RFID Shakables: Pairing Radio-Frequency Identification Tags with the Help of Gesture Recognition

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ABSTRACT

A novel approach for pairing RFID-enabled devices is introduced and evaluated in this work. Two or more devices are moved simultaneously through the radio field in close proximity of one or more RFID readers. Gesture recognition is applied to identify the movements of the devices, to mark them as a pair. This application is of interest for social networks and game applications in which play patterns with RFID-enabled toys are used to establish virtual friendships. In wireless networking, it can be used for user-friendly association of devices. The approach introduced here works with off-the-shelf passive RFID tags, as it is software-based and does not require hardware or protocol modifications. Every RFID reader constantly seeks for tags, thus, as soon as one tag is in its vicinity, the reader reports the presence of the tag. Such binary information is used to recognize the movement of tags and to pair them, if the gesture patterns match each other. We show via experimental evaluation that this feature can be easily implemented. We determine the required gesture interval duration and characteristics for accurate gesture and matching detection.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless Communication*

Keywords

RFID, Gesture Recognition, Internet of Things, Association

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Figure 1: Concept art (© Disney): RFID toys are moved on top of three readers. The two RFID identities are associated with each other and the characters can be paired in an intuitive way.

1. INTRODUCTION

The Internet of Things (IoT) refers to a growing number of networked devices such as toys, consumer electronics, electricity meters, environment sensors, and home appliances [1–3]. These devices are often mobile and battery powered. They are connected using adaptations of network protocols that are already known from today's Internet of servers, computers, and smartphones. Passive Radio-Frequency Identification (RFID) is one of the IoT's early approaches that are already widely used. Passive RFID tags are so inexpensive that can be attached to products like low-complex consumer devices and disposable price tags. When IoT networks are used, devices need to know information about each other (e.g., how to be reached, network addresses, protocols that the devices can support). Hence, association and disassociation are required: Before IoT devices can exchange data with each other, they need to discover their communication partners, establish logical channels, and set communication routes. Toys might for example communicate with each other to synchronize sounds and game effects, after placed in the same location. In addition, as part of a toy's play pattern, it might be desirable to associate two toys with each other to establish a virtual friendship and/or trust relationship. This is particularly interesting for toys that connect to game consoles. An intu-

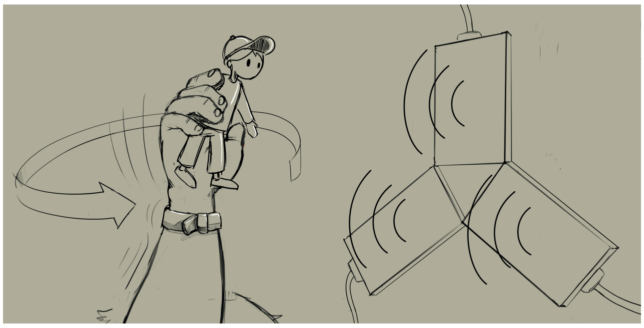


Figure 2: Concept art (© Disney): An RFID wristband and an RFID toy are associated with each other because of similar gestures.

Figure 3: Concept art (© Disney): RFID readers are used to identify similar motion patterns and pair devices (an RFID wristband and an RFID toy).

itive way to form mutual associations can be based on shake patterns [4]. In case of RFID-enabled devices, the identities of their RFID tags should be associated with each other.

In this paper, we propose a novel approach for pairing RFID-enabled devices. We do that by measuring gestures of RFID toys and matching their motion pattern to establish association based on the similarity of the patterns. Our goal is to highlight the simplicity of our proposed method to pair RFID-enabled devices, with the example application of enriching toy play patterns. Application scenarios are illustrated in Figures 1-3. The pairing of RFID-enabled devices (toys) is determined by simultaneously moving the devices together, with one hand, over an RFID reading platform (see Figure 1). When a tag moves, its motion pattern can be tracked across an area using a network of RFID readers. This can also be applied to wearable RFID devices (the wristband in Figure 2 could include an RFID tag, and the toy would be "labeled" as property of the person with the specific wristband), or in case of long range active RFID, it can be applied to devices carried by people walking through some area of a mall or theme park, as indicated in Figure 3. Instead of matching shake patterns, the mobility can be used to form the association: In controlled environments such as entertainment theme parks, the history of tag locations can be exploited. This is different to traditional GPS location tracking, because only the matched location patterns are needed in the network to associate two devices with each other. The main motivation for using RFID gesture recognition is its low complexity: There is no need for technology components inside the devices, such as batteries, accelerometers, or short range radio / infrared equipment. Passive RFID operates without batteries. In Section 2, the approach and the testbed for the evaluation are explained. Section 3 provides the performance evaluation followed by related work in Section 4 and conclusions in Section 5.

2. METHODOLOGY

Our goal is to associate passive RFID tags with each other by tracking gestures and processing their simultaneous movements. To achieve tags' association, we use multiple RFID readers. In this section, we describe the various elements of our test setup and methodology.

2.1 RFID Tag Type and Binary Information

There are many RFID tags with different characteristics (i.e., active, semi-active, and passive tags). We are mainly interested in passive tags because they do not need power supply. Among the passive tags, there are different categories. Passive backscatter tags operate in the unlicensed 915 MHz Industry, Science, Medical (ISM) frequency spectrum. Passive backscatter tags are powered by far-field propagating waves originated at the reader which can be up to several meters distant (up to 10-20 m in ideal conditions). When a backscatter tag receives radio waves, it reflects (or backscatters) those waves to communicate. Passive inductively coupled tags operate in the 13.56 MHz frequency band (also called the HF band). The communication range is on the order of a few centimetres. This is the type of tag that we use. Power is delivered to the tag and communication is accomplished via magnetic (i.e., inductive) coupling between the tag and the reader. Our experimental evaluation shows that tag pairing and gesture recognition is achievable using the reader's binary information about the presence or absence of tags, without ranging information such as tag distances based on received signal strength. Using signal strength information would only increase the complexity and time needed to identify the correct gesture. Therefore, we decide to use only the binary information of presence or absence of the tag.

2.2 Testbed

Every RFID reader consists of one evaluation board together with a multi-protocol contactless reading unit [5]. Figure 4 shows three readers. Each reader continuously emits a magnetic field oscillating at 13.56 MHz to detect

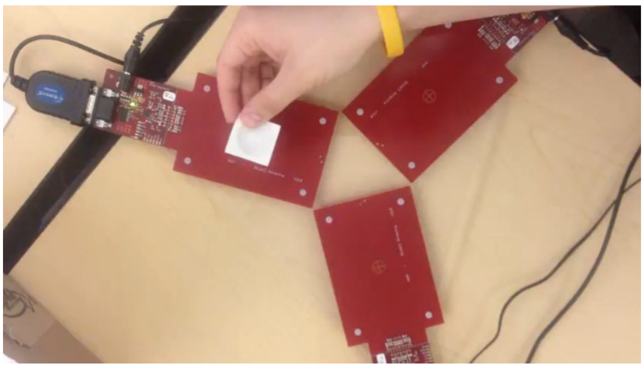


Figure 4: Testbed: Three independent RFID readers are used to recognize gestures.

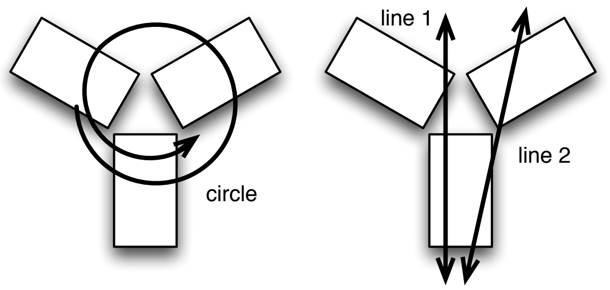


Figure 5: Example motion patterns over the readers.

the presence of tags. An important system parameter is the interval between two successful tag readings. If the tag is in the vicinity of the reader, then it communicates its tag Identity (ID) by changing the electrical load impedance connected to its antenna. Otherwise, if the tag is too far from the reader, no ID will be received. The interval between two consecutive readings is dimensioned so that the reader has the time to decode the tag ID. The power of propagated waves is constant and enables the detection of tags at distances of up to 3 cm. We performed several experiments with different combinations of number of tags and readers. With one reader, we observe how increasing the number of tags influences the average delay of tag detection. Since one reader is not enough to recognize gesture patterns, most of the measurements are carried out with three readers positioned in a triangular shape (Figure 4). Three is the minimum number of readers to be able to identify a movement pattern reliably, since the binary information from only one or two readers does not provide information about movements that are more complex than a line.

2.3 Pattern Recognition & Pattern Matching

Pattern recognition takes an input value and assigns a label to it. In our case, the value is a time series of measurements for a given RFID tag and labels are motion patterns such as line or circular movements. The tag is moved above one or multiple readers so that a motion label is assigned to every tag. In other words, pattern recognition means classification, which attempts to assign each input value to one of a given set of classes (i.e., line or circle). Pattern matching, on the other hand, is about checking a sequence of tokens (i.e., time series of measurements from two RFID tags) for the presence of the constituents of some known pattern. In contrast to pattern recognition, the pattern match usually has to be exact. Cross-correlation is a common statistical technique used for pattern matching. It is a measure of similarity of two waveforms as a function of a time-lag applied to one of them. Cross-correlation returns values between -1 and $+1$, when there is strong positive or negative correlation, respectively. A cross-correlation close to zero means that there is no correlation between the two functions.

3. EVALUATION

In this section, we present the performance of the RFID based pattern matching system. As a first step, we evaluate the performance of one reader with increasing number of tags. Then, we analyse the reading of three readers in presence of moving tags. Challenges and limitations of this type of technology are also discussed. Finally, we perform an interpolation-aided cross-correlation analysis to manage to pair the RFID tag-enabled devices.

Table 1: Average tag detection time interval for one isolated RFID reader (without interference from other readers).

number of tags	interval[ms]	stdev[ms]
1	235.7	2.7
2	416.0	5.3
3	595.9	7.2
4	793.7	82.0

3.1 Single Reader

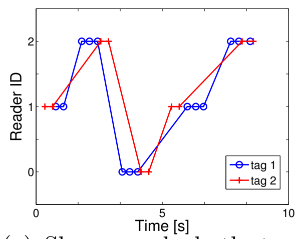
We set the readers to constant emission power and maximum scanning speed, that is, the minimum scanning time interval between readings. We determined that, for the specific reader that we have used, the minimum interval is about 236 ms. If the tag is stationary above the reader, the interval duration does not depend on the distance between the reader and the tag (measurements were carried out for tag-to-reader separation distances of 0, 1, 2, and 3 cm). The same measurements were repeated with different covers that surround the tag (i.e., plastic or paper). We found that these materials do not influence the readability, the range, and the response time of tags; hence, the technique will not be hindered by the construction materials of many toys and clothing. When two tags are within the range of the same reader, the scanning time interval for each tag is about 416 ms. As expected and as Table 1 indicates, the more the tags in a reader's range, the lower the detection frequency for each one of them. In this table, the average tag detection intervals of ten thousand independent measurements are indicated.

3.2 Multiple Readers

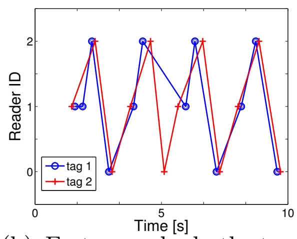
We now show measurements for the three readers deployed as shown in Figure 4. Each tag(s) is(are) moved following the the motion pattern shown in Figure 5. Both tags were held in one hand and moved at different speeds. In the following, we describe slow and high-speed movements. These speeds are subjective and defined relative to the minimum scanning interval of the readers. Figure 6 shows the slow and fast speed movement of two RFID tags drawing a circle over the three RFID readers. Figure 7 shows the readings by all readers as two tags simultaneously draw a line over them (both line 1 and line 2, as shown in Figure 5). In Figures 7(a) and 7(b) the line is drawn along the axis of the reader's triangle (line 1 in Figure 5). Therefore, only one of the readers can identify the tags during this type of movement. In Figures 7(c) and 7(d) the line is drawn along one side of the triangle, resulting in two readers being able to identify the tags, in slow and fast speed, respectively. We see that the slower the speed the higher the chance of the reader identifying both tags that move simultaneously. However, the way the tags are held could also result in one of the tags not being identified.

3.3 Pattern Matching Analysis

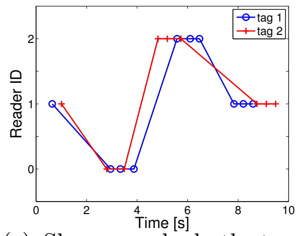
The reader software returns a tag ID, a reader ID, and a time stamp every time that a tag is detected. In a few cases, some readings are missing as Figures 6 and 7 show. Reasons for this include the speed of the movement of the tags and



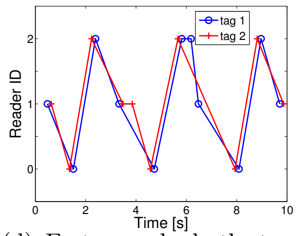
(a) Slow speed, both tags moved clockwise.



(b) Fast speed, both tags moved clockwise.

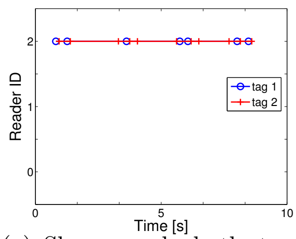


(c) Slow speed, both tags moved counterclockwise.

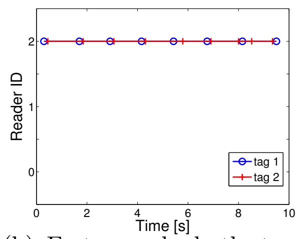


(d) Fast speed, both tags moved counterclockwise.

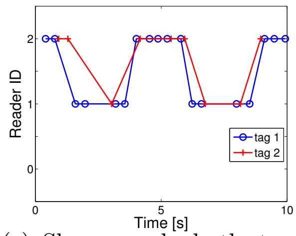
Figure 6: Readings of two RFID tags as function of time. The tags are moved in a circle fashion over three readers deployed as indicated in Figure 4.



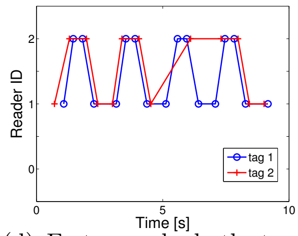
(a) Slow speed, both tags moved across line 1.



(b) Fast speed, both tags moved across line 1.



(c) Slow speed, both tags moved across line 2.



(d) Fast speed, both tags moved across line 2.

Figure 7: Readings of two RFID tags as function of time. The tags are moved drawing a line over three readers deployed as indicated in Figure 4.

the orientation of the tags with respect to the reader antenna. To be compared, each series of tag readings must have the same length (number of readings); therefore, we use an interpolation algorithm to achieve this end. We use a one-dimensional nearest neighbor-based interpolation function. The nearest neighbor algorithm selects the value of the nearest point and does not consider the values of neighboring points at all, yielding a piecewise-constant interpolation. With the interpolated series of patterns from the two tags we can use cross-correlation as described in Section 2.3. Figures 8 and 9 show the cross-correlation results for movements in Figures 6 and 7, respectively. The high positive correlation shows that the two patterns are very similar and therefore the two devices should be paired. So, we see that cross-correlation can accurately identify that the two tags moved simultaneously over the same readers. In Figure 9, again, we see that the correlation results report correctly that the two tags draw the same line, at the same time.

In addition to the cross-correlation, we decided to also employ a simple payoff function counting the mismatched reader IDs for the two tags. Its advantage compared to the correlation function is that it is much simpler and straightforward to implement in a low level driver, and much faster to run as well. With this we aim to show that even a very simple function can accurately implement the device pairing functionality.

$$\text{payoff} = \frac{\text{number of mismatched readings}}{\text{number of total readings}} \tag{1}$$

Using this methodology we can get the results shown in Tables 2 and 3. The payoff function is normalized by the number of samples (the payoff range is $[0, 1]$), where a value closer to zero (few mismatches) indicates that the vectors match. The higher this metric the more different the two vectors. The cross-correlation value shown in the Tables 2 and 3 is the maximum absolute value (peak) of the cross-correlation vector plotted in Figure 8 and Figure 9. Comparing the same results for the line and circular movement (Tables 2 and 3) we observe that both the payoff and cross-correlation can correctly pair the RFID-enabled devices.

3.4 Identifying Movement Orientations

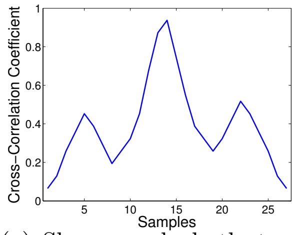
In order to only pair the appropriate devices, we need to also be able to differentiate not only between types of movement (e.g., circle) but also between different orientation (e.g., clockwise–counterclockwise). We therefore decide to use opposite direction tags and see if the cross-correlation and payoff function would pair the two tags. Figure 10 depicts the cross-correlation coefficient results comparable to Figure 8, showing that the movement pattern of different orientation tags cannot be correlated, independently of their speed. Similarly, the payoff metric results (payoff at slow speed: 0.6682, and at fast speed: 0.775) report values

Table 2: Payoff function and the cross-correlation results for circular movement (Figure 6).

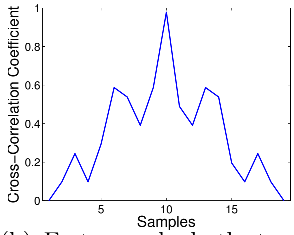
Scenario	Payoff	Cross-Correlation
Slow clockwise	0.0714	0.9374
Slow counterclockwise	0	1
Fast clockwise	0.1	0.9782
Fast counterclockwise	0.1	0.9782

Table 3: Payoff function and the cross-correlation results for line movement (Figure 7).

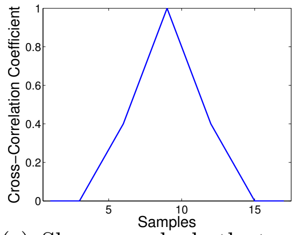
Scenario	Payoff	Cross-Correlation
Slow speed, line 1	0	1
Fast speed, line 1	0	1
Slow speed, line 2	0.2308	0.9631
Fast speed, line 2	0.1875	0.9713



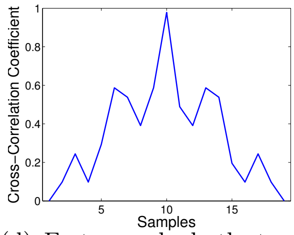
(a) Slow speed, both tags moved clockwise.



(b) Fast speed, both tags moved clockwise.



(c) Slow speed, both tags moved counterclockwise.



(d) Fast speed, both tags moved counterclockwise.

Figure 8: Cross-correlation of the two tags' interpolated signals as function of the number of samples. Results for the circular movement.

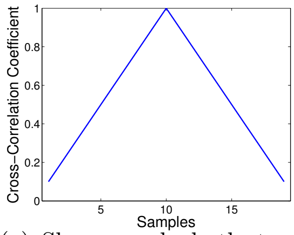
higher than 0.5, indicating correctly that the two movement patterns should not be paired.

3.5 Optimal Time Interval

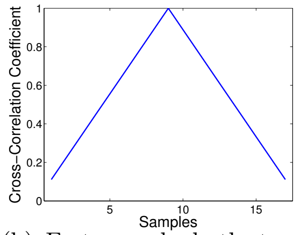
The results presented so far were computed using data collected over a ten second interval. We now examine further the optimal time interval needed in order to accurately pair two RFID tags. We examine the maximum cross-correlation coefficient and the payoff metric for various durations of the same movement. We show results for different measurement durations from 3 s to 30 s with increments of three seconds (3, 6, …, 30 s). Figures 11 and 12 show the performance of both metrics for the circle and line movements, respectively. We remark that with simpler movements (e.g., line), devices are paired with higher accuracy. Faster moving devices can still be correctly identified and paired but with less certainty for both simple and more complicated movements (e.g., circle). Finally, we also notice that after a certain time threshold (e.g., fifteen seconds) the accuracy of the metrics deteriorates, suggesting that more measurements do not necessarily improve the performance. This could be because more time allows more errors. If only a few readings are missed then the interpolation mechanism could correct the errors, whereas if multiple measurements are missing it is more difficult for the interpolation mechanism to correct the errors. We can see that the ten second interval used in Section 3.3 is a reasonable choice. The differences noticed compared to Tables 3 and 2 are because we only use ten of the thirty seconds of collected data.

4. RELATED WORK

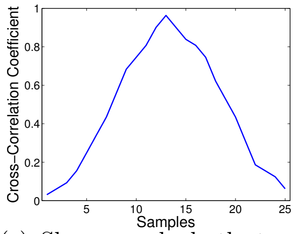
The concept of intuitively associating devices with the help of matching shaking patterns was originally reported in [4], where the use of accelerometers instead of RFID-based gesture recognition is proposed. Most of the existing research activity in RFID-related gesture or motion recognition is based on a non-real-time approach: Data is collected



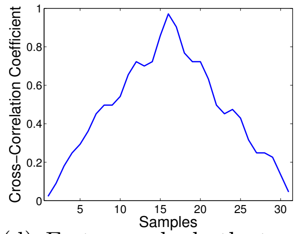
(a) Slow speed, both tags moved along line 1.



(b) Fast speed, both tags moved along line 1.



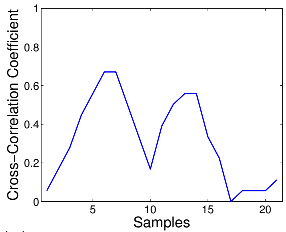
(c) Slow speed, both tags moved along line 2.



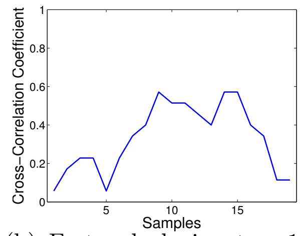
(d) Fast speed, both tags moved along line 2.

Figure 9: Cross-correlation of the two tags' interpolated signals as function of the number of samples. Results for the line movement.

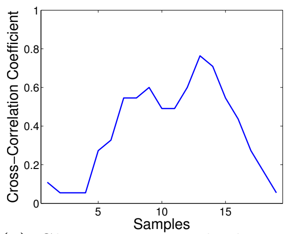
first and then processed off-line. In many cases, RFID data is combined with readings from other wireless sensors or accelerometers [7–15]. Various types of RFID tags have been used. Some are active tags that require a battery [7–9, 11]. Others use passive tags and accelerometers [12, 13]. Our work focuses on 13.56 MHz passive tags without accelerometers. Different types of gestures (e.g., hand movement or preparing coffee) can be detected using a hierarchical model combining measurements of two RFID devices with the readings of three accelerometers and one location sensor, as reported in [10]. In [16], motion pattern tracking using passive RFID tags is proposed and analyzed.



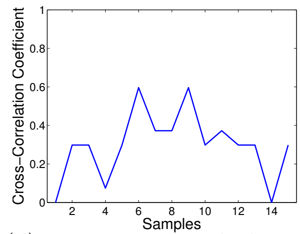
(a) Slow, counterclockwise tags 1 & 2.



(b) Fast, clockwise tag 1, counterclockwise tag 2.

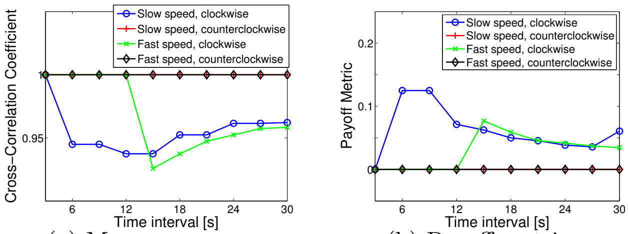


(c) Slow, counterclockwise tag 1, clockwise tag 2.



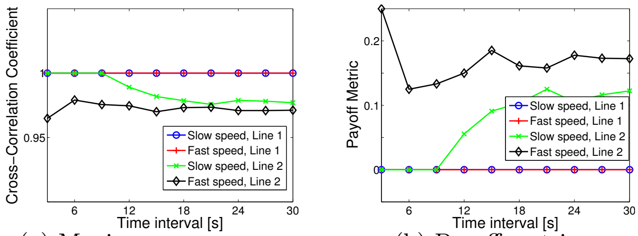
(d) Fast, counterclockwise tag 1, clockwise tag 2.

Figure 10: Cross-correlation and payoff metrics as function of measurement duration (3-30 s). The tags draw circles moving in opposite directions.



(a) Max cross-corr. (b) Payoff metric.

Figure 11: Cross-correlation and payoff metrics as function of measurement duration (3-30 s). Results for circular movement.



(a) Maximum cross-corr. (b) Payoff metric.

Figure 12: Cross-correlation and payoff metrics as function of measurement duration (3-30 s). Results for line movement.

The focus of that contribution is on a complex scenario with multiple readers located at known positions and multiple tags. In [17], it is proposed to use RFID for real-time tracking the movement of people who need assistance while getting up from bed, to provide an alarm system in case the person falls.This medical application makes use of real time gesture recognition with multiple tags, but does not require any match detection. The work in [11] describes a system that recognizes gestures by comparing real-time measurements to an initial training set. Once the training set is available, real-time data is resampled to match the sample size of the training set for comparison. In addition, the detection precision is refined using accelerometers. One potential future approach is to pair passive RFID tags by having them directly communicate with each other, as already demonstrated in [18] for short distances.

5. CONCLUSION

A novel way for pairing RFID-enabled devices is introduced. The proposed approach is simple and does not rely on additional technology (accelerometers or device-to-device radio communication). Instead of relying on dedicated communication like infrared or radio communication together with an authentication mechanism (touching, pin numbers), we employ gesture recognition to identify the movement pattern of devices, and pair them. It is shown in this paper that the proposed idea can be easily realized. The required gesture interval duration and the characteristics for accurate pattern matching are discussed in this paper. Intuitive user-friendly approaches as described in this paper will be a contribution to the acceptance of the Internet of Things. Because of its simplicity and ease of use, associating devices with the help of gesture recognition might be seen as a secure-enough low-cost way for establishing networks of consumer devices (e.g., toys). When designing such networks, security and user experience demands such as ease of use and convenience should be considered. The presented method addresses both concerns by offering an association in an intuitive and user-friendly way.

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