Accelerometer-Based Alcohol Consumption Detection from Physical Activity

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***Abstract*—Smartphones have become a common tool for researchers to collect, process, and analyze large quantities of data. This will lead to the creation of solutions that will mostly come in the form of smartphone apps, which will help solve real-life problems. One such real-life problem is the over-consumption of alcohol, since it can lead to many problems including fatality. Currently, there are very expensive or tedious alternative procedures for testing blood alcohol consumption in the market. This paper offers a cheaper alternative to address this problem by detecting if the user has consumed alcohol or not by using a smartphone. We describe an experiment and propose two features derived from accelerometer data that can help us distinguish between sober and intoxicated individuals.**

Keywords—Mobile Computing, Embedded Systems, and Machine Learning

I. Introduction

A. Problem and Motivation

Alcohol misuse and abuse is responsible for staggering amounts of personal and economic harm in the United States and abroad. Upwards of 88,000 people die from alcohol related issues each year, making it the third leading preventable cause of death in the United States [7]. Excessive drinking has been linked to damage to the heart, liver, pancreas, and immune system [8]. In addition to the detrimental health effects, alcohol misuse cost the U.S. \$223.5 billion in economic loss in 2006 alone [7].

Alcohol affects the central nervous system and brain, and its effects increase with concentration in the blood. Most crucially, judgment, reaction time, balance, and psycho-motor performance begin to become compromised above a blood alcohol level of .02-.05. [8]. These abilities are crucial to operate a vehicle, so it is unsurprising that almost 50\% of traffic fatalities involve the use of alcohol.

Several different methods are available for testing intoxication levels. A test can be done via blood draw, breath (breathalyzer), urine or saliva, and recently hairs. All these methods directly attempt to measure the physical presence of alcohol. In contrast, field sobriety tests performed by police officers often include physical tasks to gauge an individual's level of impairment. Most involve asking the subject to perform physical tasks such as walking backwards or touching the nose with the arm stretched out. The advantages of physical tests include convenience and cost. On the other hand, these breath testing devices are generally expensive (costs range from \$3000-\$5000 per unit), require routine calibration maintenance, and need costly repairs.

Since the physical tests are currently subjective, but less expensive than the chemical tests, we believe a mobile phone-based system can bridge the two methods by providing a low-cost portable device that can objectively measure sobriety levels.

The significance of mobile computing lies in the fact that it can sense real world data and respond to it based on the environment. If a smartphone app can tell the user if he is drunk or not by his physical response, then many accidents can be avoided all around the world.

B. Problem and Motivation

As seen in Fig. 1, we envision a multi-stage system that makes use of the accelerometer on a mobile phone to capture real time data from a user. This data will then be processed and fed into a classifier which will then determine whether the user is intoxicated by comparing his or her data to a model based on a large sample of historical data.

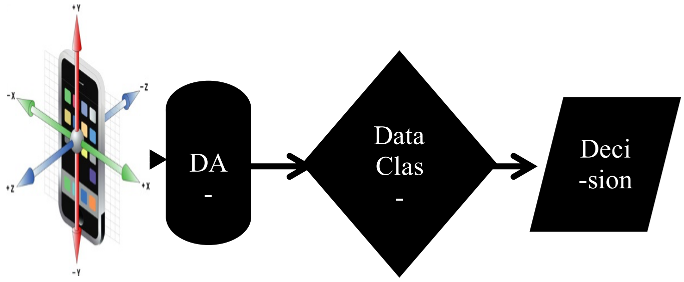

Fig.1: Block diagram of the system used for the experiment]

In this paper, we take the first step towards such a system by proposing robust features that can differentiate between sober and drunk users.

II. Related Work

A lot of researchers have been focusing on movement-pattern recognition with the aid of accelerometers, especially since the latest generation of smartphones are all equipped with precise and reliable accelerometers [11]. Interesting applications have been developed that can determine the types of activity the user is performing, such as exercises or day to day actions such as crossing the street, solely based on accelerometer data [10].

One paper [4] proposes a phone-based system to detect the gait anomalies of a person walking under the influence of alcohol. This phone-based system can sense a person's alcohol usage and record the location/time context. The paper shows the individual differences in step variance time, but differences are relative to the baseline for each user and do not cleanly separate drunk and sober for all users.

III. Methodology

A. Physiological Basis

One of the first symptoms of intoxication is decreased motor coordination and balance. This is due to the effect of alcohol on brain chemistry by altering levels of neurotransmitters. Neurotransmitters are chemical messengers that transmit the signals throughout the body that control thought processes, behavior, and emotion. It is believed that alcohol targets the GABA neurotransmitter [6].

B. Units

Given this, we designed our experiment so that we could differentiate between drunk and sober people based on their ability to maintain balance and a steady posture.

Our proposed system measures acceleration along the x, y, and z axes. Our data collection platform is a homemade Android app running on a Motorola Moto G mobile phone. The phone provides a built-in API that provides linear acceleration with the effect of gravity already eliminated. The Android app has a button which can initiate and terminate data logging.

For our experiments, the subjects held the phone in their right hands, with the arms outstretched and maintained that steady posture for 10 seconds. The right arms were extended 90 degrees from the body, the left arms were kept by the side, and the right feet were placed halfway in front of the left feet and touching it. Finally, the users kept their eyes closed during the entire trial.

Each of our two subjects were originally tested in a sober state, before any alcohol had been consumed. We then recorded data from the subjects after they consumed 3, 6, and 9 drinks of alcohol over a period of 120 minutes. One drink is defined in this paper to be 1.25 oz of 80 proof liquor i.e., vodka.

IV. Results

After the conclusion of our testing, we had 4 individual data points per subject, for a total of 8 recordings. The acceleration across the x, y and z axes was plotted against time for each of the recordings.

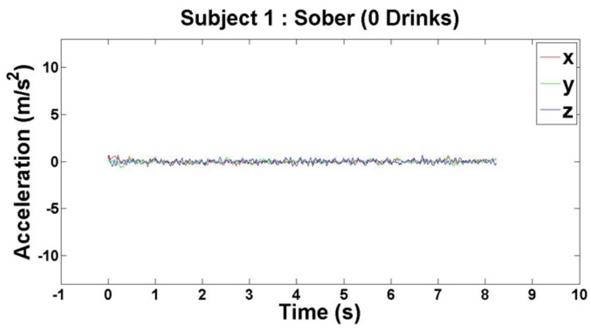

Fig. 2. Accelerometer reading when subject 1 is sober

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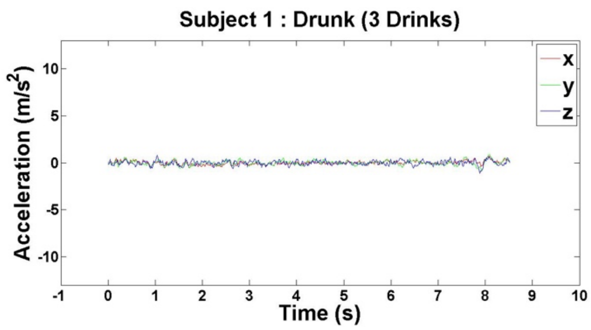

Fig. 3. Accelerometer reading when subject 1 has had 3 drinks

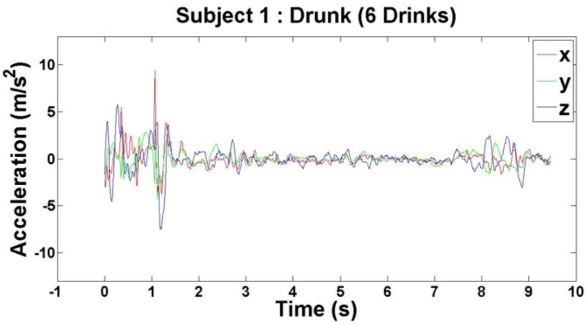

Fig. 4. Accelerometer reading when subject 1 has had 6 drinks

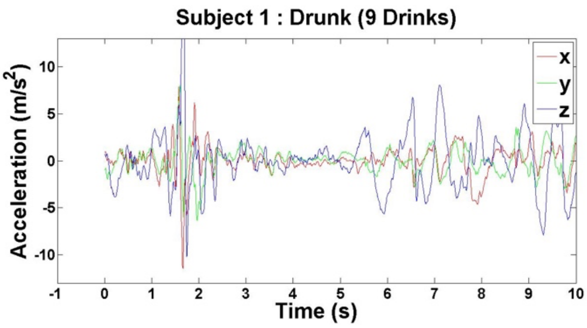

Fig. 5. Accelerometer reading when subject 1 has had 9 drinks

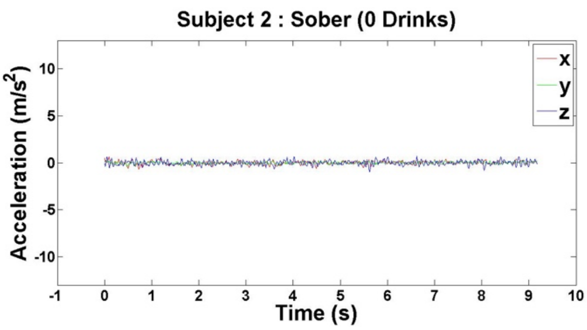

Fig. 7. Accelerometer reading when subject 2 is sober

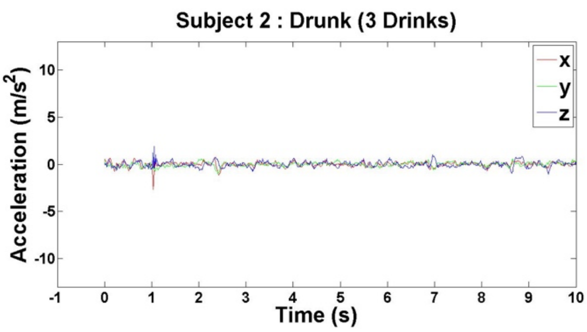

Fig. 7. Accelerometer reading when subject 2 has had 3 drinks

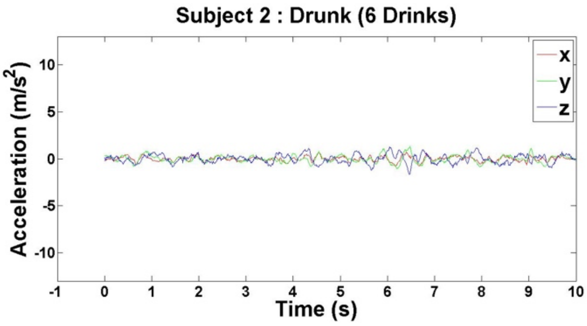

Fig. 8. Accelerometer reading when subject 2 has had 6 drinks

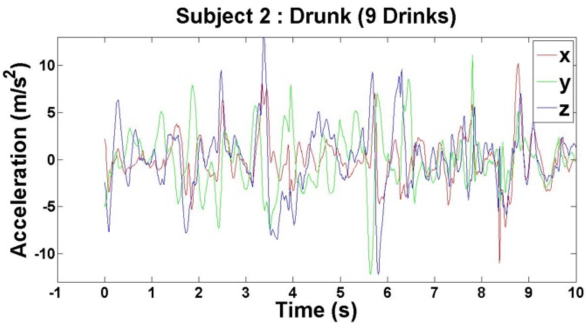

Fig. 9. Accelerometer reading when subject 2 has had 9 drinks

Figures 2 through 5 show the patterns for Subject 1 varying from sober to the having 9 drinks in steps of 3 drinks. Also, Figures 6 through 9 show the patterns for Subject 2 varying from sober to having 9 drinks in steps of 3 drinks. These graphs clearly indicate the difference made to the motor skills of the human body at different levels of alcohol consumption.

V. ANALYSIS

Based on the experimental results, we see a clear difference between the sober and intoxicated data. Additionally, there is a relationship between the number of drinks consumed and the "unsteadiness" of the data. We examined two features that could try to capture this change: variance and strongest frequency. In particular, the variance in the amplitude was calculated for each axis. Then we picked the maximum variance of all the axes. This helped to make this feature more stable under different phone grasping positions, as the variance is simply transferred to another axis.

The second discriminating feature we found was the highest frequency component of the time series data. However, here the relationship was not as simple as the linear relationship between BAC and variance. However, the highest frequency for drunk data was still higher than the highest frequency for sober data.

The variance analysis and the strongest frequency analysis was performed on the data for both Subject 1 and Subject 2. The tables given below are an indicator of the increasing variance and the strongest frequency and hence the BAC of Subjects 1 and 2. The BAC is estimated from the number of drinks and the body mass of the subject.

Number of Drinks	0	3	6	9
Estimated BAC	0	0.06	0.19	0.28
Variance	0.0382	0.06059	1.749063	9.80903
Strongest Frequency	0.1227	0.11793	2.860169	1.5984

Table. 1. Tabulation of variance, strongest frequency, and BAC for Subject 1

Number of Drinks	0	3	6	9
Estimated BAC	0	0.06	0.19	0.28
Variance	0.0556	0.06059	0.214869	12.0609
Strongest Frequency	0.1092	0.11793	2.216312	0.92764

Table. 2. Tabulation of variance, strongest frequency, and BAC for Subject 2

A two-variable SVM classifier is built based on the observation in the distribution chart shown below. The red dots show the sober state while the green points are the drunk states.

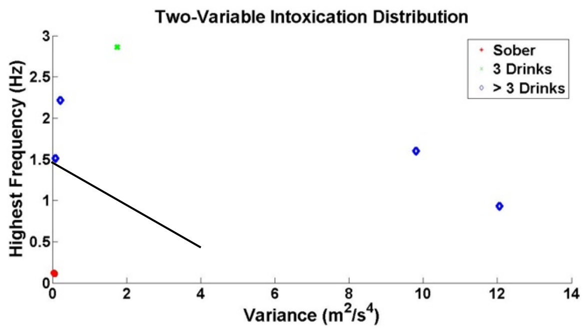

Fig.10. Two variable intoxication Distribution where variance is the X-axis and High Frequency component is the Y axis. The green points are for intoxication more than 3 drinks, the blue is for 3 drinks and the red points are sober. The two classes are seen to be generally linearly separable. A possible boundary line is shown.

The sober data is clustered around the origin, while the intoxicated data seems to be a bimodal distribution, with two separate clusters. Taken in combination, two features provide a much better separation between the drunk and sober classes than each would alone.

VI. Conclusion

The data collected shows proof that alcohol consumption can alter the accelerometer readings, which can be used to make decisions based on whether a person is drunk or not. The only limitation we observe with this approach is that clear distinctions are visible for subjects who were well beyond legal limit. To classify “less drunk” we will require a much larger data. For subjects well beyond the legal limit, the classifier model built is successful in establishing the clear difference between the sober and the drunk state.

Acknowledgment

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