A Wearable Sensor System for Monitoring Cigarette Smoking

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ABSTRACT. Objective: Available methods of smoking assessment (e.g., self-report, portable puff-topography instruments) do not permit the collection of accurate measures of smoking behavior while minimizing reactivity to the assessment procedure. This article suggests a new method for monitoring cigarette smoking based on a wearable sensor system (Personal Automatic Cigarette Tracker [PACT]) that is completely transparent to the end user and does not require any conscious effort to achieve reliable monitoring of smoking in free-living individuals. **Method:** The proposed sensor system consists of a respiratory inductance plethysmograph for monitoring of breathing and a hand gesture sensor for detecting a cigarette at the mouth. The wearable sensor system was tested in a laboratory study of 20 individuals who performed 12 different activities including cigarette smoking. Signal processing was applied to evaluate the uniqueness of breathing patterns and their correlation with hand gestures. **Results:** The results indicate that smoking manifests unique breathing patterns that are highly correlated with hand-to-mouth cigarette gestures and suggest that these signals can potentially be used to identify and characterize individual smoke inhalations. **Conclusions:** With the future development of signal processing and pattern-recognition methods, PACT can be used to automatically assess the frequency of smoking and inhalation patterns (such as depth of inhalation and smoke holding) throughout the day and provide an objective method of assessing the effectiveness of behavioral and pharmacological smoking interventions. (*J. Stud. Alcohol Drugs, 74,* 956–964, 2013)

CIGARETTE SMOKING IS THE LEADING CAUSE of preventable death in the United States. It causes more than 440,000 deaths each year and generates an estimated $167 billion in annual health-related economic losses (Centers for Disease Control and Prevention, 2006). Recent national surveys indicate that approximately 60 million people, or 25% of the U.S. population age 12 years and older, have smoked tobacco in the past month, with cigarette smoking being the most common mechanism of consumption (Substance Abuse and Mental Health Services Administration [SAMHSA], 2010). Understanding behaviors associated with cigarette smoking, such as frequency of smoking and smoke exposure (e.g., depth of inhalation and duration of smoke holding), is important for evaluating and improving the effectiveness of behavioral and pharmacological smoking interventions.

Cigarette smoking is typically assessed by retrospective self-report, which provides a crude estimate of cigarette consumption, with the accuracy limited by memory biases and intentional misrepresentations of actual levels of use (Hufford et al., 2001) and may substantially underestimate actual cigarette consumption (Hatziandreu et al., 1989). Real-time methods of assessment, which require smokers to use an electronic diary to record each cigarette as soon as they have finished smoking, may provide more accurate estimates of smoking frequency and smoking patterns (Shiffman et al., 2002; Stone et al., 1999). These methods also require people to remember to record their smoking and may produce underreporting of cigarette consumption. Regular smokers may only record approximately half of the cigarettes they smoke with electronic diary methods (Warthen and Tiffany, 2009). Biomarkers of nicotine exposure have also been used to evaluate the accuracy of self-reported smoking in epidemiological and observational studies (Caraballo et al., 2004; Patrick et al., 1994). This research suggests that conventional biomarkers may be accurate in determining levels of smoke exposure among heavy, regular smokers, but they are substantially less accurate in determining how much someone smokes at low levels of smoking.

Self-reports of the number of cigarettes smoked, even if accurate, are also limited in that they do not yield an exact estimate of smoke exposure. Studies of smoking topography reveal that smokers vary considerably in the amount of smoke they inhale when they smoke a cigarette (Kozlowski et al., 2001). Consequently, the number of cigarettes smoked over a given period is not strongly related to total smoke exposure for that same period.

Portable smoking topography devices allow for the collection of real-time data and permit the assessment of puffing behavior (and smoking frequency) in a smoker's natural environment. This approach overcomes some of the problems associated with self-report methods, but it is limited as a measure of total smoking frequency because it requires

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smokers to remember and comply with instructions to smoke their cigarettes through the device. Moreover, the majority of smokers report that smoking cigarettes through portable topography devices changes their smoking behavior (Hammond et al., 2005). Finally, conventional puff topography devices measure airflow through the cigarette but do not assess respiratory events that occur after the cigarette is removed from the mouth (e.g., postpuff breath holding; Baker and Dixon, 2006). Thus, available methods of smoking assessment do not permit the collection of accurate measures of smoking behavior that capture the real-time smoking frequency and comprehensive within-cigarette puff topography while limiting reactivity to the assessment procedures.

In this article, we propose a method based on the use of wearable sensors to detect and characterize cigarette smoke inhalations (Personal Automatic Cigarette Tracker [PACT]) through monitoring of breathing and hand-to-mouth gestures. The monitoring of breathing patterns with PACT is performed using respiratory inductance plethysmography (RIP) (Cohn et al., 1982; Fiamma et al., 2007). The use of this methodology has been extensively explored in the past to characterize breathing and inhalation patterns associated with smoking. Time and flow volume components were measured using RIP simultaneously with spirometry and body plethysmography (Sackner et al., 1982). Breathing patterns during smoke inhalation in pipe and cigarette smoking were compared with the breathing of never smokers (Rodenstein and Stănescu, 1985), with the conclusion that the former were distinctly different from normal breathing. RIP was also used to observe substantial variations in the volume of inhaled smoke and in the duration of inhalation and breath hold time across multiple subjects (Tobin et al., 1982). A similar variability was reported by Taylor et al. (1988), who studied the relation of bronchial reactivity and smoke inhalation patterns. These observations represent the starting point of our current research, that is, the identification of significant differences in breathing that can ultimately be used to automatically recognize smoking patterns by means of computer algorithms.

Another major component of the PACT system is a proximity sensor that detects a characteristic hand-to-mouth gesture that precedes most cigarette puffs. This gesture is an arm motion that is directly related to the act of smoking tobacco. If an average smoker consumes 11 cigarettes per day with 8–16 puffs for each cigarette (National Cancer Institute, 1996), the resulting number of hand-to-mouth gestures would be roughly 32,000 to 64,000 repetitions per year. A variety of methods have been used to detect hand gestures, including accelerometers (Popa, 2011) to assess the velocity of movements and infrared range detectors to detect specific directional movements (Silicon Labs, 2011). In addition, capacitive sensing (Kurita, 2010) and video (Pavlovic et al., 1997) have been used to create detailed data about exact hand positions. Gyroscopes have also been used to identify characteristic angular velocities associated with a person taking a bite of food (Dong et al., 2012). These sensors can be extremely accurate and versatile; however, they cannot provide the exact functionality needed for assessment of the hand-to-mouth gestures associated with smoking in free-living conditions. As a part of the PACT system, we developed a wearable hand-to-mouth gesture sensor (Sazonov et al., 2011) that uses radio frequency (RF) technology and is minimally obtrusive and suitable for use in free-living applications.

The goal of PACT is to be completely transparent to the end user and not require any conscious effort to achieve reliable monitoring of smoking behavior and smoke exposure in free-living individuals. PACT is based on the hypothesis that smoking produces unique breathing patterns correlated in time with hand-to-mouth gestures. This article presents a detailed description of the prototype of the PACT sensor system and results of initial testing in a laboratory study.

Method

Participants

For this study, 20 regular smokers with a history of smoking for at least 1 year were recruited. Subject recruitment targeted both men and women (10 men and 10 women, age 23.1 years, *SD* = 3.3, range: 19–32) of different races and body builds (adiposity with average body mass index = 26.0 kg/m^2, *SD* = 5.3, range: 21.1–41.7) to test PACT in a widely varying sample. The average self-reported cigarette consumption by subjects was 12.4 (*SD* = 5.8) per day (range: 2–20 per day) with an average carbon monoxide measure taken at the beginning of the experiment of 16.7 ppm (*SD* =7.1, range: 10–31). Subjects reported that they were healthy and had no acute or chronic respiratory problems. Subjects signed a consent form approved by the University of Alabama. Subjects were paid $37.50 for participation in the study.

Instruments

The PACT wearable sensor system is depicted in Figure 1. All of the sensors and electronics were mounted on a custom-sewn vest that could be worn under or over regular clothing. Breathing was monitored by a RIP module (zRIP, Philips Respironics, Murrysville, PA) kept in a vest pocket and equipped with abdominal (AB) and thoracic (TC) respiratory bands. The hand-to-mouth gesture sensor (HG) comprised two components. First, an antenna was attached to the vest at chest level using Velcro. Second, a transmitter was worn on the inside of the wrist of the dominant hand (the other hand was not instrumented). During a hand-to-mouth gesture, the transmitter comes into the vicinity of the antenna, generating a signal proportional to the distance between the antenna and the transmitter (Sazonov et al., 2011).

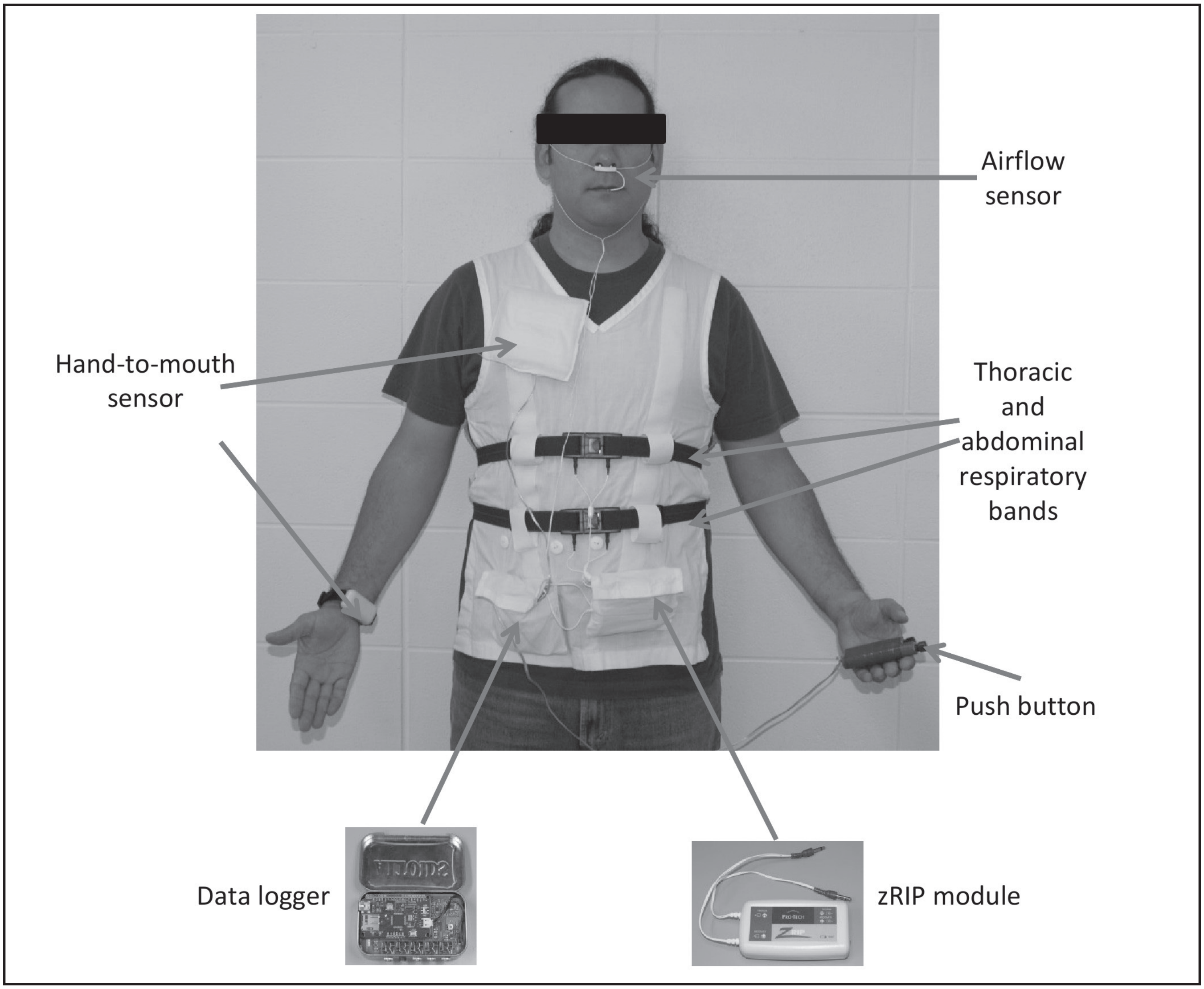

FIGURE 1. Wearable sensors comprising the PACT. The hand-to-mouth sensor captures the proximity of the subject's wrist and chest to detect the transportation of the cigarette to the mouth; the airflow sensor is a thermocouple that measures the changes in air temperature based on oral/nasal air inhale and exhale; the respiratory band and the zRIP module capture respiration; the push button is used to self-report instances such as smoke inhalations. All sensors are connected to a data logger, and the data are stored on a microSD card.

Instrumentation also included a number of devices that were needed for system development but do not represent an integral part of PACT. A thermocouple airflow sensor was worn to measure the oral and nasal airflow (AF) and to provide a reference airflow signal. A self-report push button (PB) was given to the subject to report puffs during the smoking experiments. A camcorder was used to videotape the subjects during the experiment.

All signals (AB, TC, HG, AF, and PB) were connected to a custom-designed electronic circuit for amplifying and conditioning of the signals. The same circuit incorporated a portable data logger (Logomatic V2, Sparkfun Electronics, Boulder, CO) that digitized the signals with 10 bits of resolution and a sampling frequency of 100 Hz and stored them on a microSD card. This circuit was kept in the second vest pocket. The stored data were extracted via a USB connection and processed on a personal computer. Figure 2 illustrates the sensor signals during a brief period of smoking. The battery and storage capacity of the PACT hardware potentially allow continuous use for 24 hours before a battery recharge was required.

Procedure and data analysis

During the experiments, the subjects performed 12 different activities: (a) sitting, (b) reading aloud, (c) standing, (d) walking on a treadmill at a self-selected slow pace (1.81 mph, *SD* = 0.24), (e) walking on a treadmill at a self-selected

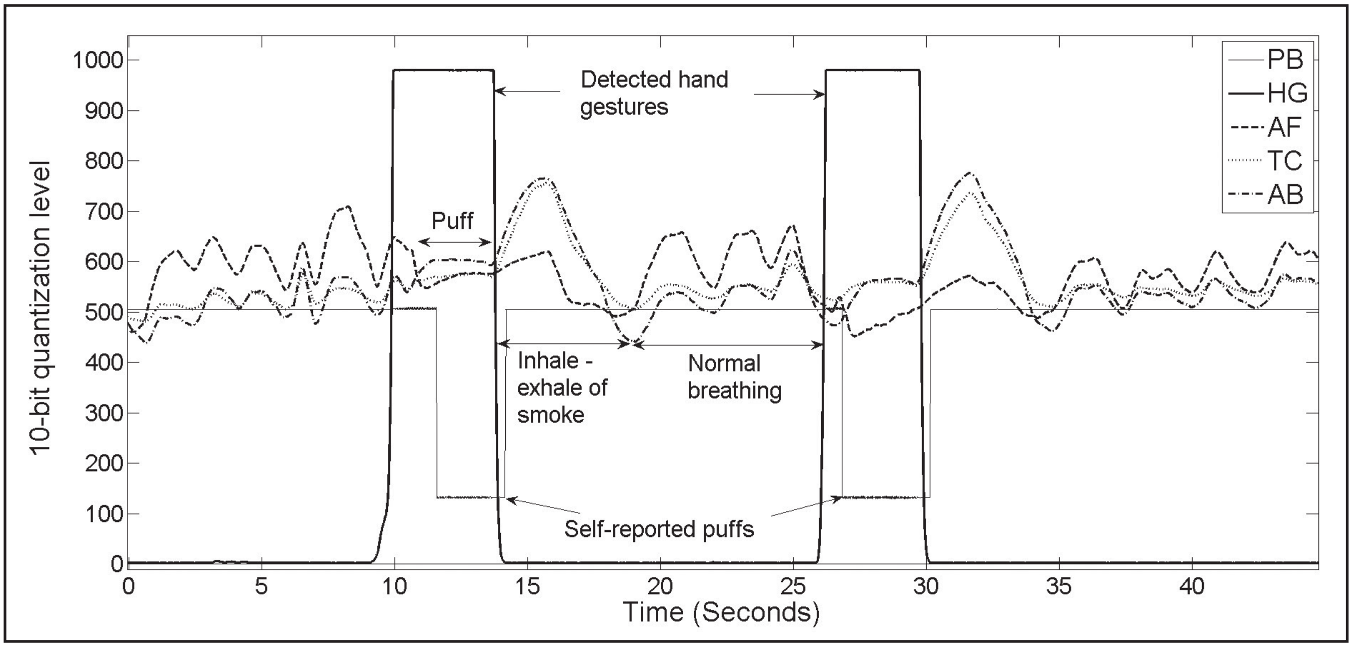

FIGURE 2. Push button (PB), hand-to-mouth gesture sensor (HG), oral and nasal airflow (AF), thoracic (TC) and abdominal respiratory band (AB) signals during smoking. A short segment of captured signals is shown here, digitized with 10 bits of resolution and a sampling frequency of 100 Hz.

fast pace (2.93 mph, *SD* = 0.40), (f) using a computer to browse the Internet, (g) eating food using hands for solids and a cup for liquids, (h) eating foods using silverware and drinking from a straw, (i) walking outside, (j) smoking a cigarette while sitting, (k) resting in a sitting position, and (l) smoking a cigarette while standing. These activities were designed to test a variety of breathing conditions (e.g., breathing with and without speech, labored breathing during physical exercise) and hand-to-mouth or other gestures proximal to the chest area (e.g., during food intake). Except for eating and smoking activities, which were not restricted in time, all the activities had a fixed time of 5 minutes to be performed. The total duration of collected data was 19.56 hours, including 531 cigarette puffs. Processing of the collected data was aimed at testing the feasibility of the main hypothesis that smoke inhalations were highly correlated with hand-to-mouth gestures and that the corresponding breathing pattern was distinctly different from breathing patterns during other activities. In this analysis, smoking a cigarette while sitting was merged with smoking while standing, because smoking in various postures represented a single activity of interest. Signal processing techniques were used to automatically detect hand gestures and all the inhalation peaks. Then, metrics describing hand gestures and breathing patterns were computed and statistically compared between different activities.

Data annotation. The signals and video were annotated by human raters in custom-designed LabVIEW software used to manually mark the boundaries of every smoking breath (including puff, smoke inhalation, and exhalation). These annotations were used along with the sensor signals to analyze the data.

Detection of hand-to-mouth gestures. When signal HG from the RF proximity sensor increased above a predefined threshold T_{HG}, the hand was considered to be in the proximity of the mouth, indicating a hand-to-mouth gesture. When the signal remained below the threshold, the hand was assumed to be away from the mouth. The value of the threshold was subject independent and defined by the electronic noise of the proximity sensor. The threshold had to be sufficiently high so that the noise present in the signal would not trigger a false detection, but also sufficiently low to capture hand gestures. Based on the direct measurement of noise level using standard measurement equipment (i.e., an oscilloscope), the amplitude of noise in the proximity sensor signal was found to be less than 90 mV under all circumstances; therefore, a T_{HG} = 100 mV was used.

Hand gesture metrics. Hand gesture metrics were computed to evaluate the ability of the HG sensor to detect hand-to-mouth gestures during smoking and to estimate their timing and amplitude. The following hand gesture metrics were computed: R_{HG} = the rate (frequency) of hand-to-mouth gestures for each activity, D_{HG} = the duration of each hand-to-mouth gesture, and A_{HG} = the amplitude of proximity signal for each hand gesture. The average and standard deviation of D_{HG} and A_{HG} were computed across all subjects to compare the values and distributions of the different activities. (Technical details for computing these and the following metrics are available from the authors on request.)

Finally, the ability of the hand gesture sensor to detect hand-to-mouth gestures resulting from smoking was evaluated by computing the number of true positives (TPs) or hits in which a hand-to-mouth gesture was detected by both the human rater and the HG sensor, false positives (FPs) or false alarms in which a gesture is detected by the sensor but not by the human rater, and false negatives (FNs) or misses in which a gesture is detected by the human rater but not by the sensor. Because of the biased data set with a very low number of TPs, true negatives (any breath cycle without a hand gesture) were not taken into account, and the hit rate (Olson and Delen, 2008) of the HG sensor was calculated as HR = TP / (TP + FN).

Derived breathing signals. Breathing patterns are typically characterized by tidal volume (VT) and airflow (AF_{EST}), which are computed from the AB and TC signals. The tidal volume signal was obtained as the average between the thoracic and abdominal signals, and the estimated airflow was then calculated as a first derivative over time.

Breathing segmentation. Breath-by-breath segmentation was implemented using extreme value detection, that is, peaks and valleys of the VT signals that represent the beginning of an expiration and inspiration, respectively. Breath-by-breath segmentation facilitates the analysis of respiratory behavior when calculating parameters like breath frequency, segment duration, amplitude, etc.

Breathing metrics. The following breathing metrics were computed to evaluate key characteristics of breathing in different activities: F = breathing frequency (respiratory rate) for each activity, $\overline{VT}^{MAX}$ = peak tidal volume, and $\overline{AF}^{MAX}_{EST}$ = estimated peak airflow.

Statistical analysis. First, a Dunnett's test for multiple comparison analysis was used to evaluate the significance of differences in breathing and hand gesture metrics between smoking and all other activities. Specifically, differences in breathing frequency (F), peak tidal volume ($\overline{VT}^{MAX}$), peak airflow ($\overline{AF}^{MAX}_{EST}$), rate, duration, and amplitude (R_{HG}, D_{HG}, A_{HG}) of hand-to-mouth gestures were evaluated using a type I error rate of = .05.

Second, average traces of hand gesture $\overline{HG}^{A}(t)$, tidal volume $\overline{VT}^{A}(t)$, and airflow $\overline{AF}^{A}_{EST}(t)$ signal waveforms were used to estimate the presence and relative timing of hand gestures related to breathing in various activities. The average trace of the tidal volume was aggregated over multiple breaths of the same activity for several subjects. The averages trace of the airflow $\overline{AF}^{A}_{EST}(t)$ and the $\overline{HG}^{A}_{EST}(t)$ signals were computed in an identical manner. Average traces during smoking only included breaths in which cigarette smoke was inhaled (as determined from the annotations by human raters). All other activities were aggregated over all breaths across all subjects.

Third, differences in average waveforms of hand gestures, tidal volume, and airflow between pairs of different activities A and B were estimated using cross-correlation X_{AB}, where activity A was always represented by an average waveform corresponding to smoke inhalation breaths. Cross-correlation provides a numeric measure of the similarity between the waveforms, where identical waveforms would have a corresponding $X_{AB} = 1$ and nonidentical waveforms would have $-1 < X_{AB} < 1$.

Results

The total number of breaths analyzed in this study was 21,411, of which 531 (2.5%) were breaths containing cigarette smoke inhalations. Table 1 shows the metrics of hand gestures detected from the HG signal: the average and standard deviation of rate R_{HG}, duration D_{HG}, and amplitude A_{HG} were computed by activity across all subjects. Note that the rate and duration of the hand gestures during smoking was most similar to eating (with hands and silverware), whereas average amplitude (which was proportional to the distance of the hand to the mouth) was substantially higher for smoking than for any other activity.

Table 1. Average rate, duration, and amplitude of hand gestures of different activities across 20 participants

	R_{HG}		D_{HG}		A_{HG}	
Activity	Average	*SD*	Average	*SD*	Average	*SD*
Sitting	0.40	0.52	8.83	21.00	0.24	0.34
Reading	0.63	0.72	16.02	35.86	0.42	0.43
Standing	0.33	0.45	22.64	49.18	0.39	0.42
Walking slowly	0.29	0.39	1.23	1.36	0.45	0.47
Walking fast	0.30	0.40	7.11	22.97	0.50	0.45
Laptop	0.95	0.76	16.40	44.69	0.24	0.33
Eat with hands	3.78	2.10	5.24	13.93	0.67	0.40
Eat with silverware	4.30	2.40	4.91	9.26	0.57	0.41
Walking outside	0.68	0.66	2.66	4.95	0.53	0.42
Resting	2.12	1.80	4.89	17.45	0.25	0.30
Smoking	3.29	1.04	3.79	5.42	0.96	0.15

Notes: The rate R_{HG} is defined as the number of hand-to-mouth gestures over a minute; D_{HG} is duration computed in seconds; A_{HG} expresses the average amplitude of the proximity sensor normalized to range 0–1.

TABLE 2. Breath frequency and signal peak-to-peak amplitude of tidal volume and airflow for different activities across all subjects.

Activity	F Average	F *SD*	$\overline{VT}^{\mathrm{MAX}}$ Average	$\overline{VT}^{\mathrm{MAX}}$ *SD*	$\overline{AF}_{\mathrm{EST}}^{\mathrm{MAX}}$ Average	$\overline{AF}_{\mathrm{EST}}^{\mathrm{MAX}}$ *SD*
Sitting	15.71	4.18	0.13	0.06	0.19	0.10
Reading	10.77	2.51	0.20	0.10	0.19	0.08
Standing	14.42	4.45	0.10	0.04	0.14	0.07
Walking slowly	21.87	4.71	0.12	0.07	0.22	0.14
Walking fast	24.60	4.52	0.14	0.09	0.28	0.20
Laptop	19.38	3.78	0.14	0.05	0.23	0.11
Eat with hands	15.97	3.32	0.17	0.07	0.20	0.09
Eat with silverware	16.06	3.11	0.17	0.07	0.21	0.09
Walking outside	24.39	4.65	0.15	0.08	0.29	0.19
Resting	20.97	3.80	0.15	0.07	0.25	0.13
Smoking	16.49	2.63	0.27	0.13	0.36	0.20

Notes: The breath frequency F represents the number of breathing cycles over 1 minute; the peak-to-peak tidal volume $\overline{VT}^{\mathrm{MAX}}$ is the average amplitude across all the breathing cycles for the corresponding activity; the peak-to-peak airflow $\overline{AF}_{\mathrm{EST}}^{\mathrm{MAX}}$ is the average amplitude across all the breathing cycles for each activity.

The proximity sensor identified 480 TPs (puffs with associated hand gestures detected by the sensor), 51 false negatives, and 0 false positives (although the sensor detected other gestures, they were not considered as false positives, as all were non–smoking related), resulting in a hit rate of 0.90.

Based on the breath-by-breath segmentation, the average breathing frequency F (breaths/min) was calculated for each activity together with peak tidal volume $\overline{VT}^{\mathrm{MAX}}$ and airflow $\overline{AF}_{\mathrm{EST}}^{\mathrm{MAX}}$ (Table 2). As Table 2 demonstrates, the maximum breathing frequency was achieved during walking, an activity that demanded the highest oxygen consumption. Smoking, on the other hand, had the highest tidal volume and airflow.

Table 3 displays the results from the Dunnett's test for multiple comparisons characterizing the differences in breathing and hand gesture metrics between smoking and all other activities. A significant difference was observed between smoking and other tested activities in maximum tidal volume ($\overline{VT}^{\mathrm{MAX}}$) and amplitude of hand gestures (A_{HG}). Among all activities tested, eating most closely resembled smoking in breathing frequency (F) and rate of hand gestures (R_{HG}). Finally, walking and smoking had similar airflow ($\overline{AF}_{\mathrm{EST}}^{\mathrm{MAX}}$) characteristics.

Figure 3 shows the average traces of VT, AF_{EST}, and HG signals for four different activities: sitting, reading, eating with silverware, and smoking. The trace for smoking demonstrated a clear correlation between the hand gesture and the respiratory signals. Eating, an activity most closely resembling smoking in other metrics, did not exhibit such correlation.

Table 4 shows the cross-correlation values illustrating the differences in the shapes of the average traces of the tidal volume signal ($\overline{VT}^{\mathrm{A}}(t)$), airflow signal ($\overline{AF}_{\mathrm{EST}}^{\mathrm{A}}(t)$), and hand gesture signal ($\overline{HG}^{\mathrm{A}}(t)$) during smoking and other activities. The values of cross-correlation were in the range of .3–.8, indicating low to moderate correlation.

TABLE 3. *P* values obtained from the multiple comparison statistical analysis of smoking compared with all other activities for the breathing and hand gesture behaviors. Each entry in the table is a *p* value obtained by a Dunnet's test comparison of a given metric during smoking (used as the reference) and another activity (Column 1).

Activity (reference = smoking)	F	$\overline{VT}^{\mathrm{MAX}}$	$\overline{AF}_{\mathrm{EST}}^{\mathrm{MAX}}$	R_{HG}	D_{HG}	A_{HG}
Sitting	.956	.002	.030	.000	.026	.000
Reading	.000	.002	.037	.000	.072	.000
Standing	.399	.000	.001	.000	.001	.000
Walking slowly	.000	.000	.255	.000	.000	.000
Walking fast	.000	.000	.998	.000	.001	.000
Laptop	.075	.000	.527	.000	.000	.000
Eat with hands	.998	.000	.115	1.000	.000	.000
Eat with silverware	.998	.000	.151	1.000	.000	.000
Walking outside	.000	.000	1.000	.000	.049	.000
Resting	.000	.000	.891	.000	.000	.000

Notes: Results from the Dunnet's statistical test using a 5% joint significance level value associated to all 10 tests for breathing rate F; peak tidal volume $\overline{VT}^{\mathrm{MAX}}$; peak airflow $\overline{AF}_{\mathrm{EST}}^{\mathrm{MAX}}$; rate R_{HG}, duration D_{HG}, and amplitude A_{HG} of hand gestures, respectively.

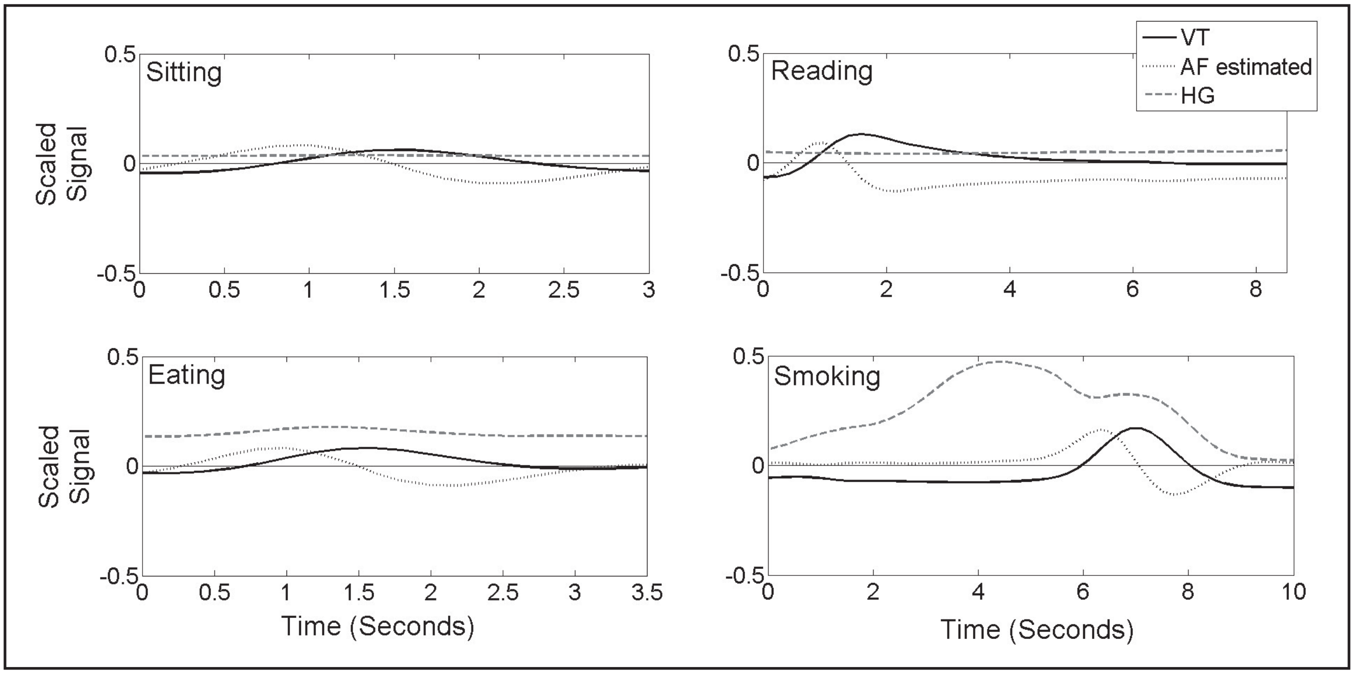

FIGURE 3. Average traces of breathing segments of four different activities: sitting (top left), reading (top right), eating (bottom left), and smoking (bottom right). Note that the graphs are on different time scales. In the smoking plot, a distinct hand gesture $\overline{HG}^{A}(t)$ peak preceding the smoke inhalation can be seen on traces of the volume tidal $\overline{VT}^{A}(t)$ and the airflow $\overline{AF}^{A}_{EST}(t)$. This characteristic, together with significant changes in the waveforms of $\overline{VT}^{A}(t)$ and $\overline{AF}^{A}_{EST}(t)$, could be used to identify smoke inhalations.

Discussion

The results indicate that hand-to-mouth gestures were reliable precursors of smoke inhalations and that the waveforms of smoke inhalations were significantly different from breaths during any tested activity. Even though the test of the pooled data is less sensitive to the differences between smoking and other groups than the test that controls for the individual subjects' variability, the conducted tests detected significant differences between groups, rendering more advanced approaches unnecessary. Significant differences were observed in the rate of hand gestures, amplitude (proximity) of hand gestures, peak tidal volume, and airflow. A significant correlation was found in the timing of the hand gestures and breathing during smoking. The details of these finding are discussed below.

TABLE 4. Cross-correlation of $\overline{VT}^{A}(t)$, $\overline{AF}^{A}_{EST}(t)$, and $\overline{HG}^{A}(t)$ between smoking and all other activities

Smoking vs. . . .	$\overline{VT}^{A}(t)$	$\overline{AF}^{A}_{EST}(t)$	$\overline{HG}^{A}(t)$
Sitting	.75	.51	.73
Reading	.44	.04	.72
Standing	.55	.55	.78
Walking slowly	.33	.41	.80
Walking fast	.38	.31	.79
Laptop	.34	.36	.71
Eat with hands	.45	.33	.73
Eat with silverware	.46	.46	.74
Walking outside	.45	.40	.77
Resting	.50	.29	.76

Notes: $\overline{VT}^{A}$ = average trace of tidal volume signal; $\overline{AF}^{A}_{EST}(t)$ = average trace of airflow; $\overline{HG}^{A}$ = average trace of hand gesture signal.

For hand gestures, there was a significant difference in the rate of hand gestures detected, with smoking having a higher rate than other activities, except for eating, where the rate was comparable. Thus, the rate of hand gestures could be used as a feature to differentiate various activities. If an activity exhibits a low rate of hand gestures, these hand gestures may be excluded from further consideration as potential precursors of smoke inhalations.

The duration of hand gestures was not very distinctive across activities. In contrast, the average amplitude of hand gestures for smoking was observed to be the highest of all activities, where it was observed that more than 99% of the hand gestures associated with smoking were higher in amplitude (more proximal to the mouth) than 95% of all hand gestures seen with the other activities. This effect is stipulated by the directional sensitivity of the RF hand gesture sensor, which is most closely aligned in a cigarette-holding gesture. Thus, the amplitude could potentially also be used to reject hand gestures not associated with smoking.

The proximity sensor reliably picked up hand gestures originating from smoking. Video examination showed that gestures not captured by the system (FN = 51) were due to use of the nondominant hand for smoking. Placing RF transmitters on both hands should increase the sensitivity of detection of hand gestures related to smoking. On occasion, people might smoke by holding a cigarette between their lips without using their hands and thus avoid detection of a hand-to-mouth gesture. This was not observed in any case across all participants in the laboratory experiments, but this possibility might arise in free-living conditions. In normal conditions, at some point the cigarette has to be transported to and from the mouth by hand gestures (i.e., lighting, or cigarette or butt removal, which should be detected by the RF sensor). Therefore, at least the beginning and end of each cigarette should be marked by hand gestures. This particular behavior has to be examined in future studies to consider all possible smoking scenarios.

Peak tidal volume and peak airflow during smoking were substantially different from breathing during most other activities. Specifically, the average peak-to-peak amplitude of the tidal volume signal $\overline{VT}^{\mathrm{MAX}}$ and airflow $\overline{AF}^{\mathrm{MAX}}_{\mathrm{EST}}$ were significantly higher during smoke inhalations. This indicates that a large volume of air and smoke is rapidly inhaled during a typical smoking breath cycle, which agrees with observations of previous studies (Rodenstein, 1985).

The average waveforms across distinct activities also demonstrate that smoking, unlike any other activity tested in this study, has a very high covariation in time between breathing and hand-to-mouth gestures. The average trace of the hand gesture signal can be thought of as a probability estimate for a hand gesture appearing at a certain time in a breath cycle. For most activities in the study, the hand gestures are not coordinated with breathing in any way and therefore can appear at any time during a breath cycle. For example, eating has a rate of hand gestures comparable to that of smoking, but such gestures are likely to happen at any given time during a respiratory cycle and the trace of $\overline{HG}^{\mathrm{A}}(t)$ for eating is virtually flat. The only activity with highly coordinated hand gestures and breathing is smoking; thus, the trace of $\overline{HG}^{\mathrm{A}}(t)$ for smoking (Figure 3) had a distinct peak preceding the smoke inhalation seen on traces of $\overline{VT}^{\mathrm{A}}(t)$ and $\overline{AF}^{\mathrm{A}}_{\mathrm{EST}}(t)$.

The low values of cross-correlation between average traces of $\overline{VT}^{\mathrm{A}}(t)$ and $\overline{AF}^{\mathrm{A}}_{\mathrm{EST}}(t)$ indicate that shapes of respiration waveforms during smoking were substantially different from other activities even if the breathing rates were not. The differences observed in the waveforms of $\overline{VT}^{\mathrm{A}}(t)$ and $\overline{AF}^{\mathrm{A}}_{\mathrm{EST}}(t)$ (as depicted in Figure 3) and the characteristic behavior of the hand-to-mouth gestures may be suitable to identify distinct features that could allow automatic computer detection of smoke inhalation and objective characterization of smoking that does not require a conscious input from the individual.

At this point, an obvious disadvantage of the presented sensor system is the relatively large size of the garment, including the vest, sensors, and electronics. However, the present incarnation of the PACT was assembled from parts readily available on the market and is not necessarily the best fit for long-term use and convenience. In the future, the system could be substantially miniaturized using more suitable electronics and reduced to a single ribcage belt with the data-capturing and RF proximity sensor fully integrated into the belt.

On the other hand, even when the subject has to be instructed to wear a possibly intrusive system for monitoring purposes, the present sensor system would eliminate the subject's burden of remembering to use an external device for every single cigarette smoked. Another promising advantage of PACT is that the sensor signals carry rich information about the full breathing cycle associated with smoking: puff, smoke inhalation, smoking apnea (smoke holding), and smoke exhalation, as opposed to conventional puff topography devices that only detect and quantify the air drawn through a cigarette during a puff. The monitoring of breathing also creates an advantage of knowing a subject's compliance, as absence of the breathing signal would indicate that the device is not being worn (it is anticipated that PACT will continuously log sensor signals without being turned on/off by the subject). Because PACT only registers the air and smoke being inhaled into the lungs, it thus has the advantage of not registering quick successive puffs (e.g., "lighting puffs") that have to be cleaned up on puff topography devices.

The next step in PACT development is to use signal processing, machine learning, and pattern recognition techniques to build classification models to automatically detect and characterize smoking behavior and smoke exposure. The results of the present study show that shapes of inhalation patterns are substantially different for different activities. Therefore, it should be possible to use methods of machine learning and pattern recognition (e.g., artificial neural networks or support vector machines) to learn and recognize smoke inhalations by looking at the shape of the breathing waveform following any detected hand-to-mouth gesture. In addition, the need for a hand gesture sensor will be evaluated because it may be possible to detect smoke inhalations entirely through analysis of the breathing signal alone. Overall, miniaturization of PACT sensors in combination with these methods may provide additional information not available from the current smoke topography monitors. In the future, PACT can also be used to study the correlation of common smoking biomarkers with the individual traits of respiration during cigarette smoking (e.g., duration of smoke holding).

A question may arise about how PACT will respond to activities not represented in the current data set but involving various hand gestures, such as placing or taking a call on a phone. Given the results described above, we anticipate that most of the activities of daily living will not have the same coordination of breathing and hand-to-mouth gestures as smoking does, and thus they will not be confused with smoking. For example, food intake, the most common activity involving repeated hand gestures, shows no correlation between breathing and hand gestures. Moreover, breathing patterns during smoke inhalations are different from those of other activities and thus provide an additional indication of the type of activity being performed. This issue can only be addressed through a multiday study in a naturalistic setting, which is one of the future steps in PACT development.

In conclusion, this study suggests a novel method for monitoring cigarette smoking and smoke exposure in free-living conditions, presents a detailed description of a wearable sensor system, and suggests that unique breathing patterns highly correlated in time with hand-to-mouth gestures are associated with smoke inhalations, which could be distinguished from other common daily activities. Future development of signal processing and pattern recognition methods should allow transparent monitoring of the smoking behavior of individuals in free-living conditions. In its current state, the PACT system might be of interest to specialists studying smoking behaviors and could provide a practical approach for unconstrained monitoring of the dynamics of smoke exposure.

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