# Smoking Behavior Detection Using A Ring-based System

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***Abstract*—In this paper, we propose a Ring-based remote smoking activity monitoring system called RingLord. The system is an end-to-end solution consisting of a wearable sensing system, a smartphone-based gateway and an analytic engine. We implemented a prototype system and conducted a clinical trail, from which sensory signals while smoking and non-smoking activities were collected. Based on this dataset, We created 180 features and selected 10 most important ones to fit several classification models. The prediction performances in cross validations showed Random Forest was the best model. The overall approach demonstrated the feasibility and effectiveness of the proposed system.**

***Index Terms*—Mobile health, Smoking detection, Wearable sensor, Remote health monitoring, Machine learning**

## I. Introduction

Cigarette smoking is one of the most pressing health issue aournd the world. According to Centers for Disease Control and Prevention (CDC) smoking causes more than 480,000 deaths each year in the United States. This is nearly one in five deaths. Smoking cessation is the most effective way to decrease the negative effects on smokers. However the nicotine addiction makes this process of quitting often very difficult. The majority of smokers who try to quit do so without assistance, though only 3 to 6% of quit attempts without assistance are successful [1]. A primary hurdle in achieving a higher success rate of smoking cessation is a lack of methods that can intervene at the right moment when an abstinent smoker is most vulnerable [6].

Many studies revealed that community interventions using ”multiple channels to provide reinforcement, support and norms for not smoking” had an effect on smoking cessation outcomes among adults. As a mobile health class project, we aimed at exploring a mobile health solution proposal that can intervene the relapse of abstinent smokers in a timely manner. We conceived and implemented a prototype of a Ring-like wearable device (RingLord) that not only can potentially synthesize multiple sensors such as inertial sensors, gas and dust sensors, but also provides considerable convenience of practical use.

The the rest of the paper, we first discuss some related work, their main contributions and potential improvements. Secondly we illustrate the architecture of the ring-based system as well as its main principles of data collection, storage, preprocessing and analysis. Thirdly we explain the process and results of classification models. Limitation of the results is also discussed.

## II. Related Work

Several important researches in these field have been conducted recent years. P. Lopez-Meyer, etc. [3] used noninvasive wearable sensors (Personal Automatic Cigarette Tracker - PACT) to monitor cigarette smoking and demonstrated feasibility of automatic recognition of smoke inhalations from signals arising from continuous monitoring of breathing and hand-to-mouth gestures by support vector machine classifiers. Subject-dependent (individually calibrated) models and subject-independent (group) classification models were used and compared. Subject-dependent showed better performance. However only support vector machine classifiers was employed in this research.

Similarly, Y. Patil, etc. [4] detected cigarette smoke inhalations from respiratory signals a combination of wearable Respiratory Inductive Plethysmograph and a hand-to-mouth Proximity Sensor (PS).This study tried to reduce number of features by using empirically-defined 27 features computed from the sensor signals. Further reduction in was achieved by a forward feature selection algorithm.

A. A. Ali, etc. [5] developed a novel system to automatically detect smoking puffs from respiration measurements. They trained models on data collected from 10 daily smokers and found that smoking puffs can be detected with an accuracy of 91% within a smoking session.

Saleheen, etc. [6] used two wearable sensors: respiration and wrists worn 6-axis inertial sensors to capture breathing pattern and arm movements. They proposed a novel method to identify windows of data that represent the hand at the mouth.

All these studies show the feasibility of detecting smoking activity using wearable devices and machine learning methodology. One common shortcoming is that all the researches involved multiple sensors that are inconvenient to use, which makes application less practical. One way to solve this problem is to use single synthesized wearable device to improve usability.

## III. System Architecture

RingLord is a three-tier, end-to-end remote monitoring system with extensive hardware and software components. The overall architecture is summarized in Figure 1. The first tier of the architecture consists of a data collection framework. It makes use of a set of sensing decices to do measurement. Then, via the second part of the architecture, the data is processed and transmitted to database. The last tier of the RingLord architecture is a backend analytics engine capable of continuously generating statistical models and predicting outcomes using various machine learning and data mining algorithms. In the following sections, we describe each component of the system in details.


Figure 1: Overall Architecture of RingLord

### A. Data Collection

The ring is basically a RFduino board connected with two external sensors: an inertial sensor and a dust sensor. We observed that every puff involves a hand-to-mouth gesture. People tend to perform it starting from an initial rest body pose, and then ending the gesture in another, possibly different, rest pose. However, unlike eating or drinking, the duration of holding a cigarette close to the mouth is much shorter. By this feature, we may distinguish other hand-to-mouth movements from smoking. The 9-axial inertial sensor (SparkFun 9 degree of freedom 10724 sensor stick) is used in the system. It is a very small sensor board and consists of a 3-axial ADXL345 accelerometer, a 3-axial HMC5883L magnetometer, and a 3-axial ITG-3200 MEMS gyro. It can operate properly up to $85C$, thus we do not need to worry about the local temperature rise caused by smoking will destroy the sensor. The 'stick' has a mounting hole which makes it easy to be attached on the RFduino board. After doing calibration, via the $I^2C$ interface, RFduino can access the nine measured data in series.

Another observation we have is that when people hold the cigarette, there is lots of smoke coming out. We initially had three candidates for detecting the smoke: $CO$ sensor, $CO_2$ sensor and dust sensor. After several experiments, we found out that the amount of $CO$ from smoke is too small that the current available $CO$ sensor doesn't have such high sensitivity to detect it. As for $CO_2$ sensor, it is indeed very sensitive, but its sensing component is very easy to be blocked by smoke and hard to be cleaned. Thus after several data collection processes, it could not detect $CO_2$ level change anymore. Finally, dust sensor (Sharps GP2Y1010AU0F) performs the job perfectly. An infrared emitting diode and a phototransistor are diagonally arranged into the sensor, to allow it to detect the reflected light of dust in air. By doing experiments, we found it is especially effective in detecting very fine particles like cigarette smoke. It can achieve high sensitivity of $0.5V/0.1mg/m^3$ and since we put the sensor on people's finger, it is very close to the smoke source so that it can have fast response to the smoke. Since we only want to detect the difference of the amount of dust between smoke and non-smoke. To make our design easier, calibration is not done on this sensor. The RFduino board only reads the analog voltage output from the sensor. When there is cigarette smoke, the voltage can change from $0.5V$ to $2-3.5V$.

### B. Data Storage and Access

Due to the increasingly ubiquitous nature of smartphones and their portability and connectivity, we decided to utilize an Android smartphone as a central hub for receiving measurements and transmitting them into server. The RFduino has a Bluetooth 4.0 module on board, thus the phone must support bluetooth 4.0. Every time, ten types of data (9-axial inertial values and one dust value) need to be transmitted from the RFduino board. By default, each of them is a 4 bytes float value. However, Bluetooth 4.0 can only transmit 20 bytes of data at one time which is not enough for ten values. Thus, in the RFduino program, we first convert all the values into "int" type and then for inertial data (dust data), we take the lower 2 bytes (1 byte) to do transmission. This is possible because we found the range of the output data will not exceed 600 (250) when users do normal activities. We developed an Android App that can run on Android 6.0 (with API23). The App design principle is to make the interface as clear as possible to make it easy to be used. And users do not need spend too long time to figure out how to use it. As illustrated by figure 2a and 2b, it only has two user interfaces, one for connecting to RFduino via Bluetooth(Figure 2a), the other one for uploading the measured data into MySQL database in the real time(Figure 2b). Because of the overhead for receiving the data in the App, the highest data transmission frequency is 100Hz in our system. A table in mhealthplay database is created to store all the data.

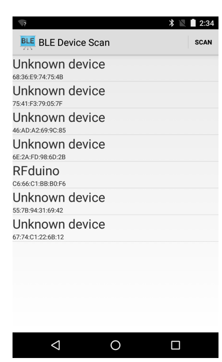


Figure 2a: RingLord Android App Screen Shots 1

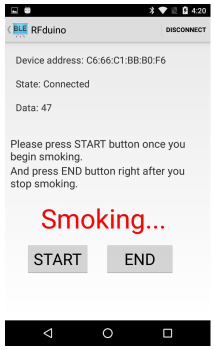


Figure 2b: RingLord Android App Screen Shots 2

At the experiment stage, we add two additional buttons for users to click on. If the user starts to smoke (right before the hand moves up), he/she needs to click the ”start” button to indicate the beginning of the event. When the user had made a puff (right after the hand moves down), he/she needs to click the ”stop” button to indication the termination of the event. Through this way, we can label the collected data and use it as the ground truth for later model training. Later on, for real usage, users do not need to worry about them and press these two buttons when they are smoking.

Accessing the data in real time is also a challenge in the project. What we do is to poll the database at a regular interval (5s). We think it is justifiable to do it. Normally a puff (from hand moving up to moving down) takes around 5 seconds. Only after we receive all the data from this duration, can we do more reliable analysis and judge if a user is smoking or not. In this sense, our system does operate in a real time fashion.

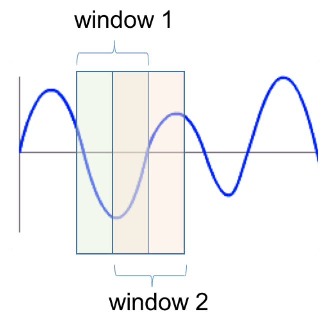


Figure 2: Data segmentation: 4-second window with 50% overlapping

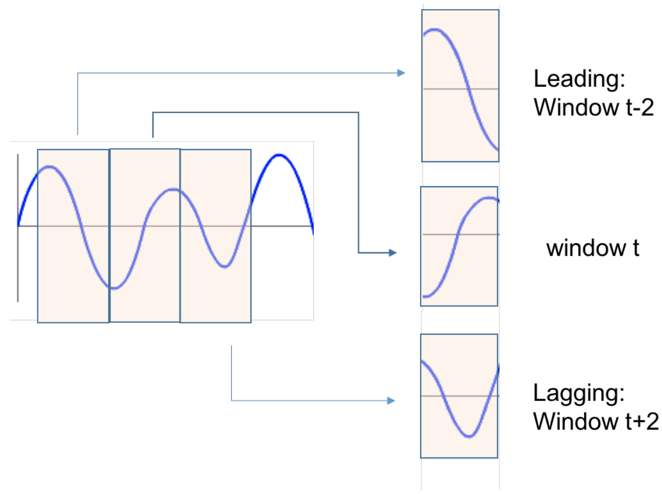


Figure 3: Asynchronization: considering current, leading and lagging window simultaneously

### C. Data Analytics

Based on the sensory data, a analytical procedure can be applied which consists mainly of data pre-processing and classification.

*1) Data Segmentation:* Segmentation is a common practice in signal analysis. By discretizing time series, classification models can be easily fitted to the data. Since our data set is mostly generated by sensors with frequency of 10 Hz, we decided to slice the signals into 4-second long windows, each of which contains 40 data points. And this window width can cover most single smoking activity.

*2) Feature Creation:* On the sliced data set, we created aggregated features b y window. For each sensor and each axis, we computed its mean, median, standard deviation, peak of absolute value, trend (regression slope), difference of mean value between first half and second half window, and its correlation with other axes. Also, we calculate all the above metrics for each windows leading window (the one before it) and its lagging window (the one behind it). By considering current window and its leading and lagging windows together, most important signal patterns will be captured rather than be ignored because of window slicing. In total, we generated 180 features.

In addition, in training phase, if the proportion of smoking labels in each window is above 0.8, we labeled this window with response variable value 1, otherwise 0.

*3) Feature Selection:* Too many features doesn’t necessarily lead to good predictive power of classification model. We examine the VIF (variance inflation factor) of the data set, and found large multicollinearity among the created features mentioned above, which would make the classification models unstable. One way to get rid of multicollinearity is using fewer but important features. In order to find those features that contain most information for classification, we employed a tree-based classification model (Gradient Boosting) that identified the relative importance of all features.

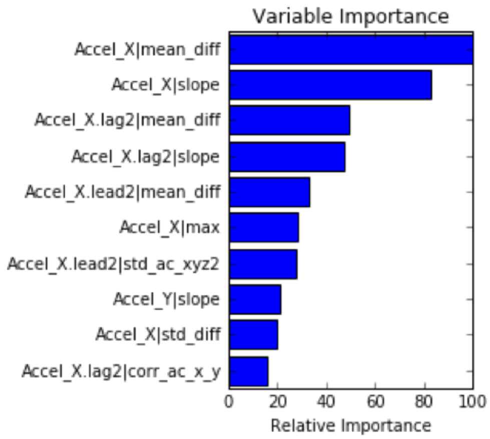


Figure 4: Top 10 important features selected by boosting tree method

The top 10 features are shown in the above figure. The meaning of the above features are as follows. Accel_X_mean_diff: the mean difference of the first and second half window of accelerometer axis X. Accel_X_slope: the regression slope of accelerometer axis X. Accel_X_log2_mean_diff: the mean difference of the first and second half window of accelerometer axis X in logging window. Accel_X_lag2_slope: the regression slope of accelerometer axis X in logging window. Accel_X_lead2_mean_diff: the mean difference of the first and second half window of accelerometer axis X in leading window. Accel_X_max: the maximum value of accelerometer axis X. Accel_X_lead2_std_ac_xyz2: the standard deviation of the squared sum of accelerometer axis X,Y,Z in leading window. Accel_Y_slope: the regression slope of accelerometer axis Y. Accel_X_lag2_corr_ac_x_y: the correlation coefficient of accelerometer axis X,Y in lagging window. A sample snapshot of these features going with smoking labels is shown following.

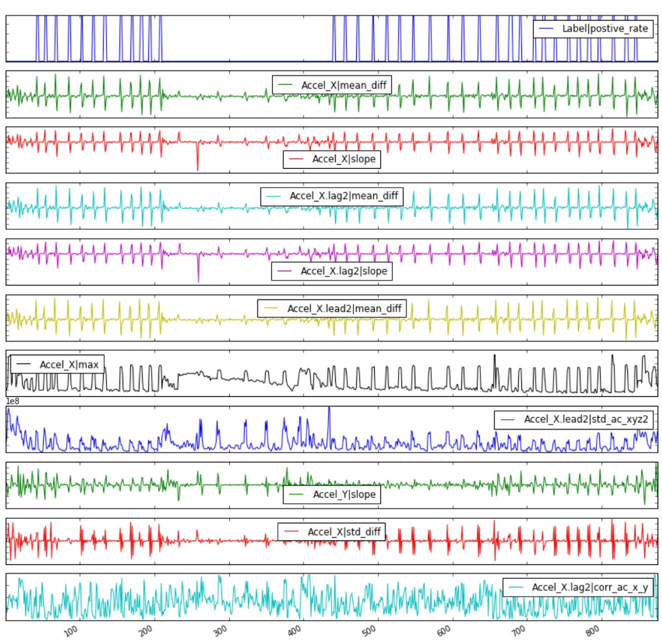


Figure 5: A snapshot of top 10 important features (the top plot is smoking label with 1 representing smoking activity)

## IV. Smoking Prediction

### A. Experiment Setup

Because of the limitation of time and resources, we could not find many smokers. At the meantime, to ensure the fairness of the experiment, equal numbers of positive and negative instances need to be used to prevent biasing toward a particular class. Thus, data were collected from 2 smokers and 2 non-smokers. To avoid data corruption, we did the experiment in a windless environment. Each tester smoked 3 cigarettes. When there is a hand-to-mouth smoking action, they need to press the ”start” button in the App accordingly to label the data in that time interval. This is used later in machine learning models as the groundtruth. We also asked them to walk around and let their arms swing back and forth. Finally, we collected data from similar actions, like drinking, to make the experiment more solid and convincing. With all the collected data, the results are then computed using ten-fold cross validation to guard against overfitting given the relatively small number of instances.

### B. Results and Discussion

We fitted 4 different classification model to the data set with 10 features: Gradient Boosting Tree, AdaBoost Tree, Random Forest and Support Vector Machines. Most of these methods are tree based which have many favorable characteristics such as high predictive power for both linear and nonlinear relationships, low computational load, no need to standardize data. These advantages make them suitable for this problem.

Scikit-learn (version 0.17) was used to train the models and make predictions. Scikit-learn is an open source machine learning library for the Python programming language.

10-folded cross validation was used to select parameters of these models. Parameter combinations that showed high prediction accuracy were chosen. For Gradient Boosting Tree, number of estimators was set as 250, maximum tree depth was 2, minimum samples in split was 1, learning rate was 0.01. AdaBoost Tree, number of estimators was set as 100. For Random Forest, number of estimators was set as 100, minimum samples in split was 1. The best 10-folded cross validation prediction accuracy as well as precision and recall of the above models are shown in Table1. All the models gave satisfactory performance with most metrics above 0.9. Among all the Random Forest showed the best performance.

Note that limited to time and resource of the class project, the training dataset we got from the clinical trial had only 876 windows and limited number of interfering activity data that help give more credentials to the models' predicting and differentiating power. Conducting more systematical experiments and obtaining larger training and test datasets are needed in future work.

## V. Conclusion

Mobile phones can play a major role in detecting and preventing harmful user behavior, such as smoking. In this paper, we have introduced the design and implementation of a Ring-based remote smoking monitoring system called

TABLE I
10-FOLD CROSS VALIDATION PREDICTION PERFORMANCE

| Model | Accuracy | Precision | Recall |
|---|---|---|---|
| Gradient Boosting Tree | 0.94 | 0.97 | 0.96 |
| AdaBoost Tree | 0.95 | 0.97 | 0.97 |
| Random Forest | 0.95 | 0.97 | 0.97 |
| SVM | 0.86 | 0.86 | 1.00 |

RingLord. The system is an end-to-end solution consisting of three parts: 1)a RFduino-based hardware sensing system that can measure and transmit data via Bluetooth 4.0, 2)a smartphone-based gateway that wirelessly collects data sets from the hardware devices and upload them into MySQL database, 3).an analytic engine capable of real-time prediction using machine learning and data mining algorithms.

Using real data collected from a clinical trial, we have demonstrated the effectiveness of RingLords analytic engine by accurately predicting if there is a smoking activity happening. The algorithm has identified the difference of acceleration and the changing speed of acceleration to be highly correlated to smoking behavior. As a result, the RingLord analytic engine is able to build prediction models that are up to $95\%$ accurate with AdaBoost Tree and random forest algorithms.

But the system still has several limitations. First of all, the system itself can be improved in multiple ways. For example, the Ring-like hardware is little bit large for user to use. Since we use commercial sensors, the dust sensor is too big for our system. Later on, we could re-design the sensor based on its working principle so that a more compact and nice looking Ring can be produced. Secondly, detection of other related behaviors (e.g., eating, drinking, brushing, driving) using our modeling approach should be re-evaluated. As the results shown in the previous section, dust sensor does not play an important role in our prediction model. This may be caused by the limited amount of collected data. One possible direction is to do more clinical trials. Then based on the new data we collect, we can use different data processing and feature extraction methods to do prediction.

## ACKNOWLEDGMENT

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