Unobtrusive and Continuous Monitoring of Alcohol-impaired Gait Using Smart Shoes

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1. Introduction

Excessive alcohol use has been associated to 4% of all death worldwide [1] and the fourth leading preventable cause of death in the United States [2, 3]. Even mild consumption of alcohol has been linked to adverse health effects, and therefore, pregnant mothers or patients with hepatic diseases are advised to maintain complete abstinence [4–6]. The rate of motor vehicle accidents, falls, assaults, homicides, and suicides has also been reported to be higher with regular alcohol consumption [7–9]. Unintentional injuries related to alcohol consumption are also identified as a major source of immediate health risks [10, 11]. Therefore, recognition of alcohol-induced effects on individuals could contribute significantly to lowering the risk for injury, and enables the medical treatment to be customized into each patient's pattern of alcohol consumption. Especially, sensor-equipped monitoring tools provide accurate information which individuals intentionally miss to report, or are hard to record [12].

The alcohol sensors had been categorized to detect blood alcohol content (BAC) and transdermal alcohol content (TAC). Breathalyzer is a widely used tool that directly measures BAC. However, breathalyzers enable relatively sporadic monitoring and require user's voluntary measurement rather than automated monitoring. As a mobile sensing tool of TAC, the SCRAM (Secure Continuous Alcohol Monitoring) system can determine alcohol levels expelled through the

Keywords
Wearable devices, personal monitoring, gait analysis, alcohol monitoring, wireless healthcare

Summary
Background: Alcohol ingestion influences sensory-motor function and the overall well-being of individuals. Detecting alcohol-induced impairments in gait in daily life necessitates a continuous and unobtrusive gait monitoring system.

Objectives: This paper introduces the development and use of a non-intrusive monitoring system to detect changes in gait induced by alcohol intoxication.

Methods: The proposed system employed a pair of sensorized smart shoes that are equipped with pressure sensors on the insole. Gait features were extracted and adjusted based on individual's gait profile. The adjusted gait features were used to train a machine learning classifier to discriminate alcohol-impaired gait from normal walking.

In experiment of pilot study, twenty participants completed walking trials on a 12 meter walkway to measure their sober walking and alcohol-impaired walking using smart shoes.

Results: The proposed system can detect alcohol-impaired gait with an accuracy of 86.2% when pressure value analysis and person-dependent model for the classifier are applied, while statistical analysis revealed that no single feature was discriminative for the detection of gait impairment.

Conclusions: Alcohol-induced gait disturbances can be detected with smart shoe technology for an automated monitoring in ubiquitous environment. We demonstrated that personal monitoring and machine learning-based prediction could be customized to detect individual variation rather than applying uniform boundary parameters of gait.

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perspiration from skin, using ankle bracelets [13]. However, the weight of the ankle bracelet may restrict an individual's movements and its direct contact to the skin may cause irritation, which influences users' long-term adherence to monitoring. Moreover, the type of ankle bracelet may reduce user's adherence to the device, since ankle monitors are also used as a deterrent to criminal behavior. As addressed in [14], wearables which are defined as electronic devices that can be embedded in the user's outfit, should not prevent the user's activities. In this respect, a wearable device for monitoring of alcohol-induced impairments requires a means for non-intrusive and automated monitoring in ubiquitous environment.

Common symptom caused by alcohol-effect on sensory-motor function can be observed in disturbed gait and balance, due to the influence in disrupting the transmission and integration of sensory and motor information [15]. For instance, Modig et al. reported that a 0.06 to 0.10% BAC (Blood-Alcohol Content) resulted in decreased stability and sensorimotor adaptation, as well as weakening the contribution of visual information to postural control [16]. Balance control is a complex process involving the integration of sensory input from multiple sensors, including visual, vestibular, proprioceptors and mechanoreceptors. The central nervous system processes these multiple sensory signals to estimate the position and motion of the body [17]. Therefore, an alcohol monitoring system could be able to monitor changes in gait as a function of sensory information available. In practice, visual observation of an individual's ability to walk along a straight line is used as a test of sobriety. A number of researchers have attempted to use sensors to objectively measure this field sobriety test. Klebe et al. measured and analyzed the influence of alcohol consumption on gait in patients with essential tremor using a sensor-equipped treadmill in a laboratory setting [18].

Apart from alcohol monitoring, wearable technology based on miniaturized sensors (e.g., accelerometer and gyroscope) is increasingly being used to monitor activity and to find possible correlation to health-related conditions. Xu et al. have used accelerometers to monitor gait quality of stroke survivors [19]. Adelsberger et al. performed automated Romberg testing for patients with benign paroxysmal positional vertigo [20]. Gietzelt et al. evaluated gait parameters measured by a single waist-mounted accelerometer during everyday life of patients with dementia [21], and Marschollik et al. developed unobtrusive method to determine individual fall risk based on the use of motion sensor data [22]. Palmerini et al. measured the acceleration of the low back to differentiate gait patterns in healthy adults and those with Parkinson's Disease (PD) [23]. Salarian et al. proposed the use of accelerometers and gyroscopes to detect early signs of progression of PD [24]. Bächlin et al. introduced the use of wearable assistant to help patients with symptoms of freezing of gait (FOG) related to PD [25]. Mazilu et al. proposed a wearable system which supports training of patients with PD and FOG in daily living [26]. Gait for Parkinson's disease appears definite on/off stages and a reduced smoothness and dynamics in trunk movement during off-stage gait [23], whereas, abnormal gait due to alcohol shows various pattern including discouraged walking, a wide-based gait and poor tandem gait [27].

Objective quantification of alcohol-induced gait was studied in recent researches. In [28], accelerometer in smartphone was utilized to detect change in alcohol-induced gait, and achieved 56% accuracy in detection. Another phone-based analysis system was developed to record the location and time context of alcohol-induced gait [29]. The inertial sensors in those systems are highly accessible through using smartphones without any additional accessory to measure spatial-temporal parameters of gait. However, monitoring gait using inertial sensors has the problem of the high rate of error associated to these sensors. Acceleration is the derivative of velocity and involves high frequency components, and the orientation of gyroscope-based system suffers from drift over time [30–32]. Therefore, understanding of gait movements using inertial sensors requires intensive computational processing and external signals to re-calibrate the units from the drift [30].

To overcome noisy data from inertial sensors, more recent research and practical applications have used pressure sensors to detect gait events. Howell et al. introduced a mobile gait system using low-cost insole for stroke patients [33]. Bamber et al. used pressure sensors to quantify movement of patients with Parkinson's disease [34]. Electronic pressure monitoring systems, placed as an insole into regular shoes, have also been used to continuously monitor pressure over the plantar surface to provide information on the process of ulcer formation [35].

In this study, we propose a remote monitoring system leveraging machine learning and sensor technology. Our system analyzes alcohol-induced gait with person-dependent model based on the individual's normal walking pattern that can be monitored and stored by sensor-equipped shoes. Being combined to daily health monitoring, detection of alcohol-induced gait can be built with wearable devices as an intelligent system that aims at empowering the capabilities of systems or people by means of machine learning and sensor technology [36, 37].

2. Objectives
The primary objective of this study was to build a personal gait-monitoring system, using sensorized smart shoe technology, for the detection of alcohol-induced changes in individuals' gait pattern. More specifically, this work utilizes a pair of smart shoes equipped with an array of pressure sensors, which is capable of providing in-depth understanding of spatio-temporal properties of human gait affected by alcohol. Our specific goals were to: (i) extract physiologically meaningful features of gait using biomechanical variables of the gait pattern, and (ii) demonstrate the accuracy of our sensor system in detecting intoxication-induced impairments in gait.

3. Methods
3.1 Participants and Study Protocol
The study was approved by UCLA institutional review board (IRB #13–000207). Twenty healthy participants (12 men and 8 women) volunteered for our study and provided informed consent. The relevant characteristics of the study group were as fol-
lows: ages of 24.78 ± 4.97, heights of 176.7 ± 11.40 cm, weights of 70.8 ± 14.65 kg, and foot lengths of 25.7 ± 1.9 cm. All participants were above the legal drinking age, which is 21 in the United States. We instrumented shoes of various sizes (M7, M8, M9.5, M11, and F6, F7, F8.5) to appropriately fit participants with their approximate shoe size for accurate localization of high-pressure regions under the foot.

Before the gait assessment, participants performed a sobriety-walking test to ensure the absence of alcohol-related effects on baseline measures. BAC was measured using a breath analyzer (BACtrack S80 Pro Breathalyzer Professional Edition). Any participant whose initial BAC was not 0.0% was excluded from the study. Then, participants were assessed for their baseline performance by walking a 12m walkway at their preferred speed of normal walking. They were further asked to walk at slow and fast speed in order to obtain sober gait pattern that deviate from the baseline walking, i.e. sober walking at preferred speed. The target BAC indicating alcohol intoxication was set to 0.06% at which stability was affected as investigated in [16]. Participants consumed three to five glasses of 1.5 ounces of 40% alcohol (Smirnoff Triple Distilled Vodka No. 21™). After a resting period of 15 minutes to wash out alcohol remaining in the lining of the mouth, BAC levels were re-evaluated to ensure the target BAC of 0.06% had been reached. Once the BAC level was reached, participants indicative of alcohol intoxication completed another set of gait trials to measure the performance of alcohol-intoxicated gait.

3.2 Task Setup, Equipment and Monitoring Software

We developed the smart shoe shown in Figure 1, with a pressure sensor array embedded in the insole. An embedded processor (Arduino Fio) was used to collect and transmit the sensor data to a gateway computer in real-time via a Zigbee (IEEE 802.15) channel. The sample rate of data acquisition was 100 Hz. Pressure sensors were placed in the insole for the detection of heel-pressure (H), mid-lateral plantar pressure (M), and big toe pressure (T). We developed a software program, Gait Performance Analysis System (GPAS), that receives and analyzes the transmitted gait data. GPAS was implemented in C#, .NET framework and MATLAB (Figure 2).

3.3 Detection of Alcohol-induced Gait Disturbance

Figure 3 shows a schematic representation of the analysis process to quantify al-

![Figure 1](image1.png) The smart shoe system, containing an embedded processor and Zigbee receiver. Pressure sensors in the insole are used to detect the following gait pressure: heel-strike (H), mid-lateral plantar pressure (M), and big toe pressure (T).

![Figure 2](image2.png) Gait Performance Analysis System (GPAS): (a) GPAS connecting shoes and analysis software; (b) plantar-pressure map shows the pressure distribution with contour plot of circles (at left heel contact) and sensor signal processing with pressure values used to detect signal peaks, segment gait events, and step-specific data.
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cohνl-induced gait impairments. The data obtained from alcohol-induced walking are labeled as GAIT-ALCOHOL (class 1) and the data obtained from sober walking with speed variation labeled as GAIT-SOBER (class 0). First, the same set of gait features were extracted from all walking tests including alcohol-induced walking, normal walking with preferred speed and walking with various speeds. Then, the features of GAIT-ALCOHOL data were subtracted from the baseline features which were extracted from the individual’s normal walking at preferred speed, in order to reflect individual’s various gait characteristics in daily life as baseline in model and validate the effect of such deviate in the detection. Similarly, the features of GAIT-SOBER were also subtracted from the baseline features. This process is referred to as the personalization process using personal gait profile (baseline). Then, a feature selection algorithm followed by a classification (random forest) algorithm was employed to create a classification model to provide prediction on a testing data (GAIT-SOBER or GAIT-ALCOHOL). All components of the analysis process shown in Figure 3 are discussed in detail in the following sub-sections.

3.3.1 Gait Cycle Segmentation and Feature Extraction

The raw sensor data was used to construct a pressure distribution map to detect important gait events, i.e. heel-strike and toe-off (Figure 1). Notations related to important gait events used in our analysis are summarized in Table 1.

A threshold-based peak detection algorithm was used to locate peak pressures at the heel and toe regions of each foot (see Figure 4). We applied noise-tolerant peak detection using threshold and selective index of each peak, which determine local peaks if each peak is significantly larger than the data around it [38-40]. Peaks must be larger than a threshold value to be maxima, and selective index measure the amount above surrounding data for a peak to be identified. The peak detection algorithm tolerates to false peaks which would be filtered by threshold and selective index that are adaptively set to sensor signal. Successive heel contacts, which generated peak pressure signals from the heel sensors, were used to determine gait cycle time GCT, defined as the temporal interval between two consecutive heel contacts of (i−1)th and ith step and quantified as CT, heel − CT, heel. Stance time, STNC, was calculated as the time du-
ration between heel contact and the corre-
sponding toe contact: $CT_{i,j}(\text{toe}) - CT_{i,j}(\text{heel})$.

A total of 44 gait features of a walking phase, which is composed of consecutive gaits, were extracted from the sensor data, based on biomechanical properties of human locomotion (Table 2). In our experimental setting, a walking phase is a 12-meter walk test, and features for current walking segment could be reflected to a personal profile which aggregates individual’s normal-walking data.

### 3.3.2 Adjustment Using Personal Gait Profile

Extracted gait parameters were individualized by a two-step procedure. First, some of the parameters whose values are inherently different due to individual anthropometrics were calibrated. These individually calibrated parameters included GCT, STNC, and SSR, which were normalized to shoe size. Each gait feature was then ‘personalized’ by being subtracted from the corresponding feature in baseline. Then, differences between baseline and alcohol-induced gait features were evaluated using paired-t test analyses. The adjusted gait features were used to build PDM (person-dependent model) to evaluate effects of alcohol intoxication. We also compared gait performance based on PIM (person-independent model) that eliminates this adjustment to demonstrate the effect of personalization in Section 4.

### 3.3.3 Feature Selection and Random Forest Classification

To classify alcohol-induced gait features from normal variations in gait, we adopted a supervised machine-learning classification method. Among various machine learning algorithms commonly used in biomechanics, we selected the RF classifier developed by Leo Breiman [42, 43]. RF is an ensemble predictor that consists of multiple decision trees. The RF method, including variations on the RF classification method, has successfully been used in the fields of computer vision and medical informatics [43, 44]. Toclassify a new queried sample with an input vector, each decision tree in the forest predicts the output class from the input, and the class with the most votes will be output as the predicted class from the RF.

RF intrinsically contains the feature selection mechanism as it randomly selects different features to construct each tree within its forest. However, there exist other works that have shown that RF combined with a feature selection algorithm can improve the results [45]. The purpose of feature selection was to identify a set of gait features containing information that would discriminate walking behavior and reduce the searching space. We have conducted Wrapper Subset Evaluation to assess subsets of gait parameters according to their contributions to the classification performance [45, 46]. The association of features was successively evaluated and then the optimal set of features was iteratively discovered through this evaluation. The number of features is also known to affect the inter-tree correlation and the strength of the individual decision tree in random forest (RF) [47].

In this study, we employed a WEKA implementation of the RF method [48].

In order to obtain more robust estimates of the classifier performance, we implemented a leave-one-out cross validation (LOOCV), since the composition of training set and test set sensitively determines the prediction of classifier [49–51]. The nested LOOCV technique contains two layers of LOOCV. First, the technique divides the entire set of data into a learning dataset and a validation dataset based on LOOCV. Then, the feature in the validation set is recursively eliminated, which performs additional LOOCV to compute the best feature set; the learning set is further divided into training and testing sets based on the inner LOOCV.

In summary, the analyses returned (i) the discrimination of alcohol-induced gait patterns from normal gait, and (ii) the expected classification when the reported feature sets are used.

### 4. Results

#### 4.1 Alcohol-induced Gait Disturbances in Individual Subjects

GAIT-ALCOHOL and GAIT-SOBER were compared for the representative features including SPEED, CADENCE, STRL, GCT-AVG, and SI (Figure 5). Although...
alcohol intoxication produced an overall decrease in SPEED, of $-0.059$ m/s (SD 0.16 m/s), there was significant inter-individual variability with 13 (out of 20) participants (65%) showing decrease in gait speed post-intoxication, whereas the remaining 35% increased their gait speed with alcohol intoxication. Individualized effects of alcohol were also identified for other gait features, as shown in Figure 5.

### 4.2 Performance of Random Forest Classifier

The classification algorithm utilized spatiotemporal gait features, pressure-related features, and personal gait profiles, normalized to foot size and baseline gait pattern. RF classifier performed with 86.2% accuracy.

Table 3 reports the classification performance with selected attributes. We evaluated the performance of our classifier for different sets of inputs, namely by PDM for individualized gait model, PIM

![Figure 5](Gait changes before and after alcohol intoxication)

<table>
<thead>
<tr>
<th>Person-Dependent Model</th>
<th>Sensing Modality</th>
<th>Target Class</th>
<th>Evaluation</th>
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<tbody>
<tr>
<td></td>
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<td>Accuracy</td>
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<tr>
<td>PIM</td>
<td>STS</td>
<td>AG</td>
<td>65.0%</td>
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<tr>
<td>PIM</td>
<td>STS</td>
<td>NG</td>
<td>77.5%</td>
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<tr>
<td>PIM</td>
<td>STS</td>
<td>Average</td>
<td>79.3%</td>
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<tr>
<td>PDM</td>
<td>STS</td>
<td>AG</td>
<td>86.2%</td>
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<tr>
<td>PDM</td>
<td>STS</td>
<td>Average</td>
<td>88.0%</td>
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PDM = Person-Dependent Model; PIM = Person-Independent Model; STS = Spatial-Temporal Sensing; STPRS = STS plus Plantar Pressure Sensing; AG = Alcohol-induced Gait; NG = Normal Gait
for monitoring without personal sensing profile, STS (SpatioTemporal Sensing) for sensing without pressure information and STPRS (STS plus Plantar Pressure Sensing) indicating sensor diversity including pressure. Performance with these different sets of input data is reported in Table 3. First, we excluded personal profile information and pressure information from the input set. Without both personal profiling and pressure values, the classifier exhibited an accuracy of 65%. In a second round of testing of our classifier, classification with STPRS exhibited an accuracy of 77.5%. The third round of evaluation with PDM and STS achieved an accuracy of 79.3% in detection, and the classification with PDM and STPRS enhances the detection performance to an accuracy of 86.2%.

5. Discussion

The proposed system aims to verify the detection capability of sensor-equipped shoes that is unobtrusive to use in daily life. The monitoring tool is feasible to be used in ubiquitous environment, since it is composed of normal shoes with sensors and wireless transmission to mobile gateway. Most wearable healthcare devices such as wristband, necklace, and shirts are designed to transmit the sensing data to mobile gateway including smart phones or home gateway.

Before performing analysis, we expected clear detection of alcohol-intoxicated gait with simple classifier. However, individual pattern of gait change under the influence was not uniform as shown in Figure 5. The importance of personal profile of activity in daily living is increased, and the result corresponds to the trend of healthcare systems in which data is more important than algorithm.

5.1 Alcohol Intoxication and Gait Performance

To circumvent the limitations of inertial sensors in this application, we have designed a smart shoe system, which uses pressure sensor data to identify changes in the spatial-temporal and pressure profiles of gait induced by alcohol intoxication (see Table 3). Using a stepwise analysis of the performance of our RF classifier, we demonstrated the added contribution of using pressure information in combination with spatial-temporal information, which improved the precision and recall of classification by 19.2% (from 0.650 to 0.775) with PIM. With PDM, combination of pressure values with spatial-temporal features achieves 9.1% higher precision (from 0.794 to 0.866) and 8.7% higher recall (from 0.793 to 0.862). In addition, the diversity of sensors affects more to PIM than PDM in all evaluation metrics.

This improvement in classifier performance results from the specific information on initial and terminal contact that can be extracted from pressure data independent of the pattern and speed of gait [32, 52, 53]. The medical application of pressure-based gait monitoring has been also demonstrated in [17, 36, 47].

5.2 Detection with Characteristics of Personal Gait Pattern

In addition to the use of multiple features in machine learning to detect alcohol-induced gait, we measured the effect of personalization of gait performance. It is generally known that alcohol prolongs the latency and reduces the amplitude of long latency muscle responses due to its dampening effect over mono- and poly-synaptic reflexes [54, 55]. However, other studies observed the ‘individualized’ and ‘variable’ nature of gait behaviors [36, 56–58], demonstrating the importance of providing the classifier system with prior information on an individual’s usual walking behavior during the training phase.

Our experimental outcomes also demonstrated that the effects of alcohol on gait speed and cadence were individualized (Figure 5). The a priori training allows the classifier to adjust the detection of alcohol-induced changes in gait to personal (baseline) gait behavior. Personalization of the classifier significantly improved detection of the intoxicated state, increasing the accuracy of the classifier by 11.2% (from 0.775 to 0.862), when pressure value analysis was applied. Without pressure value analysis, accuracy was enhanced by 22% (from 0.650 to 0.793). We believe that the main reason for the poor classifier performance without personalization is the high degree of within-subject variation in gait performance under different constraints [24, 31, 59]. We must also consider individual differences in alcohol tolerance, such that gait may have been minimally affected by intoxication levels of 0.06. These findings have motivated us to further develop our smart shoe system to monitor everyday walking in an attempt to capture the variation in gait characteristics, both within and between individuals.

5.3 Objective-monitored Gait for Quantified Self

Our results provide valuable insight regarding the requirement for monitoring technology to take into account affecting factors including type of sensors and various factors related to participants in the analysis [36]. As an example, we believe that the detection rate of intoxication could be significantly improved by combining measured gait patterns with information on the location, sensory environment, or an individual’s past alcohol history (e.g., chronic alcoholism or alcohol related offense). Furthermore, demographic information, such as sex, could further improve the detection of alcohol intoxication, as women are known to be less tolerant to alcohol compared to men. In the future, a larger study can be performed to further investigate the contribution of personal demographic information, such as the length of lower limbs [24], sex [31], and associated diseases [59]. We believe that the adequate personalizing the model will improve the detection rate.

The most significant improvement provided by our system is the objective, real-time monitoring of gait using an inconspicuous system. Patients who require complete abstinence would be able to avoid the inconvenience and discomfort of repeated BAC measurement at regular intervals. In addition, gait data would be more robust for the identification of intoxication than self-report or the horizontal gaze nystagmus test, which would be fraudulent [60]. We also have advanced knowledge and application of wearable devices, proposing an alternative to common devices...
that are heavy and highly obtrusive [61]. Our smart shoe device performs similar to patch or bandage type sensors [62, 63] or watch-shaped activity monitors [64, 65] that are easy-to-use devices.

In this study, we have investigated the detection of intoxication solely based on walking behaviors using a wearable system, and showed that the results are very promising. In addition, the system is unobtrusive, which is a necessary requirement for monitoring alcohol-related patients or criminals without constraints of place and time. The longitudinal collection of individual gait pattern using smart shoes may enable personalized BAC estimation model. We believe that this study opens new research opportunities for the remote monitoring of alcohol-related activities, which have not yet been actively investigated.

6. Conclusion

We have introduced a machine-learning based method for monitoring alcohol-induced impairments in gait using sensor-equipped smart shoes. This study investigated and demonstrated the feasibility of detection of intoxication using gait monitoring. We have found that personalized monitoring and a machine-learning technique significantly improved the detection rate of alcohol-injected gait activities. We believe that this study enables further research opportunities in the field of alcohol-related activities monitoring which requires easy-to-use and intelligent decision. Alcohol sensing with wearable devices enables participants’ adherence to monitoring, and can be utilized in various applications including customized treatment for patients.

Author Contribution

Conceived and designed the experiments: EP, SIL, DL, MS. Performed the experiments: EP, SIL, JG, AH, MA, AC, NG. Analyzed the data: EP, SIL, HN. Contributed reagents/materials/analysis tools: EP, SIL, HN, SP, HC. Wrote the paper: EP, SIL, HN. Revised manuscript for important intellectual content: HC, DL, MS.

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