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Unobtrusive Posture Recognition via Online Learning of Multi-Dimensional RFID Received Signal Strength

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***Abstract*—Activity recognition is a core component of ubiquitous computing applications (e.g., fall detection of elder people) since many of such applications require an intelligent environment to infer what a person is doing or attempting to do. Unfortunately, the success of existing approaches on activity recognition relies heavily on people's involvement such as wearing battery-powered sensors, which might not be practical in real-world situations (e.g., people may forget to wear sensors). In this paper, we propose a device-free, real-time posture recognition technique using an array of pure passive RFID tags. In particular, posture recognition is treated as a machine learning problem where a series of probabilistic model is built via learning how the Received Signal Strength Indicator (RSSI) from the tag array is distributed when a person performs different postures. We also design a segmentation algorithm to divide the continuous, multi-dimensional RSSI data stream into a set of individual segments by analyzing the shape of the RSSI data. Our approach for posture recognition eliminates the need for the monitored subjects to wear any devices. To the best of our knowledge, this work is the first on device-free posture recognition using low cost, unobtrusive RFID technology. Our experimental studies demonstrate the feasibility of the proposed approach for posture recognition.**

I. Introduction

With recent developments in cheap sensors and networking technologies, it has become possible to develop a wide range of applications such as remote health monitoring and intervention. For instance, by monitoring the daily routines of a person with dementia, we could track how completely and consistently the daily routines are performed and determine when the person needs assistance. Central to realizing these applications is *activity recognition*, which is emerging as an important area of research and development in recent years [1], [2], [3], [4].

Computer vision related human activity recognition is one of directions, but unfortunately, such solutions demand high computational cost for machine interpretation. In addition, the performance of such vision-based approaches depends strongly on the lighting conditions, camera facing angles etc, which greatly restricts its applicability in ubiquitous environments. Also, cameras are generally considered to be intrusive to people's privacy.

With the growing maturity of sensor, radio-frequency identification (RFID), and wireless sensor network technologies, activity recognition from inertial, unobstrusive sensor readings has become a popular research area in last few years. Inertial sensors are the most frequently used wearable sensors for human activity recognition [5], [6], [7], [8], [9], [2]. Although sensor-based activity recognition can better address issues such as privacy than conventional computer vision-based approaches, most work from sensor-based activity recognition require people to wear the inertial sensors and RFID tags. The main drawbacks of such solutions is that they need users' cooperation. As a result, these approaches are not always practical, particularly for monitoring elderly persons with cognitive disabilities.

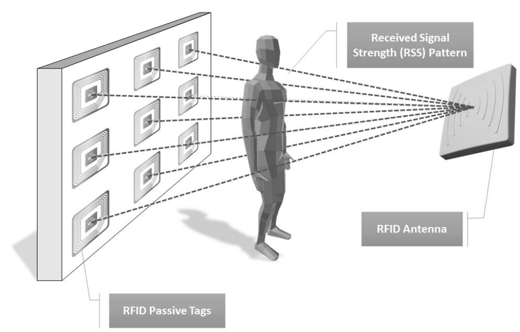

Fig. 1. Proposed lightweight setup: a person does not need to wear any devices and performs different postures between the wall and an RFID antenna. The postures can be recognized by analyzing the corresponding sensing data collected by the RFID reader.

To overcome the aforementioned issues, we have developed an effective and unobtrusive posture recognition approach using an array of low-cost, passive RFID tags. Our approach is lightweight in computational cost, and people do not need to wear any devices. Figure 1 illustrates the setup of our approach for posture recognition. Our main contributions are summarized as the following:

- We address the posture recognition problem using an array of pure passive RFID tags. Our approach is lightweight, low-cost in the sense that only passive RFID tags are used. Our proposed approach also relaxes the requirement that people need to wear sensors for poster recognition.
- To reduce the effect of intra-class variation and noise inherited from passive RFID tags, as well as to compress

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the streaming data space, we design a slope variation based segmentation method for segmenting real-time Received Signal Strength Indicator (RSSI) data collected from passive tags during the online posture recognition stage. In particular, we propose to calculate the segmentation points for each dimensional RSSI data with detecting slope variations, and the final segmentation points are selected according to the majority voting rules.
- We conduct extensive experiments to validate and evaluate our proposed approach. The experimental results demonstrate the feasibility of the proposed approach.

The remainder of this paper is organized as follows. In Section II, we review some existing work on human activity recognition. We describe our proposed approach in Section III. The experimental results and analysis are presented in Section IV. Finally, we provide some concluding remarks in Section V.

II. Related Work

The goal of activity recognition is to detect human physical activities from data collected through various kinds of sensors. There are generally two main research directions: one direction is so-called *non-contact monitoring*, which detects people postures via analyzing signal patterns related to different human activities; and the other direction is mainly based on wearable sensors.

Wearable sensors such as accelerometers and gyros are commonly used for recognizing activities [10], [3], [11]. For example, the authors in [12] design a network of three-axis accelerometers distributed over a user's body. Activities can then be inferred by learning information provided by accelerometers about the orientation and movement of the corresponding body parts. However, such approaches have obvious disadvantages including discomfort of numerous wires attached to the body as well as the irritability that comes from wearing sensors for a long duration. More recently, researchers are exploring smart phones equipped with accelerometers and gyroscopes to recognize activities and gesture patterns [13], [14]. Unfortunately, this kind of work usually requires people to keep their phones in a particular way.

Apart from the sensors, RFID has been increasingly explored in the area of human activity recognition. Some research efforts propose to realize human activity recognition by combining RFID passive tags with traditional sensors (e.g., accelerometers). In this way, daily activities are inferred from the traces of object usage via various classification algorithms such as Hidden Markov Model, boosting and Bayesian networks [15], [2]. Other efforts dedicate to exploit the potential of using "pure" RFID techniques for activity recognition. Received signal strength indicator (RSSI) has been more widely used in tag localization [16]. For example, Wang et al. use RFID radio patterns to extract both spatial and temporal features, which are in turn used to characterize various activities [8]. However, these research efforts require people to carry RFID tags or even readers (e.g., wearing a bracelet).

Recently, many researchers focus more on human activity recognition in an online style, which is easy to visualize and has great potential in real world applications (e.g., continuously monitoring patients with physical or mental pathologies, interactive games or simulators which need context information of activities and gestures). Maurer et al. [17] propose an eWatch-based online activity recognition system, which can be worn as a sport watch embedding sensors and a micro-controller. The work uses a C4.5 decision tree for classification. In the work of [18], Vigilante, a mobile application for real-time human activity recognition under the Android platform, can measure acceleration and physiological signals such as heart rate, respiration rate, breath waveform amplitude, and skin temperature etc. Unlike other approaches, Vigilante is evaluated completely online to provide more realistic results. Tapia et al. in [19] introduce a human activity recognition system which can recognize 17 ambulation and gymnasium activities such as lifting weights, rowing, doing push ups, etc., with different intensities (a total of 30 activities). The average classification accuracy is reported to be 94% for subject-dependent analysis whereas a 56% of accuracy is achieved in the subject-independent evaluation. In 2010, Berchtold et al. propose ActiServ, an activity recognition service for mobile phones [20]. The service is implemented on the Neo FreeRunner phone and makes use of a fuzzy inference system to classify ambulation and phone activities. The overall accuracy varies between 71% and 97%. When the algorithms are executed to meet a real-time response time, the accuracy drops to 71%.

Riboni et al. [21] present COSAR, a framework for context-aware activity recognition using statistical and ontological reasoning under the Android platform, which can distinguish ambulation activities as well as brushing teeth, strolling, and writing on a blackboard. The overall accuracy is about 93%. Kao et al. [22] present a portable device for online activity detection, in which domain features and the Linear Discriminant Analysis (LDA) are applied to reduce the dimension of the feature space. Then, a Fuzzy Basis Function learner uses fuzzy rules to classify the activities. An overall accuracy of 94.71% is reached for seven activities: brushing teeth, hitting, knocking, working at a PC, running, walking, and swinging.

III. Proposed Approach

In this section, before we introduce our proposed approach, we share some observations and intuitions of RFID RSSI data which underpin our proposed solution (Section III-A). We then describe our solutions in details including the probabilistic framework and slope variation based segmentation algorithm in Section III-B. We also briefly discuss some potential application scenarios of proposed work (Section III-C).

A. Observations and Problem Description

We assume a tag array containing N tags which are attached on the wall in an indoor area. An RFID antenna is set up facing the tagged wall with certain angle under best received signal strength, the whole scenario is shown in Figure 1. When a person performs different postures between the wall and the RFID antenna, the collected RSSI shows varied fluctuation patterns. The motivation of our work actually arises from the following observations of the RSSI values.

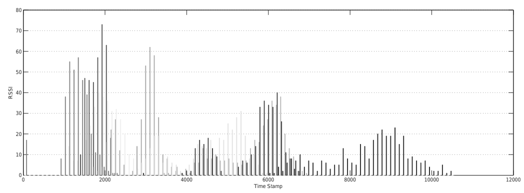


Fig. 2. Histogram of RSSI from posture *sit leaning left*

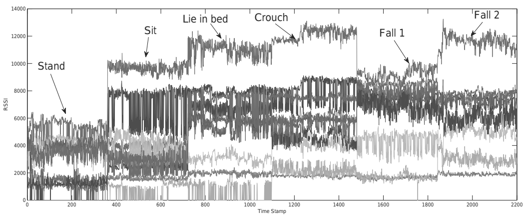


Fig. 3. Different RSSI patterns of different postures

Observations. It is well known that RSSI is quite complicated in real environments due to signal reflection, diffraction, and scattering, especially for the passive tags. It is usually severely affected by the propagation environment and the tagged object properties or human movements in the signal coverage area. Moreover, it cannot be universally approximated with a location-dependent path loss model. The signal strength of passive RFID tags is especially rather uncertain and non linear. For example, the RSSI data in a posture class (e.g., *sit leaning left*) distribute like a mixture of multiple Gaussians as shown in Figure 2.

Although RSSI reflects the uncertainty and non-linear distributed pattern, we can find some interesting observations which could be utilized to learn some underlying patterns. We particularly discover that the variations of RSSI values collected allow us to distinguish among different postures. Figure 3 shows the distinctive changes of RSSI values of our testing tag array (e.g., 9 passive RFID tags in our case) according to different postures that the subject performs.

Problem Description. From the observations, we believe that radio frequency signals embody certain patterns, which can be exploited with machine learning based methods for posture recognition. The main task is to model how the signal strengths are distributed in different postures based on a sample of measurements collected when a subject performs different postures. In general, the RSSI patterns will vary according to a person performs different activities. We assume a passive tag array of N RFID tags, the radio signal strength stream can be represented as $\mathcal{O} = \{\mathbf{o}_1, \mathbf{o}_2, ..., \mathbf{o}_N\}$. The predefined posture classes are denoted as $\mathcal{L} = \{l_1, ..., l_k\}$. Our goal is to learn the human postures in real-time for the given RSSI stream. We are mainly interested in the use of statistical learning methods for posture recognition problem by using an array of pure RFID passive tags.

B. Posture Recognition

In this subsection, we will describe our proposed approach in details. We will first overview the three typical statistical learning methods, and then introduce an approach to deal with streaming RSSI data in order to apply these learning methods.

1) Statistical Learning Approaches: In our work, we investigate three statistical learning methods for posture recognition, including the *nearest neighbor* method, the *Support Vector Machine* (SVM) method, and the *Naive Bayes* method. We briefly introduce these methods in the sequel.

Algorithm 1: Nearest Neighbor Posture Recognition

Input: Training samples $\mathcal{O} = \{(\mathbf{o}_1, l_i), ..., (\mathbf{o}_n, l_n)\}$, New testing RSSI $\mathbf{o}^*$

Output: Posture class label $l(\mathbf{o}^*)$

Calculating Euclidean distance of $\mathbf{o}^*$ to each training RSSI: $dis_i = dis(\mathbf{o}^*, \mathbf{o}_i)$

Finding the training RSSI sample $\mathbf{o}_k$ nearest to $\mathbf{o}^*$: $k^* = \arg\min dis(\mathbf{o}^*, \mathbf{o}_k)$.

Assigning posture label of $\mathbf{o}_k$ to $\mathbf{o}^*$: $l(\mathbf{o}^*) = l(\mathbf{o}_{k^*})$.

Nearest Neighbour. The nearest neighbor method is based on certain context dependent distance measurement that assigns an Euclidean distance between any two RSSI samples. Given a set of training RSSI data and a testing RSSI vector, the posture class is estimated from the training samples whose observation RSS vector has the *minimal* distance when compared with the new coming RSSI observation. In particular, a testing RSSI sample is classified by a majority vote of its neighbors, with the RSSI being assigned to the posture label that is most common among its nearest neighbors. this method simple and easy to implement. We briefly summarize the application of this method in our posture recognition in the following. The details can be found in Algorithm 1.

Given a new coming RSSI value $\mathbf{o}^*$ and a collection of the training data $\mathcal{O} = \{(\mathbf{o}_1, l_i), ..., (\mathbf{o}_n, l_n)\}$. Our objective is to find a trained data sample $\mathbf{o}_k \in \mathcal{O}$, which is the nearest to $\mathbf{o}^*$, and to assign the posture class label of $\mathbf{o}_k$ to $\mathbf{o}^*$. It can be formulated as:

$$k = \arg\min_k dis(\mathbf{o}^*, \mathbf{o}_i) \tag{1}$$

The posture label of $\mathbf{o}^*$ is derived from $l(\mathbf{o}^*) = l(\mathbf{o}_k)$.

Support Vector Machine (SVM). SVM method aims at finding the decision boundary via maximizing the distance from the closet sample to the boundary hyperplane. When there are limited training data available, SVM usually outperforms the traditional parameter estimation methods which are based on Law of Large Numbers. This is mainly due to the fact that SVM benefits from the structural risk minimization principle and the avoidance of overfitting by its soft margin. For posture recognition, SVM works like the following. It classifies postures based on the fact that the smaller the distance between two RSSI samples, the higher probability they belongs to a same posture. SVM method works directly with RSSI using the kernel functions. The topology implicit in sets of RSSI and the locations can be exploited in the construction of possibly non-Euclidean function spaces that are useful for posture estimation. Given the sequence of training RSSI and corresponding posture labels $\mathcal{O} = \{(\mathbf{o}_1, l_i), ..., (\mathbf{o}_n, l_n)\}$, where $\mathbf{o} \in \mathbb{R}^D$ and $l \in \{1, ..., k\}$, the objective function can be formulated as:

$$\begin{aligned} & \min_{\mathbf{w},b,\xi} \mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{n} \xi_i \\ \text{s.t. } & l_i(\mathbf{w}^T\phi(\mathbf{o}_i) + b) \geq 1 - \xi_i, i = 1, 2, ..., n \\ & \xi_i \geq 0, i = 1, 2, ..., n \end{aligned} \tag{2}$$

where ξ_i is the slack variables, C is the penalty of error term, $K(\mathbf{o}_i, \mathbf{o}_j) = \phi(\mathbf{o}_i)^T\phi(\mathbf{o}_j)$ is the kernel function.

The prime problem of optimization in Equation 2 can be converted to solve its duality using Lagrange multiplier. Thus, Equation 2 can be reformulated as:

$$\begin{aligned} & L(\mathbf{w}, b, \xi, \alpha, \mu) = \\ & \mathbf{w}^T\mathbf{w} + C\sum_{i}^{n} \xi_i - \sum_{i=1}^{n} \alpha_i(l_i(\mathbf{w}\mathbf{o}_i + b) - 1 + \xi_i) + \sum_{i=1}^{n} \mu_i\xi_i \end{aligned} \tag{3}$$

where $\alpha = (\alpha_1, ..., \alpha_n)^T$ and $\alpha = (\mu_1, ..., \mu_n)^T$is the Lagrange multipliers. To solve Equation 3, we can maximize the minimization of duality as:

$$\max_{\alpha,\mu} \min_{\mathbf{w},b,\xi} L(\mathbf{w}, b, \xi, \alpha, \mu) \tag{4}$$

The technical details and supporting mathematical theory can be found in the state-of-the-art [23]. Three widely used kernels are explored in our work, including the linear kernel, the polynomial kernel, and the Gaussian kernel.

- Linear kernel. $K(\mathbf{o}_i, \mathbf{o}_j) = \mathbf{o}_i^T\mathbf{o}_j$
- Gaussian kernel. $K(\mathbf{o}_i, \mathbf{o}_j) = \exp(-\frac{||\mathbf{o}_i - \mathbf{o}_j||^2}{2\sigma^2})$
- Polynomial kernel. $K(\mathbf{o}_i, \mathbf{o}_j) = (\mathbf{o}_i \cdot \mathbf{o}_j + 1)^p$

After the model is learned, we can recognize the posture class for a given testing RSSI $\mathbf{o}^*$.

Naive Bayes. Naive Bayes classifier finds the most posterior probability $Pr(l_k|\mathbf{o}^*)$ for a given testing RSSI sample $\mathbf{o}^*$ as its predicted posture label $l(\mathbf{o}^*)$.

$$\begin{aligned} l_k &= \arg\max_{l_k} \frac{Pr(l_k)\prod_j^D Pr(\mathbf{o}_j^*|l_k)}{\sum_j^k Pr(l_k)\prod_j^D Pr(\mathbf{o}_j^*|l_k)} \\ &= \arg\max_{l_k} Pr(l_k)\prod_j^D Pr(\mathbf{o}_j^*|l_k) \end{aligned} \tag{5}$$

where prior probability $Pr(l_j)$ is proportional to the size of training samples in each posture class, which is obtained via dividing number of samples belonging to posture l_j by total number of training samples, i.e., $Pr(l_j) = \frac{|\mathbf{o}_{l_j}|}{|\mathcal{O}|}$. K is the number of posture classes. Conditional probability on each dimensional RSSI $Pr(\mathbf{o}_j^*|l_k) \sim N(\mu_j, \sigma_j^2)$ can be obtained from the training dataset.

2) Slope Variation Based Segmentation: To apply the statistical machine learning methods into online posture recognition, one of the major tasks is to divide the continuous sequence of RSSI data stream into a set of individual segments. Ideally, each segment corresponds to a specific concept or a posture. For instance, one RSSI segment is corresponding *sitting*, and another segment is corresponding to *standing*.

Segmentation can help classifier understand underlying posture better, and compress streaming data as well. Some existing segmentation methods such as online time series segmentation apply an adaptive model on one dimensional data [24], [25]. Such methods are not very applicable to build segmentation for multiple dimensional streaming data (e.g., N-dimensional RFID RSSI data in our case), because each segment derived from long sequence of the RFID data are relatively independent and has a separate semantic meaning (e.g., sitting vs. lying on bed).

Intuitively, we can assume that there generally exists a posture transition when the curve emerges significant fluctuation in the observations of RSSI data. In this paper, we design a *slope variation based segmentation* algorithm (see Algorithm 2) over multi-dimensional RSSI data stream for segmentation based on analyzing a distance criteria and the geometrical content of the RSSI data. The algorithm aims to follow the shape of the RSSI fluctuation curve and works as the following. We first read the samples into a buffer. For each buffer, we mark points with slope change on each dimensional data. These points indicate the changes from peak to troughs of the curve, and represent the trend of changing from one concept or posture to another.

After finding all potential segmentation points over each dimensional data in one buffer, we adopt the majority voting rules to integrate the segmentation points. More specifically, we count the times of each potential point and selecting the points with the most repeating time as the final segmentation point for the multi-dimensional RSSI in each buffer. If some points have the same repeat times, these points could be regarded as center point. We respectively calculate the sum of horizontal geometric distances between these center points and the other potential points in one buffer. The potential points with the lowest sum of horizontal geometric distances are set as the best segmentation points. Each buffer has only unique segmentation points. The most potential segmentation points represents posture change because some RSSI values may not be changed promptly when postures change. Thus, the center of cluster with most potential segmentation points is best segmentation points.

RSSI data could be noisy and we need to develop a mechanism to eliminate the troughs or peaks resulted from the outliers in the data. In our work, we improve the algorithm to filter the results of the slope computation by adding a *backtrack mechanism* for checking. It should be noted that the connectivity among the points has a major influence on segmentation. Connections with links to the outlying points lead to poorer features and generally complicate the segmentation, while connections that avoid such links enhance the accuracy of the segmentation. As shown in Figure 4, assuming the slope between the first point and the second point is greater than 0,

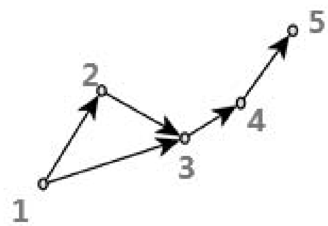


Fig. 4. Illustration of fake slope variation caused by noise

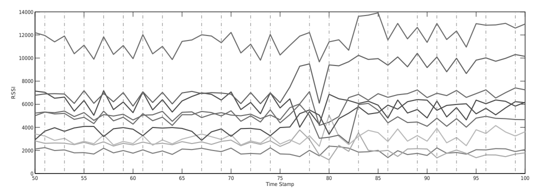


Fig. 5. Illustration of the segments obtained from Algorithm 2. Vertical dot lines indicate the segmentation points.

and the slope between the second point and the third point is less than 0. The previous algorithm would cut at the second point because it treats the second point as a turning point. However, it is actually increasing from the third point to the fifth point. If we calculate synchronously the slope between the first point and the second point, and the slope between the first point and the third point, we could find that the trend from the first point to the third point is still increasing and easily avoid unnecessary cutting in the second point. Figure 5 shows the segmentation points obtained from our proposed method.

Algorithm 2: Slope-Majority Segmentation

Input: RSSI stream $\mathcal{O}$
Output: a sequence of RSSI segments $\mathbf{S}_{\mathcal{O}}$

/* read in samples in buffer */
$\mathcal{O} \rightarrow \{b_1, ..., b_n\}$
$\mathcal{S}_{\mathcal{O}} \leftarrow \varnothing$
while *hasNext($\mathcal{O}$)* **do**
  /* calculate segmentation points for each dimensional data */
  segPointsIndex=SloptSeg(frame);
  /* select points with numerous frequency as final point */
  finalSegmentationPoint=MajorityVoting(segPointsIndex);
  /*in case of a tie, e.g., one than one points with same frequency */
  if *same repeat times* **then**
    finalSegmentationPoint=MinimumDis(segPointsIndex);
  end
  /* no individual points have same frequency */
  if *no same index* **then**
    finalSegmentationPoint=RightBound(segPointIndex);
  end
  $\mathcal{S}_{\mathcal{O}} \leftarrow \mathcal{S}_{\mathcal{O}} \cup \mathcal{S}_{\mathcal{O}}(finalSegmentationPoint)$;
  next($\mathcal{O}$);
end

C. Application Scenarios

Posture recognition has many critical applications in practice. Here, we briefly describe several application domains and provide some illustrative examples of the usefulness of our approach.

Fall Detection. As with the great progress of medical technology, many developed countries are facing the issue of aging society where there will be a lower proportion of people of working age available both to fund and to provide the necessary levels of care. Meanwhile, the problem of huge nursing cost has a big impact to aged care. The demand for developing home surveillance systems is rising and such systems help old people stay at their own homes longer and safer. Posture classification reduces the necessity for caregivers to oversee individuals (especially seniors). In particular, falls are the leading cause of fatal injuries for people aged 65 and above. By monitoring the postures of an elderly, we could detect the likely falls (e.g., getting out of bed) and issue an alert timely.

Ambulatory Monitoring. The posture recognition and monitoring are critical in medical area, e.g., ambulatory monitoring, because physiological responses, such as changes in heart rate or blood pressure, may result from changes in body position and physical activity. Continuous monitoring and automatic detection of subtle behavioral changes can be very valuable for physicians and caregivers to estimate the physical well-being of a person.

IV. Experimental Studies

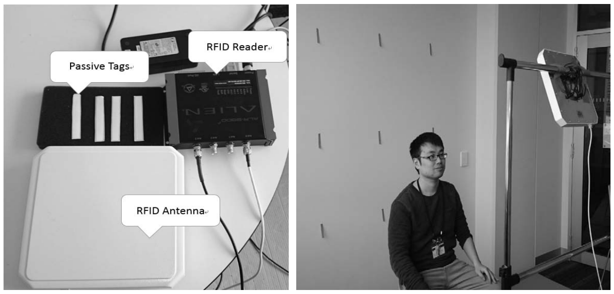
In this section, we report the experimental settings, performance metrics, and the experimental studies on posture classification and online posture recognition.

A. Experimental Settings

Hardware Setup. We used one Alien 9900+ reader, one circular antenna and nine Squig inlay passive RFID tags in our experiment (as shown in Figure 6(a)). The nine tags as anchor tags were placed at a 2×2 grid points on the wall where each grid is roughly $0.58m \times 0.58m$. We call this wall the active testing area. The antenna was arranged in $\approx 1.3m$ height facing the active testing area in $\approx 70°$ (as shown in Figure 6(b)). The subject performed different predefined postures between the wall and the antenna, and the corresponding sequence of RSSI were collected at sampling rate 0.5s.

Metrics. We evaluated our proposed approach in terms of recognition accuracy and recognition delay. Accuracy is to measure how accurately our approach can recognize a posture given new coming RSSI values, and delay is to measure how timely our approach can recognize a posture given new coming RSSI values. It represents the time gap between the segmented division point and the nearly ground-truth division.

Sampling Rate. Passive RFID tags tend to be noisy even in lab environments. For example, one challenge in RFID systems is false negative readings, caused by miss detection (i.e., an undetected tag is in the antennas reading range). In



(a) (b)

Fig. 6. In (a), we show the devices used in our experiment, including 1 RFID reader (Alien 9900+), 1 Alien Circular Antenna and a collection of Alien Squig RFID Inlay passive tags. In (b), we show the experimental layout in our implementation, one subject is sitting between tag array and antenna and performing predefined postures.

the meanwhile, RSSI data is much sensitive to environments, e.g., some disturbance from environment can cause RSSI abnormal fluctuation. Appropriate sampling rates can reduce the aforementioned problems. However, too small sampling rates make our method more sensitive to the noise of RFID readings, while too big sampling rates blur the inter-class posture boundaries. In our implementation, we collected the continuous RSSI data stream at the sampling rate $\approx$ 0.5 second.

Data Acquisition. For collecting training dataset, we conducted a series of experiments where a subject entered the active testing area and performed various pre-arranged postures (corresponding to the index shown in Figure IV-B3), indexed from 1 to 13 as: *Empty*, *Standing freely*, *Standing straightly*, *sitting*, *Sitting leaning back*, *Sitting leaning left*, *Sitting leaning right*, *Sitting leaning forward*, *Lying in bed*, *Falling back*, *Falling front*, *Falling right* and *Falling left* (Figure 7) to simulate tripping and crumpling to the floor. Two subjects participated in the experiment and each performed the set of these orientation-sensitive postures. The subjects also performed four different predefined posture sequences (Table I). The timing of all the movements was determined beforehand so that the data could later be compared to the actual timing of the postures.

No.	Postures	No.	Postures
1	Stand Stright	7	Sit leaning forward
2	Stand in free style	8	Lie in bed
3	Sit	9	lie on ground
4	Sit leaning back	10	Fall front
5	Sit leaning left	11	Fall right
6	Sit leaning right	12	Fall left

Fig. 7. Predefined orientation-sensitive postures

For collecting the testing dataset, we designed multiple posture sequences and collected them using two strategies. In the first strategy, the subject performed and held each posture for 30 seconds and then performed next posture in the order as predefined in the sequence. In the second strategy, the subject performed and held each posture for 60 seconds and then performed the next posture in the order as predefined in the sequence. Some testing sequences are listed in Table II.

TABLE I
DETAILS OF TRAINING POSTURES

No.	Posture	SubPostures
1	Standing	Standing straight/Standing in free style
2	Sitting	Sitting straight/backward/forward/left/right
3	Lying on the ground	Lying on back
4	Lying in bed	Lying on back
5	Falling	Falling front/left/right

Feature Extraction. The RSSI data in each segment are composed of series of RSSI values arranged by receiving time with each series representing the RSSI values of a specific tag read by an antenna. We carefully examined several popular extraction methods, e.g., frequency based features, and statistical features, such as the mean, variance, max, min, mean crossing rate, frequency domain energy and entropy of the RSSI values to characterize its radio patterns temporally. The temporal features are extracted for each RSSI series independently from the others. As a result, we choose the lightweight feature extraction methods, mean and variance as features by comparing different feature combinations.

TABLE II
EXAMPLES OF TESTING POSTURE SEQUENCE

No.	Posture Seq.
1	Stand straight $\rightarrow$ sit left $\rightarrow$ fall left
2	Lie in bed $\rightarrow$ stand straight $\rightarrow$ fall right $\rightarrow$ lie on ground
3	Lie in bed $\rightarrow$ stand in free style $\rightarrow$ fall right $\rightarrow$ lie on ground

B. Experimental Results

In this section, we report our experimental results in terms of identifying postures of stationary person, as well as real-time recognizing postures based on continuous RSSI. We explored three probabilistic learning algorithms in our experiments: multi-class support vector machine, nearest neighbor, and naive Bayes using Person-dependent strategy, in which part of collected data from each subject are used as training set, and the rest of the same subject is used as testing set. The reported results are the average accuracy of all subjects.

1) Recognition Accuracy: We compared the overall accuracy of our proposed segmentation algorithm and the sample-based sliding window method. In terms of activity recognition, the sliding window algorithm aims to reduce the complexity of forecast online. In real life, activity recognition based on real-time sensor readings needs to segment data flow to reduce the complexity of calculations and return the classification results. Considering sampling rates and the diversity of activities, the sliding window algorithm in different experiments sets window size and move speed of window. For RFID signals, the window size has been set to 4, and the window move speed is 2, which means that the overlapping ratio is 50% in each window movement except the first and the last time stamps. In each movement, the classifier could merely calculate data inside one window. Sliding window algorithm as the simplest segmentation method supports online recognition. However, it does not

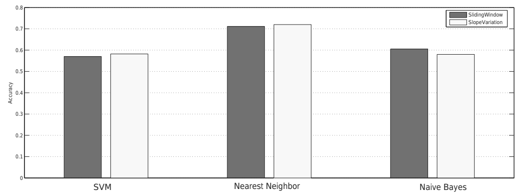


Fig. 8. Overall accuracy comparison between proposed segmentation algorithm with sample-based sliding window method in online posture recognition

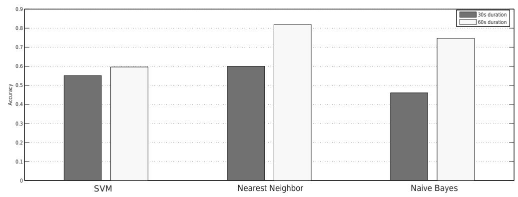


Fig. 9. Accuracy comparison of performing 30s and 60s strategies

focus on activity integrity, and unsuitable window size and movement speed always affect the accuracy of classification results. From Figure 8, we can see that all three classifiers give better performance when using our proposed segmentation method than the sliding window method.

We also compared the performance on in terms of duration a posture is held. Figure 9 shows the results under two durations (30 seconds and 60 seconds). The results clearly show that the longer the posture is held by the subject, the better accuracy can be achieved. The reason is that longer posture holding time can eliminate both inter-class and intra-class blur, to which RSSI are especially sensitive in recognizing postures.

2) Recognition Delay: In general, we would like to know how quickly our proposed approach can detect the transitions of a person from one posture to another. Specially, quick response is crucial in healthcare area. For example, for the fall detection mentioned in Section III-C, we could send an alert to the old people for possible falls, or notify the care givers as quickly as possible to offer medical assistance for the elder people after the falls happen. We conducted the experiments to quantify how quickly our proposed approach can identify the posture changes, in other words, the recognition delay. From Figure 10, we can clearly see our proposed method can promptly detect the posture changes with slight latency.

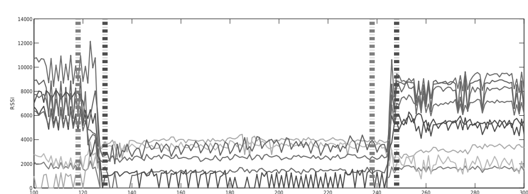


Fig. 10. Recognition latency: red dot vertical line indicates the ground-truth time point of posture change, blue dot vertical line indicates the recognition time pointe detected by our proposed approach.

3) Fine-grained Posture Classification: So far, our discussions and experiments focused on coarse-grained postures.

TABLE III
PEOPLE-DEPENDENT POSTURE RECOGNITION

Training Ratio	SVM	KNN	Naive Bayes
0.1	0.9228	0.9900	0.9705
0.2	0.9684	0.9933	0.9842
0.3	0.9580	0.9926	0.9868
0.4	0.9746	0.9957	0.9857
0.5	0.9751	0.9944	0.9893
0.6	0.9801	0.9973	0.9845
0.7	0.9744	0.9972	0.9886
0.8	0.9786	0.9936	0.9872
0.9	0.9679	0.9957	0.9915

TABLE IV
PEOPLE-INDEPENDENT POSTURE RECOGNITION

Training Ratio	SVM	NN	Naive Bayes
0.1	0.3799	0.3829	0.3859
0.2	0.3596	0.4876	0.4025
0.3	0.4226	0.4930	0.4566
0.4	0.3715	0.4613	0.4201
0.5	0.3779	0.4668	0.3977
0.6	0.4164	0.4842	0.4426
0.7	0.3847	0.4867	0.4477
0.8	0.3845	0.4805	0.4957
0.9	0.3916	0.4584	0.4563

We also conducted some preliminary experimental studies to examine the possibility of recognizing fine-grained postures using the array of passive tags. More specially, we conducted the posture classification in an offline way to see whether it is possible the fine-grained postures can be distinguished via learning uncertain RSSI. We divided our data collection as the training set and the testing set, and tested the classifiers in terms of person dependent and person independent ways. For person dependent, we mean our approach is trained by using the dataset collected from a single subject, while for person independent, the approach is trained by using the dataset collected from several subjects. The latter usually has poor performance due to considerable inter-person variability on performing postures.

Table IV shows the experimental results with three machine learning approaches over all posture classes. From the results, we can see that it is highly possible to further develop our algorithm to recognize fine-grained postures, even though RSSI from passive tags are uncertain and noisy. The classification accuracy of person dependent stands over 92% at least using the general probabilistic approaches. The accuracy of person independent also is reasonable and achieves 49% using the nearest neighbor method.

Taking a closer look at the accuracy performance from the confusion matrix over each fine-grained posture (Figure IV-B3). We can see that the most errors happen when identifying the postures with similar inter-class gap (e.g., fall to right and fall to left). Identifying orientation of postures can be valuable when combined with the layout of the place in practice. For instance, if we know that a table is on the left of an elder person, and we detect the orientation of the person's fall, we can identify how severe the fall would be (e.g., he may hit the table if falling to his left). Giving this positive

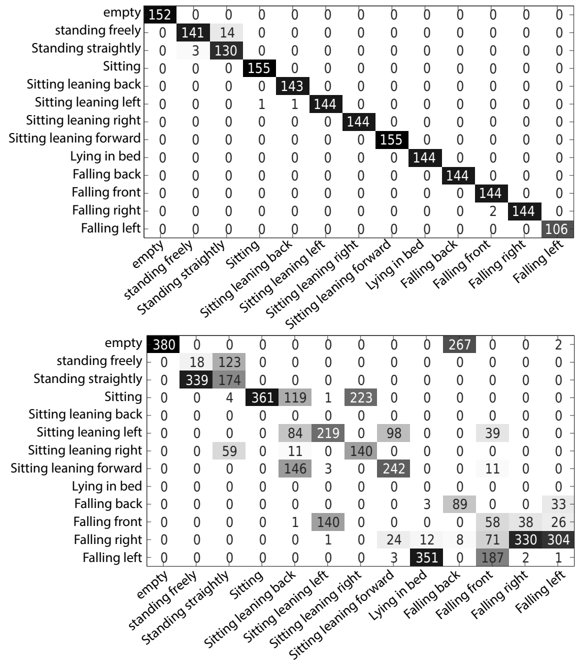


Fig. 11. Confusion Matrix (a) Person Dependent (b) Person Independent. Number 2 - 13 corresponds to posture classes in order and number 1 corresponds to empty status (no person).

initial results, using RFID tag arrays to do the fine-grained postures recognition will be one of the major investigations in our future work.

V. Conclusion and Future Work

Interpreting human activity from low-level sensor readings is a major challenge in developing a wide range of applications. Most existing approaches rely on body-worn sensors to detect human activities from observed sensor readings, which require user involvement (e.g., remembering to wear the device). Such approaches are not practical and may have limited applicability. In this paper, we have studied the *device-free* posture recognition by using an array of passive RFID tags. We exploit machine learning techniques where the recognition problem is solved by using an inductive inference via learning a sequence of RSSI data collected when persons perform different postures. In particular, we design a multi-dimensional data stream segmentation algorithm based on geometrical characteristic of RSSI fluctuation, and compare three different machine learning approaches. The experimental results show that machine learning methods perform well in posture recognition. This positive result inspires us to further explore in our future work on the possibility of identifying fine-grained postures based on this low-cost, unobtrusive RFID technology.

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