Sougata Sen | Research Statement

My research enables automatic and unobtrusive monitoring of fine-grained details of an individual's everyday activities and behaviors using sensor data from mobile, wearable, and infrastructure devices. Individuals can use this fine-grained information to improve their lifestyle. Additionally, to preserve an individual's privacy, my research explores approaches to reliably share the collected and inferred information with trusted devices.

Specifically, my research focuses on building systems that perform *lifestyle analytics*. In my work, I draw upon data from various sensing modalities: personal devices such as smartphones, smartwatches, and more recently, smartrings; also IoT and IoT prototyping devices, such as BLE beacons, and Arduino boards with sensors. I believe that every sensor present in these devices provides interesting and useful contextual insight about a certain lifestyle activity (e.g., a smartwatch might monitor the hand gestures while an individual eats, while the smartphone might determine whether the individual was sitting and eating). Fusing information from the *right* subset of sensors enables understanding of specific aspects of an individual's lifestyle. I work towards identifying these right subset of sensors; apply appropriate data processing and machine learning techniques on their data to infer an individual's activities and behaviors. While an individual can perform numerous everyday activities, my work thus far has focused on monitoring two activities – *eating* and *shopping*. Overall, systems that perform lifestyle analytics have several practical challenges. My research focuses on developing practical solutions that address these challenges.

Current Research Focus

Within the broader theme of lifestyle analytics, my recent research interests and accomplishments can be organized around: (i) daily life activity monitoring using personal sensing devices as well as infrastructure and IoT devices, and (ii) securely transferring sensitive information from these devices to a personal smartphone or tablet.

Daily Life Activity Monitoring

An individual performs various activities (e.g., eating, sleeping, shopping) throughout the day. Analyzing these activities can help in answering several important research questions related to (a) the specific activity, and (b) the individual's overall lifestyle. For example, a system that monitors an individual's eating activity might be able to determine if an individual is experiencing heart-burn because of prolonged unhealthy eating habits. Manually monitoring every performed activity can be cumbersome. In the recent past I have focused on building systems that can automatically and unobtrusively monitor and analyse the eating and shopping activities.

Eating

The eating activity has several unique attributes. An individual performing repeated hand-to-mouth gestures to feed oneself, performing repeated chewing action to breakdown the food, or swallowing the mouthful are some examples of such attributes. As a graduate student, I focused on using the using the repeated hand-to-mouth gesture to determine the eating activity. To this end, I had worked towards developing a *smartwatch-based* fully-automated deployable system, *Annapurna*.[1] *Annapurna* uses the smartwatch's accelerometer and gyroscope sensor data to continuously to determine *when* an individual is eating. Once *Annapurna* detects the eating activity, it opportunistically triggers the smartwatch's embedded camera to capture images of the food being consumed. *Annapurna* passes these images through an image processing pipeline to identify *what* an individual is eating. Finally, *Annapurna* chooses a subset of the relevant images to create an automated food journal.

While developing the system, we addressed several research challenges. Some of the challenges were (a) the eating activity is diverse – individuals eat various types of food, using various eating modalities (e.g., forks, chopsticks, fingers/hands), in different contextual setting (e.g., home, restaurant, food courts). We had to make sure that *Annapurna* was robust to various settings. (b) Since we wanted to capture image of the food that was being consumed, we had to develop a lightweight, real-time inertial sensor based eating recognition algorithm that could be deployed on a resource-constrained smartwatch. This *eating recognizer* had to quickly turn on the camera whenever eating was detected. (c) Continuous sensing and image capturing is energy intensive. We had to develop a sensing pipeline where expensive sensors were activated by less energy-consuming sensors that were always on. This work has resulted in several publications [6, 7, 8]. An initial publication of this work won the best paper award at the WristSense'15 workshop [8].

[1] `http://is.gd/annapurna`

More recently, I have focused on understanding the behavioral aspect of eating. I recently received a NIH/NIDA grant in the capacity of a PI to explore the effect of interventions on individuals with binge eating disorder.[2] This problem can be divided into three distinct sub-problems. First, we have to determine when an individual is eating. Second, on determining that an individual is eating, we have to determine if the individual is binge eating and send an intervention. Third, we have to analyse the effect of the intervention. For this pilot project, we are currently collaborating with experts from various universities, working in the fields of medicine, psychology, and behavioral sciences. In this project, we are using a head-mounted device to determine whether an individual is eating. More specifically, at Dartmouth, we have developed a custom head-mounted wearable device, *Auracle*.[3] This device uses the chewing sound captured by a microphone that is placed behind the ear to determine whether an individual is eating [1]. In addition to detecting the eating activity, the Auracle can provide details about *when* an individual is eating, *how long* did the eating session last, and *how quickly* did the individual chew during this session. We are currently using this information to distinguish normal eating from binge eating. We are developing algorithms to identify the patient's binge-eating sessions. On identifying the onset of such sessions, we will provide context-aware interventions with the goal of reducing the duration for which an individual binges.

Shopping

I have also developed methods for monitoring an individual's shopping activity. Most of the classical work on profiling shopper preferences during in-store shopping focuses principally on the analysis of the purchase data. In contrast, online retail platforms digitally capture a user's entire browsing history, including the click stream, time spent on different pages, etc., and use such history to enhance the platform's interaction with the user (e.g., personalized recommendations). To ensure that a physical retail store can offer a similar level of personalized, analytics-driven interaction as an online store, we performed some initial investigation [2] and then developed a system called I^{4}S [5]. I^{4}S applies machine-learning techniques on the sensor data stream obtained from an individual's personal devices (smartwatch and smartphone), which enables I^{4}S to identify specific items with which the individual interacted during a store visit. More specifically, I^{4}S performs in-store localization by gathering information from multiple in-store shelf-mounted BLE beacons, and combines it with smartwatch's inertial sensing information to pinpoint a shopper's shelf-level interactions.

I^{4}S focuses on inferring the shopping activity. In addition to the physical activity itself, a shop owner might be interested in knowing the shopper's behavior – whether the shopper has buying intentions, whether the shopper knows what to buy, etc. To determine the feasibility of inferring a shopper's behavior, we developed a technique called *CroSDAC* that uses sensor data from a shopper's smartphone and analyzes their in-store activity and movement pattern [3]. In this work, we tested the hypothesis that certain behaviors could be inferred from a shopper's in-store patterns. Using the inertial sensor to determine the shopper's physical activity, and Wi-Fi scan information to derive high-level features from a shopper's in-store location, we found that several in-store behaviors could be readily determined.

Secure mHealth

With the increasing availability of IoT devices to monitor an individual's health (e.g., the smartwatch used in *Annapurna*), monitoring an individual's lifestyle, including sensitive health information, is becoming easier and more unobtrusive. In most cases, the IoT-health devices function as the data collection unit and the end-user consumes this data using a more sophisticated device, such as a smartphone. Thus, the information acquired by a IoT-health device has to be transferred to these sophisticated devices, often wirelessly. Currently, the aforementioned information is transferred using popular RF channels, such as BLE. If the information is transferred in plain-text, an adversary with the right set of tools can obtain the information. To ensure that this information is not available to an adversary, the data should be encrypted.

Recently, I have started working on developing out-of-band communication techniques that will allow a trusted IoT device that serves as a proxy for an authorized user to impart a secret to the IoT-health device. The IoT-health device can use this imparted secret to bootstrap an encrypted communication channel with the authorized user's devices. More specifically, we have investigated the possibility of using vibration as the out-of-band communication channel. We have designed a custom smartring that an authorized user will wear and the ring can communicate with an accelerometer embedded IoT-health device. The smartring encodes secret information into vibration that it generates, which only the target IoT-health device that is held in the authorized user's hand can extract. We use the vibration capability of the smartring to share the secret. Our key observation here is that an object that is in contact with an individual can capture the vibration signal, but the signal attenuates quickly as the distance from the vibration source increases. To use vibration as an out-of-band channel, we have designed and developed a smartring that, in addition to vibration capability, has computational and RF communication capabilities. This work is currently under submission.

[2] https://www.c4tbh.org/funded-pilot/development-mobile-application-auracle-wearable-system-eating-behavior-monitoring-studies/
[3] https://auracle-project.org/

Future Directions

Over the years, I have worked towards developing systems that monitor several daily life activities. There are still several opportunities to improve upon these systems. In the future, I would like to extend these specific systems described above to (a) improve their monitoring capabilities, (b) provide interventions to individuals based on these system's outputs, and (c) improve the security and privacy of these systems.

Improve lifestyle monitoring systems: I have currently focused on using personal devices to monitor daily life activities. Since these devices are personal, I have previously worked on techniques (e.g., in *Annapurna*) that trade off system accuracy to ensure the usability of these devices. I believe that in future smart-space IoT devices will be ubiquitous. An area that I plan to explore in the future is the use of infrastructure-deployed IoT devices to (a) improve recognition accuracy of daily life activity systems, (b) reduce the computation cost and energy draw from personal devices while monitoring these activities, and (c) reduce privacy concerns for an individual. Although I have currently focused on monitoring the eating and shopping activities, in future I will be interested in monitoring other activities such as an individual's sleep pattern or her daily commute, and use the outcome for improving lifestyle – e.g., treat sleep disorders. To this end, I intend to impart intelligence into the IoT devices such as Wi-Fi access points, in-home custom smart-appliances and smart-furniture, or infrastructure-mounted cameras so that they collectively infer the daily life activities. I believe that the data from these IoT sensors, when augmented with intermittent data from personal devices such as the smartphone, smartwatch or the smartring, can help in not only monitoring and improving and individual's lifestyle, but can be useful in monitoring and improving the behavior of groups, families, or even the community as a whole.

Provide appropriate interventions: Next, I plan to collaborate with domain experts to bridge the gap between the activity and behavior recognition systems that computer scientists build and the techniques that behavioral psychologists use in their research. As a first step, I have already started collaborating with experts in the area of eating-monitoring from Geisel Medical School at Dartmouth and from the Department of Psychology at Drexel University. These experts have provided insights I plan to incorporate into the systems that we build. For example, we are currently working with patients who suffer from Binge Eating Disorder. Input from behavioral scientists has allowed us to understand patient behaviors that interest them and we are working towards designing algorithms that can automatically capture these behaviors, which are otherwise observed manually. This is just the initial step in bridging the gap between computer science researchers and behavioral science researchers. In the future, I plan to design and build automatic lifestyle monitoring systems that will be useful for behavioral science researchers in answering interesting behavioral science research questions such as the effect of context on disorders, identifying indicators of disorder prior to its onset, or even identifying factors that influence decisions and choices.

Improve security and privacy: The sensors in IoT devices are useful for obtaining meaningful health and lifestyle information. However, these sensors have been exploited in the past by attackers to launch various types of attacks. In the past I have explored the possibility using the inertial sensor data obtained from a smartwatch as a side-channel to infer what an individual was typing on his smartphone [4]. There are several other possible channels in these devices (e.g., the microphone, the camera, or even the pressure sensor). In the future, I plan to explore attack possibilities using these channels, and develop techniques that can be adopted to mitigate these attacks.

Other than securing devices against attacks, in the future I am interested in developing techniques to preserve an individual's privacy. With the availability of health-IoT devices at homes, it is useful that these devices know *who* is using them. For example, if Bob mistakenly wears Alice's smartwatch and goes for a run, Alice's smartwatch will assume that Alice has been active. Thus it is important that the IoT-health devices know who is using them. I am currently developing a smartring to bootstrap a secure communication channel. In the near future, I plan to use the smartring to determine the user of a health-IoT device. Not only will this ensure that data is not misinterpreted, but it will also reduce the risk of a device unintentionally divulging sensitive information to unauthorized individuals. To achieve this goal, I plan to explore techniques such as capacitive coupling, body-channel communication, and electromyography-based pairing. In case a device has multiple profiles (one for each user of the device), the device can load the person-specific profile based on who is using the device.

In a bigger perspective, my overall research vision is to build creative, secure systems for daily life activity monitoring, with the goal of understanding specific aspects of an individual's health and lifestyle, so that potential improvements can be determined and suggested. While developing these systems I am keen to address novel interdisciplinary technical challenges. So far, I have primarily worked in the fields of mobile and ubiquitous computing, and security. I am, however, open to collaborating with researchers in other areas of computing such as HCI and networking. An example long term goal is to work with HCI experts to explore innovative input techniques for devices with little or no touch input capabilities. Additionally, I have started working with experts in monitoring eating activity, but am open to collaborations with experts from other domains too.

References

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