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Location and Activity Tracking with the Cloud

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Abstract—**Helping elderly people to live independently within their homes for as long as possible, before transitioning to higher levels of care, can significantly reduce healthcare expenditures. However, achieving this vision requires continuous monitoring of the condition of elderly adults within their homes. In particular, activity, gait velocity, movement, and location of elderly adults are critical biomarkers for healthy aging. We present a prototype integrating a wearable location-tracking sensor with back-end cloud-based data processing, thereby enabling real-time tracking and analysis of a large number of people simultaneously. The resulting vertically-integrated prototype provides a basic infrastructure for future work, including new products and services that offer real-time monitoring and early disease diagnosis to help elderly people live independently for as long as possible.**

I. Introduction

The cost of living in a nursing home now nears $250/day per person, far in excess of the cost for assisted living communities ($115/day) and in-home health aides ($20/day) [1]. With the population of Americans aged 65 or older currently projected to reach 55 million by 2020 [2], trillions of dollars in expenses can be avoided every year by helping elderly people to live independently for as long as possible, before transitioning to higher levels of care. Achieving this vision, however, requires monitoring the condition of elderly adults in their homes, in order to determine when a transition to a high level of care has become necessary. For example, continuous monitoring could be used to detect when aides are required for some acute medical care.

In particular, activity, movement, and location of elderly adults are critical biomarkers for healthy aging. Recent research has shown that several disease indications and health outcomes can be inferred from activity tracking and gait velocity, including: cognitive decline [3][4][5], balance and propensity of falls [6][7], general activity/fitness level [8][9], cardiovascular health [10][11], and depression [12][13]. For example, gait velocity, performed in a conventional clinic visit as a timed walking speed test [14], is highly correlated with general health, aging, and decline [5], with researchers suggesting that gait velocity be renamed as "the sixth vital sign" [15].

In prior work, we developed a low-cost wearable sensor that tracks the location of individuals indoors using commonly available inertial navigation sensors fused with radio frequency identification (RFID) tags placed around the smart environment [16]. While conventional pedestrian dead reckoning (PDR) calculated with an inertial measurement unit (IMU) is susceptible to sensor drift inaccuracies, our proposed wearable prototype fuses the drift-sensitive IMU with a RFID tag reader. Passive RFID tags placed throughout the smart-building then act as fiducial markers that update the physical locations of each user, thereby correcting positional errors and sensor inaccuracy.

Our early prototype lacked support for tracking the location of multiple patients simultaneously in real-time. We now address this limitation, as described in the current paper, by integrating the sensor-based prototype with cloud-based data processing (Figure 1). This enables real-time-tracking of an arbitrarily large number of people simultaneously, for use in detecting and responding to changes in activities. The resulting system provides a basic infrastructure for future work, including research potentially leading to new products and services that offer real-time monitoring of early disease onset to help elderly people live independently.

II. Related and Prior Work

Existing tracking technologies are limited in their suitability for use in in-home tracking of the elderly. The Global Positioning System (GPS) has limited ability to function properly indoors. Sensors that can triangulate which room an individual is in are commonplace (whether based on RSSI wifi [17][18] or UWB radio [19]), but they are not accurate enough to measure gait velocity or to detect specific susceptibilities, such as likelihood of a fall or a loss in balance. Radio-frequency identification (RFID) tags can be placed on individuals' bodies, but these only register location when the tag is less than 1 meter from a fixed RFID reader (e.g., when a person enters a room) [20][21]. Inertial measurement unit sensors (IMUs), such as those in cell

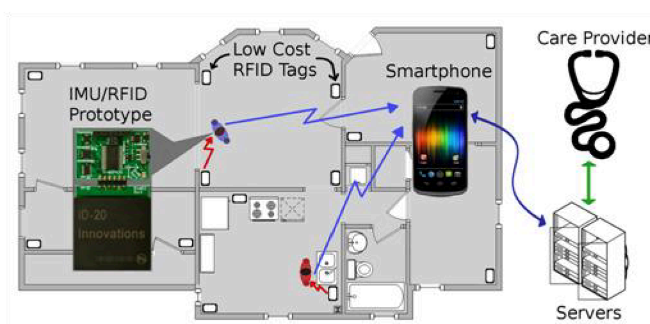

Figure 1. Integration of wearable localization sensors with cloud-based analysis. Elderly adults will be able to view and augment data through future applications, which could also provide data to care-providers

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phones, can compute the wearer's personal dead reckoning (PDR) position based on the physical motion of an internal three-dimensional accelerometer and gyroscope, but the computed PDR drifts over time and can lead to errors of many meters within several minutes of walking [22]. Many similar wearable activity devices (e.g., Fitbit or Actigraph) only track acceleration and therefore provide no information about location nor gait velocity. Passive detectors (e.g., infrared detectors and cameras [23]) have difficulty distinguishing between multiple occupants within a room.

To address these problems, we previously combined IMU and RFID technology to achieve high-accuracy, low-cost tracking of individuals' locations [16]. With our proof-of-concept localization sensor, we found that using RFID waypoints for fiducial updating improved accuracy by 1200% compared with conventional PDR alone. The sensor had an average accuracy better than 47 cm and cost less than \$100. This level of accuracy had previously been achieved only with UWB-based systems, but at more than 10 times the cost [24][19]. We expect that further accuracy improvement could likely be obtained up to the point where RFID tags are deployed at a density of approximately twice the read range of the device for passive tags.

A key limitation of this prior work was that the sensor data had to be retrospectively analyzed to calculate location, rather than tracked real-time. We now address this limitation by integrating cloud-based analysis software that enables real-time monitoring of a large number of simultaneous users, leveraging the scalability of cloud computing.

III. System Description

Several new components were implemented to meet the requirements for this project (Figure 2). These include a client application for recording and uploading sensor data, a service for storing and processing the uploaded data using the Amazon Elastic Compute Cloud (EC2) platform, a module for converting raw sensor data into location data, a service for visualizing the results, an object for archiving data in a database, and a service that allows other researchers to access the data. Each component can be replicated an arbitrary number of times, making it possible to support additional users by deploying the software onto servers as needed.

A. Data upload client

The sensor client application passes data from the wearable sensor on to the data processing application. It is run on a centrally-located computer in the vicinity of the user. The shoe-mounted sensors transmit raw binary IMU data and RFID data to the application via Bluetooth. The binary data stream from the sensor is parsed and uploaded in realtime to the data processing application (B) via TCP. Running the data upload client on a central desktop or laptop computer restricts the possible monitoring area to the maximum range for Bluetooth transmission between the sensor and the paired computer. A 2nd-generation revision will use an application running on an Internet-enabled Android phone. This will compensate for Bluetooth's limited range and allow for a larger monitoring area within the home or building.

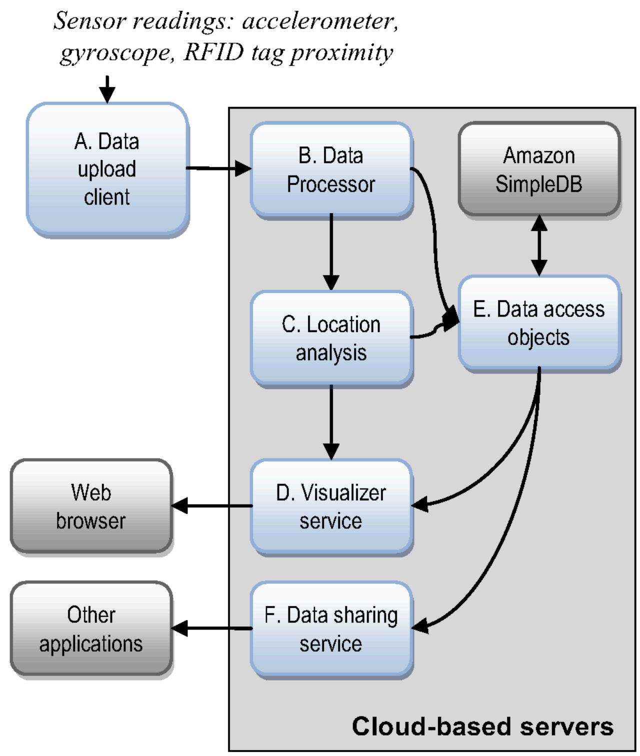

Figure 2. Software architecture integrating data acquisition from sensors with cloud-based analysis to provide real-time location tracking for an arbitrary number of users.

B. Data Processing Application

The data processing application acts as a hub with data flowing in from the sensor client application and out to the data storage and visualization applications. It invokes a location analysis component (C) that processes sensor data into location data, and is hosted on an Amazon EC2 virtual machine. Optionally, raw sensor data may be sent to the data storage and recorded to AWS SimpleDB via the data objects (E). Archiving raw data in this fashion is not necessary for location analysis and leads to higher overall costs, but may be desired in some situations, such as when another researcher wishes to retrieve the data for use in other applications via the data sharing service (F).

C. Location analysis

Raw sensor data are converted to location measurements using a Kalman filtering library written in Haskell, initially prototyped in our prior work [16]. This code has been compiled as a dynamic library where data can be streamed as part of the data pathway on a cloud server. This library is loaded using a Python script, and data are inputted and retrieved using Python ctypes module.

D. Visualizer service

The web-based location visualization application displays each user's location and recent path on a map shown in a web page (Figure 3). It also provides an interface displaying customizable statistics (e.g., for computing and displaying activity metrics and gait velocity). HTML5 was used to facilitate output to a wide range of browsers and support real-time data display by continually receiving the latest location data via the standard WebSockets API. Thus, the output of the visualization service can be embedded into any web page, including web pages on other sites, via an iframe. A future revision will improve latency by implementing a visualization tool as a Java GUI application using conventional TCP sockets.

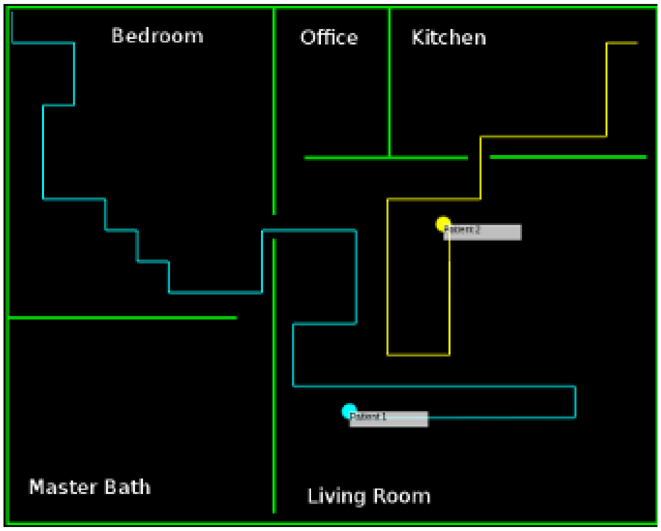

Figure 3. Visualizer servlet output, showing positions of users along with simulated paths in a virtual house.

E. *Data objects*

Servlets interact with the Amazon SimpleDB database through data access objects (DAOs), which provide an interface for retrieving, persisting, and deleting the two types of data objects: channels and packets. A channel represents a stream of data from a single source, such as a stream of gyroscope measurements. The data are contained in packets, consisting of a series of measurements over a short timespan, such as 1 second. The DAOs store and load packets for channels, while providing a query-based functionality so that packets for a specific time period can be retrieved, annotated with additional metadata, and recorded back to the database. In our system, the DAOs are used to archive data in SimpleDB so that it can be retrieved later using the data sharing service (F).

F. *Data sharing and storage service*

The data sharing service, needed for integrating our system with other programs, is a web application hosted on Amazon EC2 servers with autoscaling, managed by Amazon Elastic Beanstalk. The interface for retrieving data is an HTTP servlet implemented in Java, while Apache Tomcat was used as the JSP/Servlet implementation. The requirements for the application were to retrieve data using an Amazon cloud storage service, and provide an API for downloading the data via HTTP. This HTTP interface for stored data provides a standard mechanism for data analysis and retrieval by other tools. It can be used as a data provider for a wide range of web-based and other applications. The entire application runs on Linux (within an Amazon virtual machine) and, as with other components of our system, is easily deployed onto multiple physical machines.

IV. SYSTEM TESTING

We performed unit testing to validate functional correctness of our system components, as well as integration testing that stressed the amount of users' data that can be processed per unit of server capacity, thereby indicating how much capacity is required to track a given number of users.

A. *Unit and manual tests*

A combination of JUnit and manual tests were conducted. JUnit tests uploaded data, invoked the location analysis component, and retrieved data for visualization. The accuracy of the location analysis component had previously been tested [16]. All components of the system satisfied respective unit tests. In addition, full end-to-end tests were run manually, where the system uploaded data from sensors, invoked the location analysis algorithm, stored the results into SimpleDB, and displayed the output.

B. *Throughput and latency tests*

We configured the system to use one Amazon "large" server (equivalent CPU capacity of four 1.0-1.2 GHz 2007 Opteron or 2007 Xeon cores, with 7.5 GB shared RAM) to run our data processing and location analysis tools. A separate machine streamed IMU and Gyroscope data (collected during testing) to the server, simulating multiple users. In order to prevent network latency outside the Amazon platform from affecting performance, the data generation server was hosted on another Amazon EC2 instance within the same data center. For each of several 10 minute periods, this server sent 50 samples per second (the sampling rate that we previously demonstrated in our prior work [16]) per accelerometer and gyroscope axis to the location analysis server and recorded the time required for the system to generate location output.

We found the system latency remained relatively constant while tracking up to 6 users simultaneously (Figures 4 and 5), with an average latency of 750 milliseconds. With 7 simulated users, average latency started to increase. Thus, our system is capable of providing continuous near-real-time tracking of 6 to 7 users per server. Because additional users could be tracked with additional servers on separate data storage units, the number of servers is expected to scale linearly with the number of users.

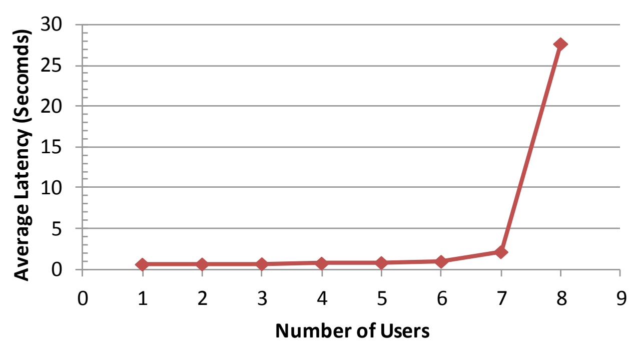

Figure 4. System latency rose when throughput reached 7 simulated users per server (~ 2.1k samples per second).

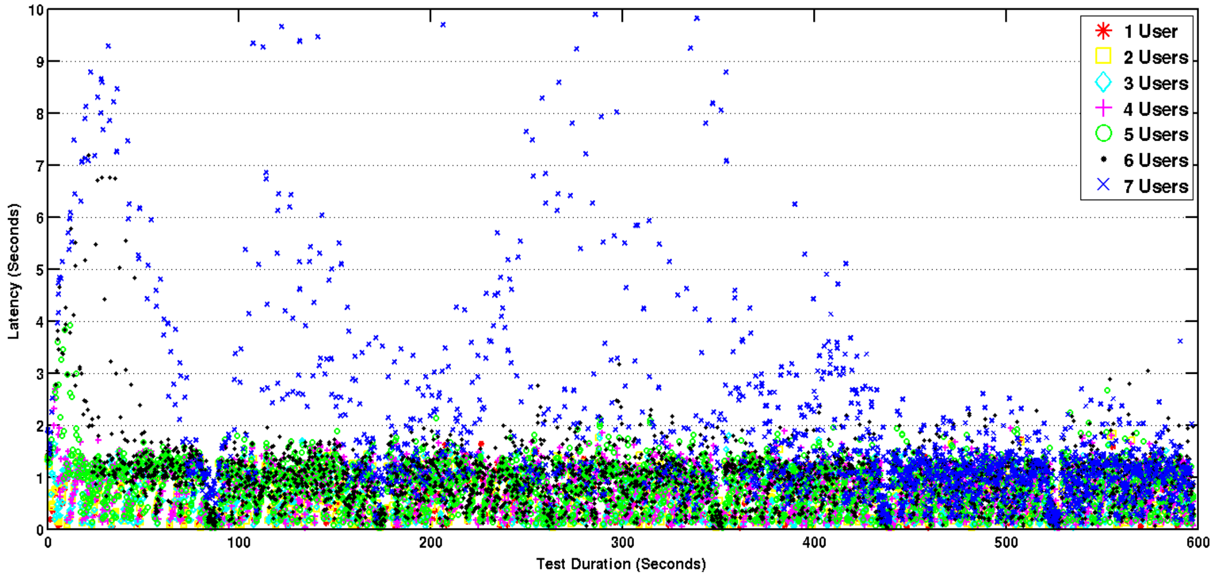

Figure 5. Latency consistently remained under 2 seconds until throughput reached 7 simulated users per server.

V. Conclusion

We demonstrate a cloud-based software infrastructure for real-time location tracking. Each server can continually track 6 people simultaneously, with no limits on the number of people that could be tracked in parallel by multiple servers. The next step will be to test reliability through a long-term field study. Security should be evaluated and tightened, to ensure that data from sensors are authentic. Further work could enhance performance so more users can be served per server. We also could augment the location-tracking algorithm with knowledge of the space being navigated, potentially allowing us to use filtering techniques based on where the device is not (e.g., no walking through walls or furniture) giving higher accuracy with relatively little computation. The resulting system is expected to serve as the basis for additional studies into the association between daily activities and health outcomes, thereby helping elderly people live independently as long as possible.

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