Challenges: Using Personal Sensor Networks for Scientific Behavioral Studies in the Wild

Santosh Kumar[⋆], Mani Srivastava[^], Mustafa al'Absi[‡], J Gayle Beck[⋆], Anind K. Dey[^], David Epstein[△]
Emre Ertin[◇], Deepak Ganesan[∨], Greg Pottie[^], Kenzie Preston[△], Justin Romberg[†], Jun Xu[†]

University of Memphis[⋆], University of California, Los Angeles[^], Carnegie Mellon University[^],
The Ohio State University[◇], University of Minnesota Medical School[‡], University of Massachusetts, Amherst [∨],
National Institute on Drug Abuse[△] Georgia Institute of Technology[†]

ABSTRACT

Our behaviors such as regular exercise and dietary habits, exposures to stress, addictive substances, environmental pollutants, etc., together with our genetic predisposition, largely determine our physical, emotional, and social well-being. Rapid advancement is underway in the development of unobtrusively wearable wireless sensors (e.g., ECG, respiration, accelerometer, pollution, etc.) that can be used to collect continuous measurements of physiology, activity, exposures, etc. from daily life. Once their suitability, acceptability, and validity for field deployment is established, and if their measurements can be processed on mobile devices to make real-time inferences about human behavior, they can be used to obtain frequency and intensity of personal exposures (e.g., drug usage, pollutants, stress, smoking, etc.) and physiological reactivity to exposures in daily life. When adopted in scientific behavioral studies, these measurements can be used to investigate cause-effect relationships underlying complex diseases such as cancer, addiction, hypertension, etc. that have eluded behavioral researchers for decades.

However, to achieve this noble vision of supporting behavioral researchers, numerous mobile computing and networking challenges must be overcome. First, the data collected from the uncontrolled environment must meet the stringent quality needed to arrive at repeatable, valid scientific conclusions. Second, reliable inferences of behavioral events (e.g., stress, drinking, smoking, etc.) must be made from noisy measurements collected by physiological sensors. Third, the processing and communication of sensor data must be optimized to ensure long lifetimes for the entire personal sensor network from wearable batteries; the need for frequent recharging increases participant burden and further complicates the logistics of the study. Finally, given that inferences made from measurements collected by personal sensor networks can be behavior-revealing, approaches need to be developed to preserve the privacy of the participants, while still satisfying the goals of a study. We describe the research challenges in each of these categories and promising directions for addressing them.

1. INTRODUCTION

Our daily behaviors such as regular exercise, dietary habits, our exposures to psychosocial stress (from our social interactions), exposures to addictive substances (e.g., smoking and drinking), exposures to environmental pollutants (e.g., diesel exhaust), together with our genetic predisposition, largely determine our physical, emotional, and social well-being [1]. Rapid advancement is currently being made in the identification of genes suspected for vulnerability to various diseases such as CHRNA5 for Nicotine dependence [2]. Similarly, unprecedented resources are currently being invested for the development of unobtrusively wearable wireless sensors (e.g., ECG, respiration, oxygen saturation, skin temperature, accelerometer, pollution, etc.) that can be used to collect continuous measurements of physiology, activity, exposures, etc. from daily life, as part of National Institutes of Health (NIH)'s Genes Environment & Health Initiative (GEI) Exposure Biology program, and other similar initiatives. The vision of these initiatives are the eventual adoption of these sensors in scientific behavioral studies conducted in the wild.

Scientific studies of exposures of human subjects to psychosocial stress, substances of abuse, environmental toxicants, panic attacks, etc., focus on investigating their causes, associated physiological responses, public health consequences, and design and assessment of appropriate intervention mechanisms. They typically involve the collection of the frequency and intensity of exposures (e.g., number of cigarettes smoked per day, calories burned per week, temporal variation in the stress level, etc.), and their correlates so that cause-effect relationships can be investigated. For example, how do the physiological responses change during a stress event; what is the effect of smoking or drug usage on physiology (before, during, and after the event); how do physical activities affect cardiovascular responses; etc.

Two mechanisms have usually been employed for data collection — self-reports and physiological measurements. While self-reports capture a subject's perception in natural settings, they are are susceptible to multiple sources of errors and bias such as memory limitations and inadequate compliance with procedures. Physiological measurements, on the other hand, provide objective measurements, but they are hard to capture in non-clinical settings. Significant noise,

Technical Report No. CS-10-003
Department of Computer Science, University of Memphis.

motion artifacts, and the existence of other uncontrollable confounding factors are the often cited reasons for not collecting physiological measurements from natural environments.

Once their suitability, acceptability, and validity for field deployment is established, and if their measurements can be processed on mobile devices to make real-time inferences about human behavior, they can be used to obtain frequency and intensity of personal exposures (e.g., drug usage, pollutants, stress, smoking, etc.) and physiological reactivity to exposures in daily life. When adopted in scientific behavioral studies, these measurements can be used to investigate cause-effect relationships underlying complex diseases that have tremendous public health burden such as cancer, addiction, post traumatic stress disorder (PTSD), hypertension, autism, Diabetes, heart diseases that include Chronic Obstructive Pulmonary Disease (COPD), Congestive Heart Failures (CHF), Coronary Artery Disease (CAD), etc. that have eluded behavioral researchers for decades. A deep understanding of the effects of personal behaviors and personal exposures is essential to the development of efficacious treatments and to the formulation of appropriate public health policies. However, to achieve this noble vision, numerous mobile computing and networking challenges must be overcome, which we describe in this paper.

First, behavioral studies require scientifically valid data so they can be replicated by independent researchers. The replication is essential before the conclusions of a behavioral study are translated to new health practices or before the conclusions are used to formulate public health policies. Consequently, *the data quality requirements for use in scientific studies are quite stringent*. For example, when the electrode of an ECG unit begins to dry out, the deterioration in data quality must be automatically detected, and appropriate instructions provided to the participant to replace the electrode.

Second, to relate the changes in physiological measurements to the behavioral events of interest (smoking, stress, drug usage, etc.), the behavioral events must be detected. Although one could instruct the participant to mark all occurrences of behavioral events of interest, say, on a smart phone (as is done in most ongoing studies), this method relies on the timely self-initiation by each participant, each time the event occurs. Automatic detection of behavioral events of interest will both decrease the burden on participants and reduce the chances of omissions. The mobile computing challenge is *how to reliably detect complex behavioral events from physiological measurements in real-time on mobile devices* such as wireless sensors and smart phones that participants will be carrying. We note that even with automated detection of various behavioral events, not all correlates or potential causes of these events will be captured automatically (e.g., what caused a sudden increase in the stress level, recalling an unpleasant experience, sighting of a snake, or something else). Participants in a behavioral study will continue to be asked to fill out a survey on a smart phone or electronic diary (called *Ecological Momentary Assessments (EMAs)*) to capture their context and thought processes. Automated detection of behavioral events, however, can be used to initiate EMAs, so self-reports are collected close to the occurrence of the event as has been envisioned [3].

Third, physiological sensors currently emerging for use in behavioral studies typically require recharging each day. As has been noted in experience reports of field deployment [4], the need for recharging adds to the participant burden and complicates the study logistics as the participants must be provided with a charger and instructed on how to take off the sensors and recharge them overnight. Since compliance is known to be one of the biggest hindrances in behavioral studies, behavioral scientists usually place a high premium on devices that can run for the entire length of the study without a need for recharging. In several behavioral studies, behavioral events of interest can occur in an instant (e.g., stress, craving for a drug, panic attack, etc.), which places a lower bound on the sampling frequency of sensors and an upper bound on the delay in inferencing of behavioral events. Given that behavioral studies may last for weeks, sometimes several months, the challenge here is how to enable sensors to *last several months on wearable batteries* (usually of < 1100 mAh capacity), while still capturing a majority of behavioral events of interest.

Fourth, while automated inferencing of behavioral events can significantly advance the field of behavioral science, continuous collection of daily behaviors (e.g., smoking, drinking, emotion, conversation episodes, craving, etc.) can be behavior-revealing, sometimes to the social discomfort of the participants. The challenge then is how to *preserve the privacy of the participants*, while still satisfying the goals of the study.

Organization: In Section 2, we describe several real-life examples of scientific behavioral studies that can be conducted with recent advances in personal sensor networks, highlighting similarities and differences between behavioral studies and remote health monitoring. In Section 3, we describe a proposed end-to-end architecture for personal sensor networks used in behavioral studies. Sections 4 through 7 describe in detail the technical challenges highlighted above. We conclude in Section 8 by emphasizing the importance of addressing these technical challenges.

2. BEHAVIORAL CASE STUDIES

In this section, we describe three examples of behavioral studies that could be conducted with wearable sensors, once the challenges described here are comprehensively addressed. We then highlight the similarities and differences between behavioral studies and remote health monitoring.

Case Study 1: Identifying Physiological Response to Panic Attacks. Within clinical psychology, a significant amount of research focuses on factors that create and/or maintain psychopathological conditions. This type of research is important for informing efforts to develop effective treatments, given evidence that treatments which are tailored to disorder-specific processes are notably more effective than more general/generic forms of treatment. However, some of the processes that are relevant in psychopathology research cannot be planned, deliberately evoked, or reliably captured within the laboratory setting. As an example, panic attacks are by definition, sudden bursts of anxiety that occur unpredictably. Panic attacks are accompanied by physiological symptoms (and presumably, rapid escalation of physiological arousal). To date, several investigators have studied participants who are experiencing panic attacks; these data reflect opportunities that occurred by chance, rather than designed by the investigator. In order to pursue greater knowledge about factors that induce and maintain panic in patients with Panic Disorder, investigators have resorted to the use of a variety of laboratory paradigms which are designed to mimic conditions that might bring on a panic attack [5]. At present, the majority of our knowledge about psychophysiological processes in Panic Disorder come from this type of paradigm, which is problematic given the artificiality of the environment and the untested assumption that responses occurring within the laboratory are indeed the same in quality and quantity as naturally occurring panic attacks.

A personal sensor network that is aimed at in-field deployment for continuous physiological data collection for days, weeks, or even months has the potential to make such data available for the first time since research on this topic began decades ago. Physiological data needed to profile a response to panic attacks include tidal volume, respiration rate, heart rate, skin conductance, and skin temperature, averaged over 15 second intervals. Of special interest is the data collected prior to, during, and after panic attacks, which can occur at any moment.

Case Study 2: Adverse Effects of Drug Usage. Research on substance abuse has grown to include a focus on timely and reliable detection of craving and use events in the field using EMA methodology. However, current methods used in the field (for nicotine, cocaine, etc.) rely on subject initiated self-reports that can be confirmed by relatively limited collection of biosamples (saliva, urine), usually during study visits to the research site. All of these methods require a high degree of compliance from subjects, and therefore may not capture all events of interest. Events that are captured, even by self report in the field, might be recorded at least a few minutes after the fact rather than precisely as they occur. These limitations make it more difficult to identify the social and environmental factors that affect addictive behaviors.

It has been shown in the lab that craving and consumption of addictive substances each produce discernible patterns of change in physiological measurements [6–8]. These patterns can be used to identify the craving and use events in the field by processing physiological measurements on the body. Pinpointing the timing of drug use in the natural environment and capturing continuous physiological measurements may also help understand the causes of sudden death from psychostimulant use or unexpected overdose after opiate use, that are not currently fully understood, primarily because the varied levels of drug doses and self-administration patterns encountered in real-life are not completely modeled in a lab environment.

Case Study 3: Physiological Response to Stress. Clinical studies are usually conducted to measure the response to exposures to psychosocial stress (by applying lab stressors such as public speaking, mental arithmetic challenges) to observe any unusual sensitivities in a subpopulation (such as the substance use population). The goal is to identify a vulnerable population, who may be susceptible to catching cardiovascular disease as a result of moderate stress in their daily life. Once identified, intervention methods may be devised to moderate their stress response so they are able to cope better. Since such studies have so far been restricted to either clinical studies or to controlled field studies for limited duration (such as few hours of driving [9]), the effect of real-life stressors that can't be simulated in these environments have never been studied. Several physiological responses that only occur as a response to some real-life stressors, therefore, remain unknown even today.

Again, a field-deployable personal sensor network that provides continuous physiological data from the natural living environments of individuals can, for the first time, enable discovery of new theories and intervention methods that have largely remained unexplored. Given their ability to collect continuous measurements, physiological response, before, during, and after a stress event, can be captured without having any prior knowledge of its imminence, despite the fact that stress can occur in a moment. The cause of stress can be captured via EMA triggered by the detection of stress event. Additionally, it can be established whether the activities that are thought to mediate stress level (e.g., physical activity, smoking, drinking, listening to music, watching TV, etc.) do indeed result in a reduction in the stress level, and if so, to what extent.

Case Study 4: Understanding Emotion Regulation. A number of different areas within the social and behavioral sciences are interested in the process of emotion regulation (e.g., clinical psychology, developmental psychology, sociology). Growing evidence is pointing to the role that parasympathetic processes play in emotion regulation, in particular heart rate variability as influenced by the vagal system. In [10], a method is proposed to measure the amplitude and period of the heart rate oscillations associated with inhalation and exhalation. This measure refers to the variability in heart rate that occurs at the frequency of breathing (respiratory sinus arrhythmia [RSA]) and is thought to reflect the parasympathetic influence on heart rate variability via the vagus nerve. It has been proposed that baseline RSA may be a measure of an individual's characteristic level of arousal and as such may reflect temperamental reactivity, which is commonly considered a traitlike individual characteristic [11]. To study the influence of RSA on the manner in which romantic couples approach and resolve conflict situations, [12] constructed an artificial laboratory task, designed to evoke conflict between members of the couple; participants were assessed in this context, which was necessary given current methods for assessing RSA. A personal sensor network could contribute greatly to the growing work in this area by permitting naturalistic assessment of RSA within participant's daily lives, which will have greater ecological validity.

2.1 Behavioral Study vs. Remote Health Monitoring

There are quite a few similarities between behavioral studies and consumer oriented remote remote health monitoring

(RHM) applications [13]. They both use physiological sensors and EMAs. Also, they both collect personally sensitive data and are subject to similar security requirements.

However, as evidenced in the above examples, there are important differences. RHMs usually have a specific disease condition that is to be monitored for and detected in real-time. The pattern in physiology for these conditions are usually known (e.g., arrythmia, elevated glucose level, etc.). Behavioral studies, on the other hand, require detection of complex behavioral phenomena (stress, craving, etc.). RHMs are usually administered in confined boundaries (assisted living, nursing home, etc.). Since patients are naturally motivated and do not have to carry these devices with them in the mobile environment, unobtrusive placement is not critical. Additionally, elaborate instrumentations can be specified to support their operation, such as in the Intel Health Guide system. But, to get participation and compliance from healthy volunteers in mobile environments for behavioral studies, unobtrusive placement is a must, so that, for example, they do not put the sensors in their car's trunk before entering office.

Consequently, although some of the challenges related to RHM such as sensor design, sensor manufacturing, sensor calibration, sensor integrity, trust, security, etc. [14] are applicable to the use of personal sensors for behavioral studies, several others become more demanding such as sensor placement, data quality, and energy-efficiency. More importantly, several new issues arise when using wireless sensors for behavioral studies that have not been addressed in the context of remote health monitoring such as behavioral inferencing and privacy preservation of daily behavior. In the following sections, we describe these challenges. We note that once these challenges are addressed, they can be incorporated in remote health monitoring to make the measurements collected from the mobile environment clinically suitable.

3. A PROPOSED SYSTEM ARCHITECTURE

We assume a similar multi-tier architecture as used in [15]. At the subject level, the system takes the form of a personal sensor network (PSN) with a variety of wearable wireless sensor nodes at different locations on the body (measuring ECG, respiration, oxygen saturation, temperature, skin conductance response, physical activity, environmental exposure, etc.) communicating to a standard mobile smart phone via low-power short-range wireless technologies such as Zigbee.

The smartphone can play multiple roles. First, it contributes its own sensors such as accelerometers, microphone, GPS, camera, light, etc. Second, it can collect measurements from all the wireless sensors and process them to make complex behavioral inferences spread across multiple sensing modalities. Third, it can use behavioral inferences to decide when to solicit inputs via EMA. This would enable capturing time synchronized measurements across both objective domain (from sensors) and subjective domain (human perception). Further, inferences made from sensory measurements can be used to request participants to provide additional information, such as taking pictures from camera. Fourth, it can act as a gateway to the wide area Internet (i.e., cloud) through WiFi and cellular networks. Finally, it can be used to notify participants to adjust the sensors (placement, adhesion, etc,) to rectify any deterioration in the quality of data being collected by the sensors, and instruct them with a step-by-step process.

4. DATA QUALITY ASSURANCE

As described in Section 1, behavioral studies require scientifically valid data so they can be replicated by independent researchers. When behavioral studies are done in lab settings, any deterioration in the quality of physiological measurements is quickly attended to and appropriate actions are taken to rectify the error. In addition, participants are explicitly supervised to ensure they comply with the protocol. Physiological measurements collected from the field are inevitably subject to several sources of errors and biases, which must be accounted for and quickly corrected so they are valid enough for use in scientific studies. We discuss these challenges below.

First, several physiological measurements are quite sensitive to how well the sensors attach to the body. For example, if fine grained features are to be computed from the ECG measurements (e.g., heart rate variability, t-wave amplitude), the electrodes must be tightly attached to the chest. If fabric electrodes are used, they must be moist enough to acquire the ECG signals. Similarly, if respiration is measured via a band that goes around the body, it must be placed around the chest or abdomen, and it must be tight enough to pick up changes in the circumference. Any deterioration in the quality of signal due to detachment or loosening, due to the weakening of battery, due to weakening of cable connectors, etc. must be detected quickly and the specific causes identified so that participants can be instructed to take corrective actions. It is critical to have low rate of false alarms so that weakening of the battery is not mistaken for loosening of belt or loosening of the belt confused with deterioration in signals due to intense physical activity. The mobile computing challenge is to determine how frequently to activate such monitoring, how to divide up the computation among the sensors and smart phones, and what combination of sensors to use to improve accuracy. Development of appropriate temporal models for physiological signals in collaboration with domain experts may help in improving the accuracies of such detections, however, these models must be parametrized so wide between-person differences can be accounted for and contextualized to vary with changes in context (e.g., change in posture).

Second, most physiological sensors are sensitive to body placement. Even accelerometers, that do not need to be attached to the skin to measure metabolic energy expenditure, must be recalibrated if their placement is changed (e.g., from torso to arm). For more sensitive sensors such as galvanic skin response (GSR) that measure bodily processes, placement is even more critical. Although the primary function of endocrine sweat glands is cooling, those located on the palmar and planter surfaces are involved in grasping behavior. As a result, these surfaces are more responsive to emotional stimuli, associated with the "fight or flight" reflex [16]. Therefore, when placed on the palm or foot, they are found to be good indicators of stress [9].

The existing knowledge base in behavioral science is predicated on traditional accepted placements of sensors. When used in the field, however, the same placements may be obtrusive (e.g., exposed body parts such as earlobe, fingers, etc.) or socially stigmatizing, and hence, new placements need to be found that are both unobtrusive and still responsive to the behavioral processes of interest. In addition, new models of how the various behavioral processes manifest or affect the measurements collected at these new locations need to be developed. Also, since any accidental change in placement from that assumed in the study is likely to lead to invalid results, it will be ideal to automatically detect changes in the placement of sensors and instruct the participants to revert to the intended placement.

Third, physiological measurements are affected by several behavioral processes. For example, stress, conversation, motor activity, etc. all affect physiological measurements. To investigate the effect of, say stress on the physiological measurements, either all other factors affecting physiology must be controlled (not feasible in field studies), or their effect filtered out. Alternatively, data collected when other behavioral activities are in progress (e.g., physical activity, when the goal is to study the effect of stress on physiology), should be flagged so it can be ignored during analysis. Each of these approaches require detecting when specific behavioral events are present, a topic we discuss in more detail in Section 5.

Fourth, wearing a suite of wireless sensors, all of which must be attached properly most of the time and providing responses whenever prompted for an EMA, are quite burdensome to the participants, and they may interfere with daily life. Participants are usually incentivized with monetary compensation for their efforts. However, these compensations are usually staged in the form of large bulk payments, i.e., certain amount for each day, certain amount for completing the study, etc. Given that mobile phones are beginning to be used in several studies, the compensation could be organized in the form of fine-grained incentives to encourage compliance and enhance both the quality and quantity of data collected. For example, the incentive provided can be based on how many minutes have elapsed between a stress event and the EMA response from a participant. The challenge is to devise appropriate structuring of the microincentives, evaluating their effectiveness, and validating that they do not compromise the original study objectives by introducing biases.

Fifth, data collected via EMA prompts are also an integral part of the measurements collected. However, these responses are also susceptible to several sources of error, deliberate or accidental. Behavioral scientists usually organize the questions so as to detect some of the inconsistencies by asking overlapping questions. If several contexts could be collected automatically (e.g., smoking, conversation, places of visit, etc.), they can be used to improve the consistency checks. The challenge is how to resolve any inconsistency observed between the objectively inferred contexts and the subjective answers on the EMA, i.e., which one to trust more.

5. RELIABLE INFERENCING OF DAILY BEHAVIORS FROM WEARABLE SENSORS

Behavioral events of interest such as stress, smoking, drug usage, etc. all induce certain patterns of physiological responses, when observed in controlled laboratory settings. Therefore, in theory, it should be possible to identify these behaviors by processing the physiological measurements on the body (say, on a smart phone). Although some progress has been made in using pictures taken from a camera for detection of diet intake [17], using accelerometers and heart rate monitors for classification of physical activity [18, 19], the detection of other psychologically richer events such as stress and craving, remain largely unaddressed. As we describe below, there are several challenges to obtaining reliable inferences of daily behaviors in real-time from measurements collected in the field.

First, physiological measurements may be affected by stress, smoking, eating, drinking, craving, speaking/listening, and motor activity, to name just a few. In particular, standing can cause base heart rate to exceed the levels typically associated with behavioral events while seated [20], making it harder to differentiate stress from a change in posture. If the goal of a study is to measure changes in physiology due to stress, all other phenomena that may affect physiology become confounding factors. Although one could limit the detection of, say, stress to those periods when other confounding factors are suspected to be absent, eventually, methods need to be developed that can be used to tease out the effects of concurrent behavioral processes on the physiological measurements, and be able to detect the event of interest, in the presence of other confounding factors. For example, additional heart rate (AHR), i.e., heart rate, above that predicted by O_2 consumption, has been proposed to filter out the effect of emotion on heart rate from that due to motor activity [21]. Although this theory has been validated in laboratory settings to some extent, this has not been replicated in field settings [22]. Given that hundreds of features spread across simultaneous measurements from multiple sensors (e.g., ECG, respiration, accelerometers, etc.) can be derived and fed to machine learning algorithms to find discernible patterns specific to each behavioral event of interest, this problem can potentially be addressed. However, this requires collection of labeled data from the natural environment when various combinations of concurrent behaviors occur naturally, and to do so without encumbering the participants. For example, semi-supervised learning methods may be used to request participants to provide labels frequently early on, and gradually reduce their involvement, as the system becomes better trained [23].

Second, appropriate models need to be built for reliable inferencing of behavioral events from noisy measurements that can be used to filter out artifacts and confounding factors. However, there are wide between-person differences in human physiology and behavioral makeup. For example, between-person differences in respiratory sinus arrhythmia (RSA) are indicative of emotional reactivity [11]. Similarly, an individual's circadian rhythm may be reflected in their physiological baselines (e.g., nightowls exhibit a delay in their early-morning peak of Cortisol levels relative to early-risers [24]). These differences make the search for a universal model futile. Most of the work in modeling behavioral phenomena by using physiological data has used time-series models such as Hidden Markov Models [25], Dynamic Decision Networks [26] and Dynamic Bayesian Networks [27]. The challenge is how to personalize the models to each individual's physiology, behavior, and their circadian rhythm, online, in the field. Also, physiological baselines may change by the context (e.g., office vs. road vs. home [28], which requires the model to be adaptive to changes in context.

6. ENERGY-EFFICIENT DESIGN AND OPERATION

With the availability of flash storage and micro SD storage on embedded platforms [29] large amounts of data can be locally stored in wearable sensors. However, to assure quality of data and to detect behavioral events in real-time, raw measurements or features derived from them must be communicated to an accompanying smart phone for appropriate actions. For intervention studies, the behavioral inferences may also need to be communicated to study sites in near real-time. The challenge is how to provide continuous monitoring for several months on wearable batteries on a single charge while still capturing most occurrences of behavioral events. Additionally, now that a smart phone is tasked with the bulk of the feature computation, computation-heavy behavioral inferencing, and display-intensive EMA administration, another major challenge is how to make the smart phone last at least a day of wake time between recharges. We discuss these challenges below. For challenges and approaches related to hierarchical activation of sensors and development of event-filters, we refer the reader to [30, 31].

First, the sampling of the sensors can be optimized using the recently emerged theory of *compressive sampling* [32,33] that permits design of efficient sub-Nyquist rate non-adaptive sampling protocols for signals that are sparse in some domain. The signal is sampled using a small number of fixed waveforms that are incoherent with the basis in which the signal is sparse. Later, the signal can be reconstructed or its features estimated from the small set of observations using sophisticated computational mechanisms. Significant reductions in sampling rates may be obtained if a parametric model of the signal or the underlying physical process is available from prior studies, for example, models of physiological signals based on population studies. Then, only enough samples need to be taken to enable identification of features that are critical for detection of behaviors of interest (say, in an intervention study). Even further reductions in sampling and subsequent event detection or feature identification are possible if the signal model is personalized and tuned to the specific individual as discussed in section 5. The challenge is to design appropriate sampling strategies for each subset of sensors and for given target behaviors that are to be monitored, so that original signals can be reconstructed with sufficient reliability on back end servers. Given that the measurements are used for real-time detection of behavioral events, another challenge is how to reliably detect behavioral events from sparse samples.

Second, the network connection from the sensors to the phone and from the phone to the cloud may be varying with time and user context. The link between sensors and the cell phone may not be persistent due to the phone being off or out of range, or the user forgetting to carry the phone. In such a case, sensors have to work with their own computing and storage resources. Even when the cell phone is reachable from the sensors (enhancing the amount of processing and storage resources now available), connection to the cloud may still be absent (e.g., cell phone in coverage hole of the cellular towers, in airplane, etc.). These variations in the connection status and processing/storage resources available, in turn, require dynamic decision making (i.e., in-network processing) about the sampling, storage, and transport policies, given the current connectivity status, resources available at the moment, and quality of service constraints/requirements. Additional factors that impact these tradeoff decisions are the remaining lifetime for the sensors and the phone (before the anticipated recharge), and cost of communication (e.g., cellular connection on prepaid data cards charge different amounts for SMS and TCP/IP connections, whereas connecting to an open Wi-Fi access point may be free [34]).

The challenges in this context are how to build models of various link states that are personalized to each user and the user's life pattern, how to obtain personalized estimates of remaining lifetimes based on daily observation of user behaviors, and then how to use this awareness of available/anticipated network state and dollar cost of connections to adjust the processing, storage, and communication strategies to best meet the quality of service requirements. Defining the quality of service requirements in terms of fidelity, accuracy, timeliness, and expected utility of various inferences as a function of these parameters, is yet another challenge.

7. PRIVACY PRESERVATION

Work on privacy has usually focussed on medical data that may reveal disease conditions [35], web search and movie rating records that may reveal potentially private behavior and preferences [36], and location data that may reveal daily movement patterns in addition to revealing identity [37, 38]. Continuous collection of daily behaviors (e.g., smoking, drinking, emotion, conversation episodes, craving, etc.) can pose new privacy risks, which we describe in the following.

First, there has been extensive investigation of privacy risks associated with medical and location data, but not so for behavior data. The challenge is to identify the privacy risks associated with continuous collection of multiple behaviors together with their associated contexts (e.g., changes in emotion during specific conversations, smoking, drinking). When these inferences are combined with place (since use of GPS helps behavioral scientists to understand the role of place on the exposures [1]), they compound the privacy risks. Again, the extent of privacy risks need to be understood. Similarly, privacy concerns associated with the collection of location data as perceived by the participants, and their comfort level in sharing these has been investigated extensively [39]. However, for the collection of daily behaviors from the mobile environment, they remain an unknown. Once these risks are understood and well modeled, then they can be used to systematically tradeoff the risks to privacy versus their utility in a behavioral study using the frameworks such as the one in [40]. We next discuss the challenge of reducing the risks to privacy from such data.

Second, the metrics of k-anonymity, ℓ-diversity, t-closeness, differential privacy, etc. [41], and the transformations applied to the data to achieve specified levels along these metrics (e.g., adding noise [42], generalization [37], omission [43], etc.) have served the needs for medical and location data. However, they are not directly applicable to behavioral studies given the need to preserve the original measurements so it can be investigated for cause-effect relationships. The challenge is to develop new transformation methods so that the study objectives are not compromised while still preserving the privacy of the participants.

Third, in behavioral studies, participation is based on consent forms, which is an agreement between the participant and the study researchers [44]. It describes what data will be collected, who will have access to it, and how it will be shared. Participants who agree to participate are bound by this agreement and data collected on them is shared as stipulated in the informed consent form. It is usually a binary decision in that either a volunteer agrees to abide by the consent and participate in the study or they decline and are not enrolled. With the increasingly private nature of the daily behaviors that can be collected by wearable sensors and real-time behavioral inferencing, the risks of privacy are greatly escalated. However, if the practice of informed consent disclosure continues to be binary, the participant pool will become increasingly biased to those who may not fully understand the privacy risks or are in need of the compensation they earn from their participation. It may pose greater privacy risks to those who eventually participate. The challenge is how to make informed consent dynamic so the participants have more control on when and where they will contribute data [45], while still satisfying the goals of the study.

8. CONCLUSIONS

Significant advances in behavioral sciences that are of tremendous importance to public health (such as relationship between addiction and stress, effectiveness of behavioral interventions, etc.) can be made if scientifically valid data from wearable sensors can be collected in subjects' natural environments. There is currently tremendous interest and hope in the behavioral science community, due to the support from National Institutes of Health, that such systems would become available. But, unless the issues described here are addressed in a timely manner, real-life deployments of personal sensor networks for behavioral studies will not live up to its promise. This may force behavioral scientists to revert to their traditional tools, and depriving the society of tremendous advancements possible in improving the quality of human life. It will be much harder to earn the interest of domain scientists back at a later time. Hence, addressing the mobile computing and communication challenges described here is urgent.

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