion sensor. They appear in the order accelerometer x-axis, accelerometer y-axis, accelerometer z-axis, gyroscope x-axis and gyroscope y-axis. For example, feature number 3 would represent s2e of accelerometer z-axis and feature number 14 would represent minvalue of gyroscope x-axis. For the CAN data, there are two signals for every feature selected. They are brake and vehicle speed. For example, feature number 29 would represent maxvalue of vehicle speed.

Using PCA and LDA, the number of features are reduced to 5 and 1 respectively. The dominant features after feature reduction using PCA and LDA are listed in Table III.

The classification accuracies of the system using K-NN, PCA with K-NN and LDA with K-NN are listed in Table IV.

TABLE II
FEATURE WITH SEQUENCE NUMBERS

Feature Numbers	Sensor	Feature
1-5	Motion	s2e
6-10	Motion	maxvalue
11-15	Motion	minvalue
16-20	Motion	Time
21-25	Motion	Amp
26-27	CAN	s2e
28-29	CAN	maxvalue
30-31	CAN	Time
32-33	CAN	Amp
34-35	CAN	maxvalue2

TABLE III
DOMINANT FEATURES FOR PCA AND LDA

Method	Dominant Features
PCA(Motion Sensor)	1, 3, 6, 9, 14
LDA(Motion Sensor)	Time (16-20)
PCA(CAN)	26, 28, 29, 32, 34
LDA(CAN)	29

TABLE IV
K-NN CLASSIFIER RESULTS FOR LEG, MANUAL

Feature reduction	Accuracy
K-NN (35 Features)	93.75%
PCA with K-NN (5 Features)	87.50%
LDA with K-NN (1 Feature)	97.30%

B. Leg data, automatic segmentation

The motion sensor and CAN data are automatically segmented as described in the previous section. They are labeled as normal or distracted by observing the video and taking the maximum of the subjective response from four people. Sixteen datasets are used to train the system for classification and the classification accuracy is obtained by testing the system with another set of sixteen data samples. A set of thirty-five features as shown in Table II is used to train and test the data samples using K-NN classifier which is similar to the procedure described in the Section VA. Using PCA and LDA, the number of features are reduced to 5 and 1 respectively. The dominant features after feature reduction using PCA and LDA are listed in Table V.

The classification accuracies of the system using K-NN, PCA with K-NN and LDA with K-NN are listed in Table VI.

TABLE V
DOMINANT FEATURES FOR PCA AND LDA

Method	Dominant Features
PCA(Motion Sensor)	1, 3, 6, 9, 14
LDA(Motion Sensor)	Time (16-20)
PCA(CAN)	26, 28, 30, 31, 34
LDA(CAN)	26

TABLE VI
K-NN CLASSIFIER RESULTS FOR LEG, AUTOMATIC

Feature reduction	Accuracy
K-NN (35 Features)	77.77%
PCA with K-NN (5 Features)	94.44%
LDA with K-NN (1 Feature)	88.30%



Fig. 8. Considered head positions

VI. FURTHER ANALYSIS AND CONCLUSIONS

The paper proposed the first step in the detection of distraction using motion sensors and CAN signals. The classification of leg movements as normal and distracted was done with a high accuracy of 97.3%.

The accuracy suggests that use of motion sensors on the body is a good approach in determining distraction in drivers. With this classification, other systems could be triggered to rectify or to take corrective measures when the driver is found to be distracted. Also, fusing data from other body movements like hand and head with the leg data could trace the driving patterns of a person in a more profound way.

As a probe study, various movements the head makes (straight, left, right and driver on the phone) as shown in Fig. 8 were considered. The data from the sensor placed on the head was manually segmented as performed for the leg data. The segmented regions were manually labeled as driver looking left, right, straight and driver on the phone.

Twenty datasets were used to train the system for classification and the classification accuracy was obtained by testing the system with another set of fifty-six data samples. A set of fifty features was used to train and test the data samples using K-NN classifier. These features are listed in Table VII.

Using PCA and LDA, the number of features are reduced to 5 and 3 respectively. The dominant features after feature reduction using PCA and LDA are listed as shown in Table VIII.

The classification accuracies of the system using K-NN, PCA with K-NN and LDA with K-NN are listed below in Table IX.

TABLE VII
FEATURE WITH SEQUENCE NUMBERS

Numbers	Sensor	Feature
1-5	Motion	s2e
6-10	Motion	Maxvalue
11-15	Motion	Minvalue
16-20	Motion	Time
21-25	Motion	Amp
26-30	Motion	s2e
31-35	Motion	Maxvalue
36-40	Motion	Time
41-45	Motion	Amp
45- 50	Motion	maxvalue2

TABLE VIII
DOMINANT FEATURES FOR PCA AND LDA

Method	Dominant Features
PCA (Motion Sensor)	16, 18, 19, 20, 50
LDA (Motion Sensor)	9, 11, 13

TABLE IX
K-NN CLASSIFIER RESULTS FOR HEAD, MANUAL

Feature reduction	Accuracy
K-NN (35 Features)	95.00%
PCA with K-NN (5 Features)	96.42%
LDA with K-NN (1 Feature)	50.00%

VII. FUTURE WORK

The use of body sensors in analyzing distractions in a

driver is an innovative idea. The high accuracy achieved after the implementation of the leg and head data segmentation is a big boost for future research. For the head movements, multiple level of classification could be used to obtain better results. Hand movements could be taken into account for completeness. A complete and safer system could be built fusing all the results. For example in Fig. 9, the labels obtained from head and leg data can be fused to identify the driver's current surroundings. The circled region suggests that the driver stopped the vehicle, looked right then left and again right before moving further. These set of actions together suggest that the driver could have been near a road intersection at that instant. Instead of this sequence of events, if the driver would have looked left and right many times before proceeding, it could be an indication that the driver is not in his normal sense (if not distracted).

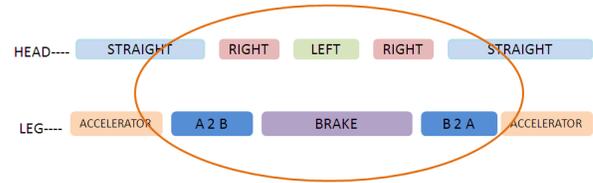


Fig. 9. Fusing head and leg decisions

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