Personalized Awareness and Safety with Mobile Phones as Sources and Sinks

Anna Yu, Athanasios Bamis, Dimitrios Lymberopoulos, Thiago Teixeira and Andreas Savvides
Embedded Networks and Applications Lab
Electrical Engineering Department
Yale University, New Haven, CT 06520
Email:{firstname.lastname}@yale.edu

Abstract

Today's mobile phones are equipped with an increasing set of sensors including GPS, accelerometers, cameras, and more that makes them ideal source nodes in urban sensing applications. The growing displays and internet connectivity also makes these phones excellent sinks of just-in-time information, including information from other sensors deployed in the infrastructure. Exploiting these features, our personalized safety and awareness system tries to enhance personal safety of users around the clock through a collection of services that process personal and aggregate community data to track, escort, flag, supervise behaviors and help users coordinate to enhance the collective safety of the group. Designed for individuals and groups that operate on campuses and beyond, it intends to make campuses safer, by going beyond the processing of individual location data and by providing services based on the application of intelligent behavior sensing algorithms and collaborative models to aggregate sensor data.

I. Introduction

Most campus security plans consist of scattered emergency phones, scheduled shuttles, and foot or vehicle escorts, but such plans are not always very effective with rising student population numbers and sudden spikes in localized security demand. Moreover, many campus security implementations are unreliable and unable to meet the needs of busy individuals. Confusing timetables, unclear pick-up locations, and limited hours of service discourage many people from actually using campus security services. To compound this problem, many people hesitate to call for a security escort out of embarrassment, or false beliefs that they are immune to danger. To address some of these challenges, our system takes a broader view to personal safety, leveraging GPS mobile phones and social networking to introduce dynamic safety practices. Our system provides user customizable activity monitoring that begins to form the basic virtual escort tracking for small trips on foot, longer term tracking during travels, and escalates up to model-driven activity monitoring and community based coordination for safety. Instead of focusing on security and privacy issues our research is directed towards the creation of semantic meaning from the sensor data, particularly reasoning with user locations in time and space, also using context information extracted form maps. Privacy issues are implicitly handled by exploiting the phones' local processing capabilities, provisioning for the use of security and privacy from other researchers [8] and by operating in community mode where users are willing to share some level of private information in aggregate form with other members of the community to enhance community-wide safety.

In this position paper we describe a personal safety and awareness framework that is currently being developed as part of the Behavior-Scope (BScope) project at Yale [1]. This is centered on the use of smartphones as sources and sinks of information and involves coordination among multiple phones as well as other sensors deployed in the environment. The mobile phones coordinate with a central server to provide a set of services to the users. For instance, when walking across campus, users can put their mobile phone client application in a virtual escort mode. This service provides a panic button option and tracks the travel progress of the user to ensure that the user safely reached the intended destination. During longer trips, a travel service sends automatic emails and text messages to family and friends providing updates about the trip. For more general personal safety, the phone also learns the daily routines of the user and notifies a set of registered recipients at different levels of behavior deviations. Finally, a set of aggregate location information and inputs from campus security are used to coordinate the movements of users and campus security personnel during late hours to ensure maximum safety coverage while moving around campus. Examples of such coordination include pairing up members of the same group to walk together at night, providing safe walking route advice (i.e route that currently has the most members or most security personnel around) and dynamically re-positioning security officers (on foot, bike or car) to the places demand surfaces. We also anticipate enhancing safety and awareness through coordination between friends and social networking. The same system can also bind into the previously developed BScope home monitoring infrastructure, to monitor user safety at home and also to notify caregivers of the status of a loved one. In all cases, the mobile phones are used are the primary user interface and sink device.

The rest of the paper outlines the system architecture in Section II; and the current application features in Section III. Section IV and provides a brief description of our results on a rule behavior engine and activity modeling engine we are developing. Section V concludes the paper with a set of research challenges considered by the BScope project.

II. SYSTEM ARCHITECTURE FEATURES

The broader personal safety model introduced by our architecture (shown in Figure 1) is driven by the interpretation of spatio-temporal properties of multimodal sensor measurements. This process is primarily driven by two interpretation engines: a probabilistic rule-based behavior engine and a dynamic activity modeling engine. The network traffic flows over a heterogeneous set of links including Wi-Fi, IEEE 802.15.4, GPRS, CDMA data links and Ethernet. This forms a dataflow graph in which data propagates in the direction of a central server and back to the sink devices. The central server controls all the data processing modules and can make decisions to diffuse them into the network as needed to improve response times, conserve bandwidth and to interpret data closer to the sinks to manage complexity and increase system robustness.

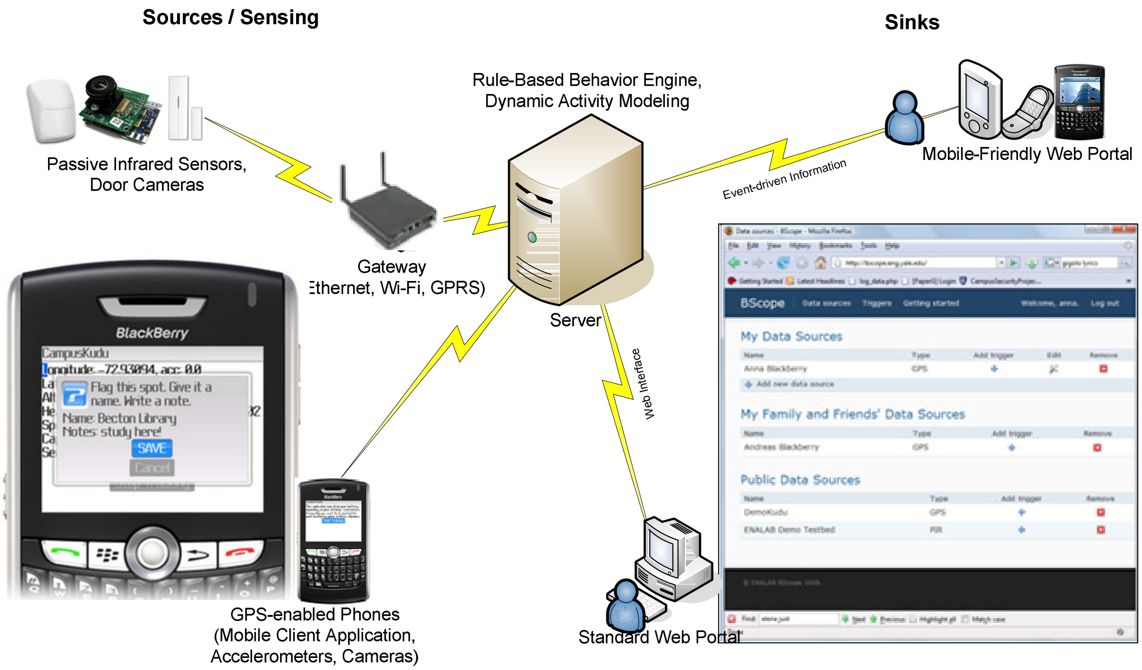

Figure 1: System Architecture

The system uses GPS phones (currently supporting BlackBerry GPS phones) for outdoor environments a collection of cameras, passive infrared and door sensors for indoor environments. Users can configure how the system should work for them and their level of participation in the system directly from their mobile phones. A more sophisticated web portal allows users to interact with the systems at different levels, allowing them to define automated notifications, develop new applications and specify how the incoming data should be processed and plotted. The users can specify how they want the system to work for them as their preferences essentially configure parameters in the rule-based behavior and the dynamic activity modeling engines described in section IV. The two engines reflect the design philosophy of the system when it comes to monitoring human behaviors and providing services. A growing part of the system is centered on learning behaviors and patterns to detect deviations from the norm. Nonetheless, our testbed experience (and of course human nature) demands checking for certain conditions and rules that are not directly extractable. Furthermore, statistical outliers are not always alarming and vice-versa. Because of this, a core aspect of our system relies on the collaboration and sharing of parameters between the two engines.

III. CURRENT MOBILE CLIENT FEATURES

Our initial deployment in an urban setting heavily relies on the client application running on mobile phones. The deployed mobile currently supports several features than enable it to be an active contributor to the overall system architecture. The mobile client automatically connects to our deployed web portal (www.sense4care.com), where users can also configure their preferences in more detail. The mobile client (currently supports GPS-enabled Blackberry phones) can also be downloaded from the web portal. Its key features are highlighted below.

A. Tracking

The mobile client contains a basic tracking feature that users can select to turn on to allow their location be sent to a central server. The user can choose to have this feature on 24-hours a day, or just during select commutes or times of day. Ideally, the application will be running continuously so as to collect as much information and allow as much personalization as possible. This location information is then accessible from any computer or mobile device that has access to the internet via either the standard web portal or the specially-designed mobile-friendly web portal. The benefit of this is that you don't need to have a GPS-enabled mobile phone in order to participate in this system. In order for individuals or groups to access a user's location information, the user must first authorize this access.

B. Virtual Escort

The "Virtual Escort" feature is an integral part of the new campus safety model. It allows users to have an escort when the user cannot find anyone else to walk with. This feature is useful for users who frequently need to walk outside late at night and are seeking a cost-effective and time-efficient solution to staying safe and gives the user access to a programmable PANIC button that can let security know there's trouble and exactly where the user is.

C. Triggers

The web interface also allows users to set up triggers that inform family and friends via SMS or e-mail alert when the user is leaving or entering a pre-defined space. It automates the process of checking a user's location by having an automated message sent out according to the pre-specified preferences. These triggers can be simple conditions about geographic locations or more elaborate behaviors as described in section IV.

D. "Auto-K.I.T"

If the user defines certain areas as being associated with specific activities, the system engine can write automatic digests of a user's day to send to friends and families. This would allow a user to automatically "keep-in-touch" with everyone, even when very busy and has no time to call or e-mail. Also, at the central security server, this is driven by a powerful behavior interpretation engine that would allow system management, and multiple levels of user-defined safety mechanisms.

E. Mobile Phone Power Management

Since the goal of this application is to make it easy to stay safe and secure anywhere, at anytime, the application needs to efficiently manage its power consumption and make its state known to the server at all times. The application informs the server of its status on power up and shutting down, loss of GPS signal, and feature usage. To conserve power, local processing, intelligent sampling and other sensors such as accelerometers need to be exploited. Our prototype experiences have shown that reading the GPS alone can take a noticeable toll on the phone's battery lifetime [4]. Such excessive power consumption could be reduced by utilizing accelerometer sensors and context inferred from the behavior monitoring applications to intelligently manage the GPS sampling and communication frequency. The BlackBerry smart phones used in our prototype deployment do not have accelerometers but other phones such as the Nokia N95 and iPhone already have them. We anticipate that more phone models will have them in the future.

IV. SENSOR DATA INTERPRETATION

A. *Probabilistic Rule-Based Behavior Engine*

This is based on BScope's hierarchical probabilistic grammar framework detailed in [2,3]. The framework follows a language-based approach that uses semantic-level sensor outputs as a sensing abstraction. To sense an activity, the environment needs to be instrumented by a set of sensors to extract a string of phonemes. The collection of phonemes is parsed by small libraries of probabilistic grammars we call *sensory grammars*. The outputs of these grammars are higher order phonemes that can be parsed by other grammars in the hierarchy. A time-abstraction layer allows the sensory grammar framework to reason with temporal quantities. Spatial quantities are implicitly considered by the system through sensor labeling.

In the personal safety system discussed here, the rule-based behavior engine can be applied in several different ways. Users can enter simple rules as regular expressions, and can then form higher-level rules using the outcomes of pre-programmed behavior grammars, or they can develop elaborate grammars from scratch. This hierarchical mode of operation can also be perceived as a higher order, sensor composition tool that can tie together simple sensors in time and space to form a more complex sensor. A detailed example of the composition of a cooking sensor can be found in [5]. The application of this system in elder monitoring and the network architecture used can be found in [6].

B. *Activity Model Extraction*

Although the Rule-Based Behavior engine can classify sensor data into pre-defined activities, the extraction of intuitive activity models directly from the data should be an integral component of an autonomous personal safety system. Ideally, the personal safety application running on a mobile phone should be able to extract the daily or weekly habits of the user and use them to measure deviations and generate alarms when behaviors deviate by a certain threshold. This is a challenging task since the system needs to identify the recurring activities over a time-window without any prior definition of the activities. The mobile phones can collect GPS locations but locations alone only provide a low-level dataset that does not directly imply specific activities. Furthermore, the models need to capture not only the spatial meaning of the data but also its temporal properties. For instance, a consistent everyday visit at a certain location has a different meaning than visits to the same location at unusual times. Our initial effort in this direction has developed a four step model extraction method that operates on the three main attributes of sensor measurements: location, time and duration. The four steps are summarized below:

1. Decritize locations using the map context, that is, name the data according to the named area on the map. This converts locations in the dataset to a series of labeled events.
2. For each event type, group together all event instances that have similar start times and durations over a time window and relabel the events with spatio-temporal labels according to their cluster classification. This part applies a new clustering algorithm we have developed to group together events that have similar start-times and durations over the course of a time-window (i.e a day or a week). This is done by applying a set of similarity metrics, without knowing the number of clusters in advance. This step essentially descritizes time into a finite set of labels and appends these labels as suffices to the labels of step 1.
3. Using the resulting sequence from step 2, extract activities by mining out the most frequently recurring subsequences. This can be done using a data mining algorithm such as the apriori algorithm described in [9].
4. The outcome of step 3 provides enough information to build a state machine that describes the activity. The spatio-temporal event labels of the mined subsequences become the states of the model. The transition probabilities between the states are computer by counting and normalizing the transitions among spatio-temporal events from step 3.

The above methodology has been tested on an indoor trace originally collected for elder monitoring. Inside homes people locations are sensed with cameras and passive infrared sensors but the mechanism of the model are very similar. Some of our initial results can be found in [7]. The modeling methodology is currently being extended and tested on GPS data collected from mobile phones.

V. FUTURE RESEARCH DIRECTIONS

The safety system described in this paper opens a new set of interesting research problems on how to collect, interpret and utilize sensor measurements across communities of mobile phone users. Several aspects of the safety coordination, route recommendations and security officer patrols could be treated as dynamic sensor coverage problems. Urban environments however, and groups make this a challenging problem. Sensors are mobile, the terrain is not a flat plane and map context should be exploited.

From an architecture perspective, our position is that a user reconfigurable data interpretation service that can distribute processing modules as needed across a network of heterogeneous wireless links would provide a powerful feature for developing new services. Finally, we advocate that mobile phone technology has reached a level where it can become the primary information sink for people. Mobile phones have become deeply pervasive to everyday lives and providing an event-driven sensing framework that can notify users about interesting matters in their lives as they happen will form the basis for a new generation of applications. The BScope project at Yale is working towards this direction by using mobile phones as part of a campus security program and as the main information sink for elder monitoring. In the elder monitoring scenario, stakeholders and caregivers get event-driven phone notifications on their mobile phones by configuring the two engines described in this paper. More up-to-date information about the project can be found on the BScope project website [1] and its affiliate website at [10].

ACKNOWLEDGMENT

This work was partially funded by the National Science Foundation under projects CNS 062802 and CNS 0751513. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation (NSF).

REFERENCES

[1] BehaviorScope Project Website. http://www.eng.yale.edu/enalab/behaviorscope.htm

[2] Lymberopoulos, D., et. al. Macroscopic Human Behavior Interpretation Using Distributed Imager and Other Sensors, Proceedings of IEEE, August 2008.

[3] D. Lymberopoulos T. Teixeira and A. Savvides, Detecting Patterns for Assisted Living Using Sensor Networks, to appear in the proceedings of SensorComm, Valencia, Spain, October 2007

[4] Yu, Anna S. "Personalized Security and Social Networking Services over GPS-Enabled Mobile Phones", Final Senior Project Report, Electrical Engineering Department, Yale University, May 2008.

[6] A. Bamis and D. Lymberopoulos and T. Teixeira and A. Savvides Towards Precision Monitoring of Elders for Providing Assistive Services to appear in the proceedings of the First International Conference on Pervasive Technologies Related to Assistive Environments, Athens, Greece, July 2008

[7] D. Lymberopoulos and A. Bamis and A. Savvides Extracting StatioTemporal Human Activity Patterns in Assisted Living using a Home Sensor Network, Proceedings of the First International Conference on Pervasive Technologies Related to Assistive Environments, Athens, Greece, July 2008

[8] Murali Annavaram, Quinn Jacobson, John Shen, HangOut: A Privacy Preserving Social Networking Application, First International Workshop on Mobile Device and Urban Sensing (MODUS), St. Louis, April 2008

[9] R. Agrawal and R. Srikant. Mining sequential patterns. Proceedings of ICDE. Washington, DC, USA, 1995. IEEE Computer Society.

[10] Sense4Care Website. http://Sense4Care.com