ManDown: Diagnostic Sensing of Motor Control and Dysarthria

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***Abstract*—With more than 10 million people in the UK drinking above low risk levels[1], it is crucial to moderate the drinking habits of people. ManDown is an app which will do just that. This report looks into the diagnostic sensing of motor control and dysarthria using an Android smartphone and smartwatch which runs Android Wear.**

I. Introduction

According to the National Health Service (NHS), even social drinkers are at risk of developing long-term health problems related to alcoholism due to many of them consuming beyond the recommended 14 units per week[1]. On top of that, there has been an estimated 1 million alcohol-related admissions into hospitals in 2013/14 in the UK[2]. As such, the app ManDown was proposed to aid in curbing these side-effects of drinking, especially amongst people looking to have a fun night out at the pub.

ManDown seeks to provide a fun app which combines active user input via games and the user interface as well as sensor data (both active and passive) to provide a diagnosis of the state of the user (be it sober, tipsy, drunk etc.). It then seeks to manage the user via notifications and the user interface to promote safe, responsible drinking. This report focuses on the sensing side. Specifically, detection of a subset of short-term symptoms related to alcohol consumption, which are loss of motor control (excluding gait) and dysarthria[3].

This report outlines the methodology for using a smartphone and common, everyday wearables such as a smartwatch to collect data which is indicative of the outlined symptoms.

II. Sub-module Requirements

The requirement for this sub-component is to be able to quantify the two effects outlined in the introduction through both active (e.g. user plays a game on the phone) and passive (i.e. gathering sensor data while user is not interacting with the phone) sensing. This ideally has to be done via internal sensors found on smartphones and a smartwatch. The reason for this is that this makes the app easy, cheap and attractive to use with hardware users will already have and use daily. It is unlikely that users will want to purchase and deliberately put on extra sensors just to go out for drinks. However, this does not completely rule out external sensors. As the project progresses and the machine learning model is trained, if it is found that currently measured parameters are not a good predictor of intoxication, additional sensors may be added.

Loss of motor control does include generally include ataxic gait which is processed by another sub-module. This focuses on detecting other aspects such as arm movement and accuracy in intended motion. The reasons for selecting those particular aspects are explained later in medical background. The detection can be performed via the 9-axis sensors (tri-axial accelerometer, gyroscope and magnetometer) within both phone and watch as well as the touch-screens to determine accuracy.

Dysarthria (slurred speech) can be detected via the phone's speaker with suitable speech recognition software or software which detects slurring in speech.

An additional feature which is nice to have is the ability to detect when the user is drinking alcohol and potentially track their alcohol consumption even when the user is seated and has minimal movement.

III. Motor Control - Medical Background

Loss of motor control can be explained as diminished psychomotor ability, an example of which is reduced performance in tasks such as tapping and tracking[4]. Loss of motor control generally includes ataxic gait, which refers to abnormal walking patterns such as widened base, unsteadiness and irregularity of steps[5]. However, this report will focus on detecting upper body movement as well as other more cognitive demanding tasks.

In medical research pertaining to effects of alcohol on motor control, participants of the experiment tend to be tested on either gait and balance as done by Modig *et al.*[6] or carrying out psychomotor tasks which require the use of hands such as simulated driving[7][8] or slotting pegs into holes with random orientations on a board[4] as done by Brumback *et al.*. In all these experiments, the results consistently show that alcohol does indeed cause motor impairment.

It is noteworthy that in the last experiment, it is shown that motor impairment is not significantly different between heavy social binge drinkers and light social drinkers in spite of the fact that heavy drinkers subjectively rate themselves lower on perceived impairment. On the other hand, there have been other studies that have shown differences in impairment, such as one studying light and moderate female social drinkers with the moderate group showing less impairment[9]. However, the test subjects are different, with the former opting for a large mixed gender group of 132 subjects and the latter only having 30 female subjects. It is also worth noting that Brumback set up the experiment to clarify past studies which have come to opposite conclusions on this topic by testing specifically for heavy social binge drinkers, which is exactly the target audience this app seeks to help.

Further literature review shows that heavy drinkers are more resilient to impairment for simple tasks such as smooth eye tracking but not for more complex and novel tasks such as Digit Symbol Substitution Test (DSST)[10] and divided attention tasks[11]. DSST is where the test subject transcribes a unique geometric symbol corresponding to an arabic number[12]. With regards to the app, this potentially simplifies the design of the app and machine learning model as they do not need to take into account a user's regular drinking habits as long as the games are sufficiently challenging.

In terms of areas of focus for tracking, based on the above medical approaches, efforts should be focused on hand and arm movement to detect inebriation. This is further supported by the fact that alcohol inhibits cerebellar function[13] and the cerebellum is responsible for coordinating and control of voluntary limb movement and grip[14]. However, it is difficult to find a paper or textbook that explicitly quantifies the effects of alcohol on arm motion (such as tremor or variance in movement), be it in general or pertaining to a task.

In order to aid sub-module design in this area, symptoms of cerebellum damage are used to understand how an intoxicated person's arm movement is affected. The same symptoms should surface albeit to a lesser extent with function inhibition from alcohol. Cerebellum damage causes poor movement control, for example reaching would be "irregular, curved, with poor targeting and oscillatory corrective movements"[15]. In addition, papers show that alcohol reduces accuracy in tasks such as pressing squares as they light up [16] and increased variance in responses to a reaction time task[17]. These symptoms can be detected via the in-built accelerometer and gyroscope on a smartwatch. In addition, tracking with regards to accuracy and variance can be implemented via games and the UI.

IV. Motor Control - Related Research and Work

A. Related Work

In terms of apps which help users control their alcohol intake, there are many competitors on the app store. Among the most popular are **Sober Time**[18] which motivates users and links them to a community to abstain from alcohol and **AlcoDroid**[19] which keeps track of a user's intake by having them manually enter it.

For arm/body motion tracking, few apps exist which detect exact motions and measures them. One which does is a $379 app called **Notch**[20] and it comes with 6 wireless sensors which attach to the body and captures a 3D picture of the user's motion. The idea is for the user to monitor and improve his/her form in exercise and sport. An app which detects speed and accuracy of tapping is called **Touch Accuracy**[21]. It is a simple game which outputs the average time it took the user to tap a target in the centre and how far off each tap was. To my knowledge, there does not exist an app which uses these features in the area of helping users restrict their alcohol intake.

B. Related Research

There have been research into using smartphones to automatically detect intoxication of users. However, these have been done via gait detection be it with just a smartphone[22] by Arnold *et al.* or in tandem with wearables (Google Glass, fitness band and smartwatch)[23] which incorporates arm movement with walking as done by Nassi *et al.*. These experiments have shown up to 70% accuracy with just the smartphone and AUC (area under curve, a standard of assessing predictive distribution models[24]) of 0.94 with the addition of just the smartwatch. There have also been research into using a car's motion to detect if the driver is drunk[25]. To my knowledge, there has been no research done in alcohol detection using motion without gait. However, they provide a good starting point for methods of data capture, pre-processing data and feature extraction.

As expected, both Arnold and Nassi use 9-axis sensor to obtain movement data in terms of linear acceleration, orientation, gravity and rotation. The data sampling rates are not mentioned in either paper, but another paper by Wang *et al.* states that human movement frequency is at 20Hz and below[26]. Therefore, the target sampling rate can be assumed to be at least 40Hz to satisfy Nyquist sampling theorem.

In terms of pre-processing, Arnold normalises the data to account for differences due to phone orientation which affects the gravity background and then smooths the data with a moving average filter. Nassi does not pre-process at all. In Wang's research, the team seeked to denoise 3D acceleration data for human movement in body sensor networks. Wang compared the median filter, Butterworth low-pass filter, discrete wavelet package shrinkage and Kalman filter and it was found that the Kalman filter gave the highest SNR (signal-to-noise ratio)[26]. Another method of denoising accelerometer data is Recursive Least Squares adaptive filter, used in the context of an accelerometer on a robot arm[27]. This method uses error between filtered data and actual movement data to continuously adapt the filter coefficients, which is not practical for our purpose where actual data is impossible to come by without extra sensors.

For feature extraction, Arnold and Nassi use different frequency domain features such as SNR and top 4 frequency values. Arnold also uses time domain features such as number of steps where as Nassi uses statistics features (mean, variance etc.), normalised histogram of values and gait features such as average velocity and rotation. Nassi specifically states that statistic features are used to detect decreased acceleration of hand movements when drunk.

With regards to classifying arm movement, Biswas *et al.* have shown that it is possible to classify distinct arm movements (including that of lifting a cup to the mouth) with sensitivities of 83 to 96% with a low-complexity linear discriminant analysis classifier[28]. This was done via extraction of features such as standard deviation (SD) and maximum peak amplitude. An alternative method which will require extra sensors is to use the mean and peak value of electromyogram (EMG) signals to classify motion as done by González *et al.*[29].

V. Dysarthria - Medical Background

The other symptom of interest is dysarthria, which is the symptom of slurred speech. In terms of detecting speech impediments, the most frequently analysed parameters are number of speech errors, the fundamental frequency, speech rate, as well as the number and length of silent pauses[30].

Linda and Mark showed that alcohol intoxication caused subjects to take a longer time to read the same passage, increased interjection of phrases and sounds, increased word omissions and revisions and, increased broken suffixes[31]. Furthermore, they also showed that these effects are more pronounced for higher intoxication levels.

Eszter *et al.* supports these findings, noting increased speech errors when subjects were made to do tongue twisters[30]. The team also found that the number of pauses increased, but fundamental frequency and articulation rate remained the same. However, based on historical research, in most cases the speech rate decreases[31][32] where as the impact on frequency is ambiguous, with studies showing an increase[32] and others showing a decrease or no change[33]. This suggests that voice frequency should not be used in our system to detect inebriation. Rather, pauses, errors and speech rate should be focused upon.

VI. Dysarthria - Related Research and Work

To the best of my knowledge, there are no apps on Android or iOS which attempt to detect alcohol intake via speech.

In terms of existing sample data, there exists a public database called the Alcohol Language Corpus (ALC) released by Ludwig Maximilian University of Munich[34] comprising of 162 intoxicated and sober speeches from both male and female German speakers. This can aid us in training and testing our machine learning algorithm.

In existing research, there have been attempts to detect alcohol intoxication from speech. Klingholz *et al.* uses 30 second segments of speech since it is found that statistical distribution of speech signal variables do not change at longer lengths and applies a moving 80ms window in increments of 20ms[35]. From this, features such as fundamental frequency, SNR, long-term average spectrum and first- and second-formant frequencies were extracted. Classification was implemented with n-dimensional Euclidean distance technique on reference vectors and test vectors. It was found that using a combination of fundamental frequency and SNR gave the lowest error rate of 0.0%, although it should be noted only 16 subjects were tested.

Schiel and Heinrich used the ALC and investigated the fundamental frequency as well as 17 rhythm features such as average difference of consecutive syllable nuclei distances, SD of duration of vowel cluster etc[36]. It is found that most speakers increase frequency when drunk and show significant rhythm differences although the influence of read vs spontaneous speech is significant.

In a separate work, Schiel *et al.* finds that rhythm features such as quarter quantile distance of the differences of the RMS values between successive maxima and median and quarter quantile distance of differences between absolute values of the same are good indicators of alcohol intoxication across all types of speech (read, spontaneous, command)[37]. Formant features (primary resonance of vocal tract) were also investigated and it was found that the median of the first formant frequency, quarter-quantile distance of the fourth formant frequency and euclidean distance of the vowel centroids are good indicators of intoxication.

Finally, an interesting method involving dialect usage was investigated, and it was found that the frequency of dialect usage decreases significantly with alcohol intake[38].

VII. Implementation

The app is to be developed on Android as it was found that iOS requires Mac computers for the developer toolkit[39] and the smartwatch (Moto 360 Gen 1) was selected for ease of development as it comes with Android Wear which is supported by the Android toolkit (Android Studio)[40].

For arm motion, the accelerometer and gyroscope on the watch can be used to detect and classify arm motion. An example of the Java code in Android Studio is as shown:

```
sensmag=(SensorManager)getSystemService(SENSOR_SERVICE);
acc=mSensorManager.getDefaultSensor(Sensor.TYPE_ACCELEROMETER);
sensmag.registerListener(this, acc, 10);
```

The last value in the last line of code is of particular importance since it determines the sampling period in milliseconds. However, it was found in testing that this value is only a suggestion to the operating system and cannot be relied upon. In other words, sensor data rates are not constant and vary (although it never strays very far from 10ms). This should not pose an issue however since existing research has already had success with alcohol detection on smartphones as discussed previously.

To classify the arm motion, the method described in [28] is deployed, extracting the SD and maximum peak amplitudes in signals. This is then passed into the machine learning portion which is out of the scope of this report, although based on [28] a linear discriminant analysis should be used. Once the user is detected to have performed the motion of drinking, the app can ask if the user is drinking alcohol or not. If yes, the amount of alcohol consumed can be estimated based on drink type entered by user and how long was the drinking motion.

For denoising the signal just to get an indication of whether oscillatory corrective movements are occurring (indicator of intoxication as stated by [15]), a simple moving average filter is deployed. Should this be insufficient, a low pass filter with a cutoff at 20Hz can be employed to restrict the data to only contain signals in the range of human motion. Alternatively, as described by [26], a Kalman filter can be deployed. This filtering can be done either locally on the user's phone or on the cloud server. A simulation in MATLAB with data from the smartwatch shows the moving average combined with the low pass filter to be effective at removing unwanted spikes and accelerometer jitter.

According to Brumback *et al.*, the impairing effects of alcohol on motor tasks scale according to the complexity of the task at hand[4]. The paper also states that impairment at lower alcohol levels is more obvious with a demanding task. It therefore follows that the user should perform suitably complex psychomotor tasks for better classification of their state by the app. An example of this is a game developed by my colleague which requires the user to balance a virtual beer glass using the accelerometer on the phone. This will naturally allow active user input and use accelerometer data and extract features such as the variance to determine if the user is drunk.

For accuracy, a game called whack_a_beer has been developed (again by my colleague) which allows for capturing of tap distance from intended origin and variance in this distance.

To my knowledge, an API for drunk speech detection does not exist. Therefore, a simple speech impediment detection would be to use Google Speech APIs on Android to perform speech to text detection and the microphone on the phone or watch to capture the user's speech. This will be done via flashing a simple phrase or tongue twister on the screen and ask the user to read it out loud. Given that research shows that speech error increases with alcohol consumption, it should be expected that the returned text will have a reduced match rate with the text on the screen as the user gets increasingly intoxicated. This matching can be done via regular expressions in Java on a word by word basis and not allow the search to go backwards in a sentence to match words.

A more advanced method will be to record the user saying the sentence and applying the methods outlined in [35][36][37], possibly on a cloud server so as not to slow down the user's phone or app and retrieving the results once it is done. However, initial testing within the team shows that the simple method works reasonably well at detecting differences between clear and deliberately slurred speech.

VIII. Conclusion

To sum it up, a sub-module to detect and extract features related to loss of motor control and dysarthria have been presented based on existing medical and technological research. Initial findings for the implemented parts seem promising.

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