SilverLink: Smart Home Health Monitoring for Senior Care

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Abstract. Senior care has become one of the pressing societal challenges faced by many developed and emerging countries, including the US (the aging baby boomer) and China (the reverse 4-2-1 family pyramid due to one child policy). Despite failing health, most senior citizens prefer to live independently at home and hence the focus of current healthcare technologies have shifted from traditional clinical care to "at-home" care for the senior citizens. We propose to develop SilverLink, a system that is unique in its smart and connected technologies and will offer: (1) affordable and non-invasive home-based mobile health technologies for monitoring health-related motion and daily activities; (2) advanced mobile health analytics algorithms for fall detection, health status progression monitoring, and patient health anomaly detection and alert; and (3) a comprehensive patient health activity portal for reporting user activity and health status and for engaging with family members. This system will initially be launched in the US, in China and in Taiwan and will aim to overcome the limitations of existing home-care solutions.

Keywords: Health big data · Home health monitoring · Health progression monitoring · Senior care · Gait analysis

1 Introduction

Senior citizens face many challenges to their independence, including a decline in mobility or cognition or chronic physical health conditions that compromise their ability to maintain their independence. For example, according to data from the National Safety Council, there were 12,900 deaths from falls in 2003 among those over the age of 65; with 7,500 of those deaths occurring in homes [1].

Presently, friends or family members provide care for most senior citizens. Family caregiving is both emotionally and physically demanding and is generally unpaid. According to a study, the estimated value of this unpaid care is $257M dollars annually [2].

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As most senior citizens prefer to "age in place," the number of older adults living alone continues to increase with at least one out of three non-institutionalized senior citizens living alone [3]. Independent living (e.g., private households) will be an important housing option for the future, particularly for the newly aged [4]. The applications of in-home monitoring technologies will have enormous potential for assuaging the burdens of caregivers and family members.

There are several potential technologies under development for remote health monitoring. These technologies range from in-house lifestyle monitoring to fall detection and monitoring of health vitals such as blood pressure, etc. [5]. The major limitations of existing products in this category include the high cost of technology, lack of flexibility in use, and limited one-dimensional data collection and analytics to "intelligently" monitor health status of senior citizens at-home. Even with recent developments, there is a need for an affordable but smart and non-invasive health monitoring system. Hence, we are motivated to develop, evaluate, and commercialize an easy to use, all encompassing smart and connected home health monitoring system, called SilverLink. SilverLink combines personal emergency response, lifestyle monitoring, and advanced analytics for providing more effective remote care to senior citizens at an affordable price. The significance of the innovation lies in the system's unique ability to combine unobtrusive assistance with real time data monitoring and emergency alerts, and preventive care including health progression analysis and fall risk prediction on an easy-to-use platform.

2 Literature Review and Related Systems

2.1 Mobile Health Monitoring Techniques

Remote monitoring devices gather data about patients' status and relay it to healthcare providers/caregivers on a regular basis. They have not only helped patients to manage a variety of chronic diseases, but also paved a path for communicating with patients beyond the acute care setting. Lifestyle monitoring is crucial to health management for the elderly, who often forget to perform everyday tasks such as taking medications, etc. Mobile health monitoring techniques often use environmental sensors, video recording tools, and/or other surveillance equipment (either alone or in combination) to monitor patients at home. These techniques are often used in conjunction with cloud computing and are often limited in their functionality. Lack of privacy is also a major issue with most monitoring techniques.

Another application of mobile health monitoring is monitoring human motion. The way a physical activity is performed by a human is highly indicative of their health and quality of life. Quantification and reliable measurement of daily physical activity can allow an effective assessment of a person's daily activities as well as the effects of numerous medical conditions and treatments, especially in people suffering from chronic diseases such as arthritis, cardiovascular or neurodegenerative diseases that can often affect gait and mobility [6]. There are several studies in the fields of activity identification, motion tracking, and exercise monitoring including gait monitoring and fall detection. Most products developed in labs use more than one sensor to gather data for analysis of gait pattern. The greater the number of sensors attached to the users, the more accurate the gait that can be modeled from this data. This research is promising but has been mainly conducted within a lab environment and may not be applicable to real life situations: a drawback of existing gait monitoring devices.

2.2 Health Activity Portals and Support

Due to health and mobility issues, an elderly person's world is often smaller — both physically and socially. Digital technology has an obvious role to play here by connecting people virtually when being together is difficult or impossible. Research shows that "persuasive technology" [7] such as in the form of personal messages, frequent communication via photos, videos, and other means can often help motivate people to change their attitudes, and in turn better manage their health. For example, portals such as DiabeticLink provide a platform for diabetics to track and easily visualize health data on the portal and improve health outcomes by monitoring how one health factor can affect another [8].

2.3 Advanced Mobile Analytics

Due to the progress in mobile and sensor technology, it is now possible to collect healthcare information about any patient in a home-based environment. Data collected can range from movement of objects (e.g., displacement of a pillbox) to human motion (e.g., walking, jogging, sitting). This collected data can be used to document medical trends and further analysis of the collected data and patterns can prove useful in predicting health outcomes, thus reducing costs associated with treatment.

Today, healthcare analytics is moving toward a model that will incorporate predictive analytics and enable creation of more personalized healthcare, by predicting patient behavior [9]. Falls are among the most common and serious problems facing older adults and are associated with considerable mortality, morbidity and reduced functioning. Presently a combination of accelerometers and gyroscopes are used to collect data for predicting risk of falls. Electrocardiogram (ECG) data is commonly used to monitor arrhythmias that cause syncope resulting in falls. Capillary finder stick glucose readings are also used to signal hypoglycemia, a condition that contributes to falls. The common algorithms used for pre-processing the signal data include low-pass filtering and wavelet filtering. Variables that can be drawn from such signals to predict the risk of falls include angular velocity, linear acceleration, etc. One limitation of existing tools is that they lack monitoring capabilities for progression of Frailty (slow and natural health deterioration) in older adults.

The existing solutions to home health monitoring are divided into two main categories: (1) Personalized Emergency Response Systems for fall detection and signaling for help and (2) Home-Use Monitoring with Sensors for mobile health.

Personalized Emergency Response Systems (PERS). This is one of the most widely used technology-based home care solutions today. PERS provides an easy way to summon assistance, with the push of a button, in case of an emergency. Advanced PERS also possess fall detection capabilities; however, they do not provide all the components of home health monitoring, e.g., activity monitoring, medicine reminders, etc. Some examples of these devices include Alert 1, Phillips Medical Alert System, Bay Medical Systems and Medical Guardian. None of these systems can actively monitor user at-home activity or health status or provide any “intelligent” or proactive assistance. In addition, Internet-connected fitness wristbands (e.g., FitBit) and health-monitoring smart watches (e.g., Apple Watch) are gaining traction with the youth. These devices use accelerometers for activity level tracking and calorie counting, sensors for heart rate and temperature measurement, and GPS for location tracking. Despite their emerging popularity, such devices do not target home care or activity monitoring for the aging population.

Home-Use Monitoring with Sensors. Some of the more basic and mature home monitoring systems such as home security systems (e.g., ADT home security) and home video surveillance (e.g., Nest Cam, ADT Pulse) do not adopt or leverage advanced multi-sensor technologies or cloud-based intelligent analytics services. Some Smart Home researchers used object sensors with pressure sensors on the floor to recognize users’ daily activities, which is not easily applicable in real home settings [10]. Among the emerging technology leaders in this space, MyLively has shown the most promise. Despite its initial validation, MyLively lacks several critical functionalities such as gait analysis; health progression monitoring; health tracking and a proactive analytics algorithm to generate automated alerts upon detection of health anomalies.

3 System Design

3.1 SilverLink Architecture

The SilverLink system consists of both hardware and software components for various types of home monitoring and analytics services. The hardware components include multiple sensors; a home gateway and an SOS alarm pendant/wristband. The software components consist of data collection API, a database, an analytics engine and a web portal. The overall service architecture is shown in Fig. 1. The SilverLink system will use object and human sensors placed inside a user’s home for the purpose of remote monitoring. The object sensors will be attached to relevant household objects that can help indicate user activity or health status based on users’ preference and lifestyle, e.g., pillbox (indicating medication compliance), refrigerator (indicating regular food intake), shower or bathroom door (indicating personal hygiene routines), front/garage door (indicating exiting/entering a home), etc. The human sensor (one for each user) attached on the user’s body at all times will continuously record any motion performed (walking, sitting, falling) by the user. The user will also be provided with an SOS alarm pendant/wristband for emergencies. A pre-configured gateway will use BLE and 3G communication techniques to receive and transmit data collected from the sensors to the Datacenter where the advanced analytics engine will then process this data and check for any abnormalities in the movement patterns.

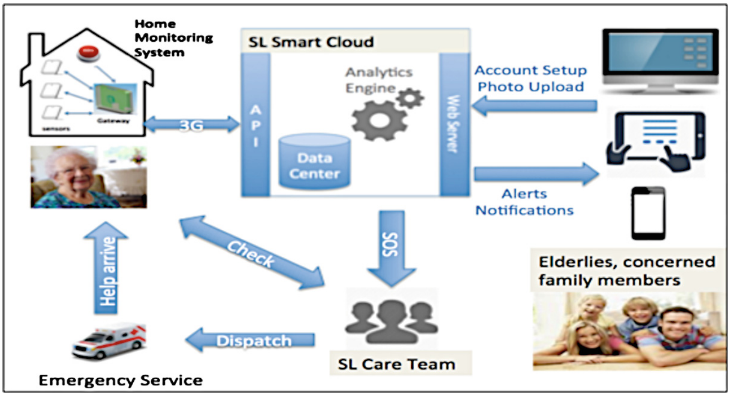

Fig. 1. SilverLink architecture: hardware (sensors/gateway), software (analytics/portal), and services

The SilverLink web portal will provide a platform (on devices such as laptops, tablets, mobile phones, etc.) to visualize the health information collected by the sensors. The analytics engine will process the data to make deductions based on pattern recognition and these deductions will in turn stimulate notifications/alerts when a shift in pattern in detected. The personalized response system with the SOS alarm button can be activated (by the user) to alert the emergency response team, who will confirm the emergency via a telephonic call and check for false alarms. Upon receiving a confirmation (or in the event that no contact is established) the emergency response team will be sent out to the user's residence to provide the necessary help.

3.2 Hardware Design for Home Activity Sensors and Gateway

SilverLink has three types of activity sensors: (1) object sensors, (2) human sensors, and (3) SOS alarm pendant/wristband (Fig. 2a and b). The object and human sensors are comprised of high-sensitivity tri-axis acceleration chips. Each sensor further includes a wireless communication system, such as Bluetooth (e.g., BLE 4.0) and will periodically emit signals to indicate the sensor status and to synchronize the sensor with other components of the monitoring system. A coin cell battery will power the sensor enclosed in a lightweight and durable casing with an attachment mechanism that allows the sensor to be attached to a variety of different objects. For human motion monitoring, the sensor will have an additional hook or loop for users to easily attach the sensor to their belt/keychain.

The SOS alarm (Fig. 2b) will comprise of an easy-to-use push button alarm sensor that will be used to send a distress signal. LEDs on the body of the alarm will indicate the status of the signal (i.e. sent to/received by the datacenter) to the user.

The home gateway (Fig. 2c) will typically be located inside the residence of a user and will be configured to receive signals and data transmitted from one or more sensors placed inside the house (object sensors) or on the user (human sensor). The home gateway comprises of a CPU, BLE and 3G module and will also be configured to transmit information to other components in the system such as the cloud-computing network. The gateway's 3G module (selected for its wide availability, low cost, and stable performance) will be used for maintaining a wireless Internet connection, while a BLE controller will be used for communication with other devices in the system, including the sensors. Programming interfaces, in communication with the gateway's CPU and BLE controller, respectively, will also be included. The gateway will include typical status indicators relating to power, connectivity, etc.

Fig. 2. **a.** (left) Customizable object and human sensors prototype; **b.** (center) The SOS alarm prototype; **c.** (right) The Home Gateway prototype.

3.3 Data Collection API and Activity Database

The data collection API will be used to collect data from the different sensors placed in a user's home. A datacenter will be configured to store raw data collected from activity sensors and send it to the datacenter via the gateway using a 3G-communication protocol. Examples of the types of data stored in the tables include gateway, sensor and system information; raw sensor log data; sanitized data for analysis; processed data representing user activities; and web portal management data such as user login and profile, links, notifications, etc.

3.4 Process Design for Advanced Analytics Engine

SilverLink's novel analytics engine is configured to process and analyze data obtained by other components of the system. Accordingly, the analytics engine employs an algorithm (e.g., an abnormal pattern detection algorithm) to perform such tasks as advanced pattern recognition. Figure 3 shows the flow of data through the monitoring system and the analytics engine. Data is sourced from the remote sensors and transmitted through the monitoring system to the data collection API such that a set of raw sensor data is generated and is subjected to data transformation and integration steps for noise reduction and sanitization. Various analytics approaches including pattern recognition and signal detection to generate user activity data and define signal patterns are then performed on the data. These signals will then either be recorded and stored in user activity tables or used to send out notifications to family members/caregivers.

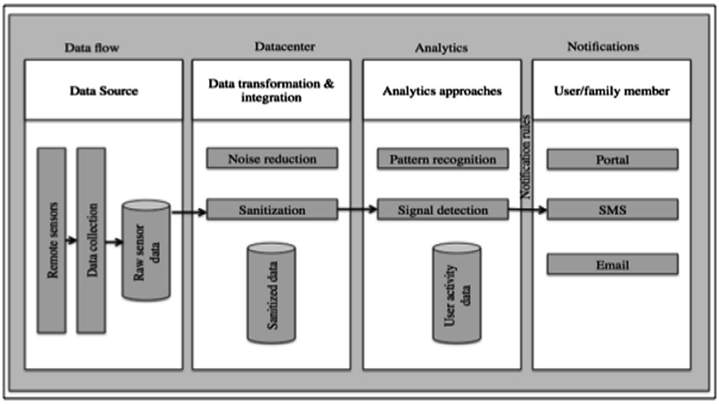

Fig. 3. SilverLink software design: data flow, datacenter, analytics, and notifications

3.5 Design for SilverLink Web Portal

The SilverLink web portal is an online monitoring and data visualization tool designed to allow family members/caregivers to remotely monitor their loved ones.

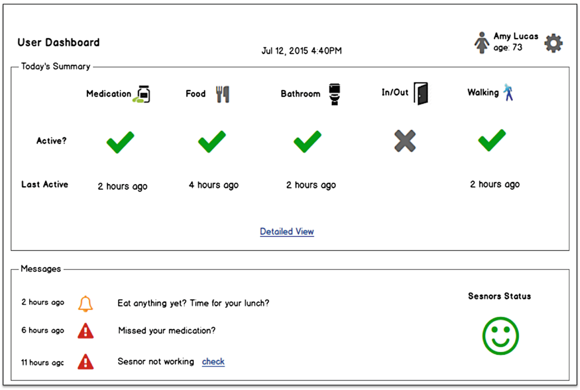

Fig. 4. SilverLink's user dashboard displaying a user's activity summary for the day

The SilverLink web portal offers utilities such as user sign in or registration (sign up), user dashboard to view monitoring data (Fig. 4), sensor configuration (sensor status and location of the sensor), notifications, notification settings (selection of the threshold for notification/alert generation) and administrative options (adding or editing a new user profile). It provides a passage for communication between the user and their family member through a feature called SilverMail, a video and photo-sharing interface. The web portal provides password-protected access to registered users and will be accessible from, or transmit information to computers, tablets or smartphones.

4 Preliminary System Evaluation

4.1 Objective

The aim of evaluating the system was to obtain feedback on various aspects of SilverLink's design and usage for system improvement and to uncover areas of potential research to help in advancing SilverLink's capabilities in the field of senior care.

4.2 System Evaluation Methodology

The SilverLink system evaluation (IRB approved through the University of Arizona) was conducted using two approaches. In the first approach we conducted introductory research by interviewing potential users (i.e., senior citizens, their caregivers/family members and physicians) to gauge user need and obtain preliminary feedback on the current version of the SilverLink prototype. The second approach was to test the prototype in a laboratory setting (or mock home environments) to evaluate factors such as the operating distance between the Gateway and the sensors (range), battery life, data transmission rate, data loss rate, system errors, stability of the website and the capabilities of the analytics engine. The preliminary interviews were conducted in the US, whereas the laboratory tests were conducted in the US and in Taiwan.

5 Preliminary Findings

The alpha prototype of the SilverLink system was developed in April 2015. Results from the preliminary evaluation (April–August 2015) of the alpha prototype are summarized below.

5.1 SilverLink Taiwan Evaluation

Internal System Testing. The internal tests were conducted in three different home settings. The floor plan and house structures were carefully selected to bring diversity to the test scenarios. There were five separate tests that were conducted on each of the sensors (1 human sensor and 4 object sensors) and their signal activity was measured at distances of 1 M through to 10 M. During the tests, the subject wore the human sensor at all times, i.e. while walking, sitting and sleeping. The object sensors were placed on objects such as pillboxes, refrigerator door, front door, and the bathroom door while a subject was asked to displace each object in predefined test cases with 5 repetitions. It was found that the pass rate (the number of times the system recorded the event divided by the actual number of events) was 70–80 % for object sensors while it was less than 60 % for the human sensors. The average range of the object and human sensors was found to be approximately 7.3 m.

5.2 SilverLink US Evaluation

Preliminary Interviews. The preliminary evaluation of the SilverLink prototype included introductory interviews conducted with several potential users. The 9 interviewees included a 72-year-old patient with Parkinson's and his wife, an 85-year-old man afflicted with Spinal Stenosis and his caregiver, a couple (female aged 68 and male aged 75) who had recently experienced a fall, two physicians, and an expert working with a local center on aging. These interviews were very useful in determining the need for a system like SilverLink. The wife of the Parkinson's patient commented, "This system will put me at ease whenever I am away from my husband." while others provided feedback on the size of the SOS wristband. One interviewee said, "It is too big and I would not like to wear it on my wrist." Another observation during these interviews was that the elderly people often have trouble wearing watches due to conditions such as arthritis and hence it was determined that a wrist band may not be the most suitable form for an SOS alarm. A domain expert also provided research findings from previously conducted form factor studies and this information was critical to the redesigning of the SOS alarm.

Internal System Testing. To estimate the signal loss rate, one internal subject (male, age 23, of average height and weight) was fitted with two sensors, then asked to perform a series of actions including sitting, standing, and walking, at locations of varying distances from the gateway. Three locations were selected to test whether the sensor-gateway distance will affect the signal loss rate. At Locations 1 and 2, all actions were performed within 5 meters from the gateway. At Location 3, the sensor was around 10 meters from the gateway, and there existed a wall between them. The signal loss rate varied between 30 to 70 % at Locations 1 and 2, but increased to 90 % at Location 3. In one instance at Location 3, the gateway did not receive any signals at all. Based on the initial test results, a future improvement will be enhancing the stability of signal transmission.

6 Preliminary Mobile Sensor Research

6.1 Research Design

While living alone, a senior person may encounter different scenarios that are worth attention from his/her caregivers. For instance, (1) walking at a normal speed around the house performing daily chores; (2) walking at a drastically decreased speed on a certain day; (3) sitting on a chair for most part of the day and seldom standing or walking; or (4) lying on a bed for 24 h. Such situations are often indicative of a person's health condition (such as healthy, improving, deteriorating or even in a state of emergency). Inferences drawn from such data can help a senior citizen's caregiver and/or doctor to formulate focused health plans. The human sensor used for activity/motion detection contains a tri-axial accelerometer, which tracks the user's actions and sends acceleration signals to the gateway. Analytic algorithms are needed to aggregate the signals to high-level parameters (e.g., walking speed and step count) and make meaningful inferences. Najafi et al. [11] proposed activity recognition algorithms based on a single tri-axial accelerometer, much similar to our setting. However, the location for the accelerometer is restricted to the center of the chest, and its orientation has to be determined beforehand, i.e., the sensor cannot be set upside-down or be tilted in an arbitrary angle. Furthermore, high sampling frequencies (40 to 120 Hz) are preferred in such studies, which, lead to a limited battery life for the sensors (15 days at maximum).

The first part of our research is focused on developing an algorithm (for the human sensor) to deliver the walking speed of a user, using a sampling rate of 10 Hz with extended battery life, 30–50 % physical data loss, arbitrary location for sensor attachment (firm and not dangling) to the user, and an arbitrary orientation of the sensor. Solving the motion detection problem in this real setting has been a challenge for researchers. We aim to solve this problem by reconstructing the inertial reference system based on the tri-axial acceleration signals. Further inferences (e.g., posture/activity recognition) will also rely on this algorithm.

The second part of our research is Activity of Daily Living (ADL) Recognition. Activity of Daily Living refers to the basic self-care activities performed by a person each day. Analysis of activity data can reveal patterns that are indicative of a person's lifestyle and can be used to improve health outcomes, especially for senior citizens. Current research is based on using only object sensors, e.g. pressure sensors for ADL recognition. However, in a real home setting, using object sensors or human sensor alone is not sufficient for ADL recognition as the activity performer's information is not included in the object sensor data. For example, in the case of a caregiver preparing lunch for a user, the activity of opening the fridge detected by object sensor (attached to the fridge door) can be associated with either the caregiver or the user in the room. The object sensor fails to distinguish between the user and the caregiver. Similarly, the human sensor alone does not provide sufficient data on the kind of activity a user performs. Our preliminary research is focused on evaluating how the use of object sensors with a human sensor (with the advanced algorithm) can give us a better understanding of a user's ADL and help in ADL recognition.

6.2 Preliminary Research Findings

As part of our preliminary research, we used our sensors to collect data patterns for different user motions such as running, walking, standing, sitting and falling down. These patterns will be instrumental in developing the algorithm for pattern recognition and health prediction for senior citizens. Figure 5a and b show a graphical representation of the patterns obtained while a person is walking, running or falling down respectively. These patterns are far more complex and varied in real life and identifying them to make meaningful inferences is an integral part of our research.

For preliminary research on ADL, we used both an object sensor and a human sensor together to determine their combined effectiveness in ADL recognition. Several experimental scenarios were set up in a home environment to understand the interaction between a user and the object. In every scenario, the human sensor was attached to the user's left shirt pocket. Object sensors were placed on a fridge door, a chair in the kitchen, a pillbox, and a bathroom door. Each pair of scenarios compared interactions

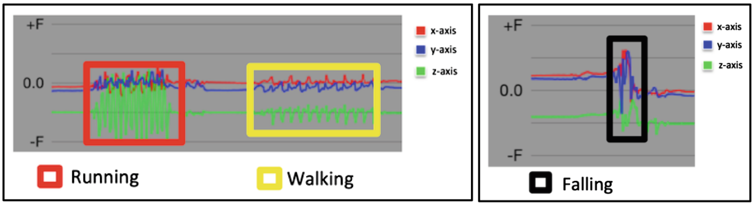

Fig. 5. **a.** (left) Represents running and walking motion; **b.** (right) Represents a person falling

between user performing the activities and others performing the activities while the user is simply moving. For example, scenario pair 1&2 involved (1) user walking to the fridge and opening the fridge door (2) Finding and grabbing items (3) Closing the fridge door and (4) Walking away. In the plots (Fig. 6a and b), the x-axis denotes the time and y-axis denotes the acceleration level. The shaded area depicts the time period when the fridge was open (from the first triggered signal to the last triggered signal). In Scenario 1, we noticed that user's interactions with the fridge resulted in a difference between motion data collected inside and outside the shaded time period. In contrast, movements captured by the human sensor in Scenario 2 were consistent throughout all time periods. We can infer that the user's movement and "using the fridge" activity has less relevance compared with Scenario 1. This observation result introduced an efficient way to extract human-object interaction that could be a helpful feature or criterion in user's ADL recognition.

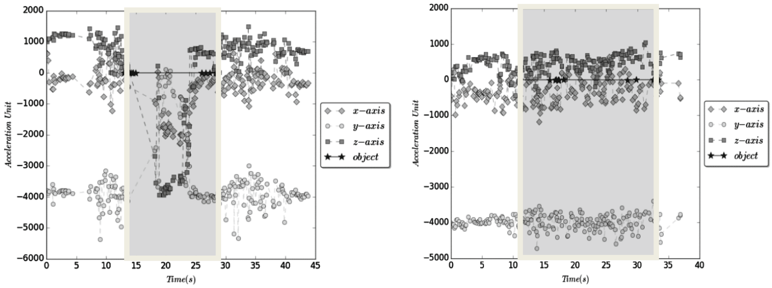

Fig. 6. **a**. (left) Scenario 1: User used the fridge. **b**. (right) Scenario 2: Others used the fridge while the user was walking.

7 System Improvement and Future Development Plans

Presently, the team is focusing on improving hardware and software functionalities such as operating range, battery life, SOS design, stability of data transmission, and data visualization on the SilverLink web portal. Further research into utilizing both object sensors and human sensors for the ADL recognition will be conducted and will be accompanied by detailed gait analysis (using human sensors) and algorithm enhancement (for determining the walking speed in users) to better understand cases with arbitrary sensor orientations (e.g., vertical to horizontal). The team will also be conducting an extensive 100-person interactive user study (in the US, China and Taiwan) to obtain further feedback on updated versions of the system.

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