HHS Public Access
Author manuscript
IEEE Int Conf RFID. Author manuscript; available in PMC 2018 October 24.

Published in final edited form as:
IEEE Int Conf RFID. 2016 May ; 2016: .

Activity Recognition for Medical Teamwork Based on Passive RFID

Xinyu Li[1], **Dongyang Yao**[1], **Xuechao Pan**[1], **Jonathan Johannaman**[1], **JaeWon Yang**[3], **Rachel Webman**[3], **Aleksandra Sarcevic**[2], **Ivan Marsic**[1], and **Randall S. Burd**[3]

[1]Rutgers University, Medical Center, Piscataway, NJ, USA

[2]Drexel University, Philadelphia, PA, USA

[3]Children's National Medical Center, Washington, DC, USA

Abstract

We describe a novel and practical activity recognition system for dynamic and complex medical settings using only passive RFID technology. Our activity recognition approach is based on the use of objects that are specific for a given activity. The object-use status is detected from RFID data and the activities are predicted from the statuses of use of different objects. We tagged 10 objects in a trauma room of an emergency department and recorded RFID data for 10 actual trauma resuscitations. More than 20,000 seconds of data were collected and used for analysis. The system achieved a 96% overall accuracy with a 0.74 *F*-score for detecting use of 10 common resuscitation objects and 95% accuracy with a 0.30 F Score for activity recognition of 10 medical activities.

Keywords

activity recognition; object-use detection; passive RFID; tagging strategies; machine learning

I. Introduction

We present a novel approach for activity recognition in fast-paced and team-based clinical work. Activity recognition in medical settings has been challenging due to potential interference by tracking devices, privacy concerns, and environmental limitations. Trauma resuscitation, the initial management of critically injured patients in the emergency department, is a complex process performed by a medical team under time pressure. Providing real-time decision support in trauma resuscitation requires strategies for tracking workflow and alerting teams to errors. Our work has focused on activity recognition as a key component in developing these strategies.

Previous work on activity recognition has used a range of techniques, including computer vision for identifying body posture, movement, and location related to different activities [1] [2]. Most previous approaches, however, are not practical in clinical settings. The use of RGB cameras can lead to privacy concerns, visual occlusion, and problems caused by variable illumination. Active wearable sensors require batteries and may hinder work. To address these limitations, we developed an activity recognition approach based on detecting object use. It relies on a common finding that an object or a combination of objects are related to specific activities (e.g., a thermometer is used only for measuring temperature). By tracking object use, our method allows activity recognition without cameras or wearable devices.

Our system accomplishes activity recognition in two steps. First, the use status of different objects is determined based on the RFID information, such as signal strength. Second, activities are predicted based on the use status of objects. For object-use detection, we used small, inexpensive, battery-free passive RFID tags attached to medical objects and fixed reader antennas. We placed tags on 10 object types commonly used in trauma resuscitation. Data from these tags were collected by eight RFID-reader antennas installed in the trauma room in the emergency department of a trauma center. By reviewing videos, medical experts of our team coded object-use data and a synchronized medical activity log from trauma resuscitations. We used these data to build our activity recognition model.

We have tested our approach using data from actual trauma resuscitations. Based on our experiments, the system achieved an average accuracy rate of 96% for detecting 10 different object types in 10 trauma resuscitations, with an average F score of 0.74, and a 95% accuracy rate for 10 resuscitation activities with an *F*-score of 0.30. Our system has the potential to achieve performance comparable to video-based systems, and can serve as a prototype for RFID systems in similar domains. Our contributions to pervasive computing are:

1. An object-use-based activity recognition in a dynamic and crowded medical setting that does not require human input or any wearable devices.
2. Object tagging strategies and features combinations for object-use classification.
3. System implementation and evaluation in a real-world setting using real-world cases.

II. Related Work

A. Object-Use Detection

Object-use detection or human-object interaction has been studied in several areas, including computer vision, sensor networks, and machine learning. Past approaches for detecting object use, however, have limited application to the unique environment of the trauma room. Computer vision largely relies on RGB or RGB-D cameras to identify objects and estimate human-object interaction based on body posture or hand gesture. This approach has been used in settings such as daily living environment and sports [3], Illumination problems, occlusion, camera resolution, identification of small objects, and privacy concerns limit the applicability of this approach in trauma resuscitation.

Approaches for human-object interaction detection in complex and crowded environments rely on wearable sensors, which may be limiting in a clinical setting [4][5][6]. Although few studies have addressed activity recognition or object-use detection in medical settings, passive and non-intrusive sensors have been used for tracking clinical tasks.[7]. Recent work [8] has used wearable sensors for recognizing surgery phases achieving satisfactory performance. Wearing and configuring wearable sensors, however, can be time consuming and inconvenient. Object-use detection and activity recognition have been evaluated in simulated trauma resuscitations using passive RFID tags and fixed antennas[9][10]. The advantages of ultra-high frequency (UHF) passive RFID systems include the use of fixed antennas and small size, battery-free tags that do not hinder work, capacity for use in dynamic environments, and cost efficiency. This previous system, however, was only tested in simulated resuscitations, which are less complex and less dynamic than actual events [10]. To make our system operational in actual resuscitations, we designed new tagging strategies for objects varying in size, shape and position. In addition, we implemented, tested, and evaluated combinations of features used for classification in prior work [9][10][11][12] and selected six features for our system.

B. Activity Recognition

Activity recognition has been based on features such as location, body posture, and work role, using video systems and other sensors [13][14]. In trauma resuscitation, posture and location of personnel are similar for most tasks and cannot be used to distinguish activities (e.g., leaning over the patient while establishing intravenous access, drawing blood or listening to breath sounds). Many activities, however, can be recognized by the objects being used to perform them, such as a thermometer for measuring temperature. For this reason, we focused on objects that are specific to medical activities.

Recent research has suggested that activities can be predicted based on object-use information [15][16]. Prior work, however, has focused on experimental settings and assumed that any manipulation signifies actual object use [15][16]. This assumption is often not observed outside of experimental setting where objects may be manipulated without being purposefully used for an activity. For example, a nurse holding a blood-pressure bulb may be testing the equipment rather than measuring blood pressure. The complexity of real-life scenarios increases the difficulty of activity recognition. Because determining if an object is used for its intended purpose based on passive RFID is challenging, we leveraged the fact that some objects are consistently used together. These combinations of used objects helped us make more reliable prediction of current activities.

III. Object-use Detection

A. Data Collection

We collected RFID data in a trauma room using two Alien 9900+ readers (with 4 ports) and 8 Alien ALR-8696 antennas (Fig.1). The RFID readers were mounted inside the ceiling. Antennas 1 to 7 were mounted on the ceiling, facing down, and Antenna 8 was mounted on the wall, facing downwards at a 45-degree angle. This arrangement ensured that all equipment were covered by at least two antennas. The RFID readers and the computer were connected via a router mounted inside the ceiling. To avoid interference among nearby antennas, we configured the system to activate a pair of antennas on the opposite sides of the room for 1-second each. Because continuous use of the RFID readers caused the hardware to overheat, an automatic approach was needed to start the readers only when needed. To address this issue, we installed a Honeywell AUROR passive infrared sensor (PIR) (Fig. 1) to monitor movement in the trauma room. If motion is detected, the PIR sensor signals the RFID system to start recording and stop recording after no motion is detected.

Both RFID readers were set to collect data with maximum power and sensitivity. The collected data were written into a file using the format: [timestamp, reader IP, reader port, RSSI]. Each file name was based on timestamp when the RFID reader was activated to allow synchronization between the recorded RFID data and the ground-truth data. The ground truth was manually coded by medical experts using videos of trauma resuscitations. We performed two types of ground-truth coding for each case. The first type was object-use ground truth, which contained information about the start and end time of object use, and the object name. We also noted whether the object was in actual use or manipulated (i.e., being relocated), and if manipulation was related to medical task (Table I). The second type was activity ground truth, which focused on medical activities performed by trauma team members. We recorded the activity name, start time, and end time for each activity, as well as the objects used for that activity, if any (Table II).

B. Objects and Tagging Strategies

We used RFID data from actual trauma resuscitations for object-use detection and activity recognition. These resuscitations differ from simulated resuscitations used in previous studies because actual resuscitations are not scripted and activities vary from case to case [9] [10]. Collecting enough data for every object in the trauma room would require thousands of cases, an impractical requirement given the time-consuming nature of this analysis. For this reason, we focused on 10 medical objects (Table III). These objects are used in most trauma resuscitations and may even be used multiple times in a single resuscitation, providing sufficient data.

The most common way to detect object use in trauma resuscitation with RFID is to place tags on objects and predict object use based on the collected RSSI data. Placing tags on different objects in a dynamic environment, however, cannot ensure adequate detection. A prior study [10] suggested that increasing the number of tags on irregularly shaped objects may lead to better performance and that different tagging methods influence object-use detection performance. Increasing the number of tags, however, is not a practical solution for many objects. For example, the blood-pressure cuff is wrapped onto itself and placed in a tray when not in use. As a result, the RSSI signal of the tag placed on the blood-pressure cuff in the tray is not only weak, but also similar to the signal when the cuff is wrapped around a patient's arm. Other objects, such as the otoscope, are mounted near the head area of the patient bed. People in this area may block or reflect the signal between the reader antenna and the tag on otoscope. causing a signal strength decrease similar to that when otoscope is held in hand and used, leading to misinterpretation of object use.

To address these issues, we devised four different strategies for tagging different objects (Fig. 2):

1. *Direct tagging*: Place one tag on an object. This method was used for small objects that are covered by a hand when in use, such as blood-pressure bulb (Fig. 2(a)).

2. *Multi-tag tagging*: Place multiple tags with different IDs on an object. This method was used for larger objects, such as the thermometer, to ensure that at least one tag is covered by a hand when the object is in use (Fig. 2(b)).
3. *Holder-slot tagging*: Place a tag in the slot that holds the object, as opposed to directly tagging the object. This method was used for objects placed into a holder, such as the otoscope. When the object is in the holder or not used, the tag's signal is blocked by the object. When the object is outside the holder, the tag is exposed (Fig. 2(c)).
4. *Differential tagging*: Place one tag inside and another outside an object. When in use, one side of the object will be in contact with the patient. The outside tag is used as a reference for the inside tag. When the object is not in use, both tags share similar RSSI values. When the object is in use, the inside tag touches the person's body and has a much lower RSSI signal compared to the outer tag. This method was used for the BP cuff (Fig. 2(d)).

We tagged 10 objects (Table III). Some objects, such as the non-rebreather mask (adult NRB), were disposable and new tags had to be placed on replenished objects.

C. Feature Extraction

We used a 4-second time window ($[(n-3):n]$ seconds) for feature extraction, as the period for antenna switching is 4 secs (each reader has 4 ports and each port is set to record data for 1 sec). A feature vector was generated every second based on a 4-second time window.

Feature selection is critical for accurate classification. We selected 14 features to extract from RFID data [9] [10] [11] [12]. Our hardware was not able to provide other useful data, such as the phase angle and Doppler frequency shift, so the related features could not be used. Not all features worked well for all 10 objects. We ran the permutation feature importance calculation provided by the Azure platform for each object and used both precision and recall as the evaluation metrics [17]. We then chose these six features with the highest importance score:

(1) Peak RSSI: The RSSI value is the most common feature for RFID-based systems. When an object is in use, we can expect a significant change in RSSI values due to different tagging strategies (Fig. 3(a)): (*i*) the RSSI drops for direct tagging and multi-tag tagging strategies, (*ii*) it increases for holder-slot tagging; and (*iii*) the difference between RSSI from inner and outer tags increases for the differential tagging strategy.

We used "peak RSSI" in each time window as an RSSI feature, rather than the "average RSSI" value feature because, a tag is always closer to some and remoter to other antennas in a room with 8 reader antennas. A tag may be too far from some antennas and the RSSI values measured by those antennas may be outliers, thereby falsely bringing down the average. For objects with multiple tags, we collected the peak RSSI of each tag and averaged them as one of the features.

(2) Time: Time is another important and often underused feature for making object use predictions. Medical personnel usually follow a routine sequence of procedures for a given case and the use of many objects often falls into certain time windows. We evaluated the discriminative power of the time feature by analyzing the RSSI recordings from 10 objects during 38 trauma resuscitations. Based on manual video review, we plotted the distribution of object use over time for 10 objects (Fig. 3(b)). The black color at each time point denotes that the object was used at that time in more than 50% of cases, while gray color denotes the use in less than 50% of cases. The timelines in all 38 cases were synchronized with patient arrival time as time zero. Our results support the assumption that use of objects follows certain time distributions, which can help us predict their use and associated activities.

(3) Visible Antenna Combination: The visible antenna combination isa set of antennas that can identify a tag in a particular time window. We implemented the “zoning positioning” method [18] to use the visible antenna combination as a feature roughly representing tag position. Objects at different locations in the trauma room can be represented by different visible antenna combinations. Our experiments showed that the objects used at the right side of the patient bed are more likely to be detected by antennas 4,5,7, and 8, while the objects used at the left side are more likely to be detected by antennas 1,2,6, and 8 (Fig.1). These results confirm our assumption that objects used at different positions will be detected by different antenna combinations.

In our experiments, we used an eight-digit binary number to represent 8 antennas installed in the trauma room. If a tag was visible to antenna i, we placed a “1” at the i^{th} digit of the binary number a value of “0” if not. Finally, we converted the binary numbers into decimal numbers and used them to represent the visible-antenna-combination feature.

(4) Spearman Rank Correlation Coefficient (SRCC): The Spearman Rank correlation coefficient is defined as the linear correlation coefficient of the ranks. We divided the RSSI data recorded in each 4-second time window into a two-second left window (L) and a two-second right window (R). Because the reading rate changes rapidly, we interpolated the data in L and R to ensure that they had the same length w. Our hypothesis was that when an object is not used and is stationary, the RSSI data in the L and R windows should be similar. When the object is in use, the tag will be occluded by a hand and the signal partially reflected or absorbed by the human body. As a result, the RSSI in the left and right windows for an object in use should not correlate well with each other. If we use and L_i and R_i to denote the i^{th} RSSI value in left and right windows, the SRCC was calculated as [19]:

$$\rho = 1 - \frac{6 \cdot \sum_{i=1}^{w} \left(L_i - R_i\right)}{w \cdot \left(w^2 - 1\right)}$$

(5) Entropy: Entropy is a measure of uncertainty and has been used as a feature for RSSI-based classification [11]. When an object is not in use, the entropy will be small due to small variance. When an object is in use, the uncertainty of the data grows. We start by dividing the RSSI range into N bins with equal bin length or BL(BL = 100 in this paper); for each object at each time window, RSSImax and RSSImin denote the maximum and minimum RSSI values, and the total number of bins, N=[($RSSI,_{max}$–$RSSI_{min}$)/BL]. Using the number of RSSI values in the i^{th} bin, x_i, we estimated the probability of RSSI values in the i^{th} RSSI interval as $p_i = x_i \Big/ \sum_{i=1}^{N} x_i$. The discrete entropy was calculated as:

$$Entropy = -\sum_{i=1}^{N} p_i \cdot \log\left(p_i\right)$$

We calculated the entropy of RSSI for different objects using data from actual resuscitations. The calculation results confirmed our hypothesis that the RF signal is more randomly distributed when people are present or use objects for work. The entropy becomes higher when object is in use (Fig. 3(c)).

(6) Dominant Frequency: The dominant frequency of sensor signal has been previously used for activity classification of data from wearable devices [12]. We hypothesized that the dominant frequency of received RSSI data will be low for stationary objects as the RSSI values for motionless tags that deviate less than those of tags in use or in motion. When an object is in use, the RSSI is unstable, leading to higher dominant frequency because of tag movement and signal occlusion by the person holding the object (Fig. 3(c)).

For object-use detection, we constructed a feature vector for each of the 10 objects based on these two observations:

1. In the trauma room, all objects are clustered in a small area. When people use an object, their body may interfere with tag signals from other objects. The changes in signal strength of other objects may help with object-use detection.
2. Some activities are performed using more than one object, e.g., measuring blood pressure requires blood-pressure cuff and bulb. Using RFID data from several objects allows better detection of individual objects during multi-object activities.

For each of the 10 objects, a feature vector consisted of the six features, which were then used for object-use detection:

$$\begin{aligned} RFID\_\ Feature\_Vector = \Big[&Time, Peak\_RSSI_{obj1:obj10}, \\ &Visiable\_Antenna\_Combination_{obj1:obj10}, \\ &SRCCobj1:obj10, Entropy_{obj1:obj10}, \end{aligned}$$

D. Object-Use Estimation

We treated the RFID-based object-use detection as a binary classification problem. We used the Microsoft Azure Machine Learning toolbox in our experiments [20]. To train the model, we used more than 20,000 seconds of raw RSSI data recorded in 10 actual trauma resuscitations. Medical objects were used only for a fraction of time relative to the entire resuscitation process (Table IV). As a result, instances of object use versus not-use are not equally represented in the RSSI data. Randomly selecting 70% of these data would not ensure sufficient number of examples for model training when objects were used. By referring to the ground-truth data, we randomly selected 70% of the data when an object was in use and 70% of the data when an object was not used. We then extracted features from these training subsets and used the remaining 30% of the data to test the model. Using this semi-random selection, we ensured balanced representation of both in-use and not-in-use classes in the training data.

IV. Activity Recognition Based on Object Use

A. Activity Definition

The 10 objects that our system tracked were associated with 10 medical activities (Table V). The activities in trauma resuscitation can be classified based on the overall goal being achieved by the activity such as airway control, assessment of breathing, and circulation control. Each goal is accomplished with several resuscitation activities. For example, airway control includes activities such as “relieve airway obstruction” and “intubation.” A resuscitation activity can be further divided into several elementary tasks. For example, the task “ear exam” consists of visual examination of the outer ear and otoscope examination of the inner ear. It is often difficult to distinguish elementary tasks (e.g., left versus right ear examination) based on RFID data. For this reason, in this paper we focused on recognizing resuscitation activities (Table V).

B. Activity Recognition

Previous research on activity recognition has focused on daily-living tasks such as meal preparation or process-phase detection in the operating room [15] [21]. Little research has addressed detailed activity recognition in a highly dynamic teamwork, such as trauma resuscitation [9][10]. Prior research has suggested that object-use status can be used for activity recognition, by assuming that an activity is performed when a related object is detected as used [10]. This assumption, however, does not always hold true during resuscitation. When we reviewed the recorded resuscitations for ground truth data, we found that a person might manipulate an object without performing the actual task. For example, people may relocate an object or prepare it for future work activity. People may also hold objects for extended time without meaningful interaction. For these reasons, we divided the types of human-object interaction into three categories (Table IV):

1. *Object in use*: The object is used for its intended work purpose of performing a specific task.
2. *Object in task-related motion*: The object is relocated from its storage place or prepared for future use.
3. *Object in task-unrelated motion*: The object manipulation is not related to any task, e.g., fiddling with the object.

We also found that several objects could be used together to complete a task, such as blood-pressure cuff and bulb to measure blood pressure. At the same time, other people may use other objects for different tasks or interact with objects without performing any task. It is unlikely, however, that relocation and accidental manipulation will follow any regular pattern for task-related use of multiple objects. To detect when an object is used for task performance, we use the combination of use-status of related objects. Manipulation of objects that were not related to tasks would appear as “noise” that needs to be addressed.

We treated activity recognition as a classification problem in which object-use detection is indicative of activity performance. The object-use status (in-use vs. not-in-use) of all 10 object types was treated as features, and classifiers made activity recognition predictions. We generated a feature vector every second based on object manipulation type as follows:

$$Object\_Feature\_Vector = \left[obj_1, obj_2, \dots, obj_{10}\right]$$

where obj_{ji} denotes the type of manipulation for i^{th} object. We used obj_{ji} =1 for objects in-use and obj_{ji}, =0 for not-in-use.

To train the activity recognition model, we used the same train-test split of data as before for training the object-use detection model. This method ensured that the testing data for object-use detection was not used as training data for activity recognition, reducing the likelihood of over-fitting. We used the object-use status of all 10 object types as a feature for activity recognition, and chose a commonly-used Random Forest as our classifier [9]. We did not use HMM, which is also commonly used for a similar purpose, because we did not have enough data to train the transition matrix. Microsoft Azure cloud computing platform was used for classification. A classifier was trained for each activity.

C. System Architecture

We used a two-step approach to medical activity recognition. We first detected when objects were in use based on RFID data and then made activity predictions based on the type of object manipulation for all 10 objects. To test the system performance, we semi-randomly selected 70% and 30% as training and testing data, and repeated the experiments 10 times with different seeds to achieve random selection. After the classifier model was trained, activity-recognition predictions were made as follows (Fig. 4):

1. The RFID system recorded RFID data from 8 antennas installed in the trauma room (Fig. 4(a)).
2. Every second the system extracted 6 features based on RFID data and generated a feature vector as described in Section III (Fig. 4(b)).
3. The features were used as inputs in the classifiers for object-use prediction (Fig. 4(c)).

The object-use prediction results were used as input for activity-recognition classifiers (Fig. 4(d)).

V. Experimental Results

A. Classifier Selection

We compared the performance of three classifiers that can assign different weights to different features: Boosted Decision Tree, Random Forest, and Neural Network. We treated object-use detection as a binary classification problem and trained 10 classifiers for 10 object types. The object-in-use instances were treated as positive samples, and object-not-in-use instances were treated as negative samples. We used *F*-measure and accuracy rate to evaluate different classifiers. The maximum height of trees in the Random Forest and Boosted Decision-Tree were set to 32 to avoid possible overfitting. The Neural Network was set to have a single hidden layer. The final decision thresholds for each classifier were set to 0.5 and were not tuned to produce unbiased results.

Based on our experiments, Random Forest (RF) achieved the best accuracy, precision, and *F*-score for most objects, while Random Forest and Decision Tree (DT) performed similarly on recall (Fig. 5). We chose Random Forest as the classifier for object-use detection.

B. Object Use Detection

To test the system performance for 10 object types, we used three evaluation metrics. We initially applied *F*-measure, which does not account for true negative samples. This is acceptable when the positive and negative samples are balanced in testing data. Our data, however, had an unbalanced ratio of positive to negative samples because many objects are used relatively briefly during resuscitations (Table IV). To address this limitation, we used the Informedness, Markedness [22] and the Matthews Correlation Coefficient [23], which are commonly used to evaluate data with unbalanced samples.

We applied the Random Forest classifier and repeated the procedure 10 times to avoid possible sampling bias, and then calculated the average performance scores for different evaluation metrics (Table VI). For each test-data selection, we used different seeds to avoid having the same random sequence generated by the computer. We also compared our object-use detection with previous methods for simulated resuscitations [10], and found that our system outperformed the other system (Fig. 6). Because prior research used a different set of objects, we cannot perform exact comparison. Our system showed improved performance due to three factors. First, we designed tagging strategies for different object types to improve RSSI data collection. Second, in addition to RSSI-based features, we introduced other feature types and combinations. Third, when predicting the use of individual objects, we used features of other currently manipulated objects.

C. Activity Recognition

Object-use detection results served as the input for activity recognition. We first applied the object-use ground truth of 70% data to train the activity-recognition model. Each activity-recognition task was treated as a binary classification. We repeated the training and testing phase 10 times with different data splits and manually tuned the decision threshold for activity prediction. We used the same evaluation metrics as for the object-use detection (Fig. 7).

Because the activity-recognition stage follows the object-use detection stage, any errors in object-use detection will propagate to activity recognition. To evaluate performance of activity recognition with erroneous input data, we compared our activity recognition using both ground truth (“perfect input”) data about object use and predictions from the use-detection stage (“erring input”). The comparison showed a decrease of roughly 20% in *F*-

Score, Informedness and Markedness for activity recognition when applying object-use predictions as input, instead of object-use ground truth.

Only a few studies have addressed the challenge of activity recognition in medical settings, limiting comparison of our work with prior work. One study achieved an accuracy of 82.8% for process-phase detection with wearable sensors [8]. Our system achieved comparable performance with fixed antennas and required no wearable sensors. Another study achieved relatively good prediction results in recognizing four phases of the process using manually generated “low-level activity” records [21]. Unlike predictions in that study, our predictions were based only on RFID data and did not require human input. In addition, instead of predicting a few high-level phases of the process, we predicted activities within the phases, which is more challenging and can be more useful for real-world applications such as workflow tracking.

VI. Conclusion and Future Work

The paper describes a novel system for activity recognition in trauma resuscitation with passive RFID tags and fixed antennas. We tested our approach in a trauma room using actual cases, and achieved comparable performance with other activity recognition systems that use wearable sensors or manually-entered log of low-level activities. Our research showed that a passive RFID system can be used for activity recognition in complex and dynamic environments.

Despite its many advantages, RFID technology has limitations, and a system only using RFID cannot detect every type of activity conducted in the trauma room. For example, RFID tags on fluid bags and metal objects produce poor radio signals, making them difficult to recognize when an intravenous fluid bag or a laryngoscope are in use. In addition, activities performed without using any objects cannot be detected by our current system. Combining different types of sensors and making activity-recognition predictions using multiple sources [24][25] may lead to a more robust and accurate system. In addition to other sensors, we plan to tag more objects to recognize more activities, as well as to use our current system in more resuscitations to further evaluate its performance. Our cascade model for activity recognition in which the activity prediction relies on object-use prediction is subject to error propagation. Erroneous object-use prediction will directly impact the activity recognition results. Finally, training separate classifiers for different activities will encounter scalability issues for a large number of activities. Applying deep learning methods and training a deeper model will be pursued in our future work.

Acknowledgments

This research was supported by the National Library Of Medicine of the National Institutes of Health under Award Number R01LM011834.

References

[1]. Kuehne H Serre T, "Towards a generative approach to activity recognition and segmentation," *arXiv preprint* arXiv: 1509.01947, 2015.

[2]. Chakraborty I, Elgammal A, et al. "Video based activity recognition in trauma resuscitation." Proc. 10th IEEE Int 'l Conf. and Workshops on Automatic Face and Gesture Recognition (FG), pp. 1–8. IEEE, 2013.

[3]. Hu J, Zheng W, et al., "Exemplar-based Recognition of Human-Object Interactions, *"IEEE Transactions on Circuits and Systems for Video Technology*, to be published.

[4]. Bulling A, Blanke U, and Schiele B, "A tutorial on human activity recognition using body-worn inertial sensors," ACM Computing Surveys (CSUR) vol. 46, no. 3 (2014): 33.

[5]. Patterson DJ, Fox D, et al. "Fine-grained activity recognition by aggregating abstract object usage," Proc. 9th IEEE International Symposium on Wearable Computers, pp. 44–51. IEEE, 2005.

[6]. Li H, Ye C, and Sample AP. "IDSense: A Human Object Interaction Detection System Based on Passive UHF RFID," Proc. CHI'2015, 2015.

[7]. Ohashi K, Ota S, et al. "Smart medical environment at the point of care: Auto-tracking clinical interventions at the bed side using RFID technology," Computers in Biology and Medicine, vol. 40, no. 6 (2010): 545–554, 2010. [PubMed: 20471637]

[8]. Bardram JE, Doryab A, et al. "Phase recognition during surgical procedures using embedded and body-worn sensors," Proc. IEEE International Conference on Pervasive Computing and Communications (PerCom), pp. 45–53. IEEE 2011.

[9]. Parlak S, Marsic I, et al. "Activity recognition for emergency care using RFID," Proc. 6th Int'l Conf. on Body Area Networks, pp. 40–46. ICST, 2011.

[10]. Parlak S, Marsic I, et al., "Passive RFID for Object and Use Detection During Trauma Resuscitation,", *IEEE Transactions on Mobile Computing*, to appear, published on IEEE Xplore in 2015.

[11]. Ding H, Han J, et al "Human object estimation via backscattered radio frequency signal," Proc. IEEE Conference on Computer Communications (INFOCOM), pp. 1652–1660. IEEE, 2015.

[12]. Zhang S, Rowlands AV, et al. "Physical activity classification using the GENEA wrist-worn accelerometer." PhD dissertaion, Lippincott Williams and Wilkins, 2012.

[13]. Zhang M, and Sawchuk AA, "Motion primitive-based human activity recognition using a bag-of-features approach," Proc. 2nd ACM SIGHIT International Health Informatics Symposium, pp. 631–640. ACM, 2012.

[14]. B Yuan, and J. Herbert, "A Cloud-Based Mobile Data Analytics Framework: Case Study of Activity Recognition Using Smartphone," Proc. 2nd IEEE International Conference on Mobile Cloud Computing, Services, and Engineering (MobileCloud), pp. 220–227. IEEE, 2014.

[15]. Wu J, Osuntogun A, et al., "A scalable approach to activity recognition based on object use," Proc. IEEE 11th International Conference on Computer Vision, ICCV2007, pp. 1–8. IEEE. 2007.

[16]. Palmes P, Pung HK, et al., "Object relevance weight pattern mining for activity recognition and segmentation," Pervasive and Mobile Computing, vol. 6, no. 1 (2010): 43–57, 2010.

[17]. Altmann A, Tolo?i L et al., "Permutation importance: a corrected feature importance measure." Bioinformatics, vol. 26, no. 10 (2010): 1340–1347. [PubMed: 20385727]

[18]. Ni R, Ye Z, et al. "Zoning positioning model based on minimize RFID reader," Proc. 2nd Int ' Symp. on Instrumentation and Measurement. Sensor Network and Automation (IMSNA), pp. 117–121. IEEE, 2013.

[19]. Ress WH, Numerical Recipes: The Art of Scientific Computing, 3rd Edition, Cambridge University Press, 2007.

[20]. Barga R, Fontama V, and Tok WH. Predictive Analytics with Microsoft Azure Machine Learning, Springer, 2015.

[21]. Forestier G, Riffaud L, and Jannin P, "Automatic phase prediction from low-level surgical activities," International Journal of Computer Assisted Radiology and Surgery (2015): 1–9.

[22]. Powers DM, "Evaluation: From precision, recall and f-measure to ROC, informedness, markedness and correlation,".Journal of Machine Learning Technologies, vol. 2, no. 1, pp. 37–63, 2011.

[23]. Matthews BW, "Comparison of the predicted and observed secondary structure of T4 phage lysozyme," Biochimica et Biophysica Acta (BBA)-Protein Structure, vol. 405, no. 2 (1975): 442–451.

[24]. Mo L, Liu S, et al., "Multi-sensor ensemble classifier for activity recognition," J. Software Eng ’g andApplic’s, vol. 5, no. 12 (2013): 113.

[25]. Gao L, Bourke AK, and Nelson J. "A system for activity recognition using multi-sensor fusion " Proc. Annual Int’l Conf. of the IEEE Eng’g in Medicine and Biology Society, EMBC, pp. 7869–7872, 2011.

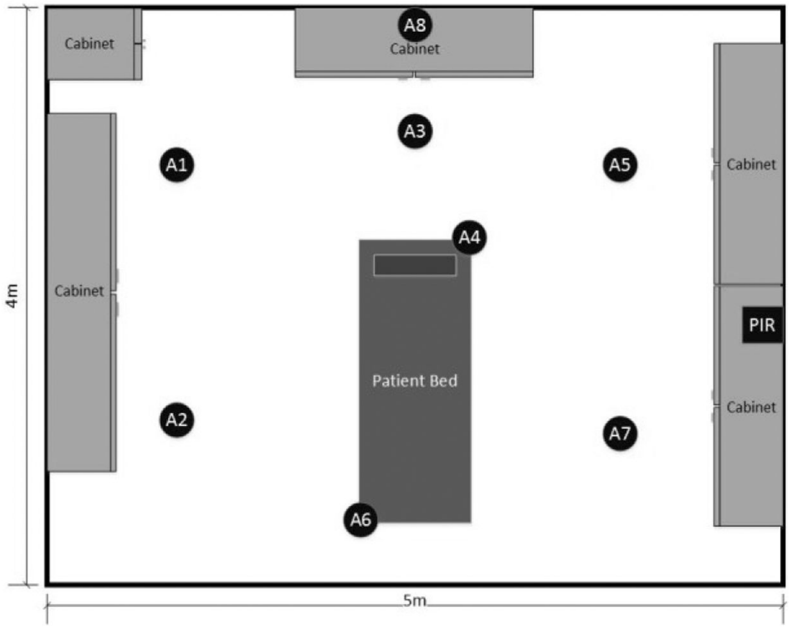

Fig. 1.

The antenna configuration in trauma room we used for data collection. Antennas 1 to 7 are mounted on the ceiling and facing down; antenna 8 is mounted on the wall and facing 45 degrees to the ground.

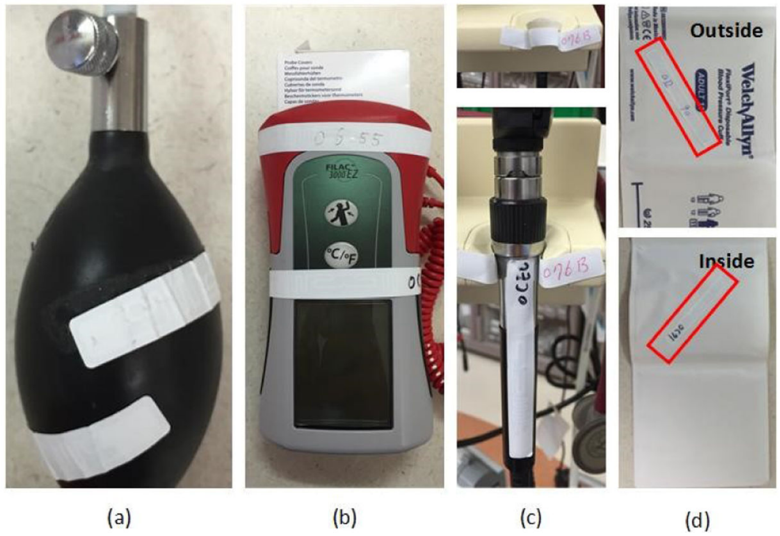

Fig. 2.

(a) Direct tagging on BP Bulb. (B) Multi-tag tagging for thermometer. (c) Holder-slot tagging for otoscope. (d) Differential tagging for BP cuff.

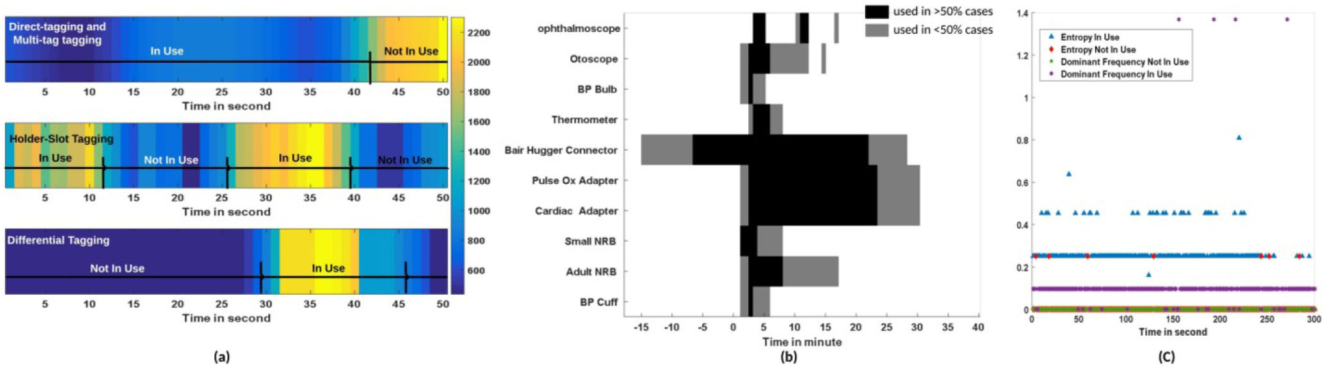

Fig. 3.

(a) Heat map of RSSI features for different tagging strategies. The RSSI decrease when the object with direct-tagging and multi-tag tagging is in use, the RSSI difference between inner and outer tag increases when the object with differential tagging strategy is in use. (b) A heat map for object-use time distribution for 10 objects used in this paper. Darker color means that the object was used in more than half of the resuscitations and lighter color means that it was used in less than half of the resuscitations. (c) The entropy and dominant frequency features for scenarios when object is in use and not in use.

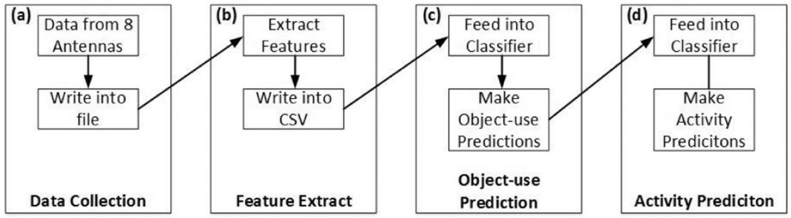

Fig. 4.

Activity recognition system diagram. (a) RFID system data collection from 8 antennas installed in the trauma room. (b) Six types of features are extracted from RFID data and feature vectors are generated. (c) Object-use detection based on extracted features. (d) Activity recognition classification based on object-use detection results.

Author Manuscript
Author Manuscript
Author Manuscript

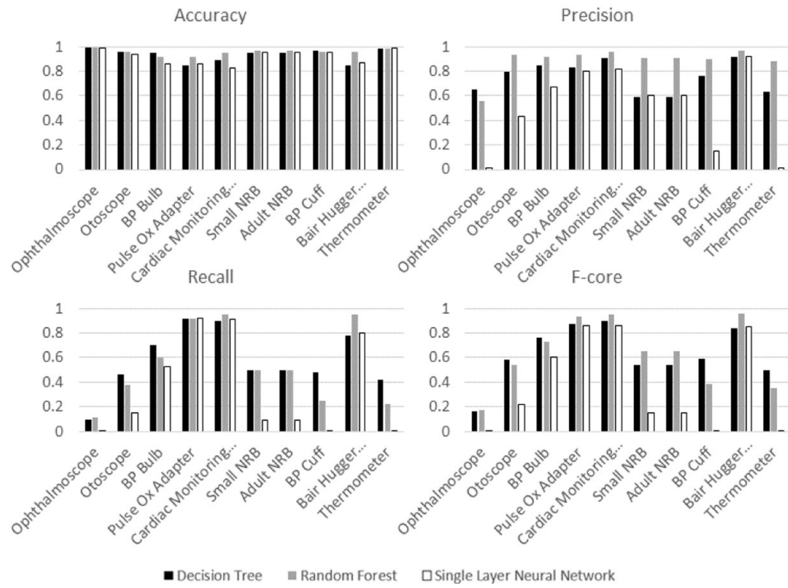

Fig. 5.

Evaluation of classifiers on object-use detection using *F*-Measure.

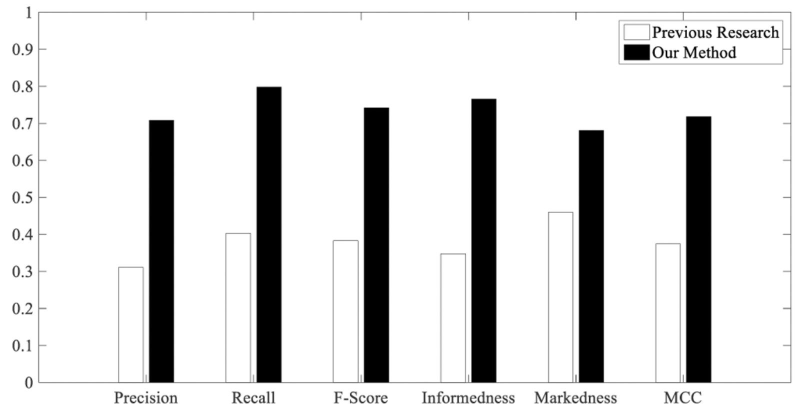

Fig. 6.
Object-use detection evaluation and comparison between our method and previous research in a similar application environment [10].

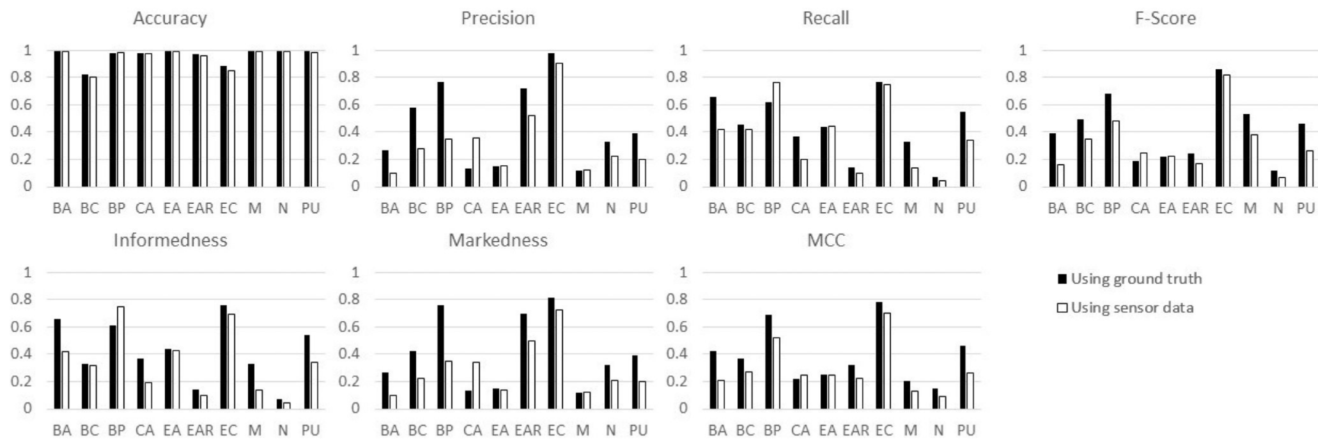

Fig. 7.
Activity recognition evaluation results using ground truth as input and using object use detection from sensor data as input.

TABLE I

THE INFORMATION CONTAINED IN OBJECT-USE GROUND-TRUTH DATA.

Key	Definition
Start Time	The start time of the object being used
Stop Time	The end time of the object being used
Object Name	The name of the object being used
Manipulation Status	Whether the object is being manipulated or being used or otherwise manipulated
Task Relation	If the object manipulation was related to or represented use during an activity
Activity	The activity for which the object was used

Author Manuscript

Author Manuscript

Author Manuscript

TABLE II

THE INFORMATION CONTAINED IN ACTIVITY GROUND-TRUTH DATA.

Key	Definition
Start Time	The time when the activity starts
Stop Time	The time when the activity stops
Activity Name	The name of the activity in progress
Related Objects	Related objects used for the activity

TABLE III

Medical objects used in this paper with related tagging strategies. BP Bulb stands for Blood Pressure Bulb, BP Cuff stands for Blood Pressure Cuff and NRB stands for non-rebreather mask.

Object	Tagging Strategy
Ophthalmoscope	Holder-slot Tagging
Otoscope	Holder-slot Tagging
BP Bulb	Direct Tagging
Pulse Oximeter Adapter	Direct Tagging
Cardiac Monitoring Adapter	Direct Tagging
Small NRB	Direct Tagging
Adult NRB	Direct Tagging
BP Cuff	Differential Taggiing
Bair Hugger Connector	Direct Tagging
Thermometer	Multi-tag Tagging

TABLE IV

The object-use time, manipulation time, and the breakdown of the manipulation time: in use, task-related motion, and unrelated motion. BP Bulb stands for Blood Pressure Bulb, BP Cuff stands for Blood Pressure Cuff and NRB stands for non-rebreather mask.

Object	In-use time (seconds)	Manipulation time, percent of total time	In-use time, percent of manipulation time	Task-related motion, % of manipulation time	Task-unrelated motion, % of manipulation time
Ophthalmoscope	243	1.17%	21.53%	5.74%	72.73%
Otoscope	1294	6.24%	29.33%	8.85%	61.82%
BP Bulb	3771	18.17%	4.90%	2.17%	92.93%
Pulse Ox Adapter	11904	57.37%	74.74%	1.40%	24.14%
Cardiac Monitoring Adapter	12517	60.32%	78.74%	1.16%	20.10%
Small NRB	1315	6.33%	41.89%	2.72%	55.39%
Adult NRB	10	≈0%	40%	5%	55%
BP Cuff	1038	5.00%	24.47%	9.04%	66.49%
Bair Hugger Connector	11107	53.53%	97.38%	0.34%	2.28%
Thermometer	416	2.00%	50.40%	8.80%	40.80%

TABLE V

Activities and related objects. BP Bulb stands for Blood Pressure Bulb, BP Cuff stands for Blood Pressure Cuff and NRB stands for non-rebreather mask.

Activity	Code	Related Objects
Pulse Ox Placement	BA	Pulse Ox Adapter
Oxygen Preparation	BC	Small NRB/Adult NRB
Blood Pressure Measurement	BP	BP Bulb, BP Cuff
Cardiac Lead Placement	CA	Cardiac Monitoring Adapter
Temperature Measurement	EA	Thermometer
Ear Exam	EAR	Otoscope
Warm Sheet	EC	Bair Hugger Connector
Mouth Exam	M	Otoscope
Nose Exam	N	Otoscope
Pupils Exam	PU	Ophthalmoscope/Otoscope

TABLE VI

Evaluation score for several objects. A for accuracy, P for Precision, R for Recall, F for F-score, I for Informedness, M for Markedness, MCC for Matthews Correlation Coefficient, BP for Blood Pressure, and NRB for non-rebreather mask.

	A	P	R	F	I	M	MCC
Ophthalmo-scope	0.99	0.22	0.50	0.31	0.49	0.22	0.33
Otoscope	0.97	0.73	0.73	0.73	0.71	0.71	0.71
BP Bulb	0.93	0.77	0.86	0.82	0.82	0.75	0.78
Pulse Ox Adapter	0.93	0.94	0.94	0.93	0.86	0.87	0.86
Cardiac Monitoring Adapter	0.94	0.98	0.93	0.95	0.90	0.88	0.89
Small NRB	0.97	0.72	0.84	0.77	0.82	0.71	0.76
Adult NRB	0.97	0.72	0.84	0.77	0.82	0.71	0.76
BP Cuff	0.96	0.56	0.60	0.58	0.57	0.55	0.56
Bair Hugger Connector	0.96	0.95	0.97	0.96	0.91	0.92	0.92
Thermometer	0.98	0.49	0.77	0.60	0.76	0.49	0.61