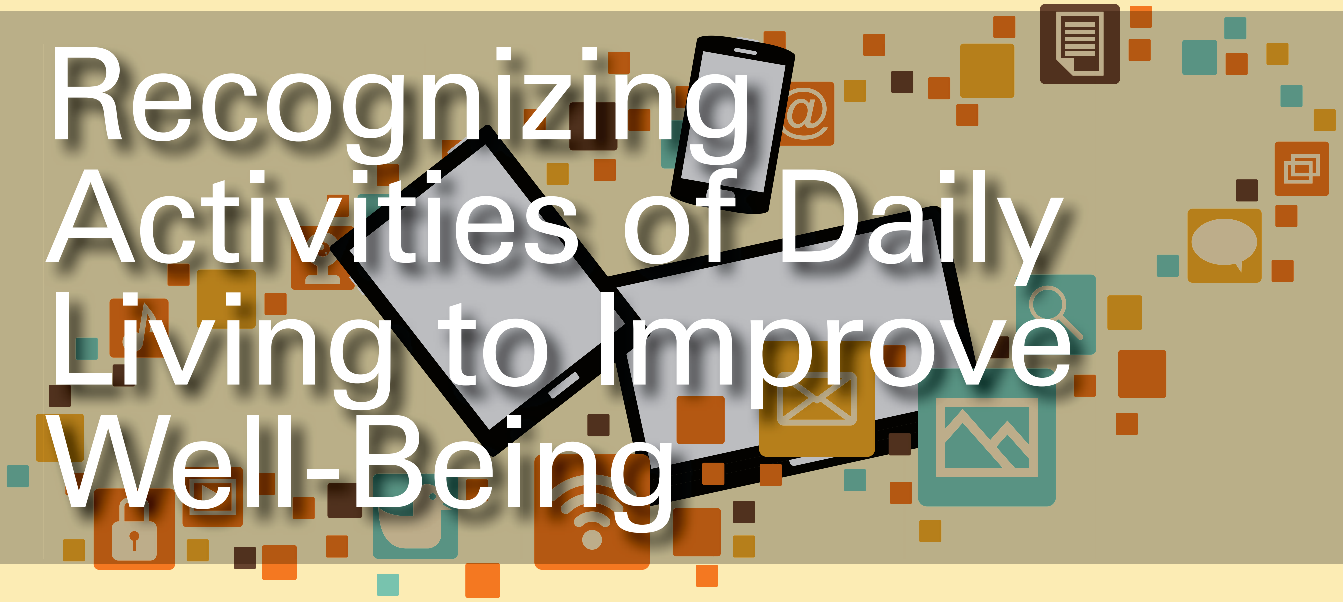
Recognizing Activities of Daily Living to Improve Well-Being



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Mobile devices such as smartphones play an important role in the Internet of Things. The authors' single-point service deployment system aims to improve people's well-being by collecting and analyzing mobile data pertaining to users' activities of daily living.

The term *activities of daily living* (ADLs) refers to those routine activities a person can finish without external help.[1] They are generally categorized into six groups—namely, eating, bathing, dressing, toileting, transferring (such as walking), and continence. The extent to which people can persistently perform ADLs serves as an important measure in evaluating their health status and need for long-term care. Older adults often suffer through several stages of physical and cognitive degradation in which ADL performance continues to decrease with age.

For example, staff members at an assisted living facility that receives government subsidies might be required by regulation to collect residents' ADL data on a 24/7 basis, especially when caring for those with cognitive impairments such as Alzheimer's disease. Specific problematic areas such as wandering, falling, sleep quality, or memory lapses have drawn researchers' attention.[2] Current off-the-shelf tracking tools hosted on smart health devices (smart watches, smart bands, walking activity trackers, and so on) fail to measure up to their potential for dealing with complex ADLs due to limited functionality. Most activity trackers on the market monitor only basic fitness data, such as calories burned, steps taken, miles run, or heart rate achieved.

To tackle these difficulties, researchers have proposed ideas such as installing numerous traditional sensors across a smart home environment for detection purposes. Examples include

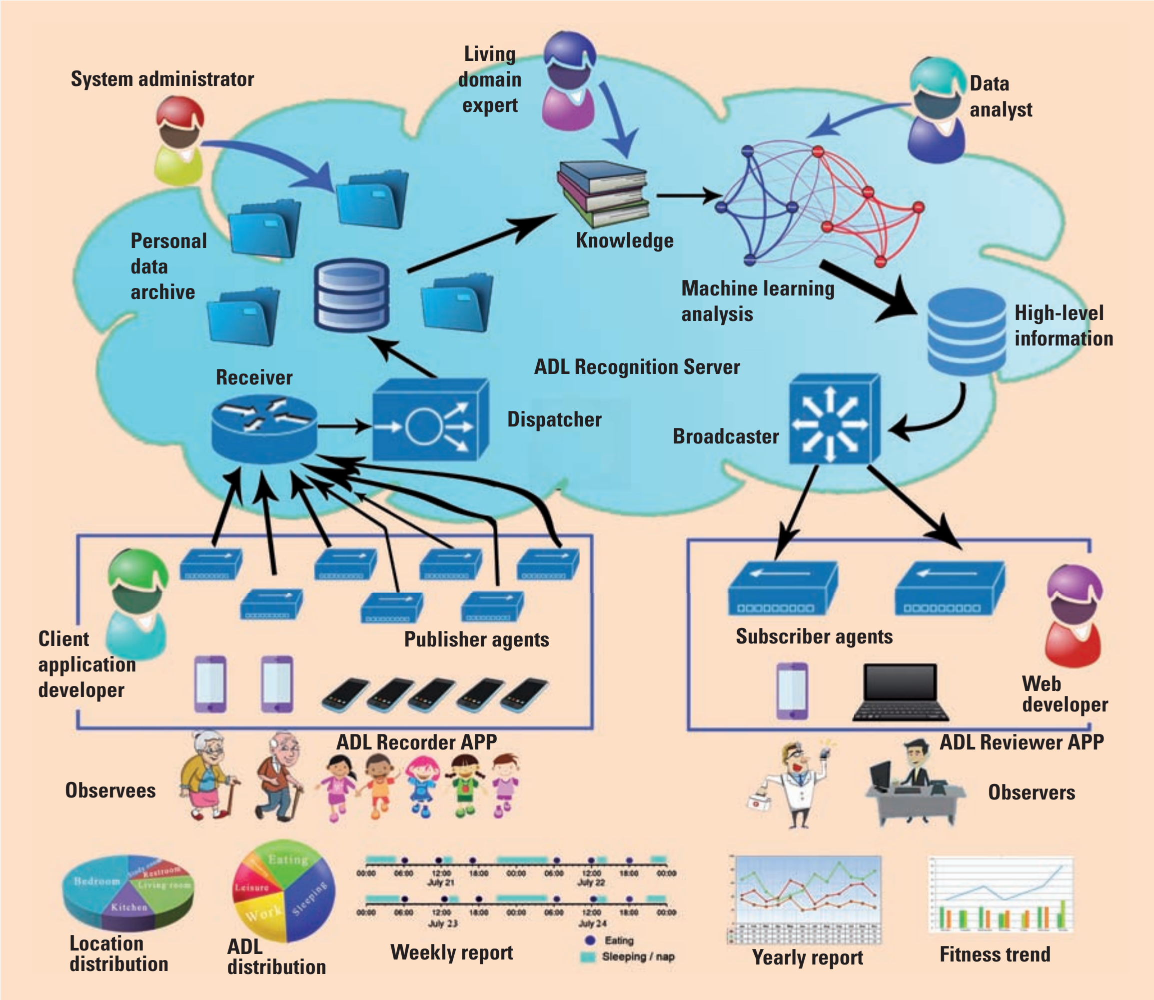

Figure 1. Architecture of the activities of daily living (ADL) recognition system. The architecture is built on an agent-based information management platform.

door contacts,[3,4] infrared sensors,[3] button sensors over lamp switches, and microphones near faucets.[3,4] Other systems exploit advanced computer vision techniques to recognize video images by either conventional camera or Kinect. However, because personal privacy is a serious concern, such vision-based monitoring systems tend to lose users' trust.[5]

Despite all these advances and trials, the deployment and maintenance costs of sensing and monitoring equipment, which is usually nonportable, remain high. A noticeable step forward is *body sensor networks* (BSNs),[6] which resort to body-contact sensors such as chest, finger, or waist nodes[7] to increase the portability of sensor deployment. However, users must be loaded with sensors, a feeling that is usually uncomfortably burdensome. Recently, researchers also suggest that a "medicalized smartphone" might enter the landscape of the "Internet of Medical Things" to help improve modern medicine.[8]

Functionality, cost, and comfort are business drivers and the major factors for subscribers to appreciate and sign onto a smart living environment. To provide those who would like to participate in smart living with enhanced user experiences at affordable costs, we present an ADL recognition system characterized as an affordable, single-point smartphone-based mobile application.

The ADL Recognition System

At its front end, our recognition system has an ADL Recorder App for ease of activity recording and an ADL Reviewer App to enable a variety of functionalities.[9] The back-end supports include sophisticated data fusion and recognition analyses deployed in the cloud. The overall system architecture is shown in Figure 1. Compared with

BSNs, our ADL Recorder App has been designed to substantially free users from excessive physical burdens and increase comfort.

Standard devices bundled with modern smartphones—in particular, various embedded sensors—directly enhance our ADL Recorder App. This app launches a background service that commands the embedded sensors to capture human users' multimodal data, reflecting both behavioral and environmental contexts. Once launched, the app works for its entire duration in the background, fulfilling its promise not to add an uncomfortable physical burden to users or require them to have any special training.[10,11]

The data collected by the ADL Recorder App starts with the device's various embedded sensors, including the microphone, Wi-Fi scan module, heading orientation of the device, light proximity, step detector, accelerometer, gyroscope, magnetometer, and time stamp. The ADL Recorder App uses the fact that, most of the time, mobile devices with embedded sensors are handily and intimately carried by human users. This negligent gap between the sensors and the application user significantly improves the odds of collecting accurate raw data originating from a user's behavior and from the surrounding environment that the user perceives. The instantly collected multimodal data then goes through data preprocessing, analysis, and fusion at the back end—that is, over the cloud—of the ADL recognition system.

Research Questions and Solutions

Our business system architecture can support the investigation of many pertinent research questions. For example, to conclude that a user walked up a stairway, the system needs a temporal sequence of that user's accurate position data. Complex problems remain. What if the user turns off her GPS module, accidentally or purposefully? What if the user moves indoors only in his less-than-spacious home (Q1)? If a user stays in one location but constantly moves her arms, or even changes her body posture, can these kinds of tiny motions be detected (Q2)? If a user is typing on a computer keyboard or turning on a microwave oven, can these kinds of motions be detected and made sense of (Q3)? Needless to say, these are all important problems to solve for the system to obtain accurate ADL details about the user.

To answer Q1 and Q2, our ADL recognition system offers robust positioning features and complies with the Global System for Mobile Communication (GSM) standard.[9] In addition to supporting GPS, its enhanced outdoor positioning solution also combines Wi-Fi fingerprinting technology supported by a localization classifier.[12,13] For indoor positioning issues, the ADL recognition system employs a light-based indoor positioning algorithm that enables positioning precision from room-level down to furniture-level. At its back end, the ADL recognition system performs data fusion operations on various sensory data from orthogonal modality dimensions. Data fusion algorithms help to determine users' activities, ranging from running, walking, standing still, sitting, lying down, taking an elevator, and so on.

To answer Q3, we resort to automatic environmental sound recognition,[14] which has been integrated into our system's back-end recognition server.[9] After the front-end ADL Recorder App records environmental sounds as an audio file for each session and transmits it to the recognition server, acoustic features are extracted from those audio files. Based on these acoustic features, the raw audio files are indexed in an audio feature database and classified into different activity categories. A state-of-the-art, hierarchical, situation-based[15–17] audition algorithm for ADL identification has also been implemented. Real-world experiments indicate that our system can be used to recognize audible events, audible actions (such as cutting vegetables and stirring eggs), remote audible events, and environmental sounds with high accuracy.

As we can see, different research questions necessitate different computer technologies and often require further study to improve the state of the art of relevant technologies. In fact, the employed business system architecture provides a suitable and inviting collaboration platform for interdisciplinary research, given that the envisioned tasks are far beyond any single research team's ability to handle.

ADL Recognition Services

To drum up acceptance and penetrate the market, we've ensured that subscribers of such an ADL recognition service need only turn on their cell phone, or any other mobile device that can be hooked up to the system. In our experience, the ADL Recorder App must evolve to embrace new types of sensor modules, or even new types of smart devices, such as smart watches, rings, or wristbands.[9] We use a minimal business model: besides being prepared for rapid market penetration as described, the business ecosystem value chain should include essential stakeholders, including a system administrator (similar to the Amazon Web Services business unit), client application developer, data analyst, web developer, and living domain expert.

We first examine the business system architecture (Figure 1) to enable the business model, with emphasis on the system components from a services computing perspective. In more concrete terms, in the age of the Internet of Things (IoT), system design, implementation, deployment, and maintenance face the following challenges:

- support the process of integrating new sensor type modules into the system as is, in an easy and less error-prone manner;
- enable the removal of dated, out-of-market sensor type modules from the system seamlessly and without errors;
- ensure the scalability and robustness of the server, given that real-time ADLs are identified through an increasing amount of data from growing customer populations;
- enable a smooth process for improving existing or adding new analysis algorithms targeting new types of sensor data without incurring unbearable system downtime; and
- lower the computational complexity for preprocessing a wide variety of data; simplify the process of audio data processing, acoustic feature extraction, and results labeling, as well as Wi-Fi-based positioning with machine learning.

To meet these challenges, our system-level design revolves around an agent-based *information management platform* (IMP—essentially, a platform as a service) that integrates service-oriented architecture (SOA) over the cloud. It features an observer-pattern-based ADL recognition server in the cloud to provide customized services (that is, software as a service) to its subscribing parties and clients. Note that there are two primary revenue streams: individual subscribers (fee-based) or a community, such as a doctor's office (license-based).

Based on the IMP, through the mechanism of publishers/subscribers, the observer pattern features an event-based asynchronous communication paradigm. It decouples service providers from service consumers. Combined with an SOA design that facilitates service reuse, our agent-based IMP gains the needed flexibility to meet the aforementioned challenges. Under the observer pattern, our IMP presents a unified set of programming interfaces—for instance, protocols and APIs—to hook up third-party publisher and subscriber agents.

An example subscriber agent is the ADL Reviewer that we offer (see Figure 1), which, as its name suggests, offers ADL record-reviewing services. The ADL Reviewer empowers both PC-based web apps and the mobile versions of web apps. An authorized family member, who takes the role of an observer, can use the ADL Reviewer to check out the historical ADL records of a particular observee. Statistical information can be provided in various visual ways according to the observer's queries, constrained by the corresponding temporal (time stamps) and spatial (location) relations. For instance, the observer can review a monthly report with inferred patterns of the observee's sleep activities.

The following users consume the services provided by the agent-based IMP.

Client application developers focus on service innovation, design, and optimization for the ADL Recorder App. The IMP registry provides URLs for the client application programmers as interfaces for posting raw data captured from an observee's environment to the cloud infrastructure server. Thus, after embedding the uploading module (publish agent), the ADL Recorder App readily publishes data packages to the IMP. To minimize data traffic for cost and energy efficiency, the ADL Recorder App offers an option for uploading data only in a Wi-Fi environment.

The *web developer* implements content presentation on the ADL Reviewer App to serve the observers. The IMP infrastructure generates the URLs for subscribers as interfaces, and each ADL Reviewer receives high-level messages via the subscriber agent. Thus, the IMP behaves as a "black box" for web developers, letting them implement the ADL Reviewer App fairly independently.

The *data analyst* is responsible for analyzing data with domain knowledge.[17] High-level outcomes

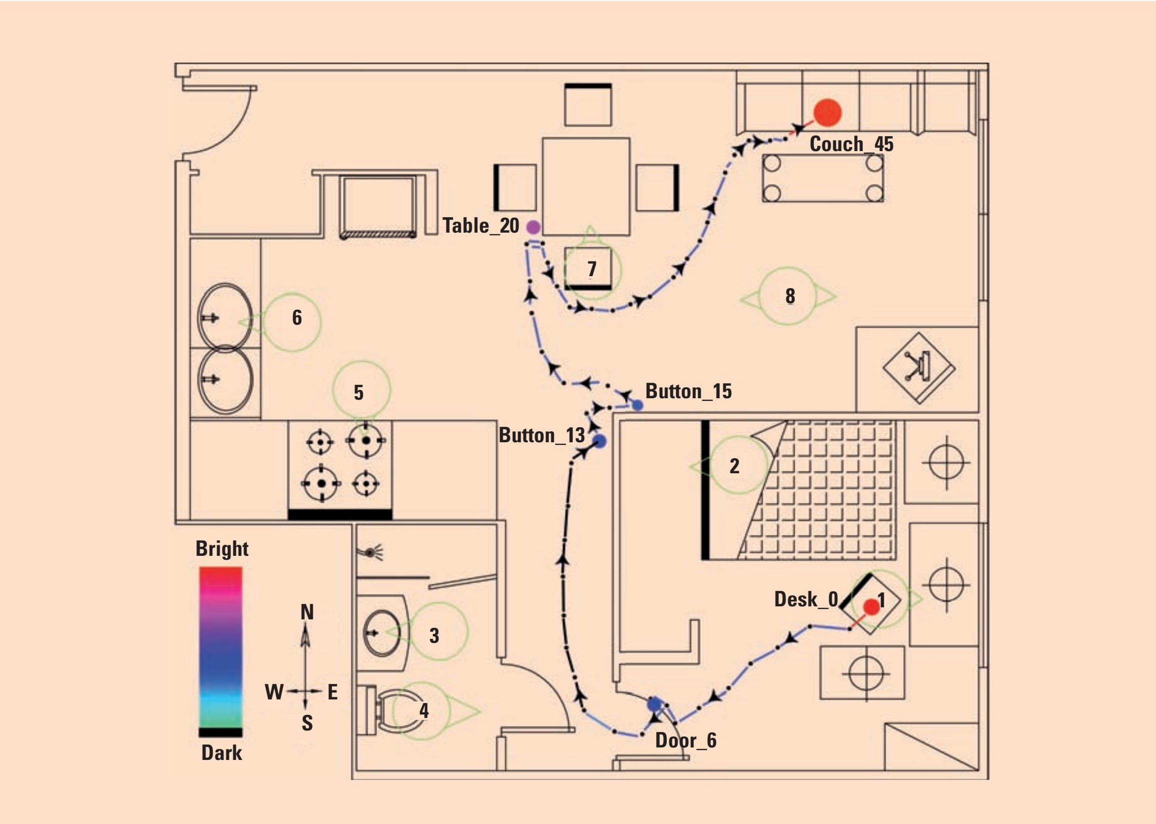

Figure 2. Visualization of activities of daily living (ADL) recognition and patterns. The size of the colored circles represents the duration of time the user spends at a certain position, and the colored lines (that is, traces of movement) represent the light illumination level in the room. Bright colors associated with a line segment mean higher light intensity, and dark colors mean lower intensity.

are stored in a knowledge database, ready for broadcasting to subscriber agents. The algorithms applied by the data analyst vary greatly from module to module. For example, the developer for the localization module does not have to learn anything from the audio processing module.

The responsibility of the *system administrator* is to configure, maintain, and administer server storage and routine automation, such as backup, upgrade, security policy maintenance, troubleshooting, and performance monitoring.

Finally, within IMP, *living domain experts* need to set some rules according to their living domain knowledge. Those rules, including standard sound seeds, basic motion features, and Wi-Fi received signal strength indicator (RSSI) templates, are fundamental for data analysts to develop useful algorithms on different modules.

ADL Recognition Performance

Figure 2 shows a visualization of ADL recognition and patterns for one resident. This 900-square-foot apartment contains a bedroom (position 1), a bathroom (position 3), and a living room (position 8) with a kitchen (position 5). The size of the colored circles represents the duration of time the user spends at a certain position, and the colored lines (that is, traces of movement) represent the light illumination level in the room. Bright colors associated with a line segment mean higher light intensity, and dark colors mean lower intensity.

Our system can detect several ADLs, including "working on PC" at position 1, "brushing teeth" at position 3, "hygiene activities" at position 4, "cooking" at position 5, "washing dishes" at position 6, "eating" at position 7, and "wandering" at position 8. The pattern surfacing here narrates that starting from the desk at second 0, the subject walks to open the door at second 6. After walking through a dark hallway, he flips the light switches at seconds 13 and 15. Then, he picks up a newspaper from the table at second 20 and walks to the couch at second 45. In a preliminary study, we tested our ADL recognition system in four apartments; the correct recognition rates ranged from 92.35 percent to 99.17 percent. It seems to us that a 90 percent or higher correct recognition rate is generally achievable for common and routine ADLs at home.[9]

This highly satisfactory performance makes a convincing case for releasing our system as a real product, currently under consideration.

Real-Life Services

Our real-life experiments were conducted in several places, including Iowa, Illinois, Wisconsin, Florida, and California in the US; Tokyo in Japan; Beijing, Shanghai, Shenyang, and Wuhan in China; and Taipei and Taoyuan in Taiwan. Because the only on-ramp for a potential user of concern (that is, the observer) is a functioning mobile device, the ADL Recorder App can serve various types of customers. For one, healthcare centers for older adults can use the ADL Recorder App to track residents' routine ADLs. Persistent tracking of ADLs for an elderly community over a long time period can allow data analysts to discover the health trends of a population of concern. Because each resident has his or her own routine data bank, nurses and doctors could master a particular resident's physical status and possible anomalies from such ADL reports. Moreover, remote surveillance to monitor older adults with, for example, aggravating dementia can be supported through building real-time ADL links. In sum, in our research, we aim for understanding and monitoring individual users' situations and providing individualized services[9,15,16] so as to maximize user experiences in using the ADL recognition system.

Note that while the ADL Recorder App provides recognition for ordinary ADLs, new algorithms for customized ADL types must be invented from time to time for some peculiar use scenarios. For example, we have been asked several different questions about possible scenarios for monitoring activities, such as whether the system can detect whether a 70-year-old woman who walks her dog every day ever misses a day, or if a housekeeper hired does indeed complete all tasks required each time. We are optimistic that such customized requests can be fulfilled because our agent-based IMP employs the publisher/subscriber protocol with personalized ADL recording (from observees) and ADL reviewing (by observers). Therefore, the flexibility and extensibility of the system naturally follows due to our adherence to time-tested software engineering principles and prevailing services computing practices.

Challenges for Future Smart Health Research

Our ADL Recorder App captures mobile data from multiple sensors embedded in mobile devices. Our primary research aim is to collect a mobile phone user's behavioral and environmental context from where he or she resides. One clear strength of our system is that it fully exploits the mobile data collected during typical smartphone usage following a user's routine. Compared to traditional smart home deployments and wearable sensors, this ADL recognition system imposes fewer burdens for end users. Key technologies in the ADL recognition system involve audio processing, Wi-Fi indoor positioning, proximity sensing localization, and time-series sensor data fusion. Outcomes from different modules are merged to derive final ADL results. The ADL recognition system not only paves the way for recording, detection, recognition, and electronic documentation of users' ADLs, but also yields some fitness and health reports through statistical analysis. Experiments in real-life situations prove the feasibility of our system.

Three important issues remain for careful study: security, privacy, and energy efficiency. Currently, because sensitive ADL data would reside in the cloud, law-compliant measures (such as with HIPAA in the US[18]) must be diligently pursued in addition to the limited support cloud vendors (such as Amazon) provide. Privacy in our application domain, although extremely important, is not much different from traditional home care and home surveillance, where privileges must be granted, such as older parents allowing adult children to monitor their ADLs for enhanced well-being. The issue is not uncommon and poses steep challenges to the industry as a whole. It is necessary to constantly adapt the system to adopt best practices. As to energy efficiency, we have purposely applied several energy-saving means and adjusted feature-oriented parameters during the fine-tuning stage of product development. The results are encouraging. Through careful optimization, the battery usage of the ADL Recorder App is less than one tenth the average battery usage of the screen and operating system.

As the world moves quickly toward a full-fledged IoT era, we are optimistic that our approach closely follows technology trends. After all, technologies are developed by humans and for humans. We believe that our single-point ADL recognition technology certainly helps improve human well-being, albeit only as a first step toward a larger vision of the Internet of Medical Things.[8]

Acknowledgments

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