Monitoring Interactions with RFID Tagged Objects Using RSSI

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Abstract. In this paper, we present SVM and HMM-based methods for monitoring interactions with passive RFID tagged objects. We continuously track the motion status of an object and declare the status as standing still, randomly moving or linearly moving. Inspired by phone transition modeling in speech processing, each interaction type is represented with two sub-states to handle transitions and continuity. Experiments were designed to simulate our target application: monitoring interactions with medical equipment during trauma resuscitation. Our system identified interaction status with 85% accuracy using an HMM. The most useful feature for discrimination was the difference between the average RSSI of two consecutive windows.

Keywords: interaction detection, RFID, ubiquitous computing, trauma resuscitation.

1 Introduction

Inferring activities based on the used objects is an efficient method for high-level activity recognition. However, automatically detecting the set of used objects is challenging due to sensing errors and spurious interactions. In most of the previous work, objects have been identified manually [7], with motion sensors [3] or with near field detectors [2, 3]. Manual labeling requires human effort. Motion sensors are not applicable when small and inexpensive objects need to be tracked. Near field detectors are usually worn or held by humans, which can be obtrusive for chaotic and high-risk environments. Another limitation is the uncertainty in the interaction-to-usage relationship: an interaction does not always signal the item usage. Consider, for instance, an emergency room where a nurse fetches a thermometer to measure the patient's temperature. Since the patient has an oxygen mask on his face, the nurse cannot obtain the temperature at the moment so she leaves the thermometer on the patient bed. After several minutes, she takes the thermometer again and measures the temperature. Because the first interaction in this example is clearly a false alarm, the assumption that any interaction indicates usage is not always correct.

In this work, we develop a minimally intrusive interaction monitoring system using passive Radio Frequency Identification (RFID) tags and fixed readers to identify the type and duration of object interactions. By identifying both the type and the duration, it is possible to filter actual item usage instants. If the detected interaction interval is

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much shorter than the expected usage interval, we conclude that the item might be interacted accidentally and not actually in-use (Figure 1). In terms of sensing, we prefer a passive UHF RFID system because passive tags are small and inexpensive, enabling small and inexpensive objects to be identified. Fixed readers scan the environment in an unobtrusive way without any human intervention. On the other hand, inferring motion with a passive RFID system is challenging due to the sensitivity to orientation change, environment characteristics and occlusion.

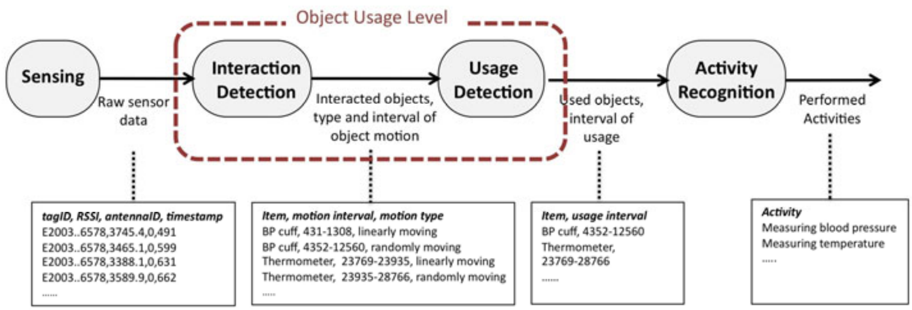

Fig. 1. Block diagram of an overall activity inference system. The interaction detection module is developed in this work.

Our target application is in healthcare domain, specifically Trauma Resuscitation[1]. Because it includes many interactions with medical equipment, trauma resuscitation has a high potential to benefit from object-based activity inference and interaction monitoring [8]. Passive RFID is a suitable technology for trauma resuscitation domain because the medical items for tagging vary in the number and size. Fixed readers are more convenient than wearable readers because urgency of the situation during resuscitation events may make the workers forget or ignore wearing readers.

By visually analyzing the trauma resuscitation videos, we observed that there are three basic types of object motion: *standing still*, *moving linearly* or *moving randomly*. For most items, a relatively long duration of random movement signals item usage. Based on this observation, we define our goal as labeling a sequence of object movements with three labels: *still*, *moving linearly* or *moving randomly*. Unlike the previous work, which used the same RFID technology [1, 4], we continuously monitor the interaction status, rather than declaring the interaction events only. To our knowledge, continuous monitoring has been attempted using technologies such as GPS [5] and Wi-Fi [6], but not with the passive RFID technology. GPS based algorithms are not appropriate for trauma resuscitation application due to high temporal and spatial granularity of GPS-tracked motion. Although Wi-Fi can provide finer granularity, it is not appropriate because of the aforementioned size and cost limitations.

[1] Trauma resuscitation consists of a series of tasks performed to identify and immediately treat life-threatening injuries.

2 Methodology

We simulated three motion types—standing still, moving randomly and moving linearly—by interacting with an RFID tagged object (Experimentation details are given in Section 4.1). As seen in Figure 2, received signal strength indication (RSSI) sequence has a distinct pattern depending on the movement type.

For feature extraction, we processed the RSSI sequence with the classical sliding window technique. Features are selected to focus on the "changes" in the signal strength, as required by motion detection applications. The features we used were: trend, standard deviation, median of difference, Δ(mean) and Δ(standard deviation).

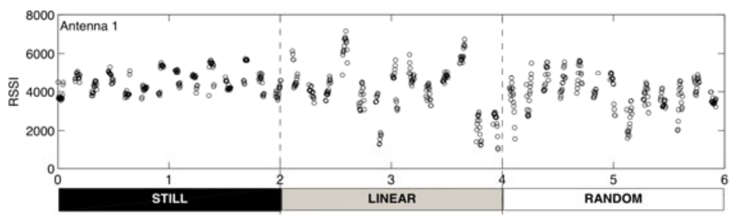

Fig. 2. RSSI values captured by a ceiling mounted antenna for a 60-second interval. Corresponding motion types, determined manually, are shown in the bars at the bottom.

We developed HMM and SVM based methods for assigning a motion label to each feature. We built two different HMMs: in the first one, named as the "uni-state representation", each motion type is represented with a single state. In the second HMM, named as the "bi-state representation", each type of motion is represented with a two-state left-to-right sub-HMM for modeling the motion transitions properly (Figure 3). *Main* is the core sub-state, representing the behavior of the state to which it belongs. *Exit* represents a pre-phase for out-transition. This idea is adopted from the modeling of phone transitions in speech recognition.

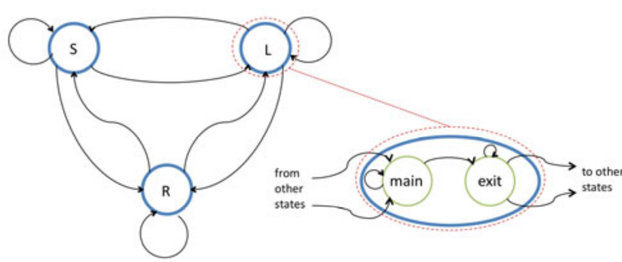

Fig. 3. HMM Topology with *main* and *exit* sub-states (bi-state representation). The dotted circle represents a magnified view of the state *moving linearly* (L).

For both uni-state and bi-state HMMs, self-transition probabilities are estimated from the expected motion durations; the other transition probabilities are distributed among the other allowed transitions equally. (For example in Figure 3 allowed transitions from the *main* state are self-transition and transition to the *exit* state.) Observations are modeled as Gaussian mixtures with parameters estimated from the training data based on the Maximum Likelihood principle. Initial state distribution is uniform among the three *main* sub-states of states L, R and S.

The sliding window technique captures the temporal relations in the sequence of observed movements and allows nontemporal learning algorithms to be used on sequential data. (It does not capture temporal relations in the hidden state sequence.) To classify motions, we used a Support Vector Machine (SVM), which is known as a maximum margin classifier with very low generalization error. Preliminary experiments showed that the label sequence obtained with the SVM included many spurious transitions, which correspond to short-term, frequently changing motions. An HMM-based post processing was applied on the SVM output to make the label sequence smoother.

3 Experimental Results

3.1 Experimental Setup

Our goal is to label a sequence of object movements as *still*, *moving linearly* or *moving randomly*. To record the RSSI dataset, an RFID tagged cartoon box (6″×4.5″×3″) was interacted with as follows:

- Not interacting at all (object standing still)
- Holding the box while walking around a table and from sidewalls to the table with an approximate speed of 40 inches/second (object moving linearly)
- Standing at the same position and playing with the box: rotating and occluding it by hand (object moving randomly around the same position).

The three interactions were performed continuously in different order. In total, our training dataset consisted of 60 interaction sequences, each of length 60 seconds.

The experimental equipment consisted of an Alien RFID reader, circularly polarized antennae and passive tags (Squiggle). The environment was designed to match a typical trauma resuscitation room. One of the antennas was ceiling-mounted, facing the center of a plastic table (mimicking a patient bed). Two antennas were mounted on the perpendicular sidewalls. In this way, our aim was to detect movements in all three dimensions. Moreover, considering that the trauma team gathers around the patient during resuscitation and frequently occludes the side antennas, a ceiling mounted antenna is crucial in our design. The laboratory included other objects that caused multipath and other adverse conditions for RF propagation.

Our evaluation metric is the percentage of accurately predicted labels in a sequence ((true positive + true negative)/total number of labels). The performance of each method is reported by averaging the accuracy rate over all sequences.

3.2 Experimental Results

We investigated the motion labeling performance using 10-fold cross-validation. In the testing data fold, the accuracy was calculated for each sequence individually and summarized in the box plot in Figure 4, on the left side.

The HMM-based method achieved an average accuracy of 77.9% and outperformed the SVM-based model (73.66%). The higher accuracy variation in the HMM-based method can be explained as follows. In a nontemporal model, all instances are labeled independently, whereas in an HMM the adjacent label predictions are dependent. An erroneous measurement, as well as a successful one, affects not only the current label, but also the subsequent ones.

The best score (83.01%) was obtained when the SVM output is smoothed with an HMM-based postprocessing. This technique combines the max-margin learning capability of SVMs with the temporal representation of HMMs. An analysis on the confusion matrix showed that most of the misclassifications are among the linear and random movement types. If we were to make a moving/not-moving decision only, the accuracy would be 89.9%. The accuracy of binary motion sensing using WLAN RSSI was reported to be 87% in [6].

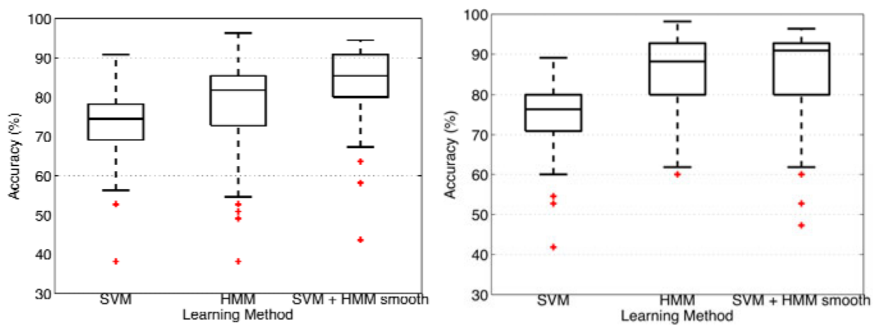

Fig. 4. Comparison of accuracy rates for various methods with uni-state (left) and bi-state (right) representations. (Central mark in the boxes: median; Edges of the boxes: 25th and 75th percentiles; Whiskers: most extreme data points not considered outliers; Plus sign: outliers.)

Next we evaluate the bi-state approach both in HMMs and SVMs. Incorporation of the *exit* state provided improvement for all methods by increasing the resolution of classification (Figure 4 - right). The improvement for the HMM (7.5%) was much higher compared to SVM (0.7%) because the idea of bi-state representation is meaningful when applied to a model that captures temporal correlations. The improvement for the SVM + HMM smoothing (1.4%) was smaller than HMM (7.5%) but higher than SVM (0.7%). This is because HMM fixes transitions on the final predicted sequence but the lost temporal information in the SVM stage cannot be restored. Moreover, as depicted in Figure 4 - left, accuracy variation of the bi-state HMM was lower compared to the uni-state HMM.

Discriminative Power of Individual Features

We also investigated which feature(s) contributed the most to the motion discrimination. In each test, one of the features was ignored and the accuracy was calculated with the bi-state HMM method. We also conducted paired *t*-tests to evaluate statistical significance.

None of the features contributed negatively to the discrimination. *Delta mean* was the most useful feature, whereas *delta standard deviation* had no effect in any setting and could be discarded. *Trend, standard deviation* and *median of difference* helped only in particular cases, such as increased tag population. Since they do not cause any degradation in the other cases, it is legitimate to include them in the feature vector.

4 Conclusions

This paper describes our work on monitoring of interactions with RFID tagged objects. We developed a continuous and multinomial labeling scheme that provides enhanced information for activity inference. Sensor and model selection, and the design of experiments were all made with respect to our target application: monitoring of the interactions with medical equipment during trauma resuscitation. However our results are generalisable to other high-risk work environments. Best scores were achieved with an HMM, where each movement was represented with a two-state left-to-right sub-HMM to model transitions. We also analyzed the individual contribution of each feature coefficient. Trend, standard deviation, median of difference and delta mean were observed to be useful features for detecting motion using RFID RSSI. Our future goal is to test the system in more challenging conditions, such as high tag population and people movement in the environment.

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