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Identification of Cigarette Smoke Inhalations from Wearable Sensor Data using a Support Vector Machine Classifier*

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Abstract— **This study presents a subject-independent model for detection of smoke inhalations from wearable sensors capturing characteristic hand-to-mouth gestures and changes in breathing patterns during cigarette smoking. Wearable sensors were used to detect the proximity of the hand to the mouth and to acquire the respiratory patterns. The waveforms of sensor signals were used as features to build a Support Vector Machine classification model. Across a data set of 20 enrolled participants, precision of correct identification of smoke inhalations was found to be >87%, and a resulting recall >80%. These results suggest that it is possible to analyze smoking behavior by means of a wearable and non-invasive sensor system.**

I. Introduction

Currently, there are about 1 billion smokers in the world [1], around 14% of the total population. Half of these smokers will eventually die due to problems related to smoking. It has been extensively reported that tobacco smoking is a significant risk factor for development of several types of cancer, cardiovascular, and pulmonary diseases. Tobacco abuse is a cause of preventable death for nearly 6 million people per year, 80% which occur in developing countries [1].

In order to be able to evaluate, improve and develop efficient methodologies for clinical interventions to reduce the tobacco epidemic, it is important to understand the different conditions and behaviors associated to this drug, such as frequency and exposure. As in many activities of clinical interest, the most common methodology to evaluate smoking behavior is by means of recalling the amount of cigarettes people consume over a given period of time. This issue has been a concern in cases where a more objective assessment is expected, since the retrospective accuracy of self-reporting methods has always been limited to underreporting due to intentional and non-intentional bias [2]. Different methodologies have been proposed in the past to overcome this issue.

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One of the most practical methods in free-living conditions has been the use of flow meters attached to the cigarette to record the smoking topography; however, it has been observed that the use of portable cigarette flow meter devices might change the smoking topography of the subject due to the difference in sensory effects [3]. Machine vision has also been studied to address the issue, where cameras are used to identify smoking effects by record smoking patterns [4], or to identify smoking events under different light conditions using face, cigarette and arm motion detection as features [5]. Although this approach makes the monitoring of smoking invisible to the subject, the need of video devices reduce the practical utilization of the system in free living conditions, and limits the analysis to constraint fixed spaces.

There is a need for better methodologies to monitor cigarette smoking in free living conditions, where the subject under evaluation does not suffer the burden of constraint techniques. Our major goal is the development of a non-invasive wearable sensor system (Personal Automatic Cigarette Tracker - PACT) that is completely transparent to the end user and does not require any conscience effort to achieve reliable monitoring of smoking behavior in free living individuals. This study presents a method for identification of cigarette smoke inhalations through pattern recognition applied to wearable sensor data capturing characteristic hand-to-mouth gestures and changes in breathing patterns during cigarette smoking.

II. Methodology

A. Sensor Description

A system comprising different sensors was implemented to be able to capture the behavior of the Hand-to-Mouth (*HtM*) gestures and the tidal volume during respiration. These sensors are shown in Figure 1. The *HtM* gestures were captured using a radio frequency transmitter-receiver proximity sensor (*PS*) exclusively designed for this purpose. A low power small transmitter (*Tx*) was placed on the wrist of the subject's dominant hand, which oscillates a sine wave at an operating frequency of 125 kHz. An antenna was attached to the pectoral area and was connected to a receiver resonant circuit (*Rx*) tuned at the same frequency, which generates a rectified signal proportional to the *Tx* and the antenna of the *Rx*. The response of the sensor is within a range of 30-17 centimeters, saturating at its maximum amplitude of 3 Volts from 17-0 centimeters. A more detailed description of this proximity sensor can be found in [6].

The respiration breathing patterns were captured using a commercially portable Respiratory Inductive Plethysmograph (zRIP, Pro-Tech Inc.), where thoracic (*TC*) and abdominal (*AB*) elastic sensor bands (DuraBelt, Pro-Tech Inc.) capture the change in volume in the subjects lungs [7]. The output signals of the zRIP module were electronically conditioned to be within an amplitude range of 0-3 Volts, centered at 1.5 Volts.

All these sensor signals were recorded into a portable data logger (Logomatic V2.0, Sparkfun Inc.) at a sample rate of 100 Hz and stored into a microSD card flash memory for offline analysis.

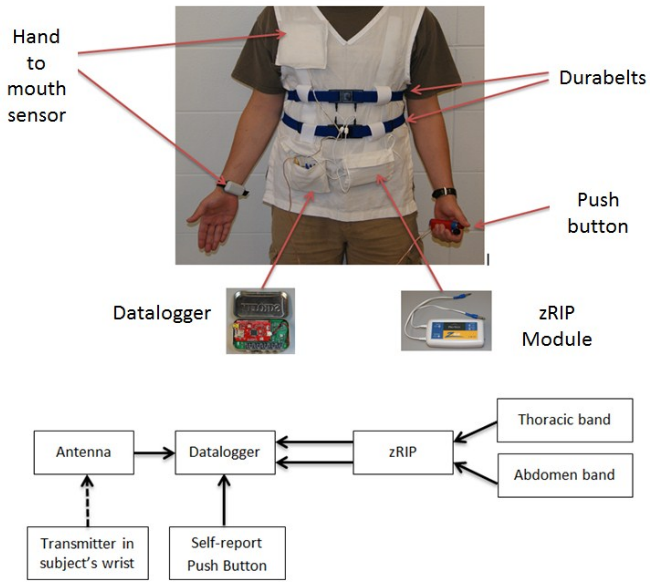

Fig 1. Hand-to-mouth detection and tidal volume capturing sensors (top), and block diagram of the system (bottom).

B. Data collection

A number of 20 regular smoker participants were voluntarily enrolled (carbon monoxide from a breath sample >10 ppm), 10 males and 10 females, ages 23.1±3.3 years, with BMI 25.88±5.24 kg/m^2. All participants reported to be healthy with no chronic respiratory problems and/or no allergies of any kind, and agreed to sign the consent form approved by The University of Alabama after the procedure concerning to the study was explained in detail. For the experiments, the participants were asked to perform 12 different activities: 1) sitting comfortable, 2)reading aloud, 3) sanding still, 4) walk on a treadmill in a self-selected slow pace, 5) walk on a treadmill in a self-selected fast pace, 6) use a computer to browse the internet, 7) eat food using the hands and drink from a cup, 8) eat food using silverware and drink using a straw, 9) walk outside the laboratory building, 10) smoke a cigarette while sitting, 11) rest in sitting position, 12) smoke a cigarette while standing. Except for the eating and smoking activities, which were unconstraint in time length, all the activities had a fixed duration of 5 minutes. A camcorder was used to videotape the participants during the complete duration of the experiments, and the recordings were used to perform manual scores of the experiments. Additionally, a push button was used to self-report smoke inhalations taken during the cigarette activities.

The data collected from each participant were analyzed with LabVIEW-based software application. This application was designed to allow a human rater to review and playback the acquired data, to label the different activities during the experiments, and to manually score smoke inhalations taken by the participants. The manual scores of the participants were used as the validation reference for the classification model described in detail in the next sections.

C. Signal Pre-processing

The captured signals described in section II.A were pre-processed offline for further analysis. First, the *PS* signal was normalized to a scale of 0 to 1. To analyze the respiration signals, the proportional tidal volume signal (*VT*) was easily calculated as the average between the *TC* and the *AB* signals:

$$VT(t) = (TC(t) + AB(t))/2\,. \tag{1}$$

This *VT* signal was then scaled in amplitude to a range of -1.0 to 1.0. To reduce the presence of artifacts, and to eliminate high and low frequency components, an ideal band pass filter was used with cut-off frequencies between 0.0001 and 10 Hertz.

Additionally, an airflow signal (*AS*) was obtained based on the resulting *VT* signal from (1). The airflow can be calculated mathematically as the rate of change over time of the tidal volume, defined as the first derivative of *VT*:

$$AS(t) = dVT(t)/dt\,. \tag{2}$$

which provides an adequate substitute for airflow measured directly by pneumotachometers [8], [9]. Examples of the scaled signals, PS, VT and AS, defined for one participant are shown in Figure 2. These signals provide the base for the extraction of features used to build a classifier of smoke inhalations.

D. Feature extraction and the use of Support Vector Machines

Based on the *PS* signal, *HtM* gestures (*HG*) were detected for amplitudes higher than a predefined threshold *Th* above the electronic noise-level observed to be 0.03 after the *PS* normalization across all data collected. For a given *PS* recorded, there would be a *HG* each time the *PS* raises its amplitude above the defined threshold *Th* and drops below the same *Th*, resulting in $i = 1,2,\ldots,n$ number of *HG*.

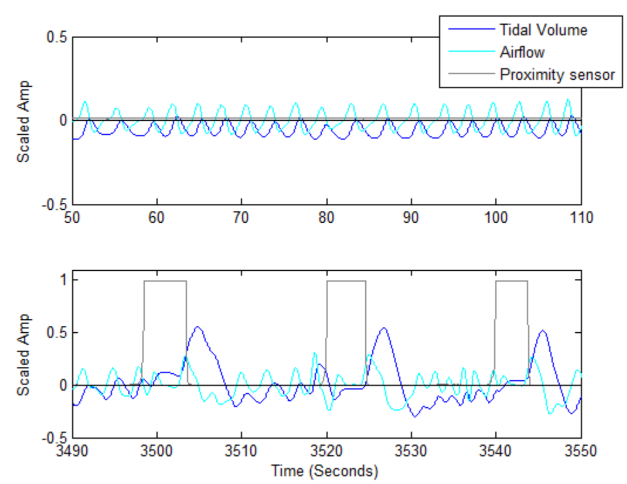

Fig 2. *PS*, *VT* and *AS* signals pre-processed from one subject for two different activities: sitting (top) and smoking (bottom).

For each HG_i detected, a feature vector x_i is constructed using different data from the *PS*, *VT* and *AS* signals. First, the duration D_i, average amplitude A_i, and the maxima value

M_i of the HG_i time interval are computed. Then, for each of the three signals, a fixed number of 500 sample points are taken from the starting of the HG_i. These data gives a feature vector of size $x_i \in \Re^{1503}$ defined as:

$$x_i = \{D_i, A_i, M_i, VT_i^{500}, AS_i^{500}, PS_i^{500}\}. \quad (3)$$

Labels were assigned to each x_i as $L_i = \{-1, 1\}$; $L = -1$ is an artifact HG not associated with a smoke inhalation and $L = 1$ is a HG associated with a cigarette smoke inhalation. These dataset pairs $X_i^j\{x_i^j, L_i^j\}$, for $j = 1,2,...,20$ participants, were used to build a Support Vector Machine (SVM) classifier capable of identifying smoke inhalations.

From the different machine learning methodologies available for classifier design, SVM is preferred when compared to other types of classifiers for its reliable performance and easy implementation for a variety of different data sets [10–12]. SVM is capable of producing very complex decision boundaries, relying on the processing of the data in a higher dimension new space, with an appropriate mapping function, to be solved by a linear function that would project into non-linear function in the original space [13], [14]. To implement a classifier using the SVM technique, the LibSVM package was used [15]. This tool set is of very simple use, it has proven its efficiency in different studies, and is accessible for free.

For the construction of the smoke inhalation classifier, Radial Basis Function kernels were selected for the model, and the parameters, penalty value C, and kernel's gamma value γ, were optimized through an exhaustive grid search procedure as $C = e^c$ for c={-15,...,15}, and $\gamma = e^h$ for h={-15,…,15}.

The SVM classifiers were implemented using a group model approach, where a significant sample of the population is used to define common representative inter-subject characteristics.

Leave-one-out validation was used to train and validate the classification models. Having a data set of 20 participants, 19 were selected for training of the SVM model, and the remaining participant is used as the validation set. This procedure was evaluated for 20 replicates, one for each participant. Precision (P) and Recall (R) metrics were calculated to evaluate the performance of the SVM models to identify smoke inhalations. Precision and recall are defined as [16]:

$$P = T_+ / (T_+ + F_+). \quad (4)$$

$$R = T_+ / (T_+ + F_-). \quad (5)$$

where $(T+)$ is the number of correctly classified smoke inhalations, $(F+)$ are the number of incorrectly classified artifacts, and $(F-)$ are the number of non-smoke inhalations. The F_1-measure was used to find the optimal C and γ values on the training of the SVM model, defined as the harmonic mean between precision and recall [16]:

$$F_1 = 2 \cdot (P \cdot R) / (P + R). \quad (6)$$

III. Results

Using the threshold methodology described in Section 2.3 to detect smoke inhalations based on the PS signal, a total of 4,402 number of HG were found across all the 20 participants and the 12 activities. The manual scores of the smoking activities reported 531 smoke inhalations over 40 cigarettes, resulting in an average of 13.3 per cigarette. Of these 531 manually scored inhalations, it was observed that 51 were not detected by the PS sensors, as some of the subjects used at some times their non-dominant hand to smoke. For each one of the 20 participants, under the leave-one-out training procedure of the SVM classifier, F_1, P and R metrics were calculated, and to evaluate the overall performance of the classifier, the average across all subjects was obtained. Table I show the results obtained in the classification smoke inhalations.

TABLE I. Classification Performance of the SVM Identification of Cigarette Smoke Inhalations.

Participant	F_1- measure %	Precision %	Recall %
1	64.71	100.00	47.83
2	65.22	55.56	78.95
3	67.92	94.74	52.94
4	90.20	82.14	100.00
5	31.58	100.00	18.75
6	100.00	100.00	100.00
7	81.25	68.42	100.00
8	77.27	68.00	89.47
9	83.33	95.24	74.07
10	86.36	82.61	90.48
11	84.00	87.50	80.77
12	66.67	76.19	59.26
13	100.00	100.00	100.00
14	95.45	91.30	100.00
15	89.23	96.67	82.86
16	95.83	100.00	92.00
17	96.88	100.00	93.94
18	79.25	72.41	87.50
19	72.00	75.00	69.23
20	97.78	95.65	100.00
Average (SD)	**81.25 (16.29)**	**87.07 (13.30)**	**80.90 (21.32)**

IV. Discussion

In this study, an SVM classification model for detection of cigarette smoke inhalations was trained and validated on a dataset obtained from 20 individuals. The model identifies smoke inhalations based on features extracted from the hand-to-mouth gesture sensor measuring proximity of the dominant hand to the mouth and from respiratory signals recorded using a portable Respiratory Inductive Plethysmograph. This non-intrusive wearable sensor PACT system can potentially reduce subject's burden in research studies that need a retrospective account on the number of cigarettes consumed, and can potentially prevent a possible change ("reporting effect") in their regular smoking activity.

An average precision of 87.07% was achieved. This result represents the presence of false positives, that is, hand artifacts identified as smoke inhalations. This result can be explained by the significant inter-subject variability observed in the participants smoking behavior. The observed variability has been discussed in literature, where the smoking topography is observed to change considerably for different smokers [17]. To solve the inter-subject behavioral differences issue, intra-subject models could be implemented. It is expected that individual implementation of models, where the implementation of the SVM classifier uses data extracted from the same participant being evaluated, will perform significantly better than the inter-subject models described in this study, since it was observed that the smoking behavior is more consistent on an individual level.

On the other hand, the lower average result of 80.90% in the recall calculation across the 20 participants indicates presence of false negatives, where some smoke inhalations were not detected by the proximity sensor. This is explained by the behavior of some participants, most notably participant number 5 (Table 1), who took some inhalations with the non-dominant hand, where no proximity sensor was used. This issue can be easily overcome by means of an additional proximity sensor worn by the participant.

The results obtained here represent the first steps towards the implementation of a wearable and non-intrusive cigarette monitoring system.

V. Conclusion

This study presented a subject-independent Support Vector Machine classification model for detection of cigarette smoke inhalations from signals recorded using a hand-to-mouth proximity sensor and a portable Respiratory Inductive Plethysmograph comprising PACT system. The SVM model achieved 87.07% average precision in identification of smoke inhalations, with false positives appearing due to misclassification of artifacts, a reflection of the high inter-subject variability. The SVM model also produced 80.90% average recall due to several undetected smoke inhalations by the proximity sensor, when participants used their non-dominant hand to smoke. The proposed wearable sensor system and classification model may be used in the development of a cigarette monitor in free-living conditions over extended periods of time.

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