Smoking Activity Recognition Using a Single Wrist IMU and Deep Learning Light

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ABSTRACT

Smoking has a strongly relation with diseases such as lung cancer, chronic obstructive pulmonary disease, and coronary heart disease. To prevent smoking, there are various passive ways including warning stickers and electronic cigarettes. However, a smart and proactive methodology might be more effective and useful to break the smoking habit by automatically and actively providing feedbacks to smokers to promote their desire of quitting smoking. In this work, we propose such a smart and proactive system using a wrist band housing a single Inertial Measurement Unit (IMU) sensor, and a smartphone App. housing artificial intelligence based on Recurrent Neural Network (RNN). To detect the smoking puffs, the proposed system uses a two steps classification scheme: first, a General model categorizes measured activities into Activities Daily Living (ADL) and Hand Gestures Activity (HGA). Then an Expert model further categorizes HGAs into smoking, eating, and drinking. Our smoking activity recognition system recognizes smoking activity with an accuracy of 91.38% and provides an active vibration feedback to smokers.

CCS Concepts

• Applied Computing → Life and Medical Science → Consumer Health, Healthcare Information Systems, and Health Informatics. • Human-Center Computing → Interaction Design → Interaction Design Process and Methods → Activity Center Design. • Human-Center Computing → Ubiquitous and Mobile Computing → Ubiquitous and Mobile Computing Theory, Concepts and Paradigms → Mobile Computing. • Human-Center Computing → Ubiquitous and Mobile Computing → Ubiquitous and Mobile Devices → Smartphones, Mobile Phones, and Mobile Devices.

Keywords

Activity Recognition; Smoking Gestures; Smart Band; IMU; Deep Learning Light; Recurrent Neural Network.

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1. INTRODUCTION

Through the last decade, many researchers and health organizations such as the World Health Organization (WHO) have made numerous studies on tobacco and its problems. According to WHO, tobacco kills more than 6 million of active smokers and around 890.000 second-hand smokers each year in the world. Also, WHO reports nearly 80% of the smokers live in underdeveloped countries. The money spent on health insurances and treatments caused by smoking represents a considerable percentage of the income of people. Each year in the United States around 170 billion dollars are spent on smoking related treatments and medical care according to the Center for Disease Control and Prevention [12]. Furthermore, in 2016, 7.2% of middle school and 20.2% of high school students confirm the use of tobacco [8], making the problem more serious and highlighting the needs of a smart system to help people who desire to quit smoking.

In general, there are a lot people who want to quit or reduce smoking: especially the middle-aged and young people who begin to feel the effects in their health. Smokers between thirteen to fifteen years old from different countries: 32.1% in Uruguay, 90.2% in Philippines, 86.3 in Kenya, 49.0% in United Arab Emirates 43.5% in Italy and 66.9% in Korea, have expressed their desire to quit smoke [2]. The process to stop smoking is a hard experience, and normally takes several attempts. Sometimes professional helps are needed involving some intervention or support groups that are only available on a determined schedule. In addition, the current methodologies such as Apps that provide inspirational messages, nicotine gum, hypnosis, and medication as nicotine replacement therapy are mostly passive methodologies as they do not recognize whether a subject is smoking or not. There is a strong need of a smart and proactive methodology via real-time detection and feedback to help smokers to quit or reduce smoking.

With the current advances in smart technology, one can develop a smart application to actively sense smoking actions and provide a real-time feedback to smokers, supporting their desire to stop the habit.

In this work, we present a preliminary work of such the smart application. We have developed a smoking activity recognition system using a single Inertial Measurement Unit (IMU) embedded in a smart band along with a deep learning AI App based on Recurrent Neural Network (RNN) running on a smartphone to recognize and provide a feedback to smokers. The proposed system recognizes or detects smoking activity (i.e., puff gestures) from similar hand gestures such as eating and drinking, then provides vibration feedbacks to smokers.

2. RELATED WORKS

In 2014, Parate et al. [10] developed a smoking detection system based on a nine-axis IMU sensor. They extracted hand-crafted features from Quaternions signals to feed into a Conditional Random Forest algorithm every minute. The latency time for detecting a smoking session was thirty seconds, making its feedback slow. They extracted features of smoking gestures based on the assumption of the smoking gesture starts and finishes in a relaxed arm position. To evaluate their system, they used different approaches: first, a ten-fold cross validation getting an accuracy of 95.74% and a recall of 81% for smoking activity detection; second, a leave-one-out test achieving a recall value of 68% for smoking detection. In 2017, Akyazi et al. [1] developed a Dynamic Time Warping based smoking detection algorithm with a wrist accelerometer. They used a single x-channel accelerometer to detect standing puff gestures based on template matching. With an analysis window of ten seconds, they classified only pure static standing puffs gestures. The similarity metric used in their work had a limitation to generalize the smoking activity detection due to the difference in the smoking gestures among smokers.

In 2016, Cole et al. [3] used Artificial Neural Network (ANN) to classify smoking gestures using an Apple watch[1]. They analyzed the use of each accelerometer channel alone comparing against all together as input, concluding that the x-channel is the most informative to differentiate smoking puffs in the continuous-time analysis. Nevertheless, the system failed when it faced complex non-smoking gestures such as eating, drinking, and scratching nose gestures. Their accuracy in the continuous-time tests was under 70%. In 2017, Cole et al [4], used ANN again towards smoke activity classification, and studied the effect of wearing a smartwatch in different positions over a wrist. They used all channels to train the ANN-based system with individual smoking gestures against a variety of non-smoking gestures. Using a Pebble smartwatch[2]. They achieved an accuracy above of 75%. However, the false positive rate was around 20%.

3. METHODOLOGY

Our proposed smoking activity recognition system is built on two hierarchical levels of recognition: the first level named as the General model categorizes human activities (i.e., IMU signals of activity motions) into ADL (i.e., walking, running, and sitting) and HGA. Once classified as HGA, the Expert model at the second level classifies hand gestures into drinking, smoking, and eating. From the Expert model, the smoking activities are recognized and upon their detection, a vibration feedback is delivered to users. The overview of the proposed system is showed in Figure 1.

3.1 Activity Data

The activity data was collected from four subjects using a smart band built with an IMU from MbientLab[3]. The single IMU provides a tri-axial acceleration and a tri-axial Gyroscope information from the dominant wrist. We collected the data using the app provided by MbientLab. We used the sampling frequency of 50 Hz as done in [9] for human activity recognition (HAR) studies.

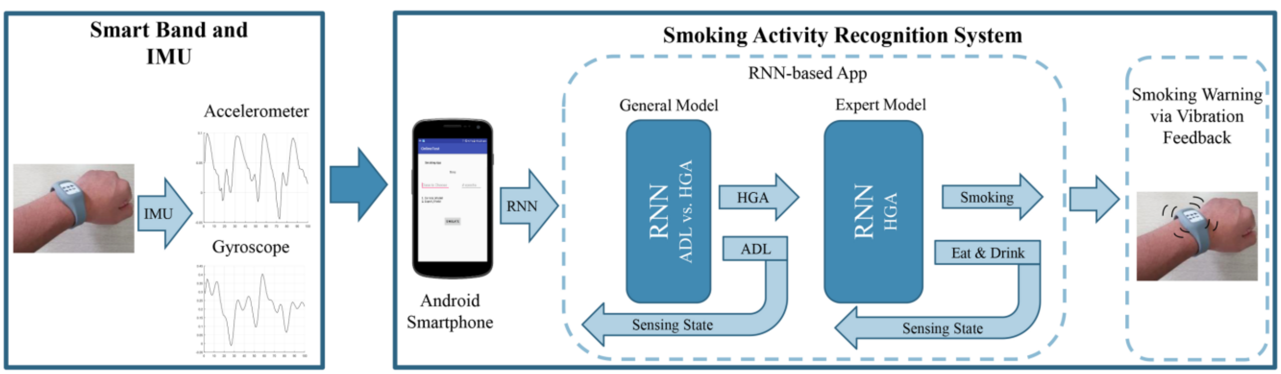

Figure 1. The proposed smoking activity recognition system consists of a single smart band housing an IMU, a vibration sensor, and a Bluetooth module. The activity recognition App runs on Android devices and uses two-level hierarchical RNN scheme: the General model categorize the activity gestures into ADL and HGA; the Expert model classifies HGA into smoking, eating, and drinking. Upon recognition of smoking gestures, there are active feedbacks via the vibration sensor.

[1] https://www.apple.com/lae/watch/

[2] https://www.pebble.com/

[3] https://mbientlab.com/

Two categories of human activities data were collected: the first one represents ADL including walking, jogging, and sitting. Walking represents moderate walking steps on a treadmill. Jogging data were collected on the same treadmill with a suitable speed from each subject. Sitting data corresponds to sitting in a desk chair while the subject is surfing on the web. Each data collection duration for ADL was for nine to ten minutes. The second category of activities represent HGA including eating, drinking, and smoking. These activities were selected due to the similarity towards smoking activity. Eating data set were collected from a complete meal (i.e., lunch or dinner) using chopsticks, spoon or fork without drinking water or juice during the meal to avoid mislabeling with the drinking class. Drinking data correspond to coffee or juice drinking in a standing or sitting position. Smoking data, the main activity in this work were collected from four active smokers. The recorded data correspond to a complete cigarette smoking without any restriction.

From the continuously recorded activity data, we created epoch data sets. Each epoch is windowed data of the same time length. The following preprocessing steps were applied in the creation of epoch data sets.

First, remove the gravity effect by applying a high pass filter [6] and then 20-point moving average filter. Finally, a slide window was used with a window size of fifteen second with an overlap of every two-second to generate the epochs. The total number of epochs according to different activities are presented in Table 1 for the General model and in Table 2 for the Expert model.

Table 2. Number of activity epochs for HGAs.

HGA	Number of Epochs
Drinking	485
Smoking	330
Eating	685

Table 1. Number of activity epochs for ADL and HGA.

Human Activities	Number of Epochs
Hand Gestures Activities (HGA)	1584
Daily Living Activities (ADL)	2073

To train and test our activity recognition system, we split the total numbers of the epochs into 80% for training and 20% for testing.

3.2 Smoking Activity Recognition System

The conventional smoking activity recognition systems employed classical classifiers such as Random Forest and ANN. Recently, deep learning is actively adopted in various fields due to no requirements of hand-crafted feature extraction. Also, it has not been tested for smoking activity recognition. In this work, we have employed one of deep learning algorithms, RNN as a classification algorithm in the General and Expert models. The main characteristics of RNN are recurrent connections between hidden units. These connections create a temporal memory giving recurrent nets an opportunity to make classification using the current input and the previous stage of the network [13]. The recurrent connections are especially useful to solve problems associated with sequential data.

Our RNN structure is presented in Figure 2. We used a Long Short-Term Memory Units (LSTM) [7] layer to avoid the

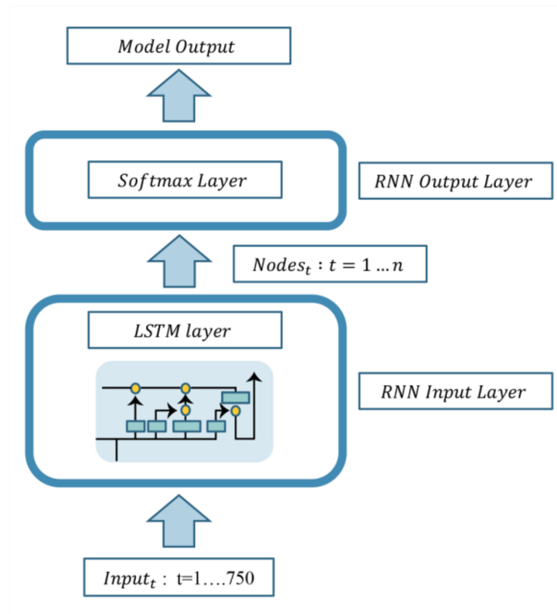

Figure 1. Architecture of RNN for the General and the Expert models.

common problems of vanishing and exploding gradient. Backpropagation Through Time (BPTT) was used to update the weights, and we used a combination of Stochastic Gradient Descent and Nesterov momentum [5] for weight optimization. Finally, a SoftMax layer gives the probability for each class. All system was implemented using DeepLearning4J library available in [11].

RNN was built to classify information as the "many to one" feeding into the system with an epoch. At the end, the system puts out a single output label representing the activity label of the input epoch. For training, we used the Mini-Batch approach with the size of forty for General model and thirty-five for Expert model. The numbers of connection between the RNN input layer and the RNN output layer were five for the General model and six for the Expert model. Hyperparameters such as the Mini-Batch size, learning rate, and the other mentioned were selected to get the maximum network performance by analyzing the loss function.

The proposed system was trained and tested first on a PC Intel Core i5-7500, CPU 3.40 GHz, 8 GB of Ram memory, and NVIDIA GeForce GTX 1050 Ti. In addition, we used IntelliJ IDEA and Android Studio IDE to transfer the built RNN-based system to an Android smartphone as an App. A feature of the system is that RNN was implemented as a light version of the deep learning approach able to run (i.e., Deep Learning Light) using only smartphone resources. This gives an opportunity to create Deep Learning-based Apps in a standalone mode (i.e., without connecting to online server to make the inference). The smoking activity recognition App was tested on a Samsung Galaxy S7 smartphone with Octa-core processor (4x2.3 GHz and 4x1.6GHz) and 4 GB of Ram memory. Also upon recognition of smoking activities, the smart band provides active vibration feedback of smoking gestures to smokers.

4. RESULT & DISCUSSION

Table 3 shows the performance of the General model in a form of confusion matrix. The values in the main diagonal correspond to the recall values for ADL and HGA. The false positive (FP) rate for HGA of 3.88% corresponds to the ADL classified by the General model as HGA. In addition, the precision for HGA of 94.75% represents the percentage of HGA correctly classified as HGA. According to the results of Table 3, it seems that the RNN-based model reasonably distinguishes between ADL and HGA.

The confusion matrix presented in Table 4 describes the performance of the Expert model. Although smoking hand gestures are similar to eating and drinking gestures, the RNN-based Expert model achieves a recall value of 91.38%. The FP rate of 3.30% reflects only confusion against the drinking gestures. Regarding the false negative rate (FN), it is 8.62% reflecting the smoking gestures classified as drinking and eating gestures. The largest misclassification of 6.90% came from the eating gesture as shown in the table.

Table 3. Confusion matrix of the General model.

Recognition Rate (%)		**Predicted Value**	
		ADL	**HGA**
Actual value	**ADL**	**96.12**	3.88
	HGA	6.17	**93.83**

Regarding processing time, the smoking activity recognition App needs 0.3 seconds to load the General model and between 1.1 to 1.4 second to infer the class label of a single epoch. For Expert model is necessary 0.02 seconds to load it, and around 1 second to get the inference.

Table 4. Confusion matrix of the Expert model.

Recognition Rate (%)		**Predicted Value**		
		Drinking	**Smoking**	**Eating**
Actual value	**Drinking**	**93.02**	3.30	3.30
	Smoking	1.72	**91.38**	6.90
	Eating	3.51	0	**96.33**

5. CONCLUSION

We present a smoking activity detection system as a smart application for smokers who desire to quit smoking. Our system is consisted of one smart band which hosts an IMU and one smartphone which hosts a deep learning based AI App. Our preliminary results show an accuracy of 94.07% with a recall value of 91.38% for smoke activity recognition. We believe that the public could benefit from our system by getting real-time feedbacks and vibration. Through our system, it might be able to promote less smoking which will possibly lead to quit smoking.

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