Stress Recognition using Wearable Sensors and Mobile Phones

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***Abstract*— In this study, we aim to find physiological or behavioral markers for stress. We collected 5 days of data for 18 participants: a wrist sensor (accelerometer and skin conductance), mobile phone usage (call, short message service, location and screen on/off) and surveys (stress, mood, sleep, tiredness, general health, alcohol or caffeinated beverage intake and electronics usage). We applied correlation analysis to find statistically significant features associated with stress and used machine learning to classify whether the participants were stressed or not. In comparison to a baseline 87.5% accuracy using the surveys, our results showed over 75% accuracy in a binary classification using screen on, mobility, call or activity level information (some showed higher accuracy than the baseline). The correlation analysis showed that the higher-reported stress level was related to activity level, SMS and screen on/off patterns.**

Keywords— stress, mobile phone, smart phone, wearable sensor, accelerometer, skin conductance, classification, machine learning

I. INTRODUCTION

Stress is one of the major problems in modern society. Sometimes people are aware of being under stress, for example, when they are occupied with deadlines of homework and projects; however, long-term conditions with high stress can be chronic and people may be less likely to notice whether they are under high stress or may be generally less sensitive to stressors. Stress detection technology could help people better understand and relieve stress by increasing their awareness of heightened levels of stress that would otherwise go undetected.

Several technologies have been developed to recognize stress level; some methods are based on physiological signals: blood pressure [1], heart rate [1], heart rate variability (HRV) [2], skin conductance [3, 4], cortisol [5, 6], pupil diameter [7]. Activity of sympathetic and para-sympathetic nervous system can be monitored through blood pressure, heart rate and HRV. In Vrijkotte's study, work stress was evaluated using blood pressure, heart rate and HRV [1]. The study resulted that the high imbalance (a combination of high effort and low reward at work) was statistically correlated with a higher heart rate during work, a higher systolic blood pressure during work and leisure time, and a lower 24-hour vagal tone. Dishman et al. showed the inverse relationship between self-ratings of perceived emotional stress and high frequency component (0.15-0.5 Hz) of HRV [2]. Skin conductance has been considered as another biomarker for stress [8], where eccrine sweat activity that is controlled by only sympathetic nervous activity is measured, For example, Hermandez et al. discriminated stressful and non-stressful calls at the call center environment using SC features [3]. Setz et al. automatically classified SC responses from cognitive load and stress with accuracy higher than 80% [4]. This group also attempted to classify the same two conditions using seating pressure data and obtained over 70% accuracy [9]. Mokhayeri et al. used multi-modal physiological signals: pupil diameter, electrocardiogram and photoplethysmogram to classify stressed and relaxed conditions [7].

Other methods are based on surveys. For example, perceived stress has been used as an objective stress marker [10]. Questions in the perceived stress scale (PSS) assess what degree in each situation a subject feels stressful. The Holmes and Rahe Stress Scale counts up the events in the prior year that could lead to stress [11].

Today we have many wearable devices, such as mobile phones and wearable sensors to measure physiological or behavioral data in our daily lives. This paper aims to use technology to recognize stress levels using data from the devices that users always carry and wear. At the same time, the advance of mobile technologies can lead addictive behaviors and as some studies have shown, may pose risks on stress, sleep and mental health [12].

Researchers have already made attempts to understand personality from mobile phone use. Butt's study revealed an association between personality category from the Big Five Test (extraversion, agreeableness, conscientiousness, neuroticism and self-esteem) and interaction with the mobile phone based on self-report about mobile phone use [13]. Recently, smart phones have begun featuring sensors (accelerometer, GPS and microphones etc.) and usage-tracking functions (call and SMS histories etc.). Some studies have worked on the mood or individual trait detection using smart phones [14, 15, 16, 17, 18]. Ma et al. estimated mood defined from displeasure, tiredness and tensity in daily lives using mobile phone use data and the previous subjective mood state [14]. Moturu et al. used social sensing data from mobile

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phones to understand the relation among sleep, mood and sociability [15, 16]. Muaremi et al. used iphone data and wearable HRV data to classify low, moderate, and high perceived stress conditions [18].

In our study, we collected 5-day physiological and behavioral data including skin conductance which is considered as a stress measure as well as mobile phone usage data and subjective measures about general health, mood and stress from 18 subjects. We then investigated whether these data would allow us to recognize whether participants felt stressed or not. Note that this study is limited to stress that participants are able to perceive and report.

II. EXPERIMENT PROCEDURE AND DATA COLLECTION

Eighteen healthy participants were recruited for the experiment (15 males, 3 females, average age=28 ± 7.8).

(a) First visit to laboratory

Participants filled out three pre-surveys, were given a wrist-worn sensor to wear on their non-dominant hand, and had the system software installed on their personal mobile phone. They were shown how to operate the devices and phone application.

(b) Pre-surveys: Perceived stress scale (PSS) [10], Pittsburgh Sleep Quality Index (PSQI) [19] and Big Five Inventory Personality Test [20] were answered.

(c) Wearable sensor: Three-axis accelerometer data (ACC), and skin conductance (SC, a measure of sympathetic nervous system activity) were measured on the inner wrists on the non-dominant hand (Affectiva, Q-sensor, USA). The data were logged on an internal memory card with sampling rate of 8 Hz.

(d) Mobile phone: On the android phones, call, SMS, location and screen on/off were monitored with funf [21]. In addition, surveys were filled out every morning and evening. The detail of the questions is illustrated in Table 1 and the captures of the screen were shown in Figure 1. Our custom questions were built into the system from Ginger.io (USA). All logs and participants' answers were sent to the server.

TABLE I. MOBILE PHONE QUESTIONS

Morning Survey	Evening Survey
Sleep time	Start and end time of nap
Wake time	# of cups of caffeinated beverages (6oz cups of coffee, soda, or others)
Last use your computer, tablet, mobile phone or TV	The time of the last cup
Sleep quality	# of alcoholic drinks (6oz cups)
General health when you woke up	The time of the last drink
Mood when you woke up	General health of the day
Alertness when you woke up	Mood of the day
Tiredness when you woke up	Alertness of the day
General stress level	Tiredness of the day
Things which affected sleep time last night	General Stress Level of the day

(e) Revisit to the lab

On the fifth day, participants returned to the laboratory and completed the post-experiment survey about their health, mood, stress etc in the past five days.
The Massachusetts Institute of Technology Committee On the Use of Humans as Experimental Subjects pre-approved this study.

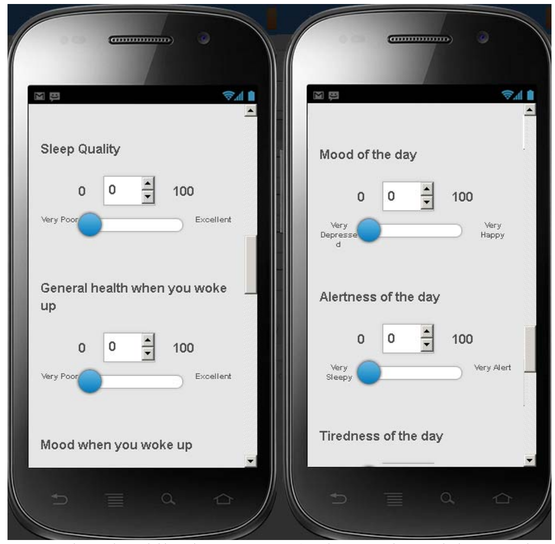

Fig. 1 Examples of mobile phone survey (Left: Morning, Right: Evening, assessment was done using 0-100 scales)

III. FEATURE EXTRACTION

The sensor and mobile phone data were analyzed as follows to extract features.

A. Pre Experiment Survey

PSS: PSS score

Sleep Survey: Regular bedtime, wakeup time, duration, PSQI score (4 features total)

Big Five Test: Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism (5 features total)

B. Post Experiment Survey

About health, stress level, life, tiredness, sleep during the 5 -day experiment (19 items total)

C. Mobile Phone survey

Morning: Mean, SD and median of the following daily features over the 5 days (30 features total)

Answer time, sleep time, wake time, sleep quality, general stress level, mood, general health, tiredness, alertness when wake up, the last use of electronics

Evening: Mean, SD and median of the following daily features over the 5 days (42 features)

Answer time, general stress level, mood, general health, tiredness, alertness of the day, the # of cups of alchoholic drinks, the time of the last cup, the # of cups of cafeinated drinks, the time of the last cup, the times of the nap

D. Phone Usage

Call: Mean, SD and median of the following daily features for 5 days (total 123 features)
Mean, SD and median of time of each call, total duration of the call, mean, SD and median of duration for calls, total # of calls, #, %, duration and duration% of incoming and outgoing calls, # of incoming calls/# of outgoing calls, # of individuals with whom a participant interacted through incoming or outgoing calls
#, %, duration and duration % of the calls in 6am-12pm, 12pm-6pm, 6pm-9pm, 9pm-12am, and 12am-6am
total # of 6am-6pm/ total # of 6pm-6am, total duration of 6am-6pm/ total duration of 6pm-6am

SMS: Mean, SD and median of the following daily features for 5 days (total 123 features)
Mean, SD and median of time of each SMS message, total length of the call, mean, SD and median of length for SMS messages, total # of SMS messages, #, %, length and length % of received and sent, # of received /# of sent, # of individuals with whom a participant interacted through received or sent SMS
#, %, length and length % of the SMS in 6am-12pm, 12pm-6pm, 6pm-9pm, 9pm-12am, and 12am-6am
total # of 6am-6pm/ total # of 6pm-6am, total length of 6am-6pm/ total length of 6pm-6am

MOB: Mean, SD and median of the following daily features for 5 days (total 24 features)
Mean, SD and median of radius and distance
Radius: The approximate diameter of an imaginary circle encompassing the various locations that a user has traveled across on a particular day (in miles)
Distance: The approximate distance traveled by the user (by foot or bike) on a particular day as estimated from the location data (in miles)

COMM: Mean, SD and median of the following 5 daily features over 5 days (total 36 features)
Mean, SD and median of missed interactions, interaction diversity and aggregate communications
Missed interactions: The proportion of unanswered calls
Interaction diversity: The total # of individuals with whom a participant interacted through calls or SMS
Aggregate communication: The total # of calls (incoming + outgoing) and SMS messages (sent + received)

SCREEN: Mean, SD and median of the following daily features over 5 days (total 45 features)
Mean, SD and median of time of each screen on, total # of screen on, # and % of screen on in 6am-12pm, 12pm-6pm, 6pm-9am, 9pm-12am, and 12am-6am, total # between 6am-6pm/ total # of 6pm-6am

E. Sensor

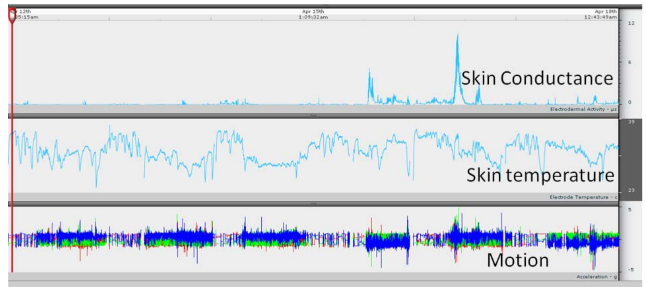

Fig.2 Example of the sensor data.

Figure 2 shows an example of the sensor data.

A) *SC* (70 features)

The skin conductance was processed first by low-pass filtering (cutoff frequency 0.4 Hz, 32nd order FIR filter) before computing the features. We then obtained the first derivative, and then determined where the slope exceeds a value of 0.004 Siemens per second. We detected SC "peaks" based on those that exceeded this threshold and counted the number of peaks per each 30-second epoch. The SC peaks during sleep provide an index of deeper sleep stages (SWS and NREM2) [22]. For sleep data, SC data that corresponded to non-sleep epochs were removed from the analysis before computing features related to sleep.

During the day 35 SC features:
Mean, SD, median of SC amplitude and # of SC peaks, and % of epochs with more than one SC peak (7 features) for the whole day, 6am-12pm, 12pm-6pm, 6pm-12am and 12am-6am (5 different sets of time)

During sleep, these additional 35 SC features were computed: Mean, SD, median of SC amplitude and # of SC peaks, and % of epochs with more than one SC peak (7 features) for the whole night, 1st, 2nd, 3rd and 4th quarter of the night (5 different sets of time)

B) *ACC* (70 features)

Standard zero-crossing detection, Cole's function and Webster's algorithm were applied to the accelerometer data to identify sleep and wake [23]. For both data in wakefulness and sleep, we computed the mean activity level based on the root square values of the 3-axis accelerometer, and movement index and the percentage of wakefulness computed based on Cole's function.

During the day (35 features):
Mean, SD, median of root mean square and movement index, and % of wakefulness (7 features) for the whole day, 6am-12pm, 12pm-6pm, 6pm-12am and 12am-6am (5 different sets of time)

During sleep, these additional 35 SC features were computed: Mean, SD, median of root mean square and movement index, and % of wakefulness (7 features) for the whole night, 1st, 2nd, 3rd and 4th quarter of the night (5 different sets of time)

IV. Correlation analysis

We applied linear correlation analysis to the features and examined which features were significantly correlated with the self-reported perceived stress scale ratings.

V. Stress recognition

We grouped the 18 participants into the following two groups: high PSS score (>=17) and low PSS score(<=12) (N=8, each). Two participants in the middle were omitted from the test. We applied several methods to classify the two groups.

We examined the performance of 15 sets of features:
1) sleep survey 2) Big Five 3) post survey 4) phone survey (morning) 5) phone survey (evening) 6) CALL
7) SMS 8) MOB 9) SC 10) ACC 11) COMM 12) SCREEN
13) Mobile phone usage (6-8, 11, 12), 14) Sensor (9, 10), 15) Mobile phone usage + sensor

We evaluated performance using six kinds of classifier:

A) Support vector machine (SVM) with linear kernel
B) SVM with Radial basis function (RBF) kernel
C) k-nearest neighbors (k=1-4)
D) Principal component analysis (PCA) and SVM with linear kernal
E) PCA and SVM with RBF kernel
F) PCA and k-nearest neighbors (k=1-4)

Methods:
1) Applied classifier A-F to the features 1-15.
2) Applied sequential forward floating selection (SFFS) and picked the best feature among each modality and applied the A-C classifier for each best feature
3) After extracting the best/the second best/the third best features for each modality, applied A-F classifiers to the each of these sets of three features
4) After extracting the best/the second best/the third best features from each modality using SFFS (for a total of 36 features), applied exhaustive feature selection according to the *J3* measure associated with the scatter matrices.to find the best combination of the features for each modality

For each classification, we examined the accuracy using 10-fold cross validation (trained the model with 90% of the data, tested with the remaining 10% and repeated this procedure 10 times).

VI. Results

A. Correlation Analysis

We summarized the features associated with the reported PSS stress level (Table 2).

A higher PSS score was correlated with poorer sleep habits, with specific personality characteristics: the tendency to be more critical, rude, harsh, or callous, and disorganized, undependable or negligent, and the tendency to be more nervous and worrying.

In the post survey, the questions related to stress were, as expected, significantly correlated with the stress reported on the perceived stress scale.

Phone surveys showed that poor general health when they woke up and poor mood and general health throughout the day were correlated with higher stress; however, stress level assessed by the mobile phone upon wake-up or at the end of the day was not correlated with the perceived stress level.

Participants with a higher stress scale showed a smaller variation of activity level between 6pm – 12am, smaller movement median during the 2nd quarter of sleep, smaller % of sent SMSs, shorter length of sent SMSs, less “screen on” time and its variation between 6pm-9pm and earlier mean screen-on time (they typically turned on the screen earlier in the day).

TABLE II. Summary of correlation analysis using features

Modality	Features significantly correlated with higher stress scale
Sleep survey	PSQI (poor sleep habit)
Big five	Low Conscientiousness, Low Agreeableness, High Neuroticism
Post survey	Often bothered by feeling down, depressed or hopeless Often felt so sad or down that you had trouble functioning in school or personal life School/work has been stressed often Poor sleep quality Often felt tired, dragged out, or sleepy during the day
Phonesurvey morning	Poor general health when wake up
Phonesurvey evening	Poor mood of the day Poor general health of the day
CALL	-
SMS	Low % of sent SMSs among all SMSs Low % of Length of sent SMSs among all SMSs
MOB	-
SC	-
ACC	Small SD of ACC level between 6pm-12am Small median of ACC level during the 2nd quarter of sleep
COMM	-
SCREEN	Small mean of % of screen ons between 6-9pm Small SD of % of screen ons between 6-9pm Small Mean of % of screen ons between 9pm-12am Small Mean of screen On time

B. Classification

1) *Method 1*

The classification results (features 1-15 + classification A-F) are shown in Figure 3.

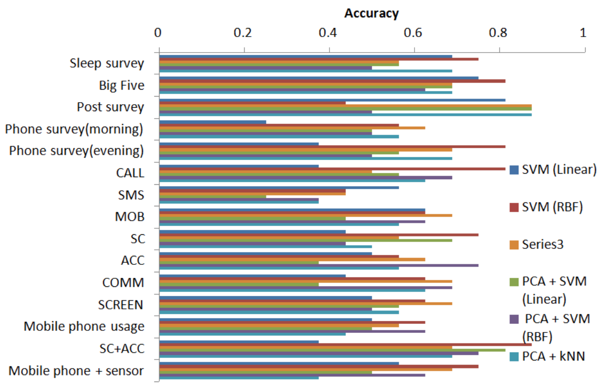

Fig. 3 Classification results
(features 1-15 + classification A-E)

The post survey, which acts as a baseline, showed the highest 87.5% accuracy as well as sensor, followed by Big Five, evening phone survey and CALL (81.25 %).

2) *Method 2*

The best feature for each modality is summarized in Table 3. Classification accuracy using each best feature is shown in Figure 4. Post survey, mobile phone + sensor (SC+ACC) and mobile phone usage showed 87.5% accuracy, followed by big five test and evening phone survey (81.3%) and MOB and SCREEN (75%).

TABLE III. SUMMARY OF FEATURES SELECTED WITH SFFS

Modality	Best feature
Sleep survey	PSQI
Big Five	Neuroticism
Post survey	Often felt so sad or down that you had trouble functioning in school or personal life
Phone survey (morning)	Median of general health when wake up
Phone survey (evening)	SD of answer time
CALL	Mean duration of calls between 9pm-12am
SMS	SD of % of SMSs between 9pm-12am
MOB	Mean of SD of mobility radius
SC	Median of day SC peaks during day
ACC	Median of movement between 12pm-6pm
COMM	SD of total missed transactions
SCREEN	SD of % of screen ons between 6-9pm

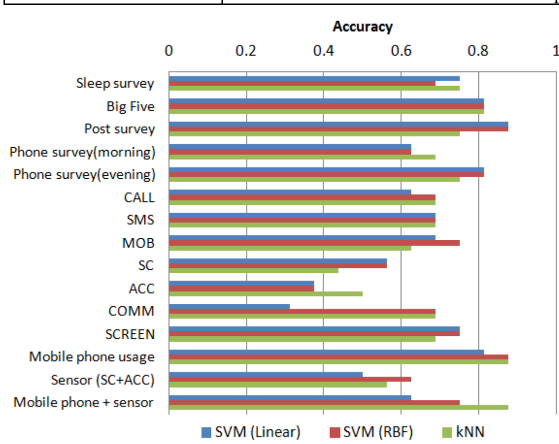

Fig. 4 Classification results using selected best features

3) *Method3*

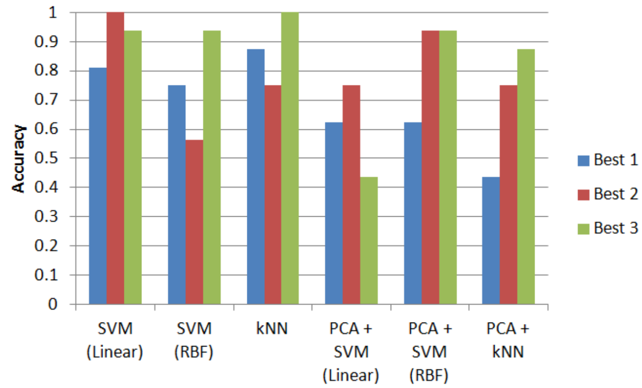

Fig.5 Classification results using selected best 1-3 features

Figure 5 shows the classification accuracies for the best 1, 2 and 3 features for each modality from SFFS and clasification A-F. Selection of the best 2 and 3 showed 100% and the best 1 feature for each modality showed 93.8% accurate stress classification.

4) *Method 4*

After SFFS and exhaustive search, we found

- Often felt so sad or down that you're having trouble functioning in school or personal life

is the best feature (87.5%) in the classification. Also, we computed accuracy for each feature from SFFS. the following list of features.

TABLE IV. SUMMARY OF FEATURES SELECTED WITH METHOD 4

Accuracy [%]	Feature
87.5	Often felt so sad or down that you had trouble functioning in school or personal life
	Often felt tired, dragged out, or sleepy during the day
81.3	Conscientiousness
	Agreeableness
	Neuroticism
	SD of answer time (Evening)
75.0	Mean of SD of mobility radius
	Mean of total mobility radius
	SD of % of screen ons between 6-9pm

Two questions in the post survey showed the highest 87.5%, followed by traits from Big Five test, mean and SD of mobility radius and SD of screen on between 6-9pm.

In method 1 to 4, most of the contribution in stress recognition derived from mobile phone usage data. The results suggest that variation in phone usage (SMS or screen on), magnitude or variation in mobility and movement during day and sleep are related to stress level. This might be because internal stress level could change behavior patterns and interaction with others. The questions in the post experiment survey and Big Five test showed higher contribution; however, the stress level assessed on the mobile phone every morning and evening did not contribute at all. The features derived from skin conductance did not contribute much to classify low and high stress groups. Since skin conductance during day included both components from non-movement and movement, we will need to distinguish responses produced by affect from those produced by movement using on the accelerometer data as the next step of analysis.

VII. CONCLUSION

Our results showed over 75% accuracy of low and high perceived stress recognition using the combination of mobile phone usage and sensor data: either one feature from screen on (SD of % of screen on between 6-9pm), mobility (median or SD of mobility radius), CALL and ACC/SC or the combination of the top 2-3 features from across the modalities. The correlation analysis suggested that small median of acceleration data during the 2^{nd} quarter of sleep, small SD of acceleration data between 6-9pm, few or short sent SMS, and small # or % of screen on between 6-9pm or 9pm-12am were associated with worse stress.

Although these results are preliminary with limited number of participants and data, it revealed that mobile phone usage and wearable sensor data both include some features related to stress level. We will continue to collect larger datasets and add both sensor and label data. We will also attempt to work on understanding not static but dynamic affect using long-term data. While our study zoomed in on some self-reported stress levels, our method is much more general and can be useful to understand which factors influence any identifiable affective changes. With rich data from real life, and the ability to reliably identify patterns relating it to affective state, people will soon be able to investigate how to not only measure, but also better improve affective conditions.

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