Table of Interest: Activity Recognition and Behaviour Analysis Using a Battery Less Wearable Sensor

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ABSTRACT

Energy overheads continue to be a major impediment for wearable based activity recognition systems. We proposed a hybrid approach, which combines wearable-based human sensing with object interaction tracking, for robust detection of ADLs in smart homes. Our proposed framework includes: (a) battery less, low sampling rate, wearable RF sensor tags, that are powered intermittently by an RFID reader, and (b) additional passive RF tags, mounted on daily use objects, that capture the presence and use of specific objects while performing such ADLs. Using an initial experimental set up, we show the ability to recognize activities like eating, typing and reading, which are generally performed on a table, with an accuracy of 96%. Moreover, by capturing the item-level interactions of a user while performing ADLs, this approach can help observe the evolution of fine-grained behavioral changes and anomalies in an individual.

CCS CONCEPTS

• **Computing methodologies → Model development and analysis**; *Machine learning*; • **Computer systems organization → Embedded and cyber-physical systems**; **Real-time system architecture**; *Sensor networks*; *Sensors and actuators*;

KEYWORDS

Battery-Less Wearable, Activity Recognition, Passive RFID tags, Behaviour Analysis, Probabilistic Model

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1 INTRODUCTION

Recognition of activities of daily living (ADLs) in smart home or office environments tends to utilize two distinct paradigms. The wearable sensing approach typically utilizes sensors embedded in wearable computing devices, such as smartwatches and smartglasses, to capture fine-grained, individual specific locomotion & gestural activities. However, *energy* remains a critical challenge for continuous sensing: with low-capacity batteries, wearable devices require frequent charging. In contrast, installing sensors in everyday 'smart objects', such as kitchen cabinets, household appliances and office equipment, supports ADL detection via indirect observations on human interaction with such objects, but cannot provide individual-specific insights in multi-tenanted environments.

Our goal is to develop a low-cost, easily deployable, but fine-grained, physical activity sensing framework. To eliminate the frequent charging requirement, we intend to utilize *batteryless wearable sensing*. Recent advances in RFID provide such an opportunity, with wearable tags, containing a 3-axis accelerometer sensor [3], effectively being operated (in short bursts) by a nearby RFID reader. We henceforth refer to such a tag as an *accelerometer tag*. This approach does promise low cost, battery-free sensing, but has certain operational challenges:

(1) To work properly, the tags should be in the range of RFID reader, with the tag and reader antennas properly aligned. As pervasive deployment of high-powered RFID readers is expensive, the ADL monitoring capability is typically confined to specific areas (in the vicinity of the installed RFID readers).
(2) Because the entire sensor system is operated from the transient RF energy harvested from the RFID reader, the accelerometer sampling frequency is very low. This reduces the accuracy of activity recognition performed purely using such wearable-generated data.
(3) Finally, in contrast to simple passive tags, the operation of the accelerometer tag requires much higher RFID reader power level (to ensure sufficient power to the sensing sub-system).

Consequently, in practice, pure wearable RFID tag-based activity recognition does not have the ideally desired ubiquity or fidelity, unless the RFID reader is constantly operated at high-power (which could lead to additional interference issues).

To tackle this limitation, we propose, in this paper, a novel paradigm of battery-free ADL recognition, whereby we *combine* body-worn battery less RFID tags with RFID tags attached to smart objects. The key idea is to use the object-mounted RFID tags to first detect the onset of relevant human interactions with those objects, and use such interaction detection to trigger the collection of wearable sensor data from the relevant individual. More specifically, we provide an exemplar of this approach in an office or home environment, where we try to capture an individual's fine-grained gesture-driven activities (such as eating, reading or typing) while being seated at a specific table. To perform such recognition opportunistically, we utilize a chair-mounted pressure sensor tag to detect when an individual sits down, and then have the RFID reader interrogate the RF-powered accelerometer wearable tag. Additional object-mounted tags help identify the objects with which the individual *interacts* during a specific ADL. The combined wearable + object data helps identify he specific gesture-driven activity. This approach has the following key benefits:

a) the accelerometer tag, that requires high powered operation of the RF-reader, is turned only when the sitting context is sensed via very low RF-power sensor tag, thereby reducing the overall energy consumption and interference profile of the RFID reader;
b) the use of a battery less wearable tag permits low-cost, individual-specific sensing (such tags currently cost $10-12, two orders of magnitude lower than wearable smartwatches), without the need to remove it periodically for recharging; and
c) the combination of wearable and additional object-mounted tags provides significantly more robust activity tracking.

Besides developing this architecture, we also explore another facet in this paper: the ability to reliably detect a user's microscopic behavior during different ADLs, and thereby infer any *anomalous* behavior of a user. In particular, even for a specific ADL, the data from the different object tags helps reveal the finer-grained, object-level interaction sequence of the user. This enables us to determine the user's *orderliness*–i.e., whether the subject has a regular pattern of interacting with a specific object while performing an ADL. The key contributions of the paper are:

- We propose a hybrid mode of inexpensive, battery-free sensing of physical activities, which combines object interaction sensing with person-specific wearable sensing to recognize individual activities in smart spaces (such as a home or office).
- We quantify a probabilistic approach that uses longitudinal observations of user-item interactions, over each individual episode, to compute the *anomalous* behavior of a user [5, 6]. In our approach, an anomaly is defined not just by the presence or absence of an ADL (e.g., eating), but by additional object-specific interactions during an ADL–e.g., whether the user interacted with her glass multiple times during a meal. Such fine-grained anomalies will help better quantify the onset or progression of *cognitive impairments* (e.g., dementia) in elderly users.

The rest of the paper is organized as follows: Section 2 outlines related work. Section 3 describes our proposed system, while Section 4 details the analytical models used to capture object-activity relationships. Section 5 presents our "Table of Interest" exemplar, which we envisage as a snacking cum working table for an elderly subject. Section 6 details initial experimental results, while Section 7 concludes the paper.

2 RELATED WORK

We first provide a summary of the prior work on RFID based activity recognition systems, and their limitations. In [11], a comparison of different radio based activity recognition is done, thereby demonstrating the feasibility of using RFID for activity detection. In [8], wrist-worn battery powered short-range RFID readers such as iBracelet and iGlove are used for activity recognition. The need for battery becomes a major bottleneck in such system. In [2], the authors have used passive accelerometer (WISP) tags on many props such as cups etc and detected activity by keeping track of the objects. In [4], they have used an Elliptic Trilateration algorithm for real time positioning of objects and have made an activity recognition model using Bayesian network. Both [2] & [4] detect activities indirectly, via the object tags. Hence, these approaches can detect an ADL only if the person uses the relevant tagged objects; moreover, this user-agnostic approach is not applicable to multi-user environments.

In [12], RFID tags are attached to the body of patients; however, the set of activities was very simple, consisting of whether a user was in or away from a bed. The idea of a battery less wearable is not utilized in [12], as the information obtained regarding the person is very limited. In [9], they have used both passive RFID tags to detect object interactions and combined such insights with wearable accelerometers (embedded in a smart watch) to perform activity detection. This approach, however, relies on the use of battery-powered wearable devices.

3 THE PROPOSED SYSTEM

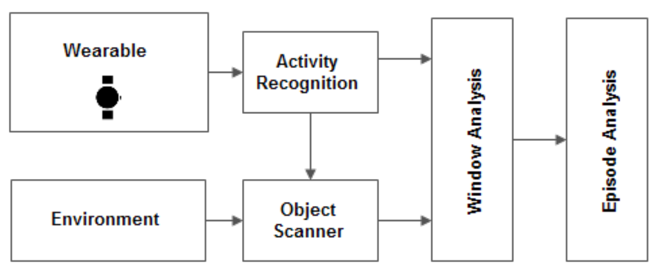


Figure 1: Architecture Diagram

The overall components and workflow of our framework is illustrated in Figure 1. Triggered by the occupancy sensor (e.g., the chair sensor), the system fist senses both (a) the wearable sensor tag (to identify individual specific gestures) and (b) the environment i.e., the passively tagged objects. The wearable data is then buffered and processed, frame-by-frame, by the *Activity Recognition* module to identify the user's current activity. In parallel, the environmental state is monitored via *Object Scanner* to detect both *presence* and *usage* of any tagged objects.

The *Window Analysis* module checks each window of data. We take a fixed duration window of 10 seconds for analysis, this consists of a single frame, the windows are rectangular and non-overlapping, to identify possible *anomalies*. Ideally, if a particular ADL is associated with a specific object, the corresponding tagged object must be present and used during an instance of that ADL. Otherwise, the window is annotated as a *Window Anomaly* (WA). All the windows with their corresponding predicted activity and anomaly annotation are stored for later use.

Later on (e.g., at the end of each day), the *Episode Analysis* performs the longitudinal analysis of the anomalies exhibited during the conduct of different ADLs. It analyses all the windows to determine the possible multiple *episodes* of each ADL. An *episode* effectively demarcates the contiguous time period for a specific ADL–e.g., a meal lasting 20 minutes. Note that a single day can have multiple episodes of the same ADL. To detect such an episode, we look at the majority ADL occurrence, over multiple consecutive windows, such that the total duration of those windows is "close enough" to the average episode duration of that ADL. After inferring each ADL episode, we additionally classify it as an *Episode Anomaly*, if the majority of windows in that episode have been tagged as "window anomalies". Finally, we compute the *orderliness* of the user, by measuring the fraction of episodes tagged as "episode anomalies".

We now use a specific testbed description to illustrate a concrete embodiment of our proposed framework. Our prototype system consists of 4 distinct devices, as follows:

- **RFID Reader**: This hardware device is usually stationary, and uses RF waves to power the RFID tags, and gather the required data. Our prototype uses the *ThinkMagic Astra EX reader* [10].
- **Battery less Wearable** (RFID passive accelerometer tag): For the battery less wearable, we utilize a passive RFID tag with a built-in 3-axis accelerometer: the *Farsens Kineo* [3].
- **Battery less force sensor** (RFID passive external sensor tag): Additional, lower-power, sensor tags are mounted on selected everyday objects, to help detect the onset of a user's interaction (and thus the triggering of the wearable accelerometer tag) within the space being monitored. More specifically, we place a pressure (piezoelectric) sensor under a chair, to help identify whenever a person sits on it. This external pressure sensor is connected to SL900A passive RFID tag [1].
- **RFID passive Tags** (Only ID): Standard passive RFID tags (with no additional sensor) are attached to everyday objects, such as cups, books, keyboard etc. These tags, subsequently referred to as *object tags*, help indicate both the presence of the corresponding object in the region of interest (the sensing zone of the RFID reader), and whether such objects are being used (via analysis of their RF signal fluctuations). This provides finer-grained insight about the individual's performance of an ADL, helping detect if the ADL was performed anomalously.

4 GENERIC ANALYTICAL FRAMEWORK

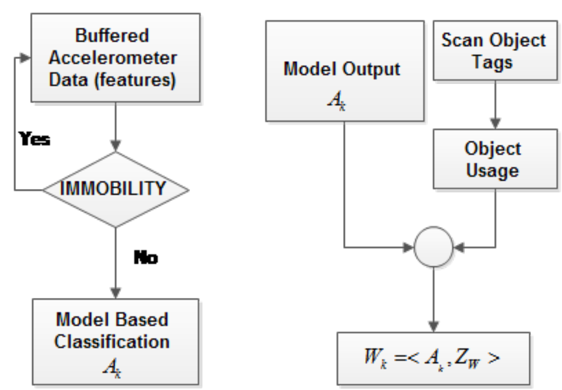
We now explain the precise steps in our computation of anomalous ADLs. For a given setting, let A denote the activity grammar such that:

$$A = \{A_1, A_2, .., A_i, ..., A_n | n \in \mathbb{R}\} \quad (1)$$

where n denotes the total number of ADLs being monitored. Data collected from the accelerometer tag is buffered to obtain a window of data for a fixed duration (i.e. window size denoted by w_s). Once a window of data is obtained, we apply an exponential smoothing filter to eliminate noise & artefacts, and then identify the user's current activity.

4.1 Activity Recognition

To predict the current activity, a set of statistical features such as mean, variance of individual axis, co-variance and correlation taking 2 axis at a time and magnitude of all 3 axis is computed for each window of incoming data. The feature vector is then first analyzed to identify *immobility* of the subject, using a binary classifier. If the subject is classified as mobile, a random forest classifier (previously trained in supervised fashion) is used, to predict the current activity label (see Figure 2a). Let the A_k denote output activity label from the machine learning model for the k^{th} window of data:



(a) Activity Recognition **(b) Window Analysis**

Figure 2: Workflow of the system modules

4.2 Object Scanner

In parallel to the activity recognition module, the Object Scanner module analyzes the data from the passive object tags to identify the presence of, and interaction with, different objects. As shown in Figure 2b, the environment is sensed in parallel with the wearable sensing. Let X denote the collection of such objects :

$$X = \{X_1, X_2, ..., X_n\} \forall X_i \in X; \quad (2a)$$

$$X_i = \begin{cases} 1 & \text{: when object is present (i.e., the tag is read).} \\ 0 & \text{: when object is absent.} \end{cases} \quad (2b)$$

Here, the system assumes that in ideal conditions, activity A_i is performed using object X_i. Furthermore, all the activities A_i are independent of each other and an activity A_i can be performed with or without the object X_i.

There might be cases, where the object may be present in the scene but are *not used*. To monitor the *usage* of the tagged objects, the system uses the change in RSSI values of the object tags. Figure 3 shows how the RSSI values changes when objects are being used (mobile) as compared to when the objects are not used (static). We use a binary classifier, using features such as the variance and standard deviation of the RSSI of the reflected signal from each tag, to identify whether a specific object is being *used* vs. *not used*. The object usage output is then fused with gesture based activity recognition for a window. Furthermore, keeping a track of such object usage, in a long run can serve as a metadata for anticipating activity of a person. For example, if a person uses a particular cup for drinking tea and also water during medicine intake then from this relationship we can trigger activity models for that object, using the personalized usage pattern.

4.3 Window-wise Analysis

Outputs from the activity recognition module and the object scanner are then analysed to detect if the current window is an anomaly or not (as shown in Figure 2b). As stated in section 3, a window is said to be an anomaly, if the the object X_i is not present or is present but not used while performing activity A_i. (Only objects that have a high *support* in the training data, i.e., were actively used in training episodes of an ADL, are considered for such anomaly determination.) A window is annotated as anomaly only when $X_i = 0$, or if $X_i = 1$, and object scanner module asserts that the object X_i is *not used*. Let ZW be defined as the anomaly status for a given window.

$$ZW = \begin{cases} 0 & : \text{when } X_i = 1 \text{ and object is used.} \\ 1 & : \textit{otherwise}. \end{cases} \tag{3}$$

The output of the window analysis module is a collection of windows and its anomaly status. Let W denote the collection of activity windows such that:

$$W = \{W_1, W_2, ...W_k | k \in \mathbb{R}\} \tag{4a}$$

$$W_k = < A_k, ZW_k > | A_k \in A \tag{4b}$$

where k denotes the time index of a window, A_k is the activity label assigned to that time window, and ZW_k is the corresponding anomaly status.

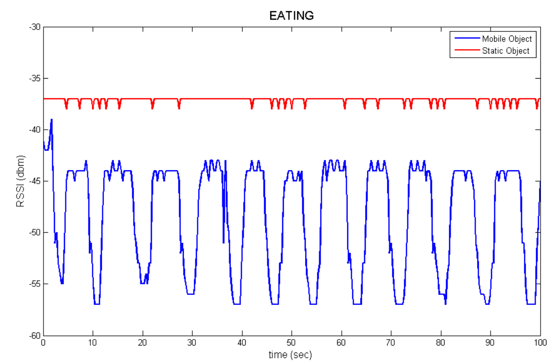
4.4 Episode-wise Analysis

With W as an input, this module computes episode occurrence of different activities and corresponding episode anomalies (if any). This stage of analysis is done offline on a longitudinal basis (at the end of every day). Episode of an activity is computed based on the average time duration T_i for A_i to occur. Let T be a collection of such duration values T_i,

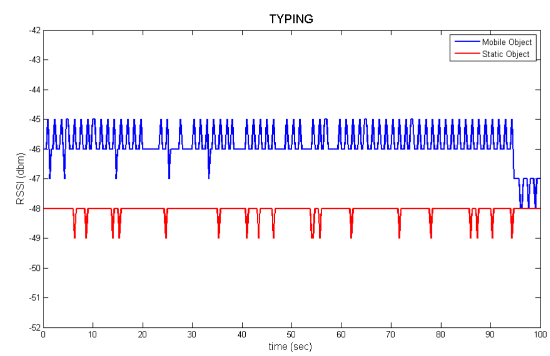
$$T = \{T_1, T_2, ..., T_i, ..., T_n\} \tag{5}$$

Let C be a collection of threshold count for each of the n activities, denoting the minimum number of windows to be predicted as label A_i, in time T_i so that the system detects it as an episode occurrence of A_i. We empirically assume that this threshold count should be somewhere within one standard deviation (σ_i) from the average duration of the episode for activity A_i.

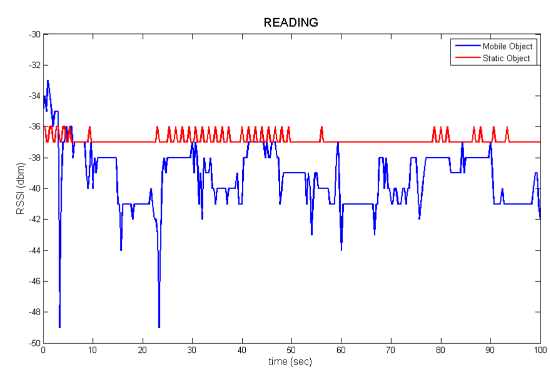
$$C = \{c_1, c_2, ...c_n | c_i = (T_i - \sigma_i)/w_s\}. \tag{6}$$



(a) Change is RSSI of a spoon while eating



(b) Change is RSSI of a keyboard while typing



(c) Change is RSSI of a book while reading

Figure 3: Change in RSSI of an Object tag on usage

4.4.1 Computing an Episode. For activity detection window size w_s and for a given activity A_i, let T_i be the duration of episode. Hence the total number of windows will be $(T_i * 60sec)/w_s$, out of which if c_i windows are classified as A_i then an episode of activity A_i has occurred. As shown in Figure 4, this computation of episode is done in post processing block. Let E denote the collection of all episodes in a day.

$$E = \{E_1, E_2, ...E_j | j \in \mathbb{R}\} \tag{7a}$$

$$E_j = < A_i, ZE_j > \tag{7b}$$

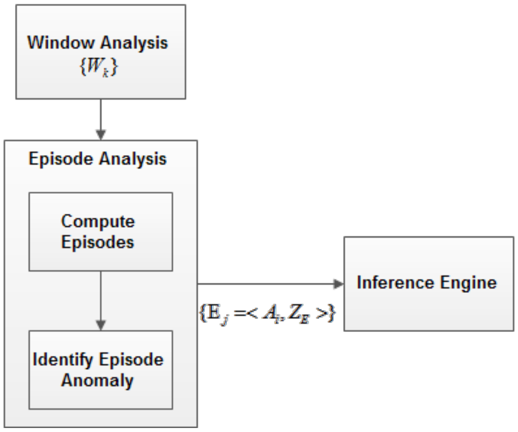


Figure 4: Detection episode anomaly

where E_j is j^{th} episode detected in a given day further denoted by a tuple of activity label A_i, for which the episode occurred and its anomaly status as ZE_j (discussed next).

4.4.2 Identifying Episode Anomaly. Once a collection of windows is identified as an Episode, each such episodes are analyzed for identifying *Episode Anomaly* (EA). If a majority of windows of the activity A_i in that episode are annotated as *window anomaly*, then that episode is considered as an anomaly denoted by ZE as follows:

$$ZE = \begin{cases} 1 & : \text{when } ZW_k = 1 \text{ for majority of windows in } E. \\ 0 & : otherwise. \end{cases} \tag{8}$$

4.4.3 Inference Engine. A collection of all such episodes are analyzed every end of the day, to check if even a single episode anomaly is detected for any given activity A_i. When an episode anomaly is detected, certain probability values (given below) are calculated and stored for future analysis and inference purposes.

$$P(E_i) = \frac{\text{number of EA's for activity} A_i}{\text{Total number of} A_i \text{episodes in a day}} \tag{9a}$$

$$P(E) = \frac{\text{number of EA's}}{\text{Total number of episodes in a day}} \tag{9b}$$

Here $P(E_i)$ indicates the fraction of episodes (for activity A_i) that were performed without using the tagged object. A very low probability value indicates that the person has used the tagged objects for doing most of his activities, whereas high value indicates a deviation from the normal conduct of such an ADL. On the other hand, $P(E)$ gives an overall probabilistic measure of the subjects *regularity* in using appropriate objects while performing their usual ADLs.

5 TABLE OF INTEREST : AN EXAMPLE USE CASE

To study the feasibility of the proposed system we discuss an example use case - Table of Interest. Considering a scenario of rehabilitation center, consisting of a table and chair, where most of the important daily chores are performed. Here the chair is the object that defines the sitting context and anticipated activities are defined in our activity grammar given by $A = \{EATING, TYPING, READING\}$ i.e $n = |A| = 3$. A trained machine learning model M is used to perform the activity recognition for a window (w_s) of 10 secs. The tagged objects were $X = \{SPOON, LAPTOP, BOOK\}$ corresponding to each activity respectively.

The sensing system is triggered opportunistically, where the RFID reader in the system works in two power modes a) Low power (at 20 dBm) to read pressure sensor tag place on the chair to sense the sitting context and b) High power (at 30 dBm) to read accelerometer tag respectively. The system starts at a low power mode to monitor the sitting context. Once the char is occupied, the power mode is changed to high, as well the the environment is scanned for the tagged objects present. Realtime accelerometer data is then buffered and analysed. When the subject leaves, the RFID reader is fails to read accelerometer data. To ensure this, a sanity check made via the state of the pressure sensor on chair. In absence of the subject, the RFID reader is switched to low power mode, else an error alert is triggered.

6 EXPERIMENTAL RESULTS

Experiments were conducted for the above mentioned use case. All the data were collected in lab environment[1]. The participants were asked to wear the wearable tag, get seated on a chair and perform 5 mins of each activity, i.e. Eating, Typing and Reading (as shown in Figure 5). As soon as the pressure sensor could sense the occupancy of a subject, accelerometer data was sensed using RFID reader (sampling rate 5Hz) and logged as different files for individual activities. Data collection involved 20 healthy subjects. Features were computed for every 10 sec window and Random forest classifier is used to generate a trained model. Table 1 gives the confusion matrix for a 10-fold cross validation testing, with an accuracy of 96%.

Table 1: Confusion Matrix

	Eating	Reading	Typing
Eating	531	13	7
Reading	6	543	19
Typing	2	19	514

The learned model was then tested in real time deployment with 5 unknown test subjects performing 3 minutes of activity (1 min for each activity, back to back) with a sequence of eating, typing and reading. The mean average error (MAE) computed considering each activity individually were 0, 0.2 and 0.17 respectively. It was

[1]The clearance on ethical issues for handling and analysis of the data collected has been acquired from relevant body in Tata Consultancy Services Ltd. (TCS). Informed consent is also taken from the participants and the data is anonymized

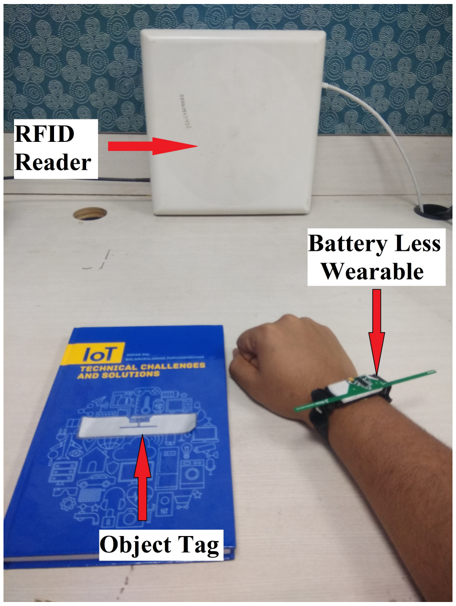


Figure 5: Experimental Setup

observed during the experiment that the windows which involved a transition from one activity to another, were some times wrongly classified hence contributing to the total MAE 0.12.

The RSSI based, object usage binary classifier was trained using 3 objects. RSSI data was collected from the passive RFID tags in different states, when in use and when not in use. A 10-fold cross-validation reported an accuracy of 82% using a random forest classifier.

7 CONCLUSION & FUTURE WORK

Overall, in this work, we have introduced the notion of a battery less wearable + object tracking framework, that utilizes cheap, battery less RFID tags to support fine-grained ADL recognition. We believe that our proposed approach presents a new design choice in the spectrum of "physical analytics" technologies. Though the proposed system is in its preliminary stages of development, it demonstrates a pathway for a practical ADL monitoring framework, that uses battery less wearable activity monitoring over specific 'regions of interest'. By using moderately large window size values of 10 secs, our early prototype is able to distinguish the three ADLs with high accuracy.

Moreover, we provide preliminary insights on how this framework can be used to study the micro-level object interactions of users while performing ADLs, thereby providing a way to monitor changes in a user's *orderliness* over time. Such orderliness measures, based on microscopic human-object interactions, may provide valuable insight in anticipating the onset or progress of cognitive ailments (e.g., dementia) in elderly patient.

There are several areas for future work. Our present prototype is a proof-of-concept: in realistic environments, multiple RFID readers will be needed to sense ADLs performed in different parts of a smart home or office. The overall energy efficiency of the RFID readers will need to be determined more carefully in such scenarios. Moreover, we need better formulations to quantify the *degree of anomaly* of an ADL (currently, this is just a binary value), based on the observed presence or absence of interaction with *multiple* different objects. We will also have to tackle the challenging problem of *interleaved activities*, where a user performs multiple ADLs concurrently (e.g., eating while typing). We anticipate that our ability to track the additional daily objects being used during such ADLs might help improve our ability to identify such interleaved activities. However, additional research is needed to develop automated techniques for adapting the episode duration T_i for such interleaved ADLs. Lastly, we foresee the feasibility and use of additional sensor like photoplethysmogram (PPG) sensor to measure the heart rate [7] of the subject, leading to a major challenge of harvesting the RF energy without compromising the needs of the existing system.

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