Detecting Distracted Driving Using a Wrist-Worn Wearable

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***Abstract*—In this paper, we attempt to detect instances of distracted driving using a wrist-worn wearable embedded with an accelerometer and a gyroscope. In our experimental study, 16 adult participants were asked to drive a driving simulator that is equipped with realistic driving conditions like brakes, accelerator, steering wheel and a large screen for road scene visualization. The simulator is also programmed for drivers to experience different environmental scenarios like day time, night time, fog and rain/ snow. While driving, participants engaged in a randomized sequence of calling, texting and reading from a phone while simultaneously driving. Throughout the experiment, each subject wore a wearable watch on the wrist which recorded the resulting acceleration and rotation of the wrist via an embedded accelerometer and gyroscope. Subsequently, we extracted a selected number of features from the sensory data, and designed machine learning techniques for detecting instances of distracted driving. Our performance evaluations reveal very good Precision, Recall, and $F1$-Scores. We believe that our paper introduces a new and potentially important application of wrist-worn wearables to enhance road safety.**

Keywords*—wearable sensing, intelligent transportation systems, distracted driving, machine learning, wrist-worn wearables, road safety.

I. INTRODUCTION

Distracted driving is one of the most significant dangers to road safety today, claiming $3,477$ lives in 2015 alone in the US [1]. In most of the above cases, usage of smartphones was identified as a major factor. When driving while simultaneously using a smartphone, drivers are prone to a phenomenon commonly referred as "inattentional blindness" or "perceptual blindness," that is studied extensively by psychologists, wherein a person while distracted may not be reacting to a stimulus even when looking at it [17]. Driving while using a smartphone causes drivers to experience this phenomenon resulting in serious, and in many cases fatal accidents. Needless to say, minimizing accidents as a result of distracted driving is a serious need of the hour.

A. Recent Technological Attempts to Deal With Distracted Driving

In recent times, many stakeholders in the government, industry, and academia are increasingly looking at technological solutions for reducing or removing smartphone usage while driving. These are partly due to people accepting such solutions, as evident by a recent finding in a study sponsored by the American National Safety Council in 2016 [5]. In that study, more than $2,400$ drivers across the country were surveyed, and 55% of drivers said that they would welcome any simple to use technological solution that will prevent distractions while driving. We present some below.

A small device called *Groove* [2] that can be plugged into the OBD 2 port beneath the steering wheel is introduced by a company named Katasi. As soon as the car reaches a speed of 5mph, the Groove device starts working automatically with a cellphone carrier via the Internet to put the phone in a drive mode that prevents notifications to it from social media, texting, and calling while driving. Users though may choose to turn off the service. *Cellcontrol* [4] is another more sophisticated technology that combines a hardware device mounted to the windshield of the car under the rear-view mirror and a smartphone app. Combined, these two will disable alerts to a phone that is detected in the vicinity of the car driver. The next version of the iPhone's operating system, iOS 11, will prompt every user to turn on an optional new *Do Not Disturb While Driving* mode while driving [3]. While these products encourage safe driving, they are not designed to detect distracted driving instances as and when they happen. Furthermore, the hardware devices have to be attached to a car, and are therefore restrictive. Also, existing technologies in the industry are primarily based on GPS data, which is more energy consuming, and also increases privacy concerns.

Researchers in the academia have also proposed interesting solutions in the space of improving driver safety using mobile technologies. Work closely related to the one in this paper are [7] and [8], where inertial sensors in smartphones are used to detect driving-related activities like acceleration, steering, braking etc. In [9], a technique is proposed to only detect texting while driving by assessing the timing differences between keypad entries on the phone. More sophisticated techniques like a) using external antennas to discover, and then jam phone use by drivers [10]; b) using acoustic ranging techniques between a phone and car speakers [11]; and c) computing centripetal acceleration due to vehicular dynamics [12] are also attempts to detect phone use while driving. However, none of these techniques aim to detect the type of distracted driving activity among texting, calling and reading on the phone, using wrist-worn wearables which we accomplish in this paper.

B. Our Problem Statement and Contributions

In this paper we propose a technique to use in-built inertial sensing functionalities of a wrist-worn wearable to detect distracted driving activities. Unfortunately, getting real data for such a purpose is tricky and dangerous that could put participants life at risk, while also precluding us from collecting driving data across multiple environmental conditions.To overcome this, we utilize a state of the art driving simulator

(a) Day time

(b) Night time

(c) Fog

(d) Snow

Fig. 1: Four Participants in the Driving Simulator in Different Environmental Conditions

called the CAREN platform [6], details of which are elaborated in the next section.

In our experimental study, 16 adult participants were recruited to drive the simulator under four different environmental conditions, namely day time, night time, fog and rain/snow. Our data demonstrate that the accelerometer and gyroscope sensors in a wrist-worn wearable show subtle changes when participants attempt to text, call or read from a phone while holding it and driving, that are also distinct from safe driving patterns (i.e., when the driver only drives without using the phone). Utilizing this insight, we design a technique to detect instances of distracted driving by processing the accelerometer and gyroscope data from the wrist-worn wearable.

Specifically, we derive 14 features from the accelerometer and gyroscope sensory data from the wearable that provide a high degree of discriminatory power. Then, we implemented a Random Forest based machine learning classification algorithm to detect instances of distracted driving in real-time. Our technique achieves an overall accuracy of 94.64%, 93.6% and 86.28% respectively for same-user cross-validation, cross-user cross-validation, and cross-user leave-one-out evaluation strategies in determining the specific type of distracted driving activity (i.e., texting, calling and reading) averaged across all environmental conditions. When we reduce the problem to merely a binary classification one in terms of detecting whether or not a subject is using the phone while driving, the accuracy reaches 94.38% even in the more stringent cross-user leave-one-out evaluation strategy, hence demonstrating the effectiveness and practicality of our proposed technique.

II. DETAILS ON OUR EXPERIMENTAL DESIGN

In this section, we describe in detail, the procedures of our experiment using the CAREN driving simulator system and our wrist-worn wearable for data collection. The experimental procedures were approved by the Institutional Review Board (IRB) of the University of South Florida. The authors performed experimental procedures in accordance with the approved guidelines.

A. The CAREN Platform

The driving simulator used for our study is the Computer Assisted Rehabilitation Environment (CAREN) system [6], which was developed by the Center for Assistive, Rehabilitation and Robotics Technologies (CARRT) at University of South Florida, in collaboration with Motek Medical. The simulator includes a six degree of freedom motion base, an optical motion capture system, a sound system, safety harness and a 180-degree projection screen. The two drive by wire (DBW) controls a lever device, which in turn controls the gas and brake components, and a small wheel device to control steering. In doing so, an electrical signal is sent to a Phidget board, which interfaces with the CAREN system. The motion platform enables the driver to feel accelerations and decelerations during driving while being in the platform's work-space. It also displays the driver's speed, surrounding traffic, and number of collisions if any.

Note that driving scenes were created using Google SketchUp 3D modeling software. After a scene was exported, it was imported into D-Flow to be used in the driving applications. Multiple environmental conditions were simulated including day time, night time, fog and rain/ snow for a highway like a scenario that comprised of a four-lane highway with speed limits of up to 70mph, while also simulating moving background traffic. Figs. 1 (a) to (d) shows four participants during our experiments driving in each of the four environments in the highway scenario for which the experimental procedure described here was conducted.

B. The Shimmer Wrist-Worn Wearable

Fig. 2: Participant Wearing a Shimmer

In our study, we have used Shimmer device as wearable, that can be comfortably worn on the wrist. The Shimmer device is very popular, and has been used for wearable related R&D for numerus applications. In our experiments, all participants wore the Shimmer wearable on their right wrist, and all of them indicated that they were comfortable to use their right hand to operate a smartphone while they drove. The core element of Shimmer is a low power $MSP430F5437A$ microprocessor with 24MHz clock rate that controls device operation. The CPU has an integrated 16-channel 12-bit analog-to-digital converter (ADC) which is used to constantly sample and capture tri-axial acceleration and rotational signals from the inbuilt accelerometer and gyroscope sensors. The accelerometer has a range of $\pm 16g$ (where g is gravitational acceleration) and the gyroscope has a range of $\pm$2000d/s (degrees per second), both of which are sampled at 102.4Hz. All sensory data from the device are then streamed via an inbuilt Bluetooth radio module within the unit to an Android phone (Samsung Galaxy S5) using *ShimmerConnect* Android Application. This data is later transferred to a computer for post-processing. Fig. 2 shows one subject with the

Shimmer wearable worn on the right wrist.

C. Participants for Data Collection

In our study, 16 adults were recruited, ranging from ages 20 to 28. Of these, 10 participants were male and 6 were female. All participants had a valid US driver's license, and at least two years driving experience and reported that they generally drove for an average of at-least ten hours per week. All participants volunteered to send/ receive texts, make phone calls, and read from the phone while driving. After signing the IRB forms, and having all their questions answered, participants were familiarized with the driving simulator using a standardized 12 minute adaptation sequence. All participants indicated that they were comfortable to participate in the experiments, and also indicated they were alert and ready to drive (meaning they were not tired or stressed or sleep-deprived).

D. Data Collection Procedure

After the practice session, participants were asked to sit in the driver seat of the car simulator and to strap the Shimmer wearable on their right wrist. Each subject drove for a total of around 11 minutes in the simulator. In the first 2 minutes the subject did not use the phone at all, so that he/ she can familiarize with the simulator. Around the start of the 2^{nd} minute, and for most of the next 9 minutes, participants were engaged in distracted driving by either receiving a phone call for voice conversation, or 2-way texting, or were sent a text message to read while driving. Each distracting activity was around 2 minutes long, with around 1 minute gap between each event to let the subject put the phone down and stabilize their driving in the simulator.

One of the co-authors was the other party in the communication with each subject during these sessions. Note that the sequence of texting, calling and reading sessions were randomized for every subject. All of the 16 participants took part in the above experiment for all four environmental conditions, namely, day time, night time, fog and rain/ snow. At the conclusion of each experiment (around the end of the 11^{th} minute), the subject gradually decelerated and exited the simulator. We point out that throughout the entire duration, each subject drove the simulator constantly and never stopped. The text messages, voice conversations, and reading content were the same for all participants, and the wearable recorded sensor data continuously for all participants while driving. Recall that Figs. 1 (a) to (d) shows four participants in our experiments driving in each of the four environments.

E. Data Tagging

In order to tag the data, we compared the times when an activity was initiated and terminated on the phone, with the times when the sensor readings were recorded in the wearable. By this, we were able to tag the various activities with the sensor readings for subsequent model development.

III. PRE-PROCESSING, FEATURE EXTRACTION AND ALGORITHMIC PROCEDURE

In this section, we present in detail our technique to detect instances of distracted driving by processing sensory readings extracted from the wrist-worn wearable. First, we present pre-processing of sensor data, followed by process of feature extraction, and finally, a brief note on our classification algorithm.

TABLE I: 14 **Selected Features**

Accelerometer Features	**Description**
Square Sum Mean $\mu_{(x^2+y^2)}$, $\mu_{(y^2+z^2)}$	Resultant acceleration in x and y, and y and z direction
Range of linear Acceleration $range(x)$, $range(y)$ and $range(z)$	Difference between minimum and maximum acceleration for given time window
Sum of Range $range(x)$+ $range(y)$ + $range(z)$	Summation of Range of linear acceleration across x,y and z components
Simple moving average of range $\frac{(range(x)+range(y)+range(z))}{3}$	Average of Range of linear Acceleration across x,y and z components
Sum of standard deviation $std(x) + std(y) + std(z)$	Standard Deviation across all x,y and z acceleration components
Other features $\mu(\frac{(x+z)}{2} - y)$	Difference between Average of x and z, and y acceleration component
Gyroscope Features	**Description**
Range of gravity vector $range(x)$, $range(y)$ and $range(z)$	Difference between minimum and maximum rotational speed for given time window
Square Sum Variance $\rho_{(x^2+y^2)}$, $\rho_{(y^2+z^2)}$	Determines variance for x and y, and y and z gravity components

Once the tagged accelerometer and gyroscope sensor data from the wearable is available, the first step is pre-processing the raw sensor data. The readings were sampled using a 2 seconds sliding window. We tried varying the window size from 1 second to 10 seconds with different amounts of overlap. After observations and analysis, we chose a sliding window size of 2 seconds with 50% overlap for our problem. In prior related work [13], it is found that 2 to 5 seconds window works best for human activity recognition using inertial sensors, and this explains the rationale for our choice.

Once the data is pre-processed, the next step is to extract features from the sensor datasets. Feature extraction and feature selection from input data are critical for the accuracy of any supervised learning algorithm. Too few features may not be representative, and too many features incur processing overhead and sometimes can even decrease accuracy by introducing noise [14]. As such, it is critical that we identify a limited set of features from accelerometer and gyroscope data that provide good discriminatory power among various activities of interest, while also keeping processing delay and energy low while computing. For our problem, we extracted 14 features from the accelerometer and gyroscope readings, which are easy to calculate, energy efficient and intuitive for our problem. Table I presents these along with a short description. Note that in Table I the notation x, y and z denote the time domain representation of corresponding axis components of the accelerometer and gyroscope sensor as applicable.

Finally, in this paper, we designed a classification algorithm based on the notion of Random Forests [15] [16]. Random Forest based algorithms are well suited for our problem scope because they handle larger datasets (that are typical with streaming sensor data) efficiently and quickly without causing over-fitting problems. This is because, in Random Forest designs, multiple decision trees are constructed that serve to minimize the variance of training samples during modeling which tends to avoid overfitting problems. Apart from that, they are easy to train and does not assume any distribution in

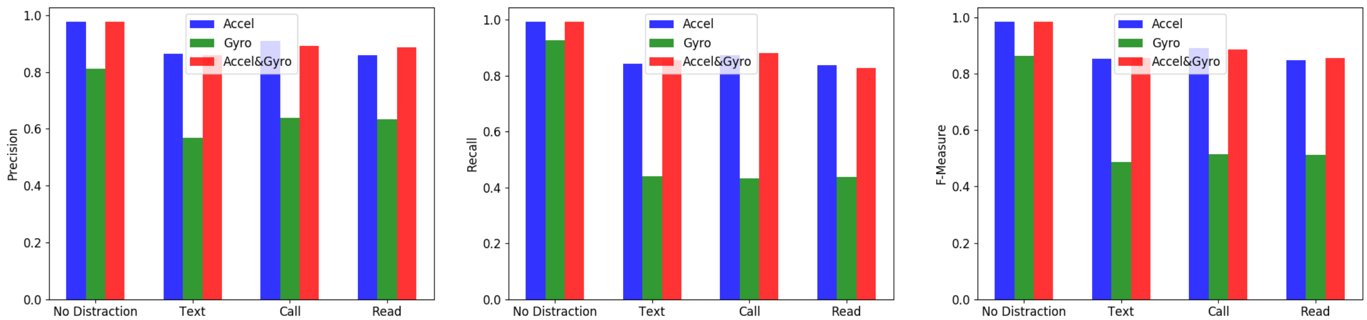

Fig. 3: Precision, Recall and $F1$-Score of our system for four activities for Same-user 10-fold cross-validation strategy for all four environmental conditions.

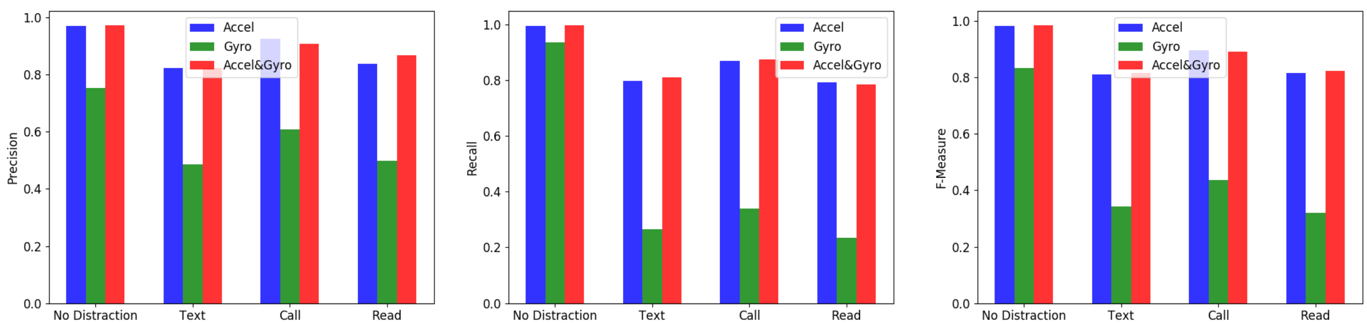

Fig. 4: Precision, Recall and $F1$-Score of our system for four activities for Cross-user 10-fold cross-validation strategy for all four environmental conditions.

data. In our design, the maximum number of trees in Random Forest is set as 100 with seed value 1, where each tree is constructed while considering 4 random features from the set of 14 selected.

IV. DISCUSSION OF RESULTS

In this section, we present results on the validation of our technique to detect distracted driving activities from processing accelerometer and gyroscope readings from the wearable across four environmental conditions – day time, night time, fog and rain/snow.

A. Metrics

The results of our evaluation are presented in terms of three standard metrics: Precision, Recall and $F1$-Score. Intuitively, Precision indicates how many of the testing samples classified as a particular activity actually belonged to that particular activity. Recall indicates how many of the instances of a particular activity were correctly classified as that activity. The $F1$-Score is a measure of the balance between precision and recall.

B. Evaluation Methods

In this paper, we evaluate the performance of our system using three well-established methods that are standard for our problem scope. These testing methods are same-user 10-fold cross-validation, cross-user 10-fold cross-validation and cross-user leave-one-out evaluation.

Note that our datasets are relatively uniform across classes to minimize any inherent biases. Also, among the three strategies evaluated, some may show better results than others. Usually, evaluations on same users show better result compared to any cross-user evaluation strategy. This is intuitive since there are subtle variations among people even when they do the same activity that is sometimes hard to detect when training and testing are done on different people. However, as we show, our algorithm still achieves high performance both within and across users for a number of activities, hence demonstrating the effectiveness of our technique.

C. Integrated Evaluation across all Environmental Conditions

Recall that each of the 16 participants in our study participated in driving experiments for four environmental conditions – day time, night time, fog, and rain/snow. Instead of training and testing our model on each condition separately (that will give us better results on accuracy), we chose to train and test our technique on a mixed model, where data from all users for all four conditions are incorporated. In other words, when testing the accuracy of our system under any one environmental condition (say night time) the training data sets includes data from all of the four environmental conditions. The same is true when testing across all other environmental conditions. As such, results presented are averaged out across all environmental conditions, for all of the three evaluation strategies presented above. This is the most practical scenario since any technique proposed to detect distracted driving activities must work for all environmental conditions, rather than be specifically tuned for a single one. This will hence

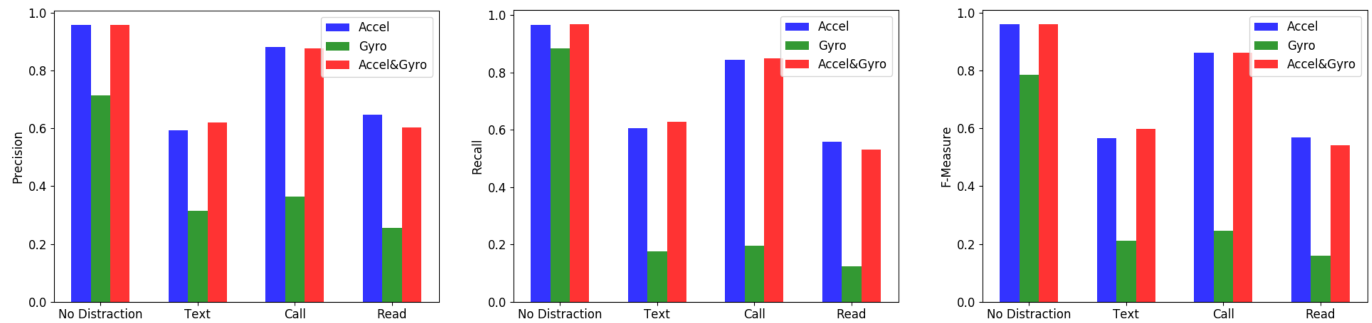

Fig. 5: Precision, Recall and $F1$-Score of our system for four activities for Cross-user leave-one-out strategy for all four environmental conditions.

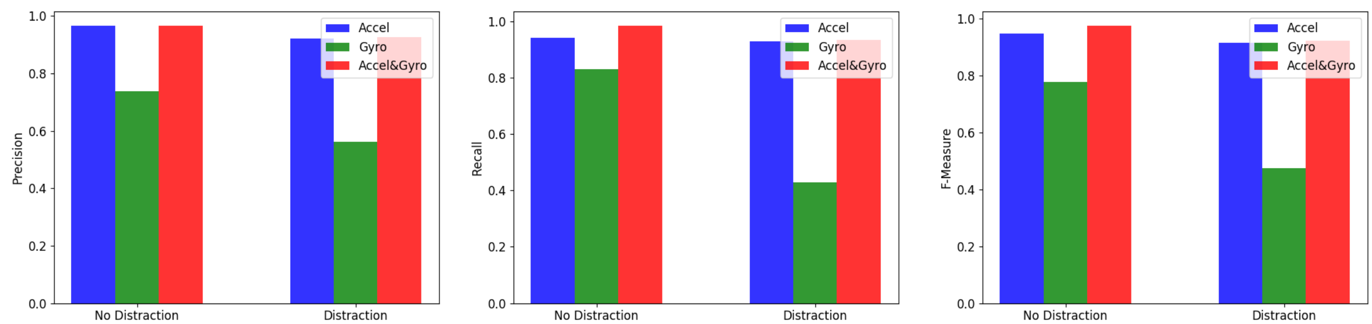

Fig. 6: Precision, Recall and $F1$-Score for Binary Classification Problem (Detecting Distraction vs. No Distraction while driving) for Cross-user leave-one-out strategy for all four environmental conditions.

provide a more realistic evaluation of our proposed technique.

D. Results

Figs. 3, 4, 5 and 6 present our results. Recall that the classification algorithm was based on the notion of Random Forests, and the input features used for classification were only the 14 features from accelerometer and gyroscope sensors in the wearable identified earlier in Table I.

a. Classification Accuracies for Random Forest based Algorithm: For the same user 10-fold cross-validation strategy, as shown in Fig. 3, the performance of accelerometer and gyroscope sensors are high to classify activities correctly, as indicated in the Precision, Recall and $F1$-Scores. The overall performance is 94.63% for Precision, 94.7% for Recall and 94.64% for $F1$-Score for both sensors combined. We also see that while integration of features from the gyroscope sensor and the accelerometer sensor does improve accuracy, for the most part, it is not significantly more than the accuracy when only features from the accelerometer sensor are used.

For the cross-user 10-fold cross-validation in Fig. 4, we can see that average performance to classify activities in terms of Precision, Recall and $F1$-Score is 93.6%, 93.8% and 93.6% respectively, which again demonstrates the validity of our technique.

Fig. 5 presents results for the more stringent evaluation strategy, which is cross-user leave-one-out. We do see a drop in performance in this evaluation strategy. While the accuracy in detecting un-distracted driving is still very high (94.38%), we see that our proposed technique does not do well in detecting instances where the subject is texting, calling, or reading (where the average accuracy is only 86.28%). It is because, different users do have subtle differences in the way they text, call and read from a phone while driving, that is enough to bring down accuracy with the leave one out evaluation strategy. We certainly hope that with more data from more participants, our proposed technique will learn better for fine-grained activity classification.

However, we also wanted to see how our current technique performs when we attempt to address a slightly simpler, but nevertheless important and practical problem, which is to classify instances of distracted driving (irrespective of the type of distraction) from un-distracted driving. Fig. 6 presents the results for the stricter cross-validation with leave one out evaluation strategy for this binary classification problem. As we can see, our proposed technique achieves near-perfect performance in terms of Precision, Recall and $F1$-Scores in differentiating distracted driving from un-distracted driving using sensory data from the wrist-worn wearable. This is important, since whether a driver picks up a phone for texting, or calling, or reading, each is a source of distraction and best avoided (we really cannot think of any other practical reason for a person to pick up and operate a phone while driving). As such, we believe that the more complex problem of determining the fine-grained activity that causes the distraction may not be necessary after all if the motivation is to ensure safer driving by detecting any instance of distracted driving from phone usage, which our system is able to determine as seen in Fig. 6.

b. A Note on Classification Accuracies with Other Machine Learning Algorithms: For comparison purposes,

TABLE II: **Performance ($F1$-Scores) Comparison Across Algorithms**

Strategy	Naive Bayes	SVM	Decision Tree	Random Forest
Classification for 4 activities (No Distraction, Text, Call and Read)				
Same-user	0.817	0.798	0.934	0.946
Cross-user	0.662	0.805	0.929	0.892
Leave-one-out	0.618	0.752	0.842	0.863
Classification for 2 activities (No Distraction and Distraction)				
Same-user	0.817	0.798	0.934	0.946
Cross-user	0.662	0.805	0.929	0.892
Leave-one-out	0.618	0.752	0.842	0.863

we present in Table II, overall performance ($F1$-Scores) of classification with three other learning algorithms (Naive Bayes, SVM and Decision Tree) for the cases of fine-grained activity classification, and binary classification only. Overall, we also see that the Random Forest Algorithm has superior performance among all other algorithms for all strategies. We also see that the performance across algorithms exhibits a reasonable degree of consistency, hence validating our features selected earlier in Table I as a representative for this problem.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we attempt to classify instances of distracted driving as a result of phone usage via processing the data generated by in-built accelerometer and gyroscope in a wrist-worn wearable. Our experimental procedure involved collecting data from 16 adult subjects driving a realistic car simulator in multiple environmental conditions. Subsequently, using effective feature extraction techniques, and machine learning algorithms, we are able to achieve high accuracy in detecting instances of distracted driving.

Our future work lies in enhancing detection accuracy by integrating intertial sensor data from multiple sources (i.e., wrist sensor, embedded phone sensor, and possibly sensing abrupt changes in the car trajectory). Fusing these data sources in real-time can be challenging though. Designing just in time interventions to enhance driver safety based on human psychology is also part of future work.

ACKNOWLEDGEMENTS

This work was supported in part by the US National Science foundations under grants CNS 1205695 and IIS 1559588. Any opinions, thoughts and findings are those of the authors and do not reflect views of the funding agency. We also appreciate the help of the staff managing the CAREN simulator at USF during data collection.

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