

# In-Vehicle Driver Detection Using Mobile Phone Sensors

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## Abstract

With the advances in smartphone technologies, automated detection and awareness of various user statuses has become a focal point of mobile computing research. In this project, I present a software-based, mobile-phone sensing system to determine if the user is the driver or a passenger in an automobile. The system helps the mobile device's identify the user's available attention and focus, enabling it to control delivery of potentially interrupting events such as incoming calls and messages. Since the system does not employ additional hardware, the phone may be carried in different locations and orientations. In addition, the paper will describe the various design challenges, including the evaluation of the system's energy consumption and operation in noisy environments using the Android 2.3.x and iPhone OS 4.x devices.

## 1 Introduction

The modern mobile phone hosts a variety of sensors capable of capturing and inferring significant amounts of information about the user's statuses and activities. One of the key causes of traffic accidents is the use of cell phones while driving. This project presents the Driver Detection System (DDS), a phone-based system to determine if the user in a car is a driver or passenger, allowing the phone to adaptively intercept incoming calls and messages based on the amount of available user attention.

Traffic safety is only one of the many important applications of the DDS. Americans and Europeans spent an average of 86 and 43 minutes per day in the car [2], amounting a significant amount during which the users' attentions are in entirely different states. For example, passengers in a car will have a greater amount of available attention, freeing them to respond to emails, social networking updates and nearby activity notifications. For the drivers, however, their attention is directed toward the road and most such notifications should be suppressed or redirected toward the passenger.

Data from the DDS can be used to track driving behaviors of users and provide greater knowledge to authorities. Transportation departments can use the data to optimize carpooling lanes and incentives, and parents of newly licensed teenage drivers can use this information to gradually increase the access of their cars as the teen becomes more experienced. Finally, with sufficiently reliable sampling, insurance companies can offer special incentives to drivers who have demonstrated safe driving behaviors. Ultimately, DDS is meant to serve as a building block for developers to create applications that benefit from the detection of driving activity.

The DDS seeks to capture and detect key user movements during the car entry process, as well as specific sound patterns unique to vehicles post-entry. The system is limited to sensors available on the modern smartphone, which creates a number of challenges in the solution design. Such events are short-lived, and power considerations limit the system's ability to run continuously in the background. In addition, different users will carry their phones in different locations and orientation, and these cases must be addressed in the detection algorithm. Thirdly, the system must compensate for noise generated by the environment and different user movement patterns. Finally, the result must be produced quickly in real-time once the user starts driving. Hence, complex processing or excessive communication with back-end servers may not be appropriate for the design.

Prior work has demonstrated the ability to determine if the user is in a vehicle [19], as well as determining the type of vehicle [27]. Available solutions only tracks the

speed of the GPS, locking the phone when the user is moving at speeds greater than specific cutoffs [26]. However, this design also prevents passengers in cars and other forms of public transportation from safely using their phones. DDS would contribute driving as a new activity within this domain of work, adding to an existing number of interesting detectable activities such as traffic tracking [28] and carbon footprint measurements [23].

Several people have contributed significantly to the DDS presented in this paper. Hence, I will describe the parts of the system which I contributed individually. These parts include the Entry Swing detection, the Handbag detection, and the power consumption measurements. A brief description of the whole system will be included in order to link my contributions to the rest of the project.

## 2 Driver Detection

### 2.1 Problem Outline

The goal of the system is to identify in real-time whether the mobile phone user is a driver or a passenger in a vehicle. Based on the discussion above, our approach will employ a completely software-based solution on the phone, without requiring additional wearable sensors or modifications to the users' vehicles. The sensors used include the accelerometer, gyroscope, compass and microphone.

#### 2.1.1 Phone Location

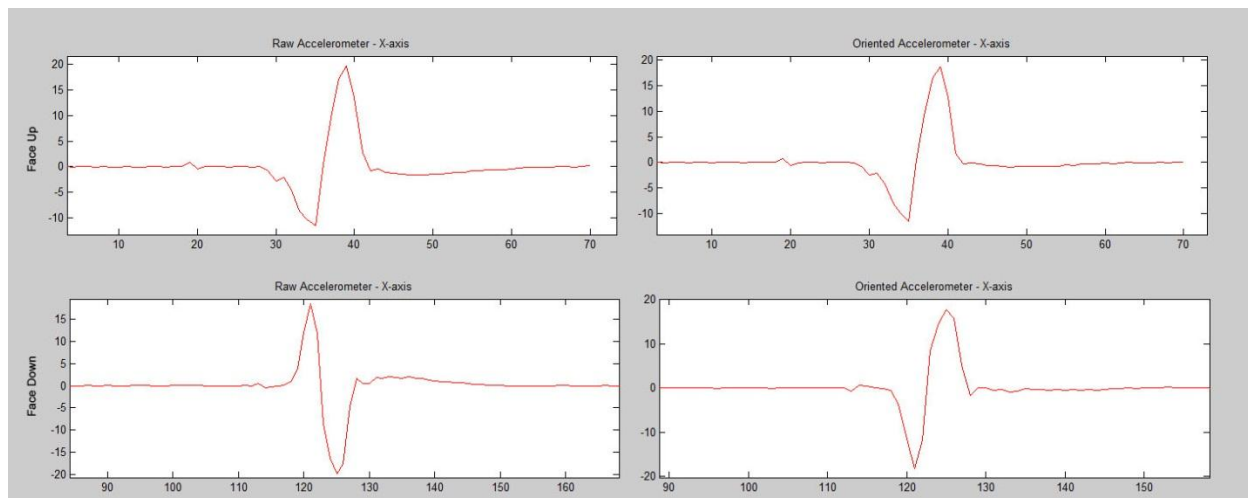
A recent study surveyed 419 users from U.S., Spain, and Finland. As shown in Table 1, the study found that 34% of all users carry their phone in their trouser pockets, 41% carry the phones in a shoulder bag, and another 5% carry their phones in the upper body pockets [13]. Together, these three locations account for 80% of the different locations users might carry their phone. Our project focuses on these three cases and runs different sensing algorithms depending on the phone's location.

**TABLE 1.** Phone locations for users surveyed in [13].

Location Type	Female	Male	Total	In DDS?
<b>Trouser Pockets</b>	8% (16)	57% (128)	34% (144)	Y
<b>Shoulder Bags</b>	66% (128)	4% (9)	33% (137)	Y
<b>Backpacks</b>	10% (19)	6% (13)	8% (32)	Y
<b>Upper-Body Pockets</b>	2% (3)	9% (20)	5% (23)	Y
<b>Belt Enhancements</b>	1% (2)	15% (33)	8% (35)	N
<b>Others</b>	14% (26)	9% (22)	11% (48)	N
<b>Grand Total</b>	100% (194)	100% (225)	100% (419)	--

### 2.1.2 Phone Orientation

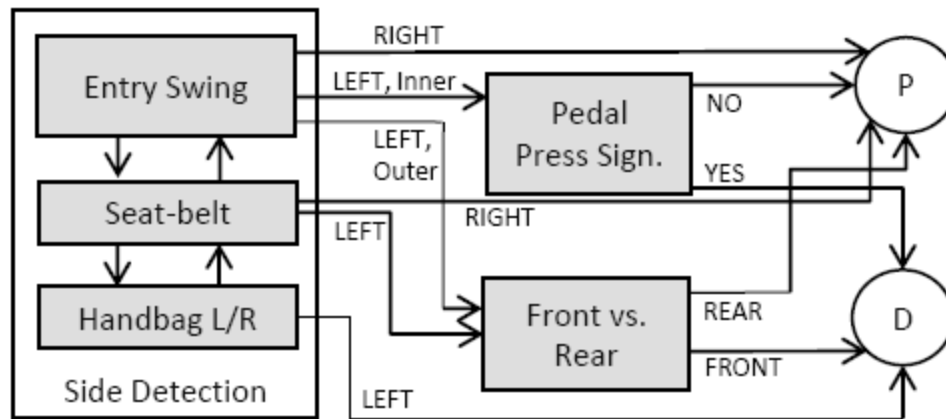
Accelerometer data is a key part of movement pattern detection in the DDS design. However, raw accelerometer data is captured with regards only to the phone's frame of reference. In other words, if the phone was placed faced up on a table, a translational movement to the left would register as a signal in the negative X direction, as shown in the upper left graph in Figure 1. However, if the phone was then flipped over, the same movement would be registered in the position X direction shown in the lower left graph in Figure 1. Different users will carry their phone in different orientations, even if the phones are located in the same position (i.e. trouser pockets). Our system uses orientation data from the gyroscope, compass and the smartphone's internal algorithms create a rotation matrix, which helps reorient the raw accelerometer data to the universal reference frame based on the magnetic poles of the earth. The right column in Figure 1 demonstrates the orientation capabilities of our system.



**FIGURE 1.** Reorientation of Accelerometer data. The left column shows the raw accelerometer readings for a leftward movement with the phone facing up (top) and facing down (bottom). The oriented accelerometer readings in the right column show that the data is unaffected by the phone's orientation.

## 2.2 Solution Design

While there are three different positions for the DDS to address, the algorithms share common components which lead to simplifications in the system design. Figure 2 summarizes the building blocks used in each of the three phone positions: trouser pockets, upper-body pocket, and handbag. In general, DDS uses a left vs. right algorithm to determine how the user entered the car. This is followed by a front vs. rear sensing scheme to determine if the user is sitting in the front row of the car or in the back. This allows DDS to determine the location of the phone inside the car and thus infer the user's status as a driver or passenger.



**FIGURE 2.** DDS decision flow tree. In the outputs shown on the right, P denotes passenger and D denotes Driver. The left box, containing Entry Swing, Seat-belt and Handbag L/R denotes the left vs. right detection scheme, while the components in the middle denotes front vs. rear detection schemes.

### 2.2.1 Left vs. Right algorithms

**Entry Swing:** The Entry Swing block is used when the phone is in the trouser pocket, and determines if the user entered the vehicle from the driver side or the passenger side of the car. In addition, due to the constraint in leg movement when the user enters the car, the block can also determine if the phone is in the user's left trouser pocket or right trouser pocket. This block uses data from the accelerometer, gyroscope and compass.

**Seat Belt:** The Seat Belt block is used when the phone is in the upper body pockets, and captures the users' movements as they buckle in their seat belts. The algorithm will detect the leftward movement as users on the driver side turns to grab the seat belt, which is followed by a rightward movement to plug in the seat belt. Users on the passenger side will perform the reverse motion, creating the distinction. This block uses data from the accelerometer, gyroscope and compass.

**Handbag L/R:** The Handbag block is used when the phone is in the users' handbag or book bag, and uses audio data to determine proximity to the turn signal source. The algorithm is similar to the Front vs. Rear block described below.

### 2.2.2 Front vs. Rear algorithms

**Front vs. Rear:** The Front vs. Rear block is used for all three positions – trouser pocket, upper-body pocket and handbag. The block determines if the phone is in the front or rear portion of the car. The block captures audio data from the car, compares the amplitude of the car turning signals to determine the phone's distance to the front

of the car. Since the vehicle cabin is separated by the front passenger seats, the algorithm is able to detect a meaningful difference in amplitude, even with various levels of background noise and pocket thicknesses. This block requires communication with a cloud server in order to perform the comparison, which might lead to higher energy consumption. Audio data recorded from the microphone is used in this block.

**Pedal Press:** The Pedal Press block is a special Front vs. Back algorithm that is only employed if the phone is in the trouser pocket. If the Entry Swing block determined that the user entered the car from the driver side, and the phone is located in the right trouser pocket, the Pedal Press block is used to detect the motion of the driver pressing the gas pedal. In this case, if the gas pedal motion is detected, the user is determined to be the driver. This block uses data from the accelerometer, gyroscope and compass.

### 2.3 Event Triggers and Timeline

The DDS system cannot run continuously – doing so would degrade the battery life of the phone significantly. Hence, triggers and timeouts must be employed in order to optimize the battery life. While the decision tree varies based on the phone's location, the initial phases are the same.

1. **Walking and Pause:** Initially, DDS will collect a 1 second accelerometer sample every minute to detect if the user is walking. Detection of walking has been demonstrated in prior works and DDS use a simple amplitude-based method to detect walking [29]. Once walking is detected, the accelerometer is turned on continuously until the user pauses, either to open a car door or simply moving to another room.
2. **Entry Swing and Seat-Belt Detection:** Once a pause is detected, the accelerometer, gyroscope and compass will be turned, and both the Entry Swing and Seat-Belt algorithms will run on the phone. These detection algorithms will timeout when vehicular motion is detected, or a threshold of 15 seconds has been reached. Vehicular detection has been shown in prior works and is easy to detect from accelerometer data [27].
  - a. If the Entry Swing or Seat-Belt signature is detected within the 15 second timeout, DDS will move on to Step 3.
  - b. If neither signatures are detected within the 15 second timeout, but vehicular motion is detected, the phone will move on to the Handbag block, which has a 3 minute timeout similar to the Front vs. Rear block in Step 3.
  - c. If none of the signatures or vehicular motion is detected, the DDS resets back to Step 1.



3. **Front vs. Rear Detection:** During this step, a 3 minute audio sample is recorded using the phone's microphone. At the end of the 3 minutes, DDS resets to Step 1.
  - a. If the phone was detected to be in the right trouser pocket, and the user entered from the driver side, the phone will also run the Pedal Press algorithm. The DDS will timeout this SVM after 15 seconds, since it is necessary to press the brake pedal in order to start the vehicle.

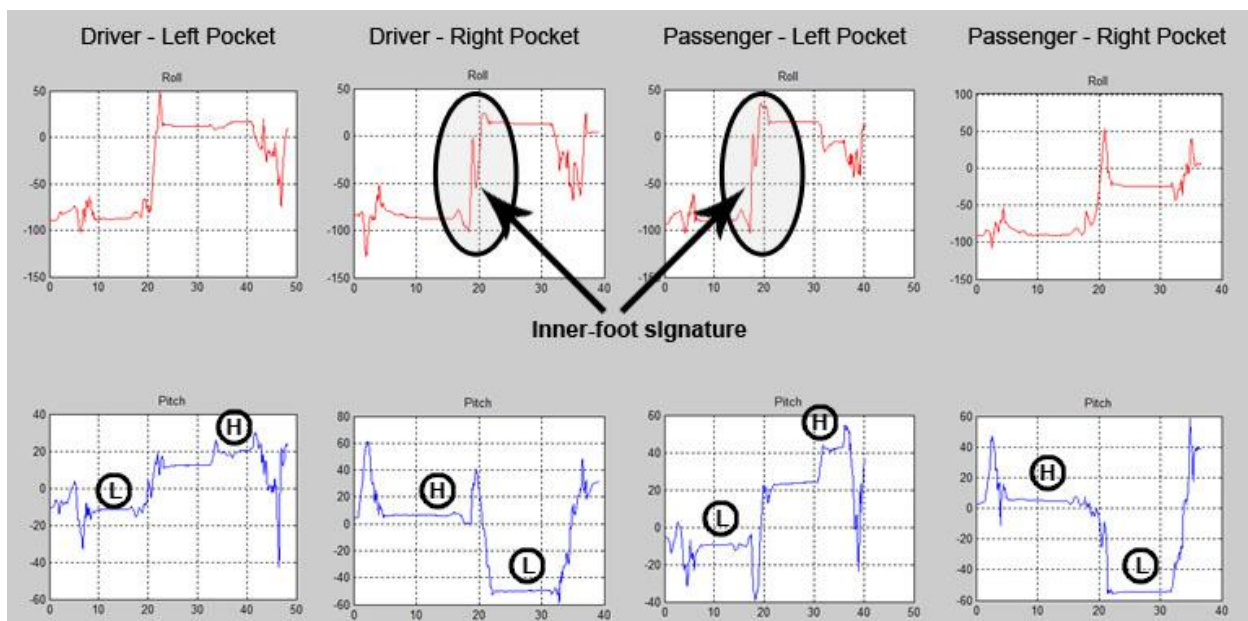
In the description above, I have assumed a left-handed vehicle for simplicity. The decision tree can be modified easily for users in a region with right-handed vehicles, which can be inferred from the phone's carrier, rough location and time-zone.

### 3 Sensing Algorithms

This section will explore my contributions to the project in detail.

#### 3.1 Car Entry Swing

The Car Entry Swing detection is based on the concept that the driver's phone will experience a different movement when entering the car compared to the passenger. Accelerometer, Gyroscope and Compass is used in this algorithm. Specifically, this Entry Swing can be broken down into two signatures, both shown in Figure 3.



**FIGURE 3.** Car Entry Swing signatures. The top row shows the inner-foot signature present on the pockets closer to the car. The bottom row shows difference in transition from H (high) to L (low) for left vs. right pockets.

The inner-foot signature can be seen on the top row of Figure 3. The signature manifests as a blip during the car entry process. Repeated trials have shown that this signature is consistently present on the inner trouser pockets, namely, the right pocket for the driver and the left pocket for the passenger. Analysis of the car entry process indicates that the blip is caused by the footstep that the inner foot takes in order to enter the car. One observation made during the testing is users will always enter vehicles with their inner foot first, and hence, the “step” will always be present on the inner foot. While it is possible to enter the car with the outer foot first, doing so is awkward and unlikely to occur. As one can see from the top row, this blip is missing from the outer foot pockets.

The second signature, termed the “pocket signature”, allows the phone to determine which pocket the phone is in, regardless of the driver or passenger status. From the bottom row of Figure 3, both the driver and the passenger’s left pockets (the first and the third column) experienced a low to high transition while the right pockets for both the driver and passenger experienced a high to low transition. Analysis during of the car entry process indicates that the transitions are caused by the swing of the phone toward the outside of the users during the car entry process. Taken together, these two signatures allow us to determine both the entry direction and which trouser pockets the phone is in. Table 2 summarizes this decision process.

**TABLE 2.** Car Entry Swing Classifications

<b>User/Phone Location</b>	<b>Inner-foot sign.</b>	<b>Pocket sign.</b>
<b>Driver/Left Pocket</b>	No	L → H
<b>Driver/Right Pocket</b>	Yes	H → L
<b>Passenger/Left Pocket</b>	Yes	L → H
<b>Passenger/Right Pocket</b>	No	H → L

### 3.1.1 Support Vector Machine

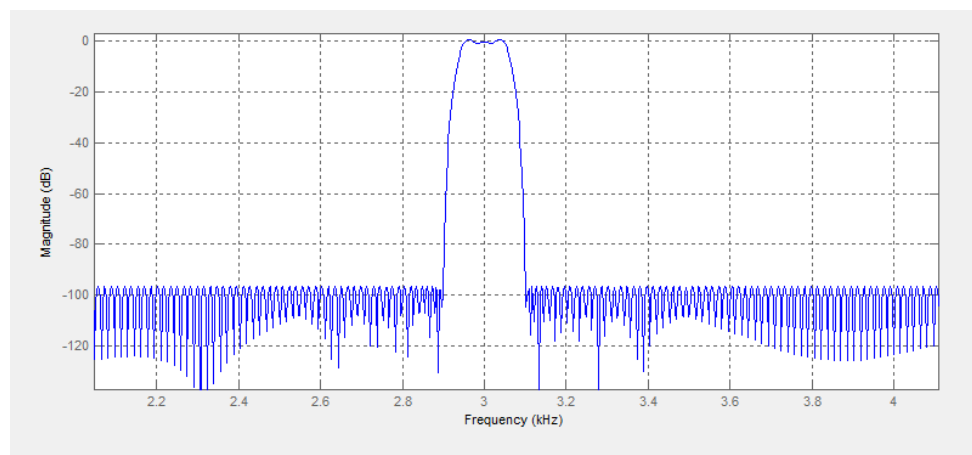
To quantify these qualitative observations, I used a support vector machine (SVM) to classify the input data into five categories – the four shown in Table 2 plus a group of “negative” data consisting of signatures from other periods of the car entry process. The features used in the SVM include segmented averages, peak and trough counts, variance, and derivatives of oriented accelerometer and gyroscope data. Peak and trough counts were used to detect the additional blips in the inner foot signature, and the variance and derivatives were used to identify the periods of transition which includes the inner foot signature. Segmented averages are used to identify the high and low transitions. LibSVM with the RBF Kernel was used to perform the classification in both MATLAB and on Android OS 2.3.x devices.

### 3.2 Handbag

The Handbag detection algorithm is based on the Front vs. Rear detection algorithm, and compares the magnitude of sound generated by the turn signals of the car. The inherent assumption is that the driver-side user will place the phone closer to the source of the turn signal – namely the dashboard area in front of the driver. This proximity generates a distinguishable amplitude difference so that a comparison can be made to determine which phone belongs to the driver. The comparison process requires the communication of the phones within the car. Rather than using Bluetooth, which requires the user to manually enter specific passwords, the Handbag detection algorithm uploads the data to a central cloud server, which handles the comparison.

The server performs two functions. First, it must match the data it received to phones from the same car. Like the Front vs. Rear case, the phones will include their rough location, timestamp and accelerometer data to help the cloud server match the data it receives. If such a match is not found, the algorithm will determine that the phone belongs to a driver with no passenger.

After the data has been matched to the same vehicle, a band-pass filter is used to separate the turn signal sound, which has been empirically observed to occur at around 3 kHz. Other sound components such as music and wind noise can still be heard in the audio samples after the filtering, but these background sounds are present in both the driver and the passenger, and hence should be canceled out in the magnitude comparison. The equiripple band-pass filter was designed to sample at 44.1 kHz, has a pass-band between 2.95 kHz and 3.05 kHz with stop bands at less than 2.9 kHz and greater than 3.1 kHz. The ripple was minimized to 0.0575. The magnitude response of the band-pass filter is shown in Figure 4.



**FIGURE 4.** Band-pass filter magnitude response for Handbag block.

### 3.2.1 Handbag Limitations

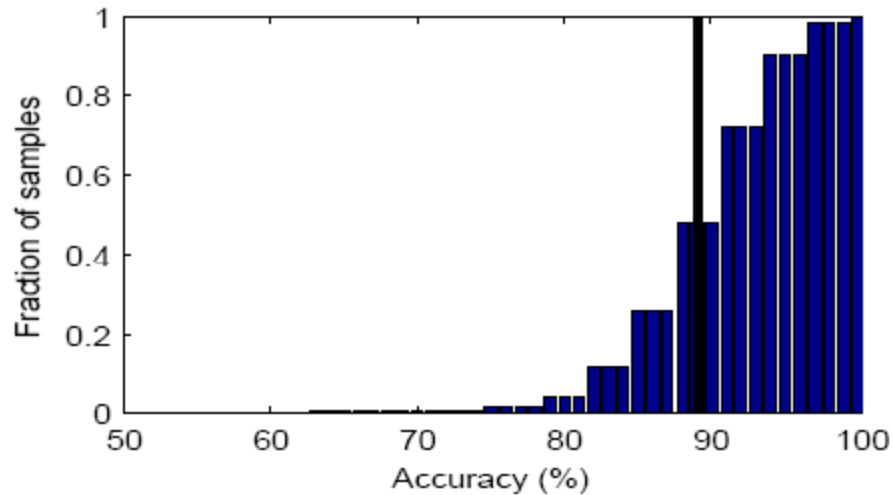
Inherent in the handbag detection algorithm is the variability of where the bag might be placed. For example, experimental trials with female users show that female drivers tend to place bags in different places depending on the presence of a passenger. Without a front-seat passenger, the preference of the driver is to place the bag in the front passenger seat. With a front seat passenger, the driver's bag might be placed next to the left leg of the driver, in the center cup holder area, or on the floor behind the front seats. In the handbag detection, only scenarios where the phones are still readily accessible by the drivers are considered. This limits the driver's phone to within the front seat areas, but does not make such an assumption for the passenger's phone.

## 4 Evaluation

The DDS was implemented and evaluated for its accuracy and energy consumption. Experimental data collection was done across five distinct users, three male and two female, using Android 2.3.x and iOS 4.x devices. The test data were done in realistic settings without controlling for the phone's orientation, the users' movements, and their bag placement preferences. More than 500 unique traces of car entry movement were captured for the Car Entry Swing SVM. For the Handbag, more than 70 samples of music were collected. To emulate varying level of music and wind noise, the samples were taken in with three levels of music (silence, low, high) and three speeds of driving (still, low, and high).

### 4.1 Car Entry Swing

The accuracy of the system is evaluated using cross-validation. The SVM was trained using 80% of the total data, and tested for accuracy on the remaining 20%. The training data is taken without regards to the user and phone orientations. To help remove bias sampling in the randomization, 100,000 of such cross-validations, each with a random 80/20 split, were performed, resulting in an average accuracy of 88.99%. The resulting CDF of the classification accuracy is shown in Figure 5.



**FIGURE 5.** Car Entry Swing SVM accuracy CDF.

## 4.2 Handbag

As mentioned previously, the handbag detection algorithm is limited to scenarios where the driver's phone is placed in the front seat area of the car. Three possible cases can arise. In the first case, the passenger's phone is placed significantly farther away from the turn signal source. For example, the drivers' phones may be placed in close to their feet area, while the passengers' phones are placed in the backseat. This case is similar to the Front vs. Rear scenario, which had an accuracy of 95.83%, and was not re-evaluated.

The second case, which was evaluated, is when phones are placed approximately the same distance from the turn signal source. For example, both the driver and the front passenger place their bag near their respective left legs. To evaluate this case, audio samples were collected, filtered and the magnitudes of the turn signals were compared. In addition to the variety of background sound levels, the system also accounted for the varying levels of thickness of handbags.

The best case scenario is when the driver's phone is outside the bag, equating to a very thin bag, while the passenger's phone is inside the bag. This would allow the driver's phone to capture the turn signal without hindrance, while the passenger's phone will almost certainly capture lower amplitudes due to increased distance and increased bag thickness. The worst case scenario is the reverse, in which the driver's phone is inside the handbag, while the passenger's is outside. Evaluation of the best case scenario was not necessary since the other three relatively worse cases (D-In, P-In; D-Out, P-Out; D-In; P-Out) are sufficient to demonstrate the system's accuracy. The results are shown in Table 3. The headers in the three rightmost columns indicate the

location of the phone relative to the bag. Note that an amplitude ratio greater than 1 is considered a successful. Based on the result in Table 3, the handbag has an accuracy of 87.50%.

**TABLE 3.** Handbag Algorithm Result

Music Level	Drive Speed	Amplitude Ratio (>1 denotes success)		
		D-In, P-In	D-Out, P-Out	D-In, P-Out
Low	Low	6.23	1.35	1.55
Low	High	1.40	2.23	0.65
High	Low	1.48	1.00	0.05
High	High	1.23	8.25	1.19

Finally, the third case is when the driver's and passenger's phones are located close to each other. Similar experiments have shown that the algorithm will fail due to the proximity of the phones to the turn signal source.

### 4.3 Other Detection Blocks

As mentioned previously, there are several other detection blocks in the DDS. While they were not personally evaluate, a brief description of their accuracies will help better portray the overall picture of the DDS. The Seat-Belt block, used to detect left vs. right movement for the upper body pocket, was ran with 100,000 cross validations and resulted in a mean accuracy of 91.08%. The Pedal Press block, used when the phone is located in the right pockets of users who entered the car from the driver side, is evaluated similarly and has a mean accuracy of 89.78%. Finally, the Front vs. Rear block, evaluated similarly to the Handbag block, yielded an accuracy of 95.85%. The Front vs. Rear block also contains a matching algorithm to match different audio samples to the same car, and demonstrated near 100% accuracy when the accelerometer trace lengths were 60 seconds.

### 4.4 Overall Accuracy

**TABLE 4.** Overall accuracies of the DDS.

Case	Left Vs. Right Algorithm	Front vs. Back Algorithm	Overall
Trouser Pocket	88.99%	95.83%	85.28%
Upper Body Pocket	91.08%	95.83%	87.28%
Handbag	87.50%	95.83%	83.85%
<b>Weighted Overall</b>	--	--	<b>84.67%</b>

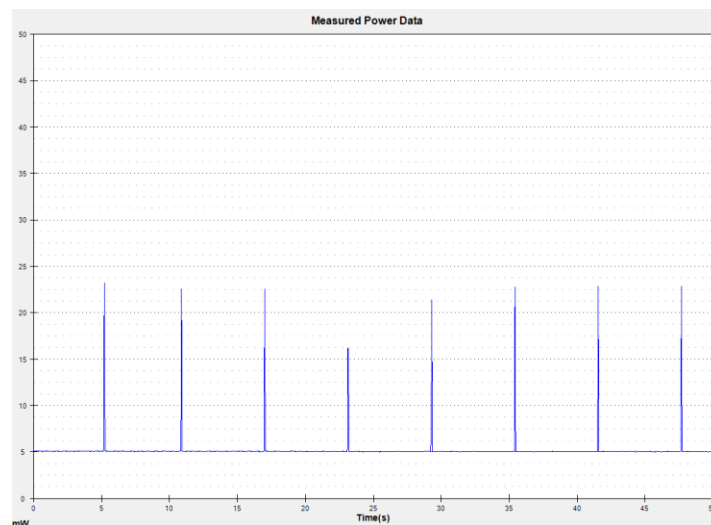
The overall accuracy of the system depends on the position of the phone and how likely the phones are located in each position. Based on data presented in Table 1, this was calculated to be 84.67% and summarized in Table 4. For the individual users

the accuracies range from 83.85% to 87.28%. The trouser pocket calculation also excludes the use of the Pedal Press block, and defaults to the Front vs. Rear block.

## 4.5 Energy Consumption

The overall energy consumption of the DDS was evaluated on the Android OS 2.3.x device, Nexus S, using a power monitor [22] since the battery terminals for the iOS devices were not accessible.

The passive power consumption of the Nexus S was captured over the course of 10 minutes, and found to be 5.89 mW. Figure 6 shows the power consumption trace for the idle case, which contains occasional spikes in power that are likely due to background tasks performed by the Android OS.



**FIGURE 6.** Power consumption trace for idle Android device

### 4.4.1 Power Consumption Segments

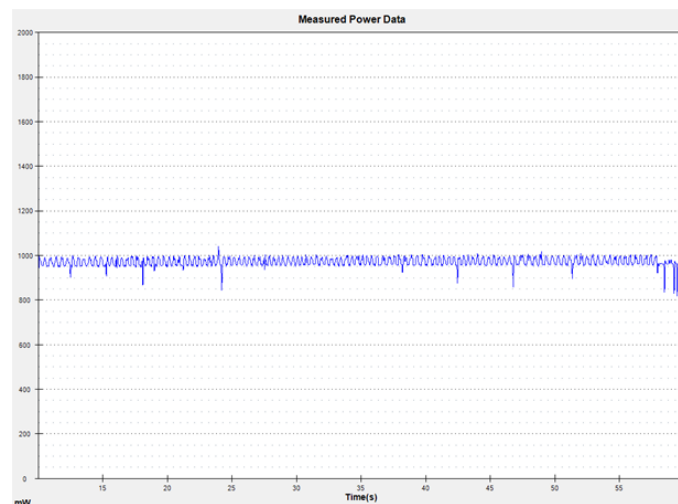
Four distinct energy consumption cases, based on the timeline presented in section 2.3, were evaluated in order to compute the overall energy consumption. The results are summarized below in Table 5.

**TABLE 5.** Power consumption data summary.

Case	Power Consumption	Max. Energy Consumed
Idle	5.89 mW	N/A
1	10.39 mW	Varies with user
2	969.09 mW	14.53 J
3	187.91 mW	43.82 J
4	947.63 mW	55.22 J

In the first case, during which the DDS turns on the phone for 1 second every minute to detect walking, the power consumption during that 1 second was 275.87 mW. Since this duty-cycled over the course of a minute, the average power consumption during this passive phrase is only 10.39 mW, or 4.50 mW above the phone's idle consumption. The total energy consumption in this case would depend on the length of the user's walk.

In the second case, the phone's accelerometer, gyroscope and compass will be turned on, and the Car Entry SVM and the Seat Belt SVM will be running with a maximum timeout of 15 seconds, as outlined in Step 2 of the decision tree. In this case, the power consumption is found to be 969.09 mW. Hence, with a 15 second maximum timeout, the maximum power consumed is 14.53 J. The power consumption trace file for this case is shown in Figure 7.



**FIGURE 7.** Power consumption trace for the Android device running SVMs and data collection.

In the third case, as outlined in Step 3 in the timeline, the phone will collect audio samples for 3 minutes, and upload the data to the cloud server. The power consumption for recording the audio was found to be 187.91 mW. We also determined the power consumption for uploading approximately 12 kB data, which was found to be approximately 10 J over 3G. Changes in file size will not impact power consumption significantly since 3G does not turn off instantly after data transfers [25]. The total energy consumption in this case was calculated to be 43.82 J.

Finally, in the last case, the power consumption in Step 3a is measured. In this case, the phone is collecting audio data as in the third case, but it is also collected accelerometer, gyroscope and compass data, while running the Pedal Press SVM. The power consumption during this scenario is 947.63 mW. Note that the Pedal SVM will cease to run after 15 seconds, leaving only the audio to run for the remaining 2



minutes and 45 seconds. The total energy consumption in this case was found to be 55.22 J. The power consumption traces for the last two cases are not shown since they are similar to the one shown in Figure 7.

#### *4.4.2 Overall Energy Consumption*

The overall energy consumption of the DDS will depend heavily on user movement pattern. Consider a normal case when the phone is found in the right trouser pockets of the driver. Walking is detected within the first minute, and the user walks 5 more minutes to the car, during which the DDS will consume 275.87 mW, or a total of 41.38 J. The Car Entry and Seat Belt algorithm will then runs for 15 seconds, consuming 14.53 J. The phone then enters case 4 looking for the Pedal Press Signature and Front vs. Rear, which consumes 55.22 J. The total energy consumed for this case is 111.13 J. With the Nexus S's 5.55 Wh (19,980 J) battery, this represents 0.55% of the total battery capacity.

The actual battery life reduction will depends on user movement patterns. However, since the DDS duty cycles 1 second out of every minute, walks that last less than 1 minute will have no impact on battery life. In the worst case that the user is continuously walking and never stops, the DDS would consume 16.55 J per minute, which would give the Nexus S a battery life of 20.12 hours. This battery life is still acceptable for users who charge their smartphones every night.

## **5 Discussions**

The DDS presented above demonstrates the power of sensor data and machine learning algorithms to infer specific usage patterns and user activities. This section will seek to address some of the weaknesses and alternatives to the approach used.

### **5.1 Weaknesses**

#### *5.1.1 Vehicle Types*

The DDS system was only tested in two vehicles – a four-door sedan and a four-door hatchback, both of Japanese make. Based on observations of car entry to two-door convertibles and coupes, the DDS should be extendable to accommodate these vehicle types trivially. The trouser pocket, upper body pocket and handbag cases all will produce similar signatures with smaller vehicles. A potential problem may arise when the DDS is used with larger sports utility vehicles or minivans. For the trouser pockets, users will still have to enter the car with a step, but they might be stepping up into the car, rather than down as in the case with sedans and hatchbacks. This might cause the

Entry Swing algorithm to fail, although adjustments to the algorithm to accommodate this case will not be difficult since the essential feature, the step, will still be present.

### *5.1.2 Assumptions*

The Seat-Belt block within the DDS assumes that all passengers in the car will wear a seat belt. We believe it is safe to assume that the driver and front passenger will always wear a seat belt, especially if they are concerned enough about traffic safety to use the DDS. However, in areas where the rear passenger does not wear seat belts, the Seat Belt algorithm will fail, in which case the Front vs. Rear block can be used to perform detection of back passengers without the need of the Seat Belt block.

The DDS design also assumes that at minimum, the driver will have the system deployed. In cases where a passenger with DDS enters the car of a driver without DDS, the system will still work for the passengers who entered the car from the passenger side if the phone is located in the trouser or upper body pockets, since those blocks do not require comparison with other phones. However, for the case when the phone is in the handbag, or when the rear passenger entered the car from the driver side, DDS will not function properly and, by default, will denote the user incorrectly as a driver.

### *5.1.3 Other phone positions*

Table 1 show that 8% of cell phone users place their phone on some type of belt-enhancements. While DDS does not address this position, the proximity of belt enhancements to trouser pockets suggests that modifications can be made to the Entry Swing block to incorporate belt enhancements, improving the applicability of the system.

Another possibility might be that the phone is in the hand of the users during the car entry process. This can be easily detected using light and proximity sensors. If the phone detects user interaction greater than a threshold timeout after vehicle motion is detected, DDS can assume the phone's user to be the passenger.

## **5.2 Other Signatures**

Other signatures were considered and may be helpful in further increasing the accuracy of the DDS. One observation made during lengthy experimental drives is that, if the phone is in contact with the driver, the phone experiences lower variance level than the passenger's phone. This is because the operation of a vehicle demands the full attention of the driver, who is deliberating controlling the gas pedal with small movements, which helps to steady his or her body. On the other hand, the passenger is relaxed and will not provide such stability. However, implementation of this algorithm would be comparison based, since road conditions and traffic patterns will also impact

the variance of the accelerometer. The present, non-comparison based approach was chosen due to its flexibility.

Another signature explored was the speed bump or pothole signature. This signature is based on the intuition that when passing over a speed bump or pot hole, the front passenger will experience a larger acceleration as the front wheel passes over the obstacle, followed by a smaller acceleration cause by the back wheel. The reverse would be true for the passenger in the rear seats. Experimental data collected, however, showed that this signature is only detectable when the car is driven at high speed over large obstacles, an unlikely scenario. In addition, the algorithm would also fail when there are no speed bumps of potholes in the area of the user.

### 5.3 Alternatives

Other methods to realize driver detection are possible, but most involve the modification to the vehicle. One such approach incorporates the use of near field communication (NFC), which has appeared in the latest generation of smartphones and is used in some vehicles to unlock car doors [24]. There are two main issues with using the NFC system: only a small fraction of cars deploys such a system, and such driver detection systems would only work on with the user's own car. Another approach modifies the car's speaker to play a specific sequence of sound when the car is first started. As with NFC, this approach, requires significant modification to the car and will only work with specially modified cars. A third approach uses the pressure sensors on the seats of the cars, which is typically use to notify users to wear their seat belts. This approach suffers the same issue as the previous two. In addition, since average car in the U.S. remains on the road for 9.2 years, it is unlikely that these modifications will become practical in the next decade.

## 6 Conclusions

I presented DDS, a system to detect if a mobile phone user is the driver or the passenger inside a vehicle. The system allows mobile phones to selectively deliver notifications based on available user attention, as well as new, personalized information depending on the user's status. Without the use of external sensors, the DDS design shows that the sensor data available are capable of inferring large amounts of information from the user. DDS achieves near-practical level of accuracy of 83.85% to 87.28% for majority of mobile phone users. Its event triggers allows it to operate in an energy-efficiency manner with minimal impact to battery life, demonstrating that the system is applicable for everyday use.

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