Discovery of Behavioral Markers of Social Anxiety from Smartphone Sensor Data

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ABSTRACT

Better understanding of an individual's smartphone use can help researchers to understand the relationship between behaviors and mental health, and ultimately improve methods for early detection, evaluation, and intervention. This relationship may be particularly significant for individuals with social anxiety, for whom stress from social interactions may arise repeatedly and unexpectedly over the course of a day. For this reason, we present an exploratory study of behavioral markers extracted from smartphone data. We examine fine-grained behaviors before and after smartphone communication events across social anxiety levels. To discover behavioral markers, we model the smartphone as a linear dynamical system with the accelerometer data as output. In a two-week study of 52 college students, we find substantially different behavioral markers prior to outgoing phone calls when comparing individuals with high and low social anxiety.

Keywords

social anxiety, behavioral dynamics, behavioral markers, smartphone use

1. INTRODUCTION

Social anxiety is characterized by intense fear and avoidance of socially evaluative situations [1]. Socially anxious individuals tend to exhibit behaviors (e.g., trembling, sweating, and fidgeting) consistent with this subjective state when a social interaction is perceived as threatening [12]. The experience of high social anxiety levels often results in severe avoidance of social interactions. Therefore, it is important to find behavioral markers indicating individuals' social anxiety.

Traditionally, psychological research on factors linked to social anxiety has relied on laboratory-based methods that limit the ecological validity of findings. In contrast, recent advances have made it possible to passively monitor how behavioral systems unfold in people's natural settings by leveraging sensors embedded in personal smartphones [6, 4, 2, 7]. This approach has key advantages over traditional self-report surveys, which are subject to reporting bias, since behaviors suggestive of anxiety can be inferred passively and *in situ*. However, naturally arising variations among smartphone user behaviors and the link between physical and psychological dimensions of human behavior are not yet well understood.

In this paper, we examine passively sensed micro-motions captured via smartphone accelerometers before and after phone call and text message communication events. We hypothesize that social anxiety levels are related to subtle differences in user motion before and after these communication events. We refer to these motions as the user's *behavioral dynamics*, and we use a linear dynamical system (LDS) to extract behavioral features from smartphone accelerometer data shortly before and after communication events. For phone calls, we also distinguish behaviors for outgoing and incoming calls. Using the extracted features, we then compare effect sizes across social anxiety levels and communication types.

This paper is structured as follows: section 2 introduces relevant prior work; section 3 describes the study design, including the data collection, preprocessing, modeling, and analysis procedures; section 4 presents the effect-size analysis results; and sections 5 and 6 discuss our findings and limitations and present concluding remarks.

2. RELATED WORK

This research is motivated by previous studies in clinical psychology and emerging work in engineering that establish a connection between smartphone data and mental health. Our work aims to propose a new approach for exploration of behavioral markers from smartphone sensor data for social anxiety.

The emergence of smartphone sensing research has created new opportunities to understand how mental health disorders manifest in real-world settings. Smartphone usage data and sensor data streams (e.g., accelerometers, microphones, and GPS data) provide continuous, unobtrusive measurements that are critical to mental health status (e.g., social interactions, location semantics, and physical activity) [13, 6].

In particular, several studies have explored the relationship between social anxiety and patterns of smartphone usage and communication [9, 3, 11, 4]. For instance, these studies investigated preferences for communicating via phone calls or text messages among anxious and lonely people,

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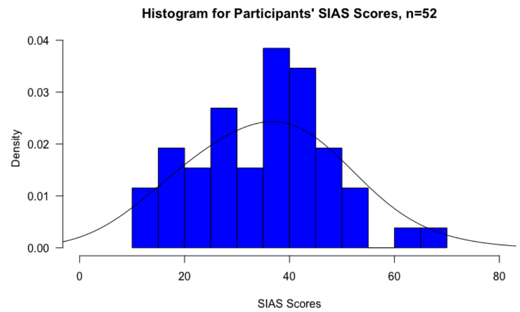

Figure 1: The distribution of SIAS scores for recruited participants.

along with the relationship between smartphone use, academic performance, anxiety, and satisfaction with life in college students. These results demonstrate differences in smartphone usage tied to mental health status. However, these studies have not examined micro-level behavioral dynamics associated with social anxiety. Prior psychological research has shown that anxiety is linked to somatic tension and arousal (e.g., increased trembling, sweating, and fidgeting during a threatening social interaction [14]). Thus, examining accelerometer data associated with smartphone usage may provide critical information about socially anxious individuals' behaviors.

3. STUDY DESIGN

In this section, we introduce our data collection procedures, and participant recruitment approach. We then present the data preprocessing, feature extraction, and analysis procedures.

3.1 Data Collection

With approval from the University of Virginia (UVa) Institutional Review Board, we recruited 52 undergraduate participants from the Psychology Department's participant pool. Participants received course credit as compensation. Before the study began, each participant was assessed on the Social Interaction Anxiety Scale (SIAS) [8]. The SIAS measures the longterm characteristic reactions to social interactions based on 20 items that are rated from 0 to 4 (e.g., "I have difficulty talking with other people."). Total SIAS scores range from 0 to 80, with higher scores indicating greater anxiety associated with social interactions. Figure 1 shows the histogram distribution of SIAS scores among the 52 participants in our study. Our participants' SIAS scores have a mean of 35.02 and a standard deviation of 12.10. In total, we collected 1,642 phone calls and 28,381 text messages from all the participants during the study period.

During the initial lab session, we installed a general-purpose mobile sensing app (Sensus [15]) on each participant's personal smartphone to passively collect accelerometer data at 1Hz as well as phone call and text message logs, all of which were uploaded to Amazon Web Services (AWS) Simple Storage Service (S3).

3.2 Data Preprocessing & Feature Extraction

3.2.1 Communication Events

In our study, communication events refer to phone calls and text messages. To explore the effects of social anxiety on behavior around communication events, we first preprocessed the communication events data as follows:

Phone calls: We distinguish outgoing calls and incoming calls in which outgoing calls are individual initiated and planned social interactions while incoming calls are unexpected social interactions.

Text messages: These are grouped as one event if two consecutive texts are fewer than 10 minutes apart. We could not distinguish the direction of text messages because phone numbers were randomly hashed to protect privacy of participants.

3.2.2 Accelerometer Data

Before processing accelerometer data, we first defined two observation periods as shown in the top part of Figure 2:

- Pre-event observation period: 10 minutes before a communication event happens

- Post-event observation period: 10 minutes after a communication event finishes

In this exploratory study, we use 10 minutes as the observation length before and after a communication event. Then, we used the accelerometer data within the pre-event and post-event observation time period to analyze behavioral dynamics. Figure 2 gives an example of a 9-minute outgoing phone call of a subject. It shows the accelerometer data during the pre- and post-call observation periods, which we use to analyze the behavioral dynamics before and after communication events. Before conducting further analysis of behavioral dynamics, we first applied a sliding window process to segment the accelerometer data into smaller, fixed-size chunks. We provide additional details for these steps in the following section.

3.2.3 Feature Extraction

After data preprocessing, we extracted features from the accelerometer data. We aimed to find behavioral markers that identify smartphone use behaviors as a function of social anxiety level and the relationship between different communication situations and behaviors.

Sliding Windows of Accelerometer Data.

$AC(i)(j)$ represents the accelerometer data in an observation period j (could be either pre-event or post-event) for individual i. We first segmented $AC(i)(j)$ with sliding windows. Recall that both pre- and post-event observation periods span 10 minutes. Essentially, multiple small fixed-size windows over the length of the observation period are considered. In our study, we use a 2-minute single sliding window length and a 1-minute stride into the observation period. Thus each observation period $AC(i)(j)$ can be represented as

$$AC(i)(j) = \{AC(i)(j)(1), \cdots, AC(i)(j)(k), \cdots, AC(i)(j)(n)\} \quad (1)$$

where k is the k^{th} sliding window in the observation period j.

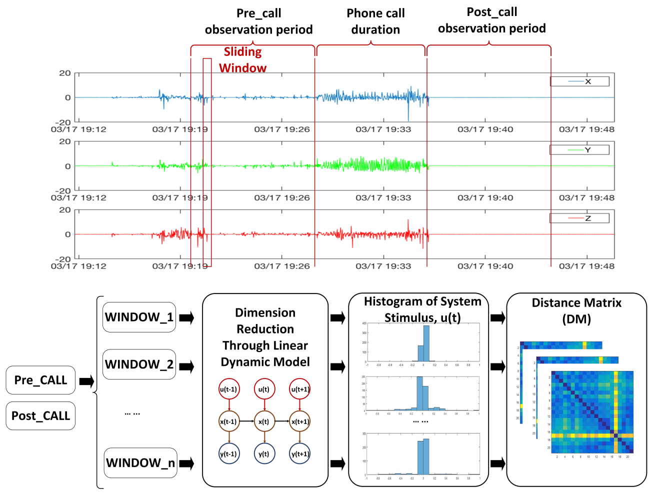

Figure 2: The diagram of the study design: an example of a 9-min outgoing call. The motion data in pre- and post-event observation periods are segmented into fixed sized sliding windows. The bottom half shows the feature extraction procedure using linear dynamic model and distance matrices.

Linear Dynamical System.

We adopted a model-driven technique [5] to reduce the dimensionality of the data $AC(i)(j)(k)$. Using this analogy, the human can be viewed as a control system, the smartphone as an observer system with certain states, and the accelerometer as the measurement. The salient information are the motion stimuli generated by each participant's behavioral dynamics, which we expected to vary as function of a participant's social anxiety level. Therefore, we adjusted the linear dynamical model to estimate the motion stimulus of the accelerometer data. The proposed linear dynamic model is described as follows:

$$\begin{cases} \| u(\bullet) \|_{\iota 0} \leq k \\ |u(t)| \leq 1 \qquad \forall t \\ \Sigma_t \| CA^t B \|_1 \leq \mu \\ x(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + N \end{cases} \tag{2}$$

In this model, $y \in R^{3\times T}$ represents the data piece $AC(i)(j)(k)$, while T is the dimension of data in a sliding window. Also, $y(t) \in R^{3\times 1}$ is the output of the linear dynamical system (the smartphone) driven by a one-dimensional sparse and bounded stimulus, $u(t) \in R$. The dynamical system for estimating the motion stimulus includes two parts: the linear state-space transition is defined by the matrix A and B in the fourth line in Equation 2 and linear observation is defined by matrix C in the fifth line in Equation 2. $\| u(\bullet) \|_{\iota 0}$ is the number of nonzero elements in the stimulus sequence and the $N \in R^{3\times 1}$ is the random noise. An expectation-maximization (EM) algorithm was applied to estimate A, B, C, x, and u with the assumption of system linearity and time invariance. Here u has a dimension of $1 \times T$. To construct a feature to represent y, we extract the histogram of the stimulus vector u, $h(u)$. Each histogram is quantized-into 11 bins, equally spaced in a range from -1 to 1. Ultimately, the previous high-dimensional accelerometer data piece is reduced to 1×11 dimensions. This 11-dimensional feature is represented as $HU(i)(j)(k)$, which is extracted from $AC(i)(j)(k)$.

Features and Metrics.

Next, we developed features to capture the behavioral dynamics of a communication event $AC(i)(j)$ as shown in the bottom part of Figure 2. Our work adopts several statistical features to explore the relationships between social anxiety levels and behavioral dynamics before and after communication events.

After dimensionality reduction through the linear dynamic model, the raw high-dimension accelerometer data of a communication event $AC(i)(j)(k)$ are represented as a series of low-dimension features:

$$AC(i)(j) = \{HU(i)(j)(1), \cdots, HU(i)(j)(k), \cdots, HU(i)(j)(n)\} \tag{3}$$

We then generated statistical features that characterize motion variation by first creating a distance matrix, DM, that computes the similarity between pairs of $HU(i)(j)(k)$ of an observation period, $AC(i)(j)$. Each element of the distance matrix $DM(i)(j)$ is the Euclidean distance between the pairs of the 11-dimensional features, $HU(i)(j)(k)$:

$$DM(i)(j)(a)(b) = Dist[HU(i)(j)(a), HU(i)(j)(b)] \quad a, b \in \{1 \cdots n\} \tag{4}$$

Finally, we used the mean value and standard deviation of the distance matrix $DM(i)(j)$ as the metrics for an observation period $AC(i)(j)$:

$$FAC_1(i)(j) = \overline{DM(i)(j)} \tag{5}$$

$$FAC_2(i)(j) = std(DM(i)(j)) \tag{6}$$

In summary, after preprocessing and applying the linear dynamic model, we were able to reduce the high-dimensional raw temporal motion data to an array of low-dimensional features. These arrays were considered in a pairwise fashion to construct a distance matrix that uniquely characterizes each subject's behavioral dynamics before and after a smartphone communication event.

3.3 Data Analysis

We used the features and metrics developed in section 3.2.3 for the behavioral dynamics analysis. We distinguished the behaviors before and after phone calls and text messages to explore the behaviors associated with social anxiety. Then we used effect-size analysis to discover the behavioral difference between low and high social anxiety groups. We also distinguished outgoing and incoming phone calls to further understand how individuals behave when they are going to initiate a social communication and when they have just ended a social communication event. In our study, we used Cohen's d to calculate the effect size. Generally, a > 0.5 Cohen's d shows a medium effect size while > 0.8 shows a large effect size [10].

4. RESULTS

Table 1 summarizes the features and metrics used for the effect-size analysis. In the analysis, we grouped the participants in two ways according to their SIAS measures:

- The Two-Group setting: We used one SIAS threshold to divide the participants into two even groups (i.e., a median split), and then we computed the effect size when comparing the two groups.

Table 1: Definition used for features and metrics.

Term	Definition
$\overline{FAC_1}$	The average of the mean values of all distance matrices ($DM(i)$) belonging to a subject
$\overline{FAC_2}$	The average of the standard deviations of all distance matrices ($DM(i)$) belonging to a subject
MC_pre	The metric for the pre-event observation period of a phone call
MC_post	The metric for the post-event observation period of a phone call
MT_pre	The metric for the pre-event observation period of a text message group
MT_post	The metric for the post-event observation period of a text message group

- The Three-Group setting: We used a low-SIAS threshold and a high-SIAS threshold to split the participants into three groups: 1) low social anxiety risk, 2) medium social anxiety risk, and 3) high social anxiety risk. We analyzed the effect size between the low social anxiety risk group and the high social anxiety risk group. This setting provided a more nuanced grouping of the participants.

With the two approaches for grouping participants, Table 2 and Table 3 show the effect-size analyses. Table 2 presents the effect-size analysis of the behavioral dynamics before an outgoing and after an incoming phone call between low and high social anxiety groups using the mean value of FAC_1 and FAC_2.[1] Table 2a uses the two-group setting we described at the beginning of the section, whereas Table 2b uses the three-group setting. Our choices for the low and high SIAS thresholds in Table 2b are based on making the number of participants of the low and high social anxiety groups equal. The three pairs of SIAS low and high scores ($(27, 44)$, $(28, 43)$, $(30, 39)$), generate groups of 15, 17, and 20 participants, respectively, for the low and high SIAS groups. In both the two-group and three-group settings, different behavioral dynamics between the low and high social anxiety groups can generally be seen during the time before outgoing phone calls using feature FAC_2. This difference is more pronounced with the three-group setting in which the distributions of SIAS scores of the low and high social anxiety groups are farther apart.

Table 3 summarizes the effect-size differences between the before- and after-text groups. As we explained in section 3.2.1, we do not distinguish the direction of text message groups as we do for phone calls. For behavioral dynamics before and after text messaging, we observe a difference for both of the observation periods. This difference is particularly strong in the three-group setting. However, due to the nature of texting activities and our IRB protocol constraints mentioned in 3.2.1, our conclusions from these finding are limited.

5. DISCUSSION

Our results suggest that behavioral metrics observed before outgoing phone calls have stronger associations with social anxiety scores than metrics observed after incoming phone calls. Our results also suggest that individuals behave more distinctly before an active social interaction (when initiating a social interaction) between low and high social anxiety groups. These results may indicate that individuals with different social anxiety levels experience different levels of anxiety and associated behavioral variations (e.g., fidgeting and shaking) before calling others. These findings may ultimately advance early detection, diagnosis, and the evaluation of treatment progress for social anxiety disorder.

Limitations and Future Work.

In our study, we used smartphone motion data before and after phone calls and text messages to identify digital markers of human behaviors associated with social anxiety. Although promising, our results have several limitations. First, the sample size might not be large enough to draw reliable conclusions about the effects of social anxiety on human behaviors. Second, given the fact that we conducted our experiments in the field without any experimenter present, we do not know which physical interaction between the smartphone and the participant was actually occurring prior to the communication event (e.g., talking on the speaker while putting the phone on the table). We have checked the system stimuli data using the linear dynamic system model for all phone calls and texts. The results show that 3.65% of phone calls (60 out of 1,642) have no obvious motions (i.e., the system stimuli are all zero), whereas 3.68% of text messages (1,045 out of 28,381) have no obvious motions. This reduces the likelihood of effects from motions such as putting the phone on the table. However, we cannot exclude certain motions like using earphones while driving, which might produce different observations. Third, we used 10 minutes as the pre- and post-event observation period because as a exploratory study, we assume 10 minutes can be a reasonable length of period to observe behaviors. But it might require more work to compare different lengths of observation period. Last, as mentioned, we have minimal contextual information about the communication events, particularly for text messages (e.g., who initiated the text conversation and who the individual is interacting with). These are likely to be important factors with respect to social anxiety, and integrating these contextual details will be an important direction for our future work.

6. CONCLUSION

Current methods to monitor social anxiety are usually based on retrospective self-report in the lab with little data to illuminate individuals' real-world behaviors. This paper presents a knowledge exploration study of the behavioral dynamics of smartphone use before and after phone calls and text messages. We created metrics to represent behavioral dynamics using accelerometer and communication history. We demonstrated that there is an observable difference in motions across social anxiety levels and that these behaviors further vary across different communication situations. This work opens up possibilities of passively monitoring behavioral markers of social anxiety. By passively sensing micro-level motion patterns, researchers and clinicians may better understand behavioral markers of social anxiety that can potentially be used to optimize treatment and intervention delivery.

[1] We only show the effect-size results before outgoing calls and after incoming calls due to space limitations. We also suggest that behaviors before an incoming call are very uncertain and we hypothesize that the act of initiating a phone call to an individual creates more anxiety.

Table 2: Effect-size analysis of the motion data before outgoing calls and after incoming calls between groups with (relatively) low versus high levels of social anxiety. In this table, two features are explored: 1) the average of all distance matrices' means belonging to one observation period ($\overline{FAC_1}$), and 2) the average of all distance matrices' standard deviations belonging to one observation period ($\overline{FAC_2}$). Results that have at least a medium effect size (≥ 0.5) are shown in bold typeface.

	Outgoing calls (MC_pre)		Incoming calls (MC_post)	
SIAS threshold	$\overline{FAC_1}$	$\overline{FAC_2}$	$\overline{FAC_1}$	$\overline{FAC_2}$
23	0.3423	0.4338	0.3858	**0.6837**
28	0.1338	0.2969	0.1136	0.4478
33	0.3852	**0.5345**	0.2167	0.4474
38	0.2962	**0.5196**	0.0805	0.3083
43	0.2966	**0.5063**	0.2988	0.0867

(a) Two-group setting

		Outgoing calls (MC_pre)		Incoming calls (MC_post)	
SIAS low	SIAS high	$\overline{FAC_1}$	$\overline{FAC_2}$	$\overline{FAC_1}$	$\overline{FAC_2}$
27	44	0.2452	**0.5234**	0.3099	0.1748
28	43	0.3007	**0.5556**	0.0835	0.2976
30	39	0.2771	**0.5490**	0.2028	**0.5103**

(b) Three-group setting

Table 3: Effect-size analysis of the motion data before and after text message groups between participants with (relatively) low versus high levels of social anxiety. In this table, two features are explored: 1) the average of all distance matrices' means ($\overline{FAC_1}$), and 2) the average of all distance matrices' standard deviations ($\overline{FAC_2}$). Results that have at least a medium effect size (≥ 0.5) are shown in bold typeface.

	Text groups (MT_pre)		Text groups (MT_post)	
SIAS threshold	$\overline{FAC_1}$	$\overline{FAC_2}$	$\overline{FAC_1}$	$\overline{FAC_2}$
23	0.2284	**0.5938**	0.4004	0.4294
28	0.1277	**0.5443**	0.3148	0.3301
33	0.2760	0.3465	0.1385	0.2680
38	0.4002	0.2180	0.0350	**0.5136**
43	0.2041	0.3534	0.1185	**0.6403**

(a) Two-group setting

		Text groups (MT_pre)		Text groups (MT_post)	
SIAS low	SIAS high	$\overline{FAC_1}$	$\overline{FAC_2}$	$\overline{FAC_1}$	$\overline{FAC_2}$
27	44	0.3140	**0.6075**	0.0768	**0.9209**
28	43	0.2261	**0.6171**	0.1665	**0.7320**
30	39	0.3647	0.4208	0.1895	**0.5899**

(b) Three-group setting

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