Understanding Smoking Behavior using Wearable Sensors: Relative importance of various sensor modalities

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Abstract— **The Personal Automatic Cigarette Tracker (PACT) system, which consists of abdominal (AB) and thoracic (TC) breathing sensors, and a RF hand-to-mouth proximity sensor (PS), has proven to be useful in the detection and characterization of cigarette smoke inhalations. In this research, we further analyze the impact of subjects' anthropometric characteristics on the quality of sensor signals and evaluate the contribution of each sensor modality to the accuracy of the classifier for smoke inhalations detection. Results indicated that subjects with medium BMI, high BMI, and in a standing position were, respectively, 1.91, 4.74 and 4.32 times more likely to affect the quality of the breathing signal. Features extracted from TC+AB+PS, TC, AB, and PS sensors for individual detection models, resulted in F-scores of 94%, 85.39%, 88.54% and 90.48% respectively. For group models, the F-scores were 67.12%, 41.46%, 46.56% and 59.14%. This indicates higher contribution of abdominal breathing and hand gestures to detection of smoke inhalations.**

I. Introduction

According to the US Department of Health and Human Services the prevalence of cigarette smoking among adults has declined from 42% in 1965 to 18% in 2012. However, more than 42 million Americans still smoke, killing more than 20 million people since 1964 [1]. According to the Surgeon General's report, the burden of smoking and related mortality rate are expected to remain unacceptably high for decades to come unless urgent action is taken.

The Personal Automatic Cigarette Tracker (PACT) system was developed to monitor smoking behavior in smokers in free living conditions. The PACT system consists of wearable Respiratory Inductance Plethysmograph (RIP) sensors (abdominal and thoracic breathing bands) and a hand-to-mouth proximity sensor. Detailed information regarding important parameters of smoking and smoke exposure such as volume of smoke inhaled, duration of smoke holding, and smoke exhalation period useful for understanding the psychopharmacology of smoking cannot be obtained by current technologies in free living conditions. The PACT system has proven useful in these situations and data can be collected unobtrusively. A study that included 20 regular smokers performing a variety of activities (including cigarette smoking) under observation of a research assistant demonstrated the feasibility of PACT system in detecting smoke inhalations [2]–[5]. A Support Vector Machine (SVM) classifier applied to raw sensor signals from PACT achieved 83.35% of average precision and recall for group models and 90% for individual models [4]. Use of a SVM classifier in combination with various features automatically extracted from breathing signals [2] achieved 67 % of average precision and recall for group models and 94% for individual models. These results indicate that automatic classification of breathing signals may be feasible for automatic detection of smoke.

In related work, Ali et al [6] introduced a similar system called mPuff to monitor smoking behavior. Seventeen features from respiration signal were used to classify individual respiration cycles into smoking puffs or non-puffs. Supervised and semi-supervised SVM models were implemented and trained on data collected from 10 daily smokers. For the supervised SVM model, an accuracy of 84.5% was obtained, which improved to 86.7% by using a semi-supervised model.

Although the use of RIP breathing sensors may be helpful in collecting smoking topography in free living conditions, to our knowledge, no one has identified the factors that affect the output of a RIP sensor system during cigarette smoking events. In this paper we analyze the factors affecting the output quality of the RIP sensors. For each subject, anthropometric variables of Gender, BMI (Normal, Overweight, and Obese), Dominant Hand, as well as Posture (sitting or standing) were taken into consideration. A logistic regression analysis was carried out, and significant factors were selected using log-likelihood test.

Another important consideration is relative contribution of each sensor to the final classification accuracy. The original PACT sensor suite included both abdominal and thoracic respiration sensors, which may be redundant. Moreover, men and women may exhibit different types of breathing (abdominal or thoracic) [7] requiring gender-specific breathing band placement. Thus studying the relative contribution of features extracted from different sensors is required to estimate the relative contribution of each sensor to the final result.

II. Methodology

A. The Sensor System

Breathing patterns were captured with commercially available wearable Respiratory Inductance Plethysmograph (zRIP, Pro-Tech Inc.) producing thoracic $TC(t)$ (Fig. 1(i)) and abdominal $AB(t)$ (Fig. 1(ii)) signals from elastic respiratory band sensors (DuraBelt, Pro-Tech Inc.) . To capture the typical cigarette smoking hand-to-mouth gestures, a radio frequency (RF) operated proximity sensor consisting of a transmitter and a receiver was used, producing the signal $PS(t)$ proportional to the distance and between the wrist-worn transmitter (Fig. 1(iii)) and chest-mounted receiver (Fig. 1(iv)). More detail about the proximity sensor can be found in [3]. A portable data logger (Logomatic V2.0, Sparkfun Inc.) recorded the RIP output signals, $TC(t)$ and $AB(t)$ and the $PS(t)$ signal, at a sampling rate of 100 Hz [3].

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B. Data Collection

Twenty subjects, with a smoking history of more than 1 year, participated in the study (10 males and 10 female). The distribution for the BMI and Age was 25.88 ± 5.24 kg/m2 and 23.1 ± 3.3 years respectively. Each subject was asked to perform 12 activities, including two smoking sessions – smoking while standing and smoking while sitting. The study was approved by the IRB at the University of Alabama. Each experiment was videotaped and later manually annotated for start and end time of each activity. These annotations were used to label the instances of smoke inhalations.

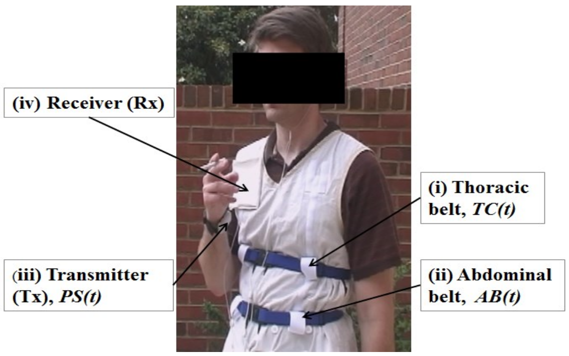

Figure 1. The PACT system, (i) Thoracic elastic band, (ii) Abdominal elastic band, (iii) wrist worn RF transmitter of the PS system, (iv) Chest mounted RF receiver of the PS system.

C. Signal Pre-Processing

The tidal volume signal *VT*(*t*), which represents the volume of air inhaled or exhaled, was calculated as the average between the TC(t) and the AB(t) signals: $VT(t) = (TC(t) + AB(t))/2$. Using min-max normalization, the amplitude of *VT(t)* signal was scaled from range of -1.0 to 1.0.The signal was passed through an ideal band pass filter with cut-off frequencies between 0.0001 and 10 Hertz to reduce out-of-band artifacts. The airflow signal *AS(t)*, which is defined as the rate of change of tidal volume signal over time, was calculated from the filtered *VT(t)* signal and was computed as $AS(t) = \mathrm{d}VT(t)/\mathrm{d}t$.

During individual sensor analysis, outputs from the thoracic belt *TC*(*t*) and abdomen belt *AB*(*t*) were utilized individually instead of their average, i.e. *VT*(*t*). Each signal was processed similar to *VT*(*t*) to obtain air-flow estimates AS'_{AB} and AS'_{TC}.

The proximity signal *PS*(*t*) was normalized on a scale of 0 to 1. Some of the artifacts in *PS*(*t*) related to non-smoking activities and movements (scratching head, touching eyes or nose, etc.) were eliminated using a technique described in [3]. All signals were synchronized to a common time scale.

D. Logistic Regression

A Binary Logistic regression model was implemented to analyze the relationship between the dichotomous dependent variable – perceived quality of the output signal of the RIP system and independent variables such as – Gender, BMI, Dominant Hand, Weight, Height, and Posture. Only the *VT*(*t*) signal was considered for this analysis. As the logistic regression analysis was carried out to estimate the probability of faulty measurement occurrence; the dependent variable was coded as 0 (negative) for *VT(t)* signal following the typical pattern of smoke inhalation and 1 (positive) otherwise. For example, as shown in Fig. 2(A) the typical smoke inhalation pattern consisted of a short period (~1-2 sec) apnea corresponding to a puff (drawing of smoke into the mouth), followed by deep inhalation, optional period of smoke holding, and a potentially extended period of exhalation. Such pattern was not visible for the signal shown in Fig. 2(B), which was most likely corrupted by a motion artifact resulting from movement of clothing or tissue under the belt during arm movement. The *VT(t)* signal for each known smoke inhalation in the dataset was reviewed by an experienced human rater and labeled 0 or 1 according to similarity to the typical smoke inhalation pattern.

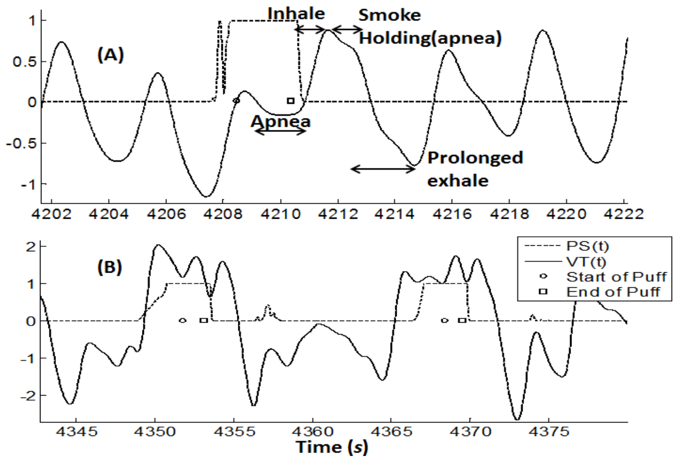

Figure 2. VT Signal captured by RIP system, (A) typical smoking signal, (B) smoking signal corrupted by an artifact.

To avoid issues of multicollinearity, height and weight were discarded from further analysis, as they show strong correlation with BMI. BMI was coded as a trichotomous variable and categorized into – (1) Normal BMI (18.5 – 24.9), (2) Overweight BMI (25.0 – 29.9) and (3) Obese BMI (30.0 - above) [8]. As BMI was a trichotomous predictor, Normal BMI was considered as a reference cell (dummy variable) and the odds ratios were calculated with respect to normal BMI. Variable posture was coded as a dichotomous predictor, with standing as 1 (positive) and sitting as 0 (negative). The dominant hand variable was not used as a predictor because of the preponderance of right handedness in the sample.

The minimum sample size required was calculated using the Peduzzi et al [9] technique. In this analysis, there were k = 5 explanatory variables, and the proportion of positive cases were p = 0.45, therefore the minimum number of cases required was N = 10·k/p = 10·5/0.45 = 111. As the number was not less than 100, it was concluded that the present data size was sufficient for multiple logistic regression analysis [10].

E. Support Vector Machine Classifier, Features and Forward Feature Selection

The SVM classifier with radial basis kernel function was used to detect smoke inhalations because of its reliable performance and ability to generate non-linear decision boundary [11]. To find the optimal combination for the cost function *C* and kernel's gamma value *γ*, a simple exhaustive grid search procedure with $C = e^{c}$ for c = {-5… 5}, and

$\gamma = e^h$ for h = {-5… 5} was implemented [12]. In order for the SVM classifier to detect smoke inhalations, 27 features *Fx* representing the characteristic behavior in a smoking act were extracted (Fig. 3, e.g. F4 represents the duration of a hand gesture, F10 represents expiration duration, F11 represents the breath volume) [2]. Features were extracted only for the breathing cycles where a hand-to-mouth gesture was detected by the PS.

Several sets of features extracted from various sensors comprising PACT were formed to estimate relative contribution of each sensor to the classification accuracy. For detected hand gestures, i = 1,…,n feature vectors were constructed as:

$$f_i^{PACT} = \{PS_i^4, VT_i^{10}, AS_i^{13}\},$$

$$f_i^{TC} = \{TC_i^{10}, AS_{TC\,i}'^{\,13}\},$$

$$f_i^{AB} = \{AB_i^{10}, AS_{AB\,i}'^{\,13}\},$$

$$f_i^{PS} = \{\, PS_i^4\},$$

where the superscript index denotes the number of features extracted from the signal. Labels were assigned to each feature vectors f_i as $L_i = \{-1, 1\}$; $L = -1$ if the feature vector was not associated with a smoke inhalation and $L = 1$ if the feature vector was associated with a smoke inhalation. The dataset pairs $F_i^j\{f_i^j, L_i^j\}$, for $j = 1,2,\ldots,20$ subjects, were used to train a SVM classifier.

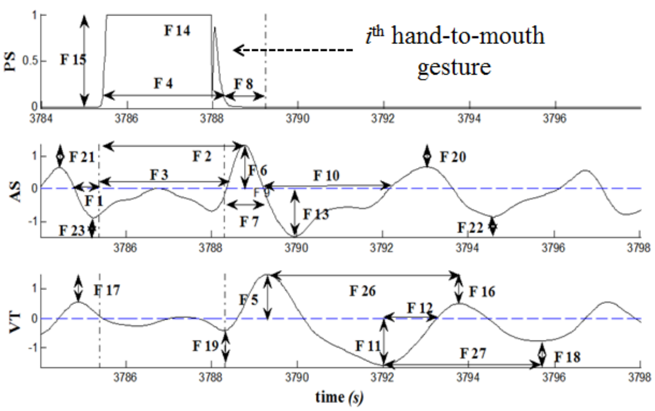

Figure 3. Features extracted from PS, AS and VT during a hand-to-mouth gesture related to smoking activity.

Two types of classification models were trained - individual models (which were subject specific) and the group model (which was subject independent). The individual models were trained using a dataset from randomly selected 5 non-smoking activities and 1 smoking activity and validated on the remaining dataset to avoid over-fitting of the model. For the group model training, a dataset from 19 subjects was selected for training and the remaining subject was used for validation. This process, usually referred to as leave-one-out validation method, was implemented for 20 replicates, one for each subject [13]. During the training process, the F-score was used to select the optimal C and γ values for the SVM model defined as: $\mathrm{F-score} = 2 \cdot \left(\frac{\mathrm{P \cdot R}}{\mathrm{P+R}}\right)$, where P is precision and R is recall.

A feature selection procedure was implemented to obtain a subset of features for efficient classification [14]. This approach was used because some of the 27 extracted features might not contribute as much as others to discriminate the respiratory signals between smoking and non-smoking inhalations. The forward feature selection technique that begins with an empty feature set (*R.Feat. set*) was used. Initially a single feature from the total 27 feature set was selected and added to the *R.Feat. set*. This single feature was then used to build either an individual or group model. If the selected feature resulted in increment of the F-score, the feature was included in the *R.Feat. set*. The selected feature was discarded from the original 27 feature set, and the process of feature addition to the *RF set* continued until the F-score ceased to increase further.

TABLE III. STATISTICAL TEST FOR INDIVIDUAL PREDICTORS

Term	*β*	*SE(β)*	χ^2	*p*	LOWER 95%	UPPER 95%
Intercept	-0.401	0.142	7.8	0.0050*	-0.686	-0.124
BMI Overweight	0.322	0.104	9.4	0.0021*	0.117	0.529
BMI Obese	0.778	0.143	29.3	<.0001*	0.501	1.06
Gender	0.045	0.098	0.21	0.6471	0.544	0.925
Posture	0.732	0.096	57.0	<.0001*	0.148	0.238

TABLE IV. ODDS RATIO FOR SIGNIFICANT PARAMETERS

LEVEL1	LEVEL2	ODDS RATIO	*p*	LOWER 95%	UPPER 95%
BMI Overweight	BMI Normal	1.91	0.0020	1.27	2.88
BMI Obese	BMI Normal	4.74	0.0001	2.72	8.43
Stand	Sit	4.32	0.0001	2.97	6.36

TABLE V. CLASSIFICATION ACCURACY FOR INDIVIDUAL MODEL WITH AND WITHOUT COMBINATION OF INDIVIDUAL SENSORS

	***F*-score %**	**Precision %**	**Recall %**
f_i^{PACT}	68.67±27.28	73.48±24.28	68.38±28.85
R. Feat.(f_i^{PACT})	94.00±10.66	99.55±1.11	90.80±15.35
f_i^{TC}	56.68±26.12	69.18±23.94	57.25±29.50
R.Feat. set (f_i^{TC})	85.39±15.44	91.08±11.81	82.55±19.46
f_i^{AB}	61.28±29.02	68.81±28.25	61.68±30.75
R.Feat. set (f_i^{AB})	88.54±15.88	95.37±9.69	85.29±21.02
f_i^{PS}	72.12±28.87	76.68±23.58	71.74±31.64
R.Feat. set (f_i^{PS})	90.48±12.45	94.25±9.48	88.25±15.52

TABLE VI. CLASSIFICATION ACCURACY FOR GROUP MODEL WITH AND WITHOUT COMBINATION OF INDIVIDUAL SENSORS

	***F*-score %**	**Precision %**	**Recall %**
f_i^{PACT}	65.09±21.64	76.56±17.96	61.32±26.51
R.Feat.(f_i^{PACT})	67.12±22.89	81.53±14.80	63.38±27.15
f_i^{TC}	42.99±19.61	45.47±18.77	52.88±32.32
R.Feat. set (f_i^{TC})	41.46±19.25	52.65±19.34	40.41±25.79
f_i^{AB}	47.46±21.14	67.39±25.03	45.80±25.78
R.Feat. set (f_i^{AB})	46.56±21.81	55.55±26.73	48.88±25.18
f_i^{PS}	59.98±28.21	75.94±27.04	53.68±31.09
R.Feat. set (f_i^{PS})	59.14±28.57	76.55±25.72	53.08±31.75

III. RESULTS

The log likelihood ratio test for the logistic regression model gave a χ^2 value of 94.48 (p <0.0001). Table III shows the parameter estimate for individual predictors. Predictors BMI and Posture showed significant p-values. Table IV presents the odds ratio for the significant predictors, with BMI Obese and Stand having large odds ratio values. Results for individual and group models are shown in Table V and VI. In both cases, the F-score was highest for the classifier trained with f_i^{PACT} reduced features, followed by f_i^{PS}, and then by f_i^{AB}.

IV. DISCUSSION AND CONCLUSIONS

The results of this study demonstrate that anthropometric characteristics of the person being observed had a direct impact on the quality of the obtained sensor signals that the classifier accuracy depended on the signals included in the feature set. Application of the sequential forward selection technique improved the classifier accuracy significantly.

From Table III, the p-value for BMI Obese category and posture was significant (<0.0001), producing strong evidence that these two factors had a significant impact on the quality of breathing signals. As per Table IV, the odds ratio indicated that the overweight BMI user was 1.91 times more likely to affect the RIP signal than individuals with normal BMI. But users with BMI in obese category were 4.74 times more likely to affect the system output than individuals with normal BMI. From data in Table IV, it can be inferred that individuals in standing posture were 4.32 times more likely to affect the system output than users in sitting posture. These findings indicate that we need to be careful in carrying out experiments when person is smoking in a standing posture and has a BMI in the obese category.

The features extracted by the combination of sensors improved the performance of the classifier significantly as compared to features obtained from individual sensor signals. Further, the reduced feature set for each case significantly increased the classifier accuracy as compared to the overall features. Although the accuracy level for the classifier using features from PS signal (F-score – 90.48%) was less than the accuracy using features from PACT system (F-score – 94%), it should be noted that only 4 features were extracted from PS signal. The PS signal features assisted in better performance of the classifier as compared to the features from TC and AB, because the PS signals were consistent and captured the smoking behavior pattern more precisely as compared to RIP system. RIP system is more prone to faulty measurements and may degrade the classifier accuracy. It is also important to note that classification of the abdominal signal resulted in higher accuracy that from thoracic signal, suggesting that use of the abdominal belt may be preferred in a single belt system.

The results for group model from Table VI indicated that the combination of sensors provides better features for classification as compared to individual sensor modules. The results for group model were not comparable to that of individual models, indicating that the behavior or breathing pattern for smoking activity may be subject specific.

In conclusion, these results demonstrate the importance of multiple sensors that can achieve reliable smoking behavior analysis. Features derived from only a single sensor explain less variance and accordingly decrease the detection rate.

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