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Monitoring of cigarette smoking using wearable sensors and Support Vector Machines

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***Abstract*— Cigarette smoking is a serious risk factor for cancer, cardiovascular, and pulmonary diseases. Current methods of monitoring of cigarette smoking habits rely on various forms of self-report that are prone to errors and underreporting. This paper presents a first step in the development of a methodology for accurate and objective assessment of smoking using non-invasive wearable sensors (Personal Automatic Cigarette Tracker - PACT) by demonstrating feasibility of automatic recognition of smoke inhalations from signals arising from continuous monitoring of breathing and hand-to-mouth gestures by Support Vector Machine (SVM) classifiers. The performance of subject-dependent (individually calibrated) models was compared to performance of subject-independent (group) classification models. The models were trained and validated on a dataset collected from 20 subjects performing 12 different activities representative of everyday living (total duration 19.5 hours or 21,411 breath cycles). Precision and recall were used as the accuracy metrics. Group models obtained 87% and 80% of average precision and recall, respectively. Individual models resulted in 90% of average precision and recall, indicating a significant presence of individual traits in signal patterns. These results suggest the feasibility of monitoring cigarette smoking by means of a wearable and non-invasive sensor system in free living conditions.**

***Index Terms*— Wearable sensors, smoking, Support Vector Machines, Inter and Intra subject variability.**

I. INTRODUCTION

ACCORDING to the World Health Organization, as of 2011 there were about 1 billion smokers in the world. Half of these smokers will eventually die due to problems related to smoking. 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% of these deaths occur in developing countries [1]. It is estimated that in the U.S. only, smoking is responsible for 440,000 deaths each year. With regard to associated costs, smoking results in approximately $167 billion in annual health-related economic losses [2].

In order to be able to develop efficient methodologies for clinical interventions to reduce the problems of tobacco use, it is important to understand the different conditions and behaviors associated with the frequency of smoking and the degree of smoke exposure. However, as with many activities of clinical interest, the most common methodology to evaluate targeted behavior relies on the subjective recall of specific behaviors. In the case of smoking, people are commonly asked to recall the number of cigarettes consumed over a given period of time. Subjective recall is a concern in cases where a precise assessment is required, as the retrospective accuracy of self-report is limited due to intentional and non-intentional bias [3]. Different methodologies have been proposed to overcome this issue.

One of the most practical methods in free-living conditions has been the use of flow meters attached to the cigarette to record smoking topography; however, it has been observed that the use of portable cigarette flow meter devices might change the smoking behavior of the user due to the difference in sensory effects [4]. Machine vision has also been studied to address the issue. Video cameras have been used to identify smoking events under different light conditions using face, cigarette and arm motion detection as characteristic features of smoking [5], [6]. Although use of video monitoring makes the process of smoking assessment invisible to the subject, the need for video devices makes the approach impractical in free living conditions and limits the analysis to restricted locations.

There is a need for flexible, non-invasive methodologies to monitor cigarette smoking in free living conditions where the subject under evaluation is not restricted to a certain location. This paper presents initial stages in the development of a non-invasive wearable sensor system (Personal Automatic Cigarette Tracker - PACT) aimed to be completely transparent to the end user and suitable for use in free living individuals. As envisioned, PACT does not require any conscious effort to achieve reliable monitoring of smoking behavior. PACT detects smoking events through monitoring of cigarette-to-mouth hand gestures and recognition of characteristic patterns of respiration during smoke inhalations.

The main focus of this paper is demonstrating the feasibility of automatic recognition of smoke inhalations by Support Vector Machines (SVM) classification models applied to the signals of wearable sensors of the PACT prototype.

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This paper is organized as follows: Section II describes in detail the PACT methodology including the sensors used for the experimental data collection, the signal analysis for feature extraction, and the use of SVM. Section III presents the performance of different SVM models. Section IV and V present the Discussion of the results and the overall conclusions of the study, respectively.

II. Methodology

A. Sensor System

A wearable sensor system was implemented to capture characteristic Hand-to-Mouth Gestures (HMGs) and respiration patterns during smoking. These sensors are shown in Fig. 1, and explained in detail below.

The HMGs were captured using a radio frequency transmitter-receiver proximity sensor designed for this purpose. A low power small transmitter operating in 125kHz RFID band was placed on the wrist of the subject's dominant hand (Fig 1a). An antenna was attached to the pectoral area and was connected to a receiver resonant circuit tuned at the same frequency (Fig 1b); a conditioning electronic circuit (Fig 1e) generated a rectified proximity signal *PS(t)* proportional to distance between the transmitting and the receiving antennas. The maximum range of this sensor was 30 cm, with signal strength inversely proportional to the square of the distance in the range 30-17 cm, and saturating to the maximum in the range 17-0 centimeters. A more detailed description of the proximity sensor can be found in [7].

Respiration patterns were collected using a commercially portable Respiratory Inductive Plethysmograph module (zRIP, Pro-Tech Inc.); thoracic and abdominal elastic respiratory bands (DuraBelt, Pro-Tech Inc., Fig 1c) captured the change in volume proportional to the subject's lungs expansion and contraction [8]. The output signals of the plethysmograph (Fig 1f), *TC(t)* and *AB(t)* for the thoracic and abdominal bands, respectively, were electronically conditioned (Fig 1e) to be within an amplitude range of 0-3 Volts, centered at 1.5 Volts.

A self-report button (Fig 1d) was pressed and held by the subjects for the duration of smoke puffs, thus providing a reference signal that was used for annotation of the experiments. The button itself was only used during development of the PACT system and will not be used in community monitoring.

All sensor signals were recorded by a portable datalogger (Logomatic V2.0, Sparkfun Inc., Fig 1b) at a sample rate of 100 Hz and stored in a microSD card flash memory for offline analysis.

B. Subjects and Data Collection

The sensor data were collected from 20 regular smokers (smoking history > 1 year, carbon monoxide from a breath sample >10ppm), 10 males and 10 females, ages 23.1±3.3 years, with BMI 25.88±5.24 kg/m^2. Recruitment targeted subjects of both genders with a broad spectrum of anthropometric characteristics (such as weight and height), duration of smoking history (1-17 years) and cigarette

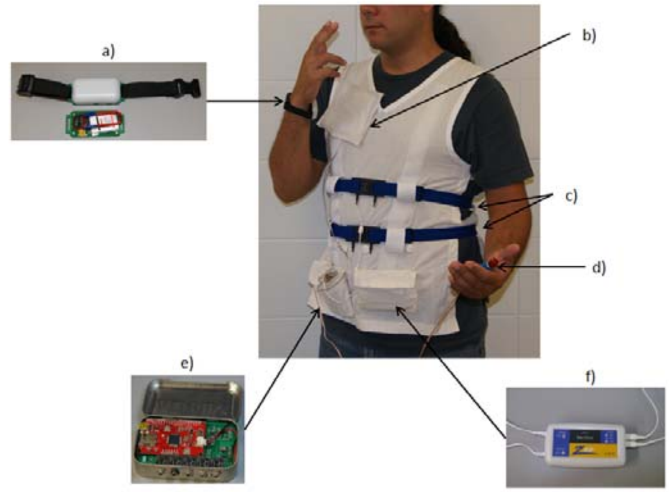

Fig. 1. The wearable sensors of the PACT prototype, including the hand gesture sensor and the respiration sensor: a) transmitter of the hand gesture sensor worn on the inner side of the wrist; b) chest-mounted receiving antenna of the hand gesture sensor; c) thoracic and abdominal respiration bands of the respiratory plethysmograph; d) self-report button; e) datalogger and signal conditioning circuitry; f) electronic module of the portable plethysmograph (zRIP).

consumption (2-20 per day) to test applicability of the proposed methodology to various populations. All subjects reported that they were healthy with no chronic respiratory problems and no allergies of any kind, and they agreed to sign the consent form approved by the University of Alabama after the study procedure was explained in detail. For the experiments, subjects were asked to perform 12 different activities: 1) sit comfortably, 2) read aloud, 3) stand 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. This selection of activities represented different everyday activities varying in hand use and breathings patterns. Except for the eating and smoking activities, which were unconstrained in time length, all activities had a fixed time duration of 5 minutes, resulting in a dataset with total duration of 19.56 hours. A video camcorder was used to videotape the subjects during the complete duration of the session, and the recordings were used to perform manual annotation of the experiments. The annotation was performed in a Labview application specifically designed for this purpose. This application allows a human rater to review and playback the acquired sensor signals, to label the different activities during the experiments, and to manually annotate smoke inhalations taken by the subjects. These manual annotations were used as reference for training and validation of the smoking detection models described in detail in the next sections.

C. Signal Pre-processing

The sensor signals were pre-processed offline for further analysis. First, the proximity signal *PS(t)* was normalized to a scale of 0 to 1. Second, the tidal volume signal (*VT(t)*) was calculated as the average between the *TC(t)* and the *AB(t)* signals:

$$VT(t) = (TC(t) + AB(t)) / 2 . \quad (1)$$

The *VT (t)* signal was then scaled in amplitude to a range of -1.0 to 1.0. Denoising of the tidal volume signal was performed by means of a Gaussian average of 25 data-points width sliding window. Additionally, in order to reduce possible artifacts and eliminate high and very low frequency components, an ideal band pass filter was used with cut-off frequencies between 0.0001 and 10 Hertz.

An airflow signal *AS(t)* was computed from the filtered tidal volume signal as the rate of change over time, defined as the first derivative of *VT(t)*:

$$AS(t) = dVT(t) / dt , \quad (2)$$

which provides an adequate substitute for airflow measured directly by pneumotachometers [9], [10]. An example of the scaled signals, *PS(t)*, *VT(t)* and *AS(t)*, extracted from the data of one subject is shown in Fig. 2 for two different activities, sitting and smoking. These signals provided the base for the extraction of features used detect cigarette smoke inhalations.

D. Feature Extraction and Support Vector Machine Classification

The basic hypothesis underlying the proposed method for smoke inhalation detection is that each smoke inhalation is started by bringing the cigarette to the mouth, taking a puff and then inhaling the smoke, all of which results in a characteristic breathing pattern (Fig. 2). Thus, classification starts by detecting HMGs, forming feature vectors for each detected hand gesture and then applying SVM classification.

HMGs were detected from the proximity sensor signals when signal amplitude was higher than a predefined threshold $T_H=0.04$ established above the electronic noise level (observed to be 90mV across all data collected, or 0.03 after the *PS(t)* normalization).

For each one of the hand gestures detected $\{HMG_i\}$, $i = 1,2,\ldots,n$, a feature vector x_i was constructed with data computed or sampled from *PS(t)*, *VT(t)* and *AS(t)*. Computed features were derived from *PS(t)*. They characterized hand-to-mouth gestures in terms of gesture duration D_i, the average amplitude A_i, and the maximum amplitude M_i. Sampled features captured the signal waveforms characteristic of cigarette smoking. A smoke inhalation typically starts with an apnea period (puff, or smoke inhalation into the mouth) that manifests as a HMG with no significant changes in the tidal volume and the airflow for the duration of the hand gesture. The initial apnea period is followed by the drop in the amplitude of the proximity signal (as the cigarette is removed from the mouth) and sharp increase in tidal volume and airflow, which represents the cigarette smoke inhalation into the lungs. The rapid inhalation is then followed by a period of smoke holding and an exhale. Similarly to [13], the characteristic waveforms of these events were used as features directly sampled from the sensor signals. The features for *PS(t)*, *VT(t)* and *AS(t)* were formed by sampling 500 points for each one of these signals from the beginning of the HMG_i (a point in time where a hand gesture was detected). The combination of the described computed and sampled features resulted in 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 $L_i = \{-1, 1\}$; $L = -1$ if this HMG and the feature vector were not associated with smoke inhalation (as for example, following a HMG during food intake) and $L = 1$ if this HMG and the feature vector represented a smoke inhalation. The dataset pairs $X_i^j\{x_i^j, L_i^j\}$, for $j = 1,2,\ldots,20$ subjects, were used to train a SVM classifier capable of detecting smoke inhalations.

From the different machine learning methodologies available for classifier design, SVM has been preferred in many applications when compared to other classifiers for its reliable performance over a variety of different data sets [11–14]. SVM can produce very complex decision boundaries, relying on the processing of the data in a higher dimensional new space [15], [16]. The implementation of SVM models was performed using the LibSVM package [17].

Radial Basis Function kernels were selected for the SVM models, since they can handle the case when the relation between class labels and features is nonlinear [16]. The kernel's parameters, cost value *C,* and kernel's gamma value γ, were optimized through a simple exhaustive grid search procedure as $C = e^c$ for c = {-15,…,15}, and $\gamma = e^h$ for h = {-15,…,15}. In this manner, all pairs of (C, γ) were evaluated, and the combination with a higher classification performance during training was selected as optimal.

Four types of classification models were built. First, a subject-independent (group) model was evaluated (G-model). The advantage of the group model is that can be applied to any subject without the need for individual calibration. For the group model, a leave-one-out cross-validation procedure was used for training and validation [16]. Having a data set from 20 subjects, 19 were selected as the training instances of the SVM model, and the remaining subject was used as the validation instance. This procedure was performed for 20 iterations, one for each of the 20 subjects.

The second type of model (I-model) was studied as a subject-dependent (individual) model, where the individual behavior of a subject is learned and used to implement a model specifically designed for that particular subject. For this individual model, half of the data of each subject were selected randomly as training instances for the SVM model, and the rest of the data were then used as validation instances. To overcome the variability of the randomization process, 10 replicates were made for each subject and their average was calculated.

Precision (P) and Recall (R) metrics were calculated to evaluate the accuracy of the SVM models to identify smoke inhalations. Precision and recall are defined as [18]:

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

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

where *(T+)* is the number of correctly detected smoke inhalations, *(F+)* is the number of false positives or breaths incorrectly labeled as smoking, and *(F-)* is the number of false negatives or non-detected smoke inhalations. During the training process, the F_1-measure was used to find the optimal C and γ values o of the SVM model, defined as the harmonic mean between precision and recall [18]:

$$F_1 = 2 \cdot (P \cdot R)/(P + R) \tag{6}$$

The third model (GAR-model) used a simple HMG artifact rejection that was introduced in the preprocessing of the group model to increase the overall accuracy of the smoke inhalation detection. Based on the data used for this study, a significant number of HMGs detected could be considered as artifacts not related to smoking (for example, HMGs resulting from supporting one's chin with an arm while resting or reading), and therefore rejected beforehand. Hand artifacts can be rejected based on three parameters: the amplitude of the gesture, its duration, and the closeness between successive gestures. From the analysis of the data across all subjects, it was observed that gestures with the amplitude of the normalized proximity signal ($PS(t)$<0.46) could be considered artifacts. Also, gestures with a duration D_i < 0.68 and D_i > 23 seconds could also be considered as artifacts. Lastly, sequential gestures with a time gap < 0.96 seconds can be merged together into a single HMG.

The fourth classification model (IAR-model) was implemented again with a subject-dependent approach with the addition of the artifact rejection described above.

III. Results

A total of 21,411 respiratory cycles (inhale/exhale) approximately evenly distributed across 12 tested activities were analyzed in this study. The total number of HMG detected by the proximity sensor across all subjects and activities was 5,113. Using the artifact rejection, the total number of gestures was reduced to 1,637 (68% reduction). The manual annotation of the smoking activities identified 531 smoke inhalations over 40 cigarettes, resulting in an average of 13.3 inhalations per cigarette across all subjects. Out of the 531 smoke inhalations, 51 of the corresponding HMGs were not detected by the proximity sensor, as some subjects occasionally used their non-dominant hand to smoke. These data were used to train the SVM-based smoke inhalation detection models described in the Methods section. The performance of the classification models across all subjects is summarized in Fig. 3.

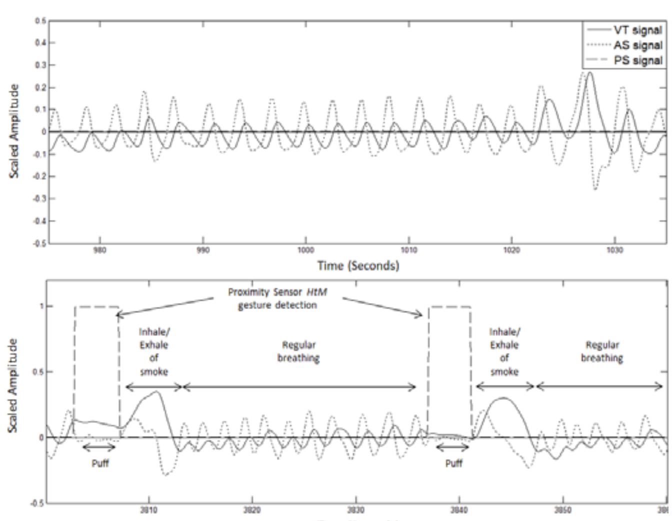

Fig. 2. *PS(t)*, *VT(t)* and *AS(t)* signals pre-processed from one subject for two different activities: sitting (top) and smoking (bottom).

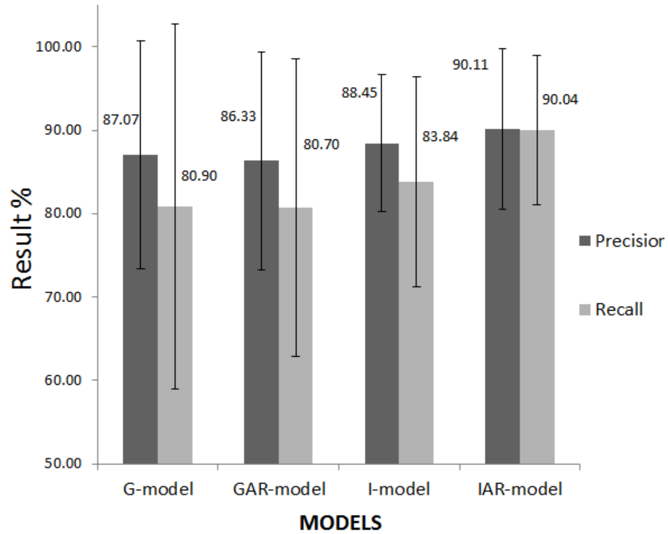

Fig. 3. Overall precision and recall obtained for the group and individual classification models.

IV. Discussion

In this study, four different SVM models for the detection of cigarette smoke inhalations were trained and validated on a dataset obtained from 20 subjects. The models identified smoke inhalations based on features extracted from the HMG sensor measuring the proximity of the dominant hand to the mouth, and from respiratory signals recorded using a portable plethysmograph.

The major advantage of the proposed approach in comparison to commonly used methods (diaries or portable puff topography devices) is that it does not rely on any form of self-report or conscious effort from the subject. This property is useful from two perspectives. First, being an objective measurement, PACT should not be biased toward underreporting. Current research shows that subjects may report as little as half of their actual cigarette consumption using the most advanced methods such as portable puff topography devices [19]. Second, the use of PACT is not associated with conscious effort and only requires subject cooperation in wearing the system. This property has the potential to reduce observation effect or change in subject behavior under observation, as the subjects are not constantly reminded that they are being observed by the need to perform self-report.

Another major advantage of PACT is the potential to monitor parameters of smoke exposure not available from any other method. Through continuous monitoring of breathing, PACT can objectively measure depth of smoke inhalation and duration of smoke holding in the lungs. It is anticipated that these measures may better explain health outcomes of smoke exposure and provide a link to biomarkers of smoke exposure such as blood levels carbon monoxide and cotinine. Thus, PACT may potentially improve accuracy of smoking monitoring in research studies that need a retrospective account of the number of cigarettes consumed and/or a measure of smoke exposure.

The recognition of smoking inhalations by SVM models resulted in promising accuracy. For the G-model, an average precision of 87% was obtained. This result indicates the presence of false positives, that is, non-smoking breaths identified as smoke inhalations. This result may be explained by the significant variability in smoking-related breathing patterns. Similar variability has been observed with smoking topography [20]. On the other hand, average recall of 80.9% indicates presence of false negatives, where some smoke inhalations were not detected. This may be explained by the behavior of some subjects who took some inhalations with the non-dominant hand, where no proximity sensor was used, and thus missing the detection of a hand gesture. This issue could be easily overcome by having subjects wear an additional proximity sensor on their non-dominant hand.

The I-model resulted in a similar accuracy to that of group model (P=88.4% vs. 87%, R=88.5% vs. 83.8%); however, the spread of the results decreased. These observed results indicate the characteristic behavior of individual models to overcome the presence of inter-subject variability.

Although artifact rejection appears not to benefit average precision and recall in the GAR-model, a slight decrease in the results spread can be observed (Fig. 3.), suggesting that artifact rejection yields a more consistent classification model across all subjects. However, the introduction of artifact rejection improved precision and recall more clearly in the IAR-model with values >90% for both metrics. This was driven by a significant increase in the detection of true positives, that is, correct detection of cigarette smoke inhalations, together with the reduction of false positive detection when potential HMG artifacts were eliminated from analysis. The number of false negatives remained the same across all models, as the number of undetected cigarette smoke inhalations was constant across all model implementations affecting directly the recall performance.

The effectiveness of artifact rejection is explained by the large number of HMGs eliminated from further analysis based on amplitude and duration. The reason for such selectivity to HMGs originating from smoking is the sensor design [7], where the receiver and transmitter antennas are best aligned (and thus have the highest sensitivity and signal amplitude) when the inner side of the arm is brought to the mouth during a cigarette puff.

Some limitations present in the current system will need to be addressed before PACT can be used in research studies. First, PACT hardware needs to be further miniaturized and implemented in a convenient to wear package. For example, a thoracic respiratory belt based on a different technology, i.e. piezoelectric belt, may eliminate the need for bulky electronics of the inductive plethysmograph and enable system implementation as a chest-worn belt device. Second, although the accuracy obtained by the implemented classification models was promising, it needs to be further improved to accurately monitor smoking in free-living conditions. Because the characteristic waveforms of the tidal volume and airflow signals associated with a HMG were used as features for identification of smoking, the feature vectors used for classification resulted in 1,503 variables. It may be possible to use different variable significance analyses, e.g. PCA, to identify more relevant features from these vectors. New and/or different features are currently being studied to evaluate more reliable characteristics of the smoking behavior, i.e. the intrinsic presence of apneas during a puff, the duration of the smoking inhale/exhale, etc. Additionally, although it was not observed in the current study, some smokers may hold the cigarette between their lips and take some puffs without intervention of any hand gestures. In such situation it might be possible to monitor smoke inhalations using more sophisticated techniques through analyses of respiratory waveforms, simplifying the implementation of the system. Finally, a larger human study may be necessary to fully examine the behavior of the proposed methodology over the wide variety of activities of daily living. Such a study would involve a greater number of individuals wearing the sensor system for significantly longer periods of time, e.g. several days in unconstrained conditions. This will be addressed in future research.

V. Conclusion

This paper presents a feasibility study of a wearable sensor system and Support Vector Machine classification for automatic detection of cigarette smoke inhalations. Group models achieved 87% average precision in identification of smoke inhalations, a reflection of the high inter-subject variability and 80.9% average recall due to several hand-to-mouth gestures undetected by the proximity sensor. A significant increase in the detection of true positives was observed in the individual model combined with motion artifact rejection resulting in average precision and recall of 90%. Overall, the results suggest that detection of smoking from the sensor data collected by a wearable and non-intrusive cigarette monitoring system (PACT) is feasible and deserves further investigation. With further improvement in classification accuracy, the proposed PACT system may be used as a foundation studying cigarette smoking in free-living conditions over extended periods of time.

Acronyms and Abbreviations

A	Average amplitude
AS	Airflow signal
AR	Artifact Rejection
D	Duration
HMG	Hand-to-Mouth gesture
M	Maximum amplitude
PACT	Personal Automatic Cigarette Tracker

PS	Proximity Signal
SVM	Support Vector Machines
VT	Tidal Volume Signal

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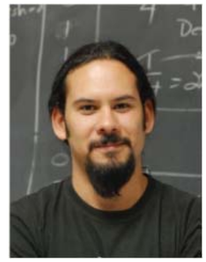

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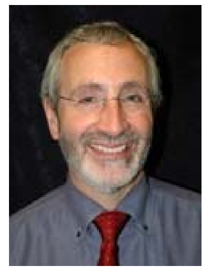

Stephen Tiffany, PhD, his research is in the area of drug addiction. He does studies on the processes of drug craving, the causes of drug dependence, the diagnosis of dependence, adolescent drug use, and the interaction of biological and psychological factors in the control of addictive behaviors. His work focuses on understanding the role of drug craving in addiction. He has done research on the variables that regulate the development of addiction in young cigarette smokers. In addition, he conducts basic animal and human research on the processes that motivate addictive behavior.

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