A Wearable RFID System for Real-time Activity Recognition using Radio Patterns

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Abstract. Much work have been done in activity recognition using wearable sensors organized in a body sensor network. The quality and communication reliability of the sensor data much affects the system performance. Recent studies show the potential of using RFID radio information instead of sensor data for activity recognition. This approach has the advantages of low cost and high reliability. Radio-based recognition method is also amiable to packet loss and has the advantages including MAC layer simplicity and low transmission power level. In this paper, we present a novel wearable Radio Frequency Identification (RFID) system using passive tags which are smaller and more cost-effective to recognize human activities in real-time. We exploit RFID radio patterns and extract both spatial and temporal features to characterize various activities. We also address two issues - the false negative issue of tag readings and tag/antenna calibration, and design a fast online recognition system. We develop a prototype system which consists of a wearable RFID system and a smartphone to demonstrate the working principles, and conduct experimental studies with four subjects over two weeks. The results show that our system achieves a high recognition accuracy of 93.6% with a latency of 5 seconds.

Key words: Activity Recognition, Wearable RFID, Real-time

1 Introduction

With the rapid advances of wireless networking and sensing technologies in recent years, recognizing human activity based on wearable sensors has drawn much research interest. In this paradigm, wearable sensors with sensing and wireless communication capabilities are organized in a body sensor network (BSN) to capture different motion patterns of a user. Continuous sensor readings are collected and processed at a centralized server for extracting useful features, training an appropriate activity model, and recognizing a variety of activities. Recognizing people's activities continuously in real-time enables a wide range of applications, particularly in health monitoring, assistive living, rehabilitation, and entertainment.

While BSNs have shown the effectiveness, they do have several limitations. First, the human body affects the quality of the wireless links between sensor nodes causing packet loss [1]. This will result in incomplete sensor data received at the server, undermining the accuracy and the real-time performance of the recognition system. To improve packet delivery performance, the system can either use re-transmission mechanisms or increase the transmission power level [2]. However, this solution complicates the underlying MAC protocol, increases sensor power consumption, and degrades the real-time performance of the system. Moreover, in order to capture the user's activities, BSN nodes are equipped with sensing, computing, storage, and communication devices, making the sensor nodes large in size and high in cost. Finally, batteries are required to keep the sensor nodes alive, making energy consumption a challenging issue in BSN. The daily maintenance of the system (e.g., monitoring the remaining power and changing the batteries for multiple sensor nodes) is labor-intensive.

Recent studies show that Radio Frequency Identification (RFID) technologies have the potential to build low-cost, reliable systems to detect certain activities such as moving trajectories or gestures based on radio information [3–5]. Motivated by these work, we explore the possibility of using ultra-high frequency (UHF) RFID system for complex human activity recognition. Our system is based on two observations: 1) there exists heavy attenuation of the human body to radio communication band in which the UHF RFID operates, and 2) RFID radio communication is highly affected by the tag-antenna distance and orientation. Based on these observations, if we deploy an RFID system on a human body, user motions may result in different radio patterns which can differentiate activities. In our system, packet loss and fading provide useful information for activity recognition. Thus, simple MAC protocols and low transmission power levels are preferred. Further, we use passive tags instead of sensor nodes which are smaller and lighter that can be embedded into the clothes and daily objects. The passive tags are more cost-effective and, due to their simple structure and protective encapsulation, more robust than the sensor nodes. Finally, the passive tags operate without batteries. Once deployed, no further maintenance is required. The only device that requires battery power in our sensing system is the RFID reader. According to our previous experience in BSN-based recognition system [6] in which careful battery management is required for every sensor node to keep the system operate, we argue in this paper that using only one battery for the entire system significantly reduces the human-effort and increases its reliability. Moreover, recent technical trends show that low-cost, low-power RFID readers are becoming commonly available by integrating into the smartphones [7], making our work potentially beneficial to the mobile users in the future.

The system consists of a wearable RFID system for capturing radio patterns, and a smartphone device for collecting and processing such patterns. To make use of the radio patterns, we extract temporal and spatial features to characterize the radio patterns. These features are carefully selected to tolerate large variances in tag performance, avoiding labor intensive calibration which is typically required in many RFID and RSS-based systems [3]. We design an effective algorithm to address the false negative issue of tag readings in RFID systems. To achieve real-time recognition, we use a fixed-length sliding window to control latency bound, and develop a fast, lightweight, online algorithm based on Support Vector Machine (SVM) to be executed on smartphones. We conduct comprehensive experiments involving multiple human subjects. The results show that our system achieves a high recognition accuracy with a low delay.

The rest of the paper is organized as follows. Section 2 introduces related work. Hardware setup and preliminary experiment results are presented in Section 3. We present the details of our system design in Section 4. Section 5 reports results of empirical studies and Section 6 concludes the paper.

2 Related Work

Much work have been done based on sensor readings for activity recognition. These sensing based solutions [6, 8] usually deploy accelerometer sensors on a human body to capture body movement. The sensor nodes are self-organized into a BSN where appropriate MAC and routing protocols are operated to ensure the quality of sensor data. Different from these work, we exploit RFID radio information for activity recognition.

RFID has been used in indoor localization and activity recognition. For example, fixed RFID readers and reference tags are deployed in the environment with known locations to track the mobile tags or persons using RSS values [3, 4]. In [5], the authors use RFID for tracking hand movements in a table-size scale. The tags are placed in a grid-like structure on a table with readers located at three corners. They use tag counting information received at different readers to keep track of hand movements. Different from the above work relying on fixed RFID readers or tags for tracking locations or detecting simple moving patterns, we design a wearable RFID system to recognize human activities involving complex movements of different body parts continuously. In [6], wrist-worn HF RFID readers are used to capture the object usage information by reporting the passive tags attached to objects within its reading range (less than 7 cm in reading distance). Different from this work, we use a UHF RFID system with a larger reading range covering a user's entire body, and exploit the RFID radio patterns to recognize body movements.

Recent work have explored 2.4G RF radio information for activity recognition. In [2], the authors use the radio communication patterns extracted from a BSN to recognize activities. Their BSN consists of two on-body sensor nodes, which send simple fake packets to the sink at a low power level. The communication patterns (i.e., such as packet delivery ratio and the mean of RSSI values) from arrival packets within a time window are extracted and used as a signature to recognize the corresponding activity. Similar RSSI information of the radio communication have also used been in [9] for activity recognition. Different from these work, we design a novel RFID system with passive tags which can be potentially unobtrusive to user experience since tags can be easily embedded into clothes. Unlike the sensor nodes, the passive tags do not rely on battery power to operate. We discover rich RFID radio patterns and extract complex features, and demonstrate how they are used in a real-time activity recognition system.

3 Preliminary Experimental Studies

In this section, we introduce our system hardware setup and conduct preliminary experiments to show the tag reading performance under different conditions and the potential of using radio patterns for activity recognition.

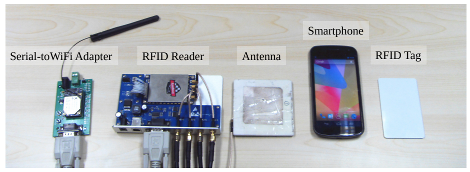
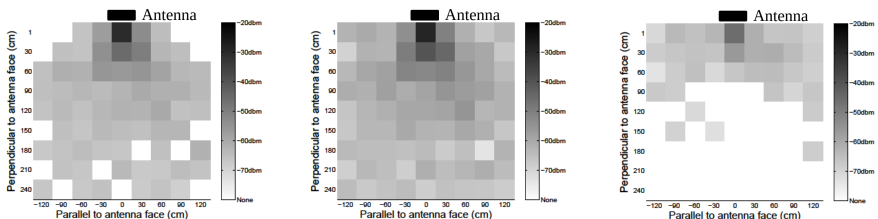


Fig. 1. Hardware setup.



(a) Power = 20 dbm, Angle = 0 ° (b) Power = 30 dbm, Angle = 0 ° (c) Power = 20 dbm, Angle = 90 °

Fig. 2. Average RSS values of tags at different positions with different transmission power levels and tag-antenna orientations.

3.1 Hardware Setup

The hardware used in this work is shown in Fig. 1. We use Impinj R2000 RFID reader module powered by a Li battery with 9000mAh capacity. The size of the reader is 15×9×2.5 cm. We use UHF RFID tags with a credit card size. We have four antennas, and each has a size of 7.8×7.8×0.5 cm. The transmission power level of each antenna is adjustable from 0dbm to 30dbm with a minimum level of 0.1dbm. The RFID reader module operates at 840-960MHz and supports UHF RFID standards such as ETSI EN 302 208-1. The agility of the module is -95dbm. When set to the tag inventory mode, the reader can read as many tags as possible (maybe multiple readings per tag) using an anti-collision protocol. For the reader we used, over 50 tag readings can be obtained in one second. Each tag reading contains the tag ID[1] and the RSS value. Tag readings obtained from the reader are sent wirelessly through a Serial-to-WiFi adapter. The readings are then received by a smartphone for processing. We use Samsung Nexus 3 smartphone with a dual-core 2.4G processor, running Android 4.0.

3.2 Reading RFID Tags

We first study the tag reading performance of the reader under different settings in transmission power level, tag-antenna distance, and orientation.

First, Fig. 2(a) shows the RSS values obtained at different positions in the detection area of an antenna. The antenna is placed on the top of the area facing downward with the transmission power level set to 20dbm. The tag under test is placed in an area 0cm to 240cm perpendicular to, and -120cm to 120cm parallel to the antenna face (negative values for positions on the right side of the antenna). The tag-antenna angle is 0 degree, i.e., the tag face is parallel to the antenna face. As shown in Fig. 2(a), the RSS

[1] We use the Electronic Product Code (EPC) stored on a tag as its ID.

Fig. 3. (a) Wearable RFID system, (b) average RSS readings with different motions over time.

gets stronger when the tag is placed closer to the antenna. Specifically, in the direction perpendicular to the antenna face, the tag can be stably read when placed within the distance of 60cm to 90cm. For a distance less than 60cm or larger than 90cm, the tag is not detected in some locations. In the direction parallel to the antenna face, the tag can be stably read when placed in the distance of -60cm to 60cm. For locations out of this range, the tag is not detected sometimes.

Next, we change the antenna's transmission power level to 30dbm and repeat the previous experiment. The results are shown in Fig. 2(b). It is clear that all the RSS values get increased as compared to the 20dbm results in Fig. 2(a), and the antenna's reading range covers the entire 240cm $\times$ 240cm area with no miss detection. Finally, we repeat the first experiment with a power level of 20dbm, but we turn the tag-antenna orientation from 0 degree to 90 degrees. The results are shown in Fig. 2(c). We observe that the antenna's reading area has changed significantly. Tags can be read farther in the positions parallel to the antenna's face but significantly closer (no more than 60cm) in the direction perpendicular to the antenna's face compared to Fig. 2(a).

In summary, the tag RSS values are affected by factors including tag-antenna distance, orientation, and transmission power. Moreover, human body is known to affect RFID communication [4], which is also observed in our experiments (detailed experiment results are omitted due to page limits). If the tags and antennas are worn on the user's body, the above factors will change by the movements of different body parts when performing activities, and can be potentially used for activity recognition.

3.3 Potential of Activity Recognition

In this section, we demonstrate the potential of using RFID radio patterns extracted from RSS values for activity recognition. The experiment is carried out by one male subject performing three basic motions including standing, sitting, and walking. Four antennas and 36 tags are attached to the user as shown in Fig. 3(a) and introduced later in Section 4.1. During this experiment, we use the all antenna inventory mode of the reader which automatically activates the antennas for tag reading. Under this mode, the readings from the four antennas are mixed together. Also the four tags attached around the same body part share the same tag ID.

The average RSS values of tags attached to different body parts are shown in Fig. 3(b). From this figure, it is clear that different motions result in different RSS patterns. For the sitting activity, the RSS values of tags attached to the body, right leg, and left/right ankles are clearly stronger and more stable than other activities. For the s-tanding activity, the RSS readings of the above mentioned body parts are also relatively more stable than the walking activity but the RSS values are lower than the sitting activity. Additionally, it can be seen from Fig. 3(b) that the RSS values of tags attached to the left wrist and left arm are stronger and more stable than other activities. For the walking activity, rhythmic variances in RSS values can be observed for tags attached to nearly every part of the human body, and they seem matched with arms and legs waving during the walking activity.

4 System Design

The above preliminary studies have shown the feasibility and potential of using RFID radio patterns for activity recognition. In this section, we present the detailed design of the proposed RFID-based real-time activity recognition system including sensing, data segmentation, feature extraction and recognition algorithm.

4.1 Antenna / Tag Placement

We present the antenna and tag placement strategies in this section and show a subject wearing the antennas and tags in Fig. 3(a).

Antenna Placement. As suggested by Fig. 2 in our preliminary studies, we place four antennas on a human body – two antennas (one on the chest and the other on the back) for detecting hand/arm movements, and one antenna on each of the feet for detecting lower body movements (as shown in Fig. 3(a)). Such placement ensures a total coverage of different body parts, and also meet user's comfort need.

Tag Placement. To capture the movement of different body parts, RFID tags are attached to nine body parts including both wrists, arms, ankles, legs, and the body. To increase the reliability of tag readings, we attach four tags at each body part. For example, for the right wrist, we attach four tag located at the front, left, right, and back of the wrist. This redundant tag placement strategy ensures that no matter how the user moves his/her wrist, at least one tag will face the antenna and can be read by the reader with high probability. A total number of 36 tags are attached on the user's body with each tag having an unique ID.

Inventory Mode. Instead of using the all antenna inventory mode used for our preliminary experiment, we use single antenna inventory mode to discriminate the readings of one antenna from others. The four antennas connected to the RFID reader are activated sequentially to detect tags within their reading ranges. The dwell time of each antenna is set to the default value of two seconds and the time to complete an inventory cycle is eight seconds. The tag readings obtained during the activation time of an antenna is a series of tag IDs and their RSS values.

The transmission power level of the RFID reader is a key parameter in our system, and it influences the system's performance on both recognition accuracy and battery consumption. We find the optimal transmission power level by experiments in Section 5.3. We also evaluate the effect of different antenna and tag placement strategies in Section 5.2.

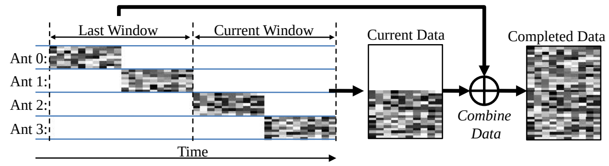


Fig. 4. Data completion method.

4.2 Data Segmentation and Completion

Given the continuous flow of tag readings, we first apply a sliding window to segment the data. In this paper, we focus on real-time activity recognition with a restricted recognition latency defined by the application. We use a fixed window size specified by L combined with the real-time activity recognition algorithm introduced later to achieve stable time performance. L is a key parameter in our system for it affects both the recognition accuracy and latency.

As mentioned in the introduction, one of the challenges in existing RFID systems is false negative readings [4,5], caused by miss detection – a tag is in the antenna's reading range, but not detected. In addition, in our system if the sliding window size is too short for the reader to complete readings for all four antennas, it may also cause false negative readings. To address this issue, we use recent historical data to complete the current readings. The intuition behind this approach is *temporal locality* – tags recently detected are likely to be detected again with similar RSS values. We illustrate the method in Fig. 4, assuming the false negative reading is caused by a short window size of 4s. While the data from antenna 0 and 1 are missing in the current data because the current window is only long enough to complete two antennas' readings, we use the last window's data to complete the current data. The same strategy is applied to the case of miss detection, technical details are omitted in this paper due to page limits.

4.3 Temporal and Spatial Features

For each data segment, we extract both temporal and spatial features to characterize the radio patterns. An known performance issue of tag readings commonly exists in RFID-based systems is that readings from different combinations of tags and antennas may be different even with the same condition [4]. One possible solution is through calibration. However, data calibration [4] is infeasible in our system because the complexity of our feature set. As a result, we carefully design our feature set that can tolerate the tag performance issue.

Temporal Features. The data in each segment are composed of series of RSS values arranged by receiving time with each series representing the RSS values of a specific tag read by a specific antenna. Seven features are extracted from each RSS series including the mean, variance, max, min, mean crossing rate, frequency domain energy and entropy of the RSS values to characterize its radio patterns temporally. The temporal features are extracted for each RSS series independently from the others. As a result, data calibration is not required for there is no cross-reference between readings from different tags and antennas.

Spatial Features. To characterize the radio patterns spatially, we extract the correlation coefficients of RSS series for different tags read by different antennas. The correlation coefficient quantifies the degree of dependency between a pair of RSS reading series by observing the similarity in their changing patterns. As shown by our preliminary experiment results, the RSS values are stronger with a closer tag-antenna distance and a smaller tag-antenna angle when the transmission power level is fixed. The performance issue of tag readings may cause different RSS values obtained by different combinations of tags and antennas even with the same condition but cannot fundamentally change their changing patterns caused by body movements.

4.4 Real-time Recognition Algorithm

The design goal of our system is to achieve real-time activity recognition. We identify two key requirements described as follows.

1. **Online**. An recognition algorithm is offline if it requires the complete instance of an activity to be presented for recognition [6]. Offline systems cannot perform real-time recognition for they need to wait for the current activity to finish before recognition and the waiting time is uncertain. To achieve real-time recognition, the algorithm must be online that can recognize the current activity without being presented with the complete activity instance, i.e., only using data already obtained.
2. **Continuous**. To achieve real-time, the recognition result must be generated before the delay bound. Considering that the recognition system works iteratively to generate recognition results, we adapt the real-time concept from the signal processing field [10] to activity recognition systems. The acceptable recognition latency is specified by the sliding window size L which determines the data collection time. The processing time must be less than the data collection time [10] so that the recognition results can be obtained before the next data segment arrives, providing continuous recognition results without extra delays.

While the online property of our recognition system is guaranteed in our system for activity instances are generated only using the data already obtained, the continuous property is determined by the execution time of the recognition algorithm. We design a fast recognition algorithm based on a multi-class support vector machine (SVM) with radial basis function kernel. SVM is widely used in activity recognition [2]. The advantage of using SVM for activity recognition includes: 1) designed on a sound theoretical basis, SVM is promising to have accurate and robust classification results; 2) SVM scales well to the number of features; 3) the model training can be performed on very few training cases; and 4) the recognition can be executed fast at runtime [2]. The performance of our recognition algorithm is determined not only by its time complexity but also the hardware platform. We have implemented the recognition algorithm on Android smartphone, and will evaluate its real-time performance in the next section.

5 Empirical Studies

In this section, we present empirical studies to evaluate the performance of our system. The experiments are conducted in an area of our office building, including two rooms

Table 1. Four subjects involved.

Subject	Gender	Height (cm)	Weight (kg)	Body Type
1	Male	177	70	Normal
2	Female	159	45	Slim
3	Male	180	75	Normal
4	Male	193	110	Strong

Table 2. Eight activities studied.

No.	Activity	No.	Activity
1	Sitting	5	Cleaning Table
2	Standing	6	Vacuuming
3	Walking	7	Riding Bike
4	Cleaning Window	8	Going Up/Down Stairs

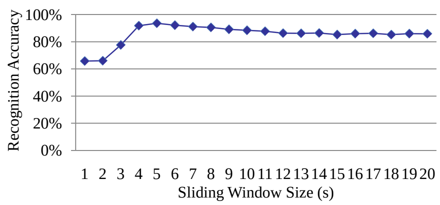


Fig. 5. Sliding window size vs. recognition accuracy.

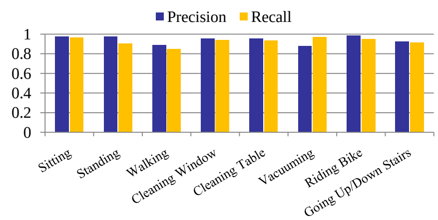


Fig. 6. Breakdown of precision and recall.

and a corridor, as well as outdoors. Our data collection involves four subjects (three males and one female). The subjects are carefully selected to represent different heights and body types as summarized in Table 1. Each subject is required to perform eight activities as summarized in Table 2. Each activity is performed for at least five minutes. The data collection is carried out over a period of two weeks and a total number of over 200 activity instances are collected.

5.1 Recognition Accuracy and Real-time Performance

In the first experiment, we evaluate the recognition accuracy which is defined by the number of correctly classified instances over the number of the total instances, and the latency which is determined by the sliding window size.

The recognition accuracies with different sliding window sizes are illustrated in Fig. 5. As we can see from the figure, when the sliding window size is small (i.e. from 1s to 4s), the recognition accuracy rapidly grows from 65.8% to 91.8%. The recognition accuracy reaches its peak at 93.6% when sliding window size is 5s. It is interesting to see that the recognition accuracy drops slowly afterwards and stabilizes at around 86% when the sliding window size increases further. This result suggests that a larger sliding window does not always result in a higher recognition accuracy.We breakdown the precision and recall of different activities with a window size of 5s and show the results in Fig. 6. Fig. 6 shows that the precision and recall for most of the activities are above 0.9. By analyzing the results, we find that some of the *walking* activity are recognized as *going up/down stairs*, a few instances of the *walking*, *cleaning table*, and *cleaning window* activities are recognized as *vacuuming*. Overall, our system achieves the best recognition accuracy of 93.6% when the sliding window size is set to 5s.

Next, we evaluate the real-time performance of the system. The online property is guaranteed by using only the current and historical data for recognition. The continuous property is determined by the execution time of the recognition algorithm. Fig. 7 compares the data collection time and the maximum processing time on our smartphone (data completion + feature extraction + recognition) under different sliding window

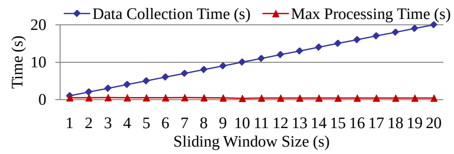


Fig. 7. Data collection time vs. maximum processing time.

Table 3. Antenna placement configurations.

Configuration	Back	Chest	Left Foot	Right Foot
Upper Antennas	✓	✓		
Lower Antennas			✓	✓
Mixed Antennas		✓	✓	

Table 4. Tag placement configurations.

Configuration	Left Wrist	Right Wrist	Left Arm	Right Arm	Body	Left Leg	Right Leg	Left Ankle	Right Ankle
Upper Tags	✓	✓	✓	✓	✓				
Lower Tags					✓	✓	✓	✓	✓
Mixed Tags		✓		✓	✓	✓		✓	

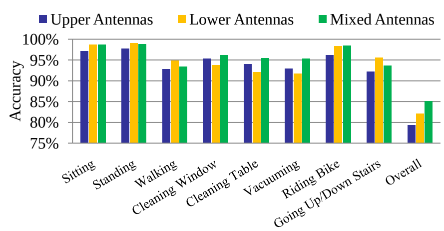


Fig. 8. Recognition accuracy under different antenna configurations.

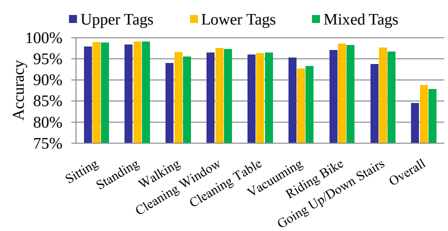


Fig. 9. Recognition accuracy under different tag configurations.

sizes. As shown in the figure, our system performs real-time recognition even when the delay bound is down to 1s (by fixing the sliding window size to 1s). The maximum processing time is always less than the data collection time and remains low (around 450ms) when the sliding window size grows.

5.2 Antenna and Tag Placement

We evaluate the performance of different antenna and tag placement strategies in this experiment. We designed three placement configurations for both the antennas and the tags as shown in Tables 3 and 4, respectively. Note that we assume the user wears all the tags when choosing different antenna configurations and wears all the antennas when choosing different tag configurations.

The recognition accuracies under different antenna configurations are illustrated in Fig. 8. To compute the accuracy of each activity, we use the same metric as in [2] defined as follows.

$$activity\_accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative}$$

The metric for the overall accuracy is the same as we used in our first experiment. Fig. 8 shows that the lower antennas are effective to activities involving more lower body movements (e.g., *sitting*, *standing*, and *walking*), and the upper antennas are more

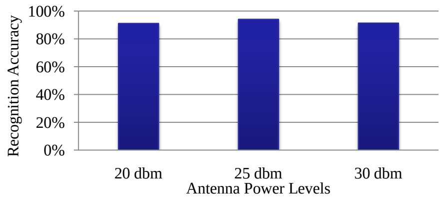


Fig. 10. Recognition accuracy of different antenna transmission power levels.

Table 5. Optimal transmission power levels for different subjects.

Subject \ Power Level	20dbm	25dbm	30dbm
1	85.2%	**90.2%**	89.1%
2	**94.6%**	93.2%	92.8%
3	89.9%	**93.9%**	91.6%
4	84.2%	**91.0%**	87.0%

effective to activities (e.g., *cleaning window*, *cleaning table*, and *vacuuming*) with more upper body movements. The *Mixed Antennas* configuration achieves the highest overall accuracy of 85.1%. For different tag configurations, the results are illustrated in Fig. 9. We have similar observations as in the antenna configuration experiment. The *Lower Tag* and the *Mixed Tag* configurations achieve similar overall accuracy of 88.8% and 87.8%, respectively.

In summary, the antennas and tags attached to the lower and upper body are effective in recognizing activities involving different lower and upper body movements, respectively. A good choice is to use the mixed configuration that places the tags and antennas on one side of the upper body and the other side of the lower body.

5.3 Antenna Transmission Power Level and Battery Consumption

In this experiment, we evaluate the system's performance with different antenna transmission power levels (i.e., 20dbm, 25dbm, and 30dbm). Fig. 10 illustrates the overall recognition accuracies of different power levels. The recognition accuracy is above 90% for all transmission power levels and the highest accuracy of 94.0% is achieved at power level of 25dbm. We further study the optimal power levels for different subjects. As shown in Table 5, we discover that for all three male subjects, the optimal recognition accuracy is achieved at the power level of 25dbm, followed by 30dbm and 20dbm. This result explains the reason for the overall optimal power level of 25dbm shown in Fig. 10. For the female subject, the optimal power level is 20dbm. It is possibility because the female subject is smaller in size and the fading effect is stronger with a lower transmission power level. This result suggests that the optimal power level is not the highest level but the one most sensitive to RSS radio patterns resulted from different activities.

To evaluate battery consumption, for the RFID reader, we measure the output current for the battery. The battery output current is 180mA, 223mA, and 253mA, for the transmission power level of 20dbm, 25dbm, and 30dbm, respectively. For the smartphone, we use a battery monitoring software built on top of the Android OS's battery consumption APIs to record the battery consumption data. The results show our recognition software introduces an additional consumption of about 38mA. Though the reader consumes a larger amount of battery power compared to BSN-based systems [2, 6], according to our previous experience in data collection using a BSN [6], we find that managing only one battery for the reader is much easier than managing batteries for multiple nodes in a BSN.

6 Conclusion

In this paper, we present a novel wearable RFID systems for real-time activity recognition. We implemented the prototype system, and the experiment results show our system achieves high accuracy and low delay. As our first prototype, there are some limitations. For example: 1) the current devices are a little cumbersome; 2) a large number of tags and antennas are used. In our future work, we plan to improve our system design by: 1) using smaller RFID readers, or smartphone integrated RFID readers; 2) studying more antenna and tag placement strategies and exploring the minimum number of tags and antennas necessary to achieve better system performance.

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