Activity Recognition for Medical Teamwork Based on Passive RFID

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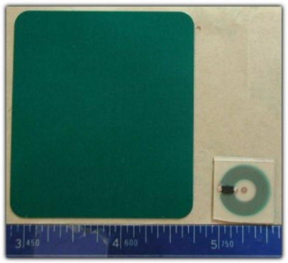
Brief Introduction

- Activity Recognition in Medical Teamwork (Trauma Resuscitation)
  - Trauma resuscitation, is a ***complex process*** performed by a ***medical team*** under ***time pressure***.
  - Highly ***privacy sensitive***.
  - The trauma room has strict requirements for hardware***, no potential interferences to medical equipment or obtrusive to tasks***.
- Why it is challenging
  - Privacy preserving, no RGB cameras.
  - No wearable devices, no Bluetooth.
  - Fixed equipment, less maintenance is preferred.
  - Has to be commercially available.

Related Work – Activity recognition based on human object interaction



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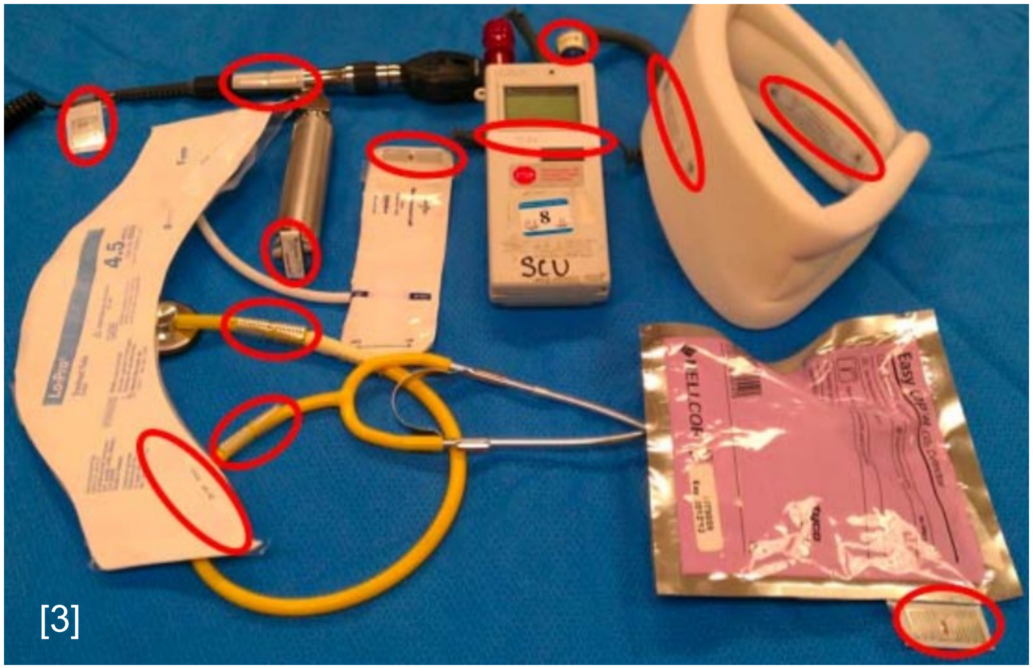
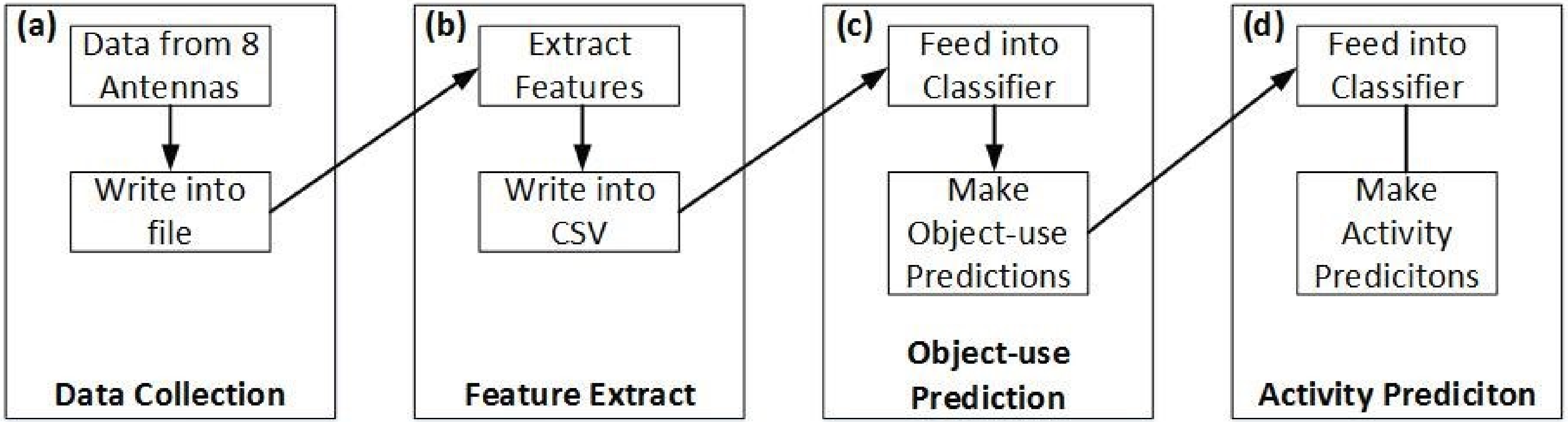


[3]

[1] D.J. Patterson, D. Fox, et al, "Fine-grained activity recognition by aggregating abstract object usage," *Proc. 9th IEEE International Symposium on Wearable Computers*, pp. 44-51. IEEE, 2005.
[2] J.E. Bardram, A. Doryab, 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.
[3] S. Parlak, I. Marsic, 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.

System Overview



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.

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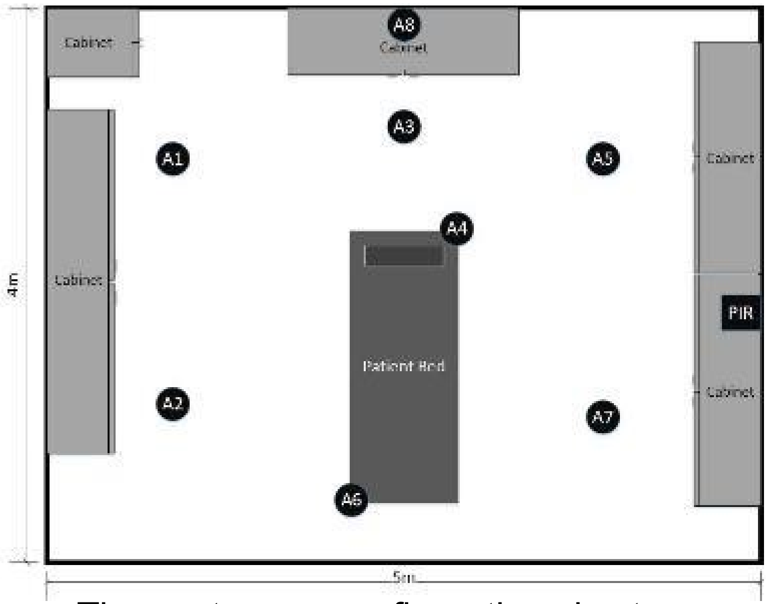
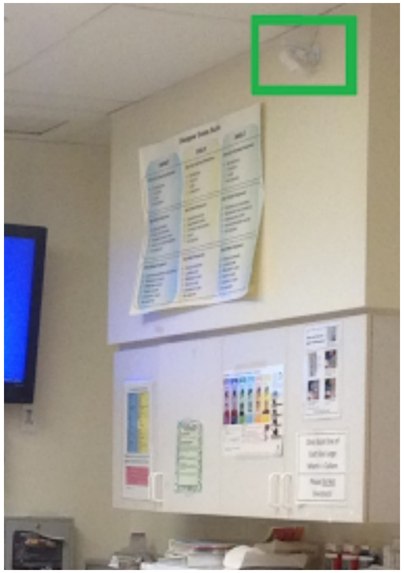
Data Collection – Hardware Configuration



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.

The photo of the trauma room we used for experiments, all 8 antennas are labeled with blue square.



The Honeywell AUROR passive infrared sensor (PIR) used for detecting motion in the trauma room.

Object Tagging Strategies

(a) (b) (c) (d)

a. 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.

b. 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.

c. 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.

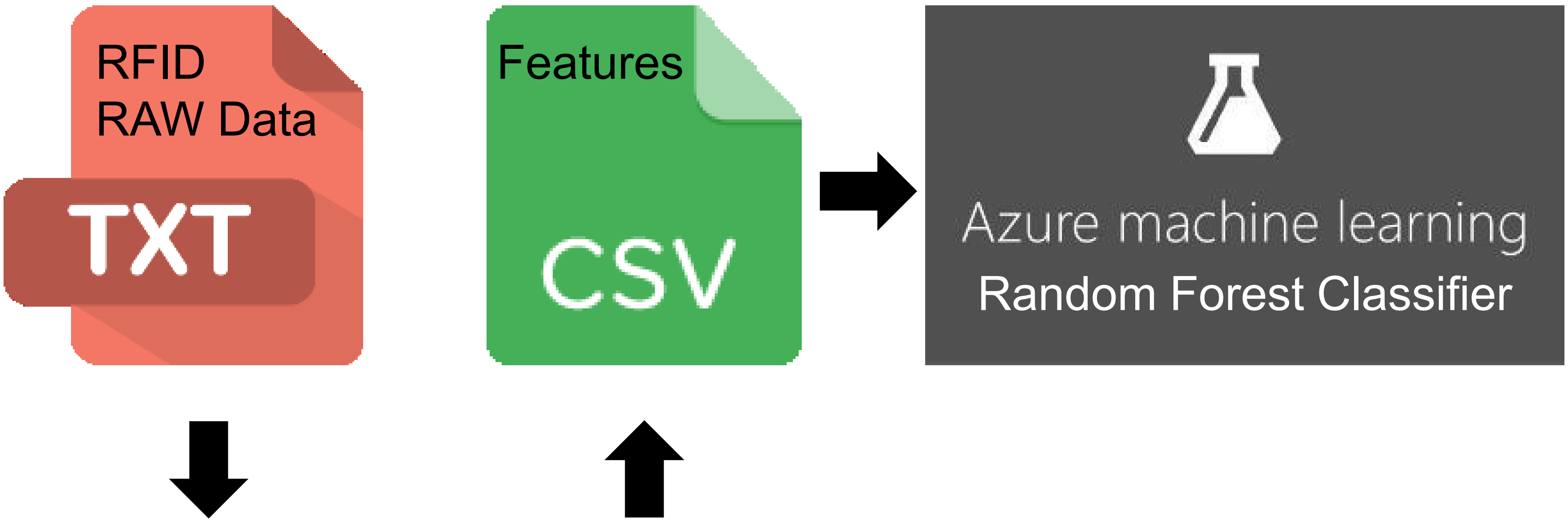
d. Differential tagging: Place one tag inside and another outside an object. When in use, one side of the object will be in contact with the patient. The outside tag is used as a reference for the inside tag. When the object is not in use, both tags share similar RSSI values. When the object is in use, 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.

Feature Extraction

Peak RSSI	The measurement of signal strength of tags attached to different objects. Different objects with different tagging strategy will have different peak RSSI.
[redacted]	
Visible Antenna Combination [1]	Objects at different position will have different visible antenna combinations.
[redacted]	
Entropy [2]	[redacted]
[redacted]	

[1]. R. Ni, Z. Ye, et al. "Zoning positioning model based on minimize RFID reader," *Proc. 2nd Int'l Symp. on Instrumentation and Measurement, Sensor Network and Automation (IMSNA)*, pp. 117-121. IEEE, 2013.
[2]. H. Ding, J Han, et al, "Human object estimation via backscattered radio frequency signal," *Proc. IEEE Conference on Computer Communications (INFOCOM)*, pp. 1652-1660. IEEE, 2015
[3]. S. Zhang, A.V. Rowlands, et al, "Physical activity classification using the GENEA wrist-worn accelerometer." PhD dissertation, Lippincott Williams and Wilkins, 2012.

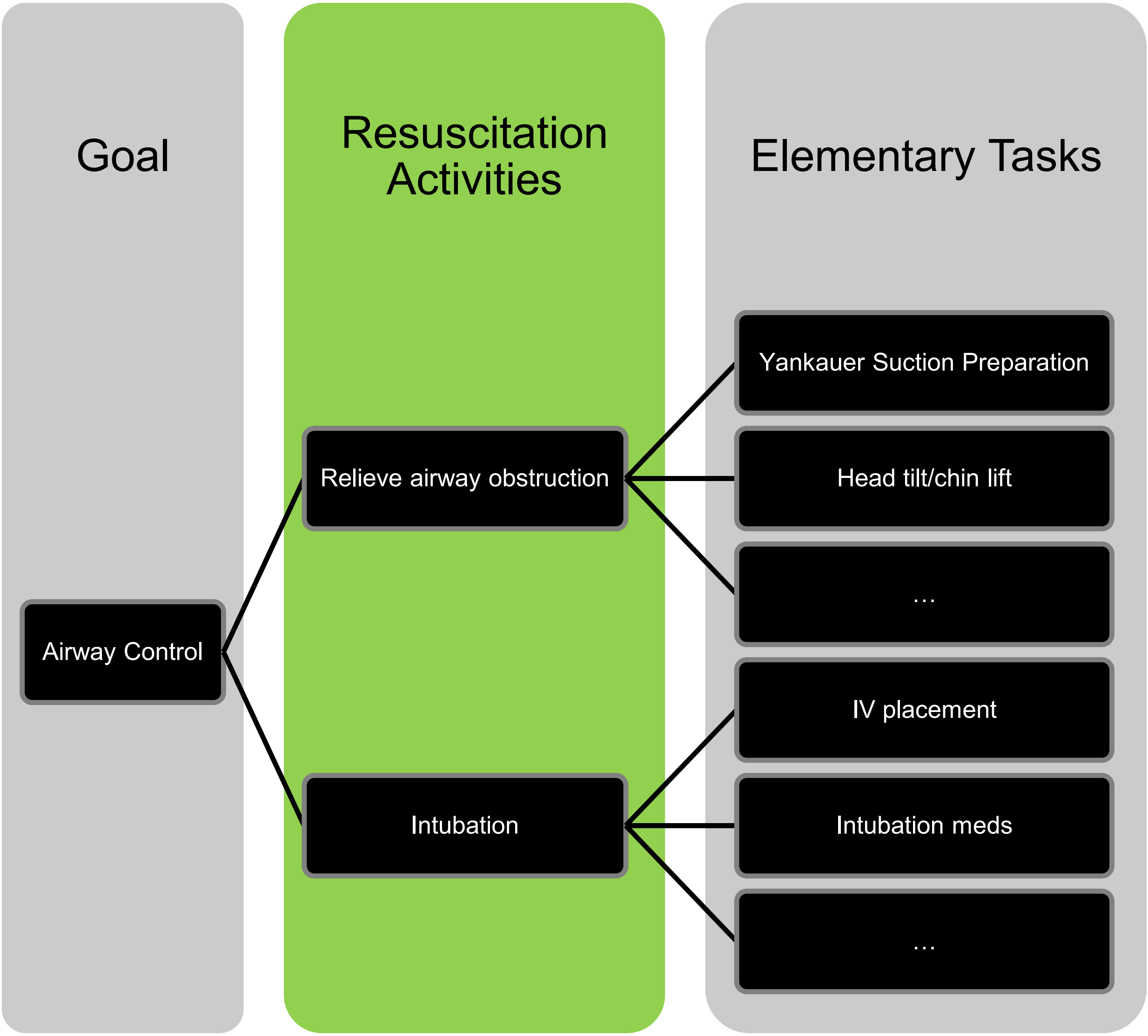
Object-Use Detection



Simi-Random Data Selection

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.

Activity Recognition



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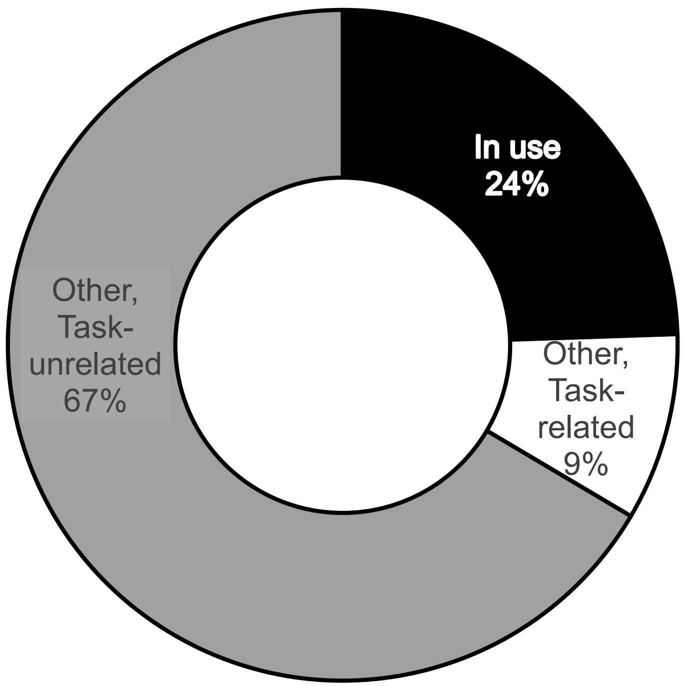
Activity Recognition Based on Object-use Combination

- Activity cannot be directly inferred from Object-Use information, because object might be manipulated even when not used for task-related purpose.
- Instead, use object-use combination (for all tagged objects).

BP Cuff Manipulation



Experimental Results – Object-use detection

	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

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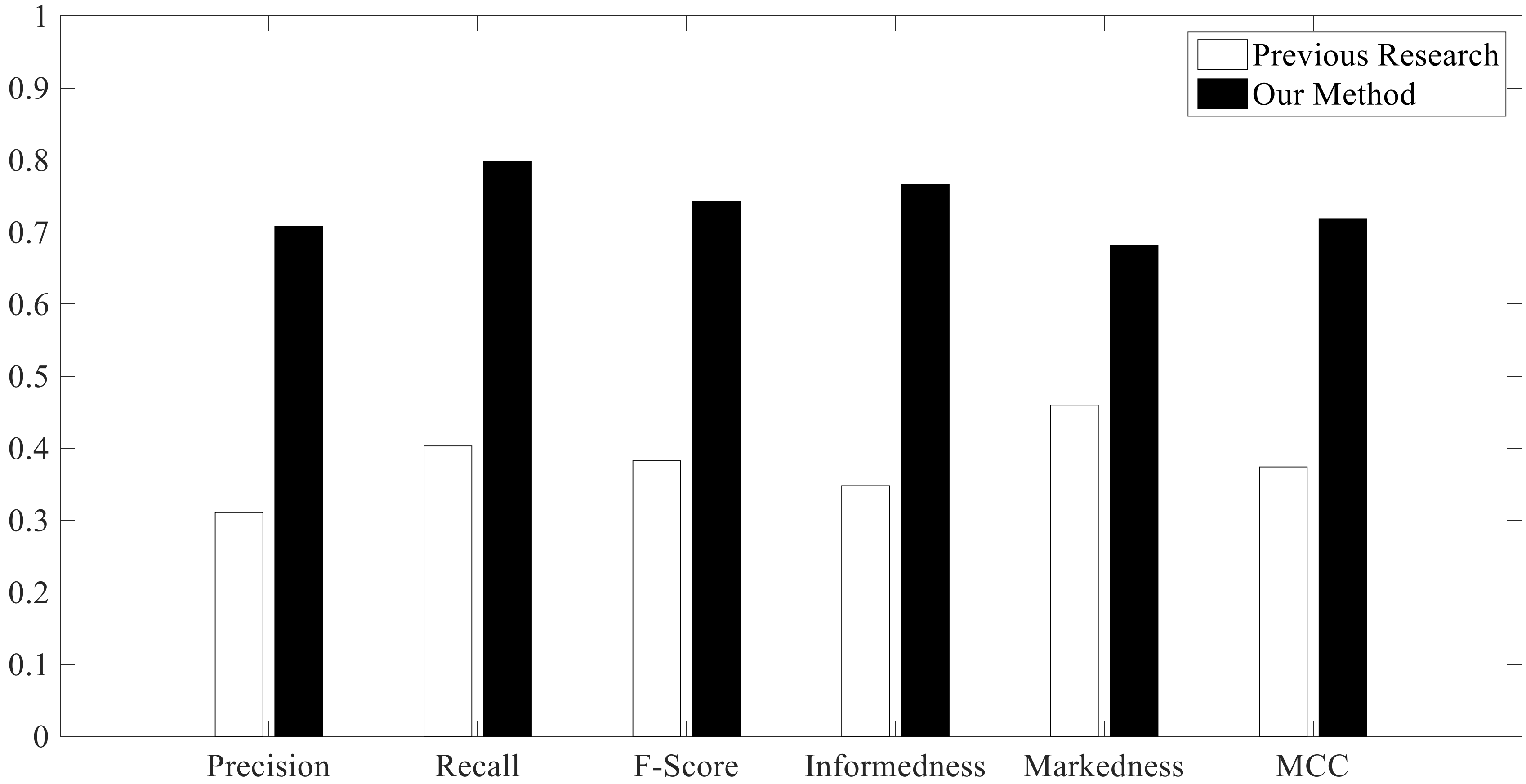
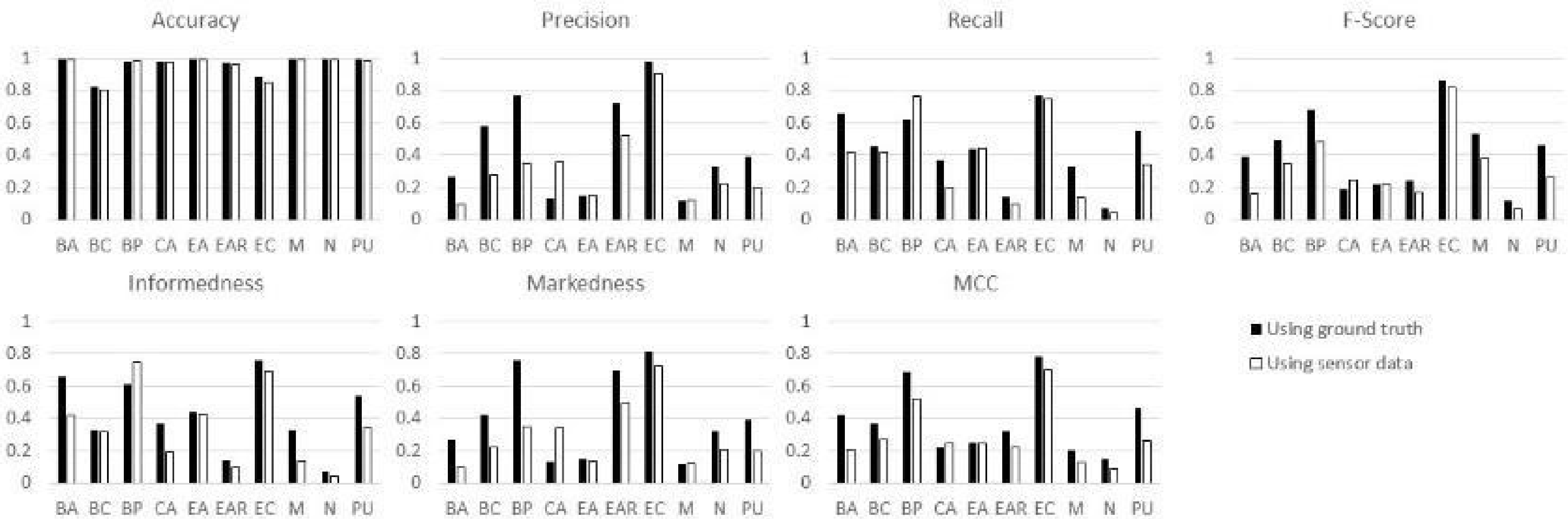
Experimental Results – Comparison



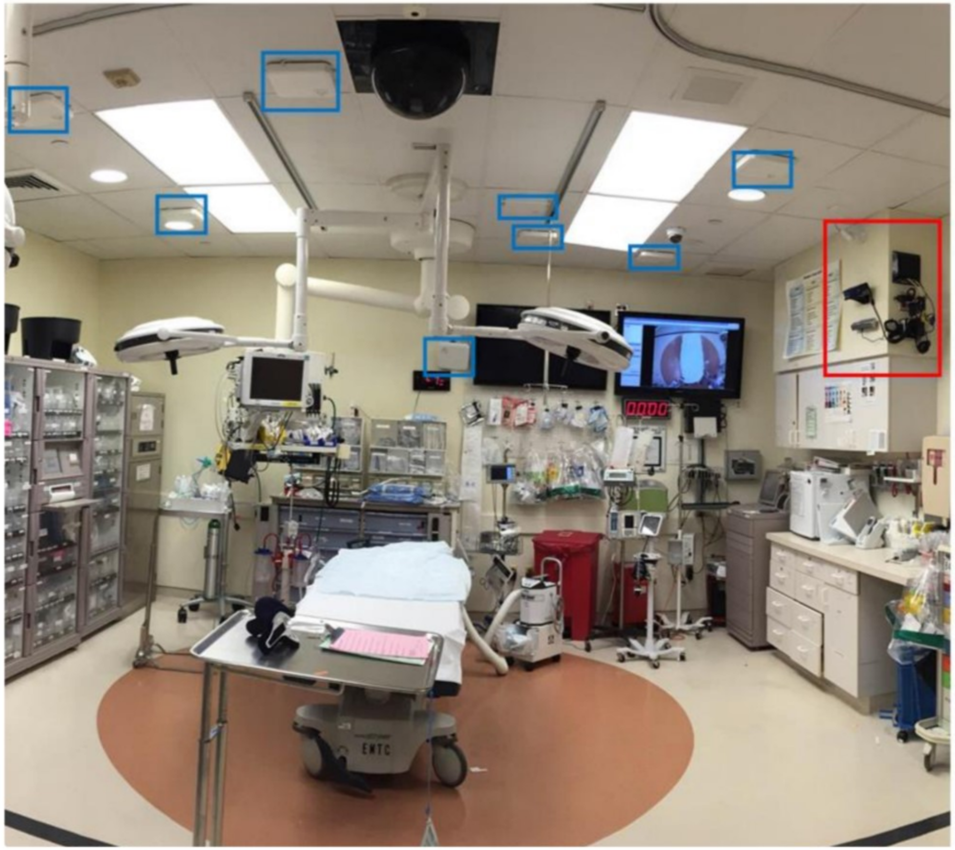
Ref: S. Parlak, I. Marsic, et al, "Passive RFID for Object and Use Detection During Trauma Resuscitation,", *IEEE Transactions on Mobile Computing*, to appear, published on IEEE Xplore in 2015.

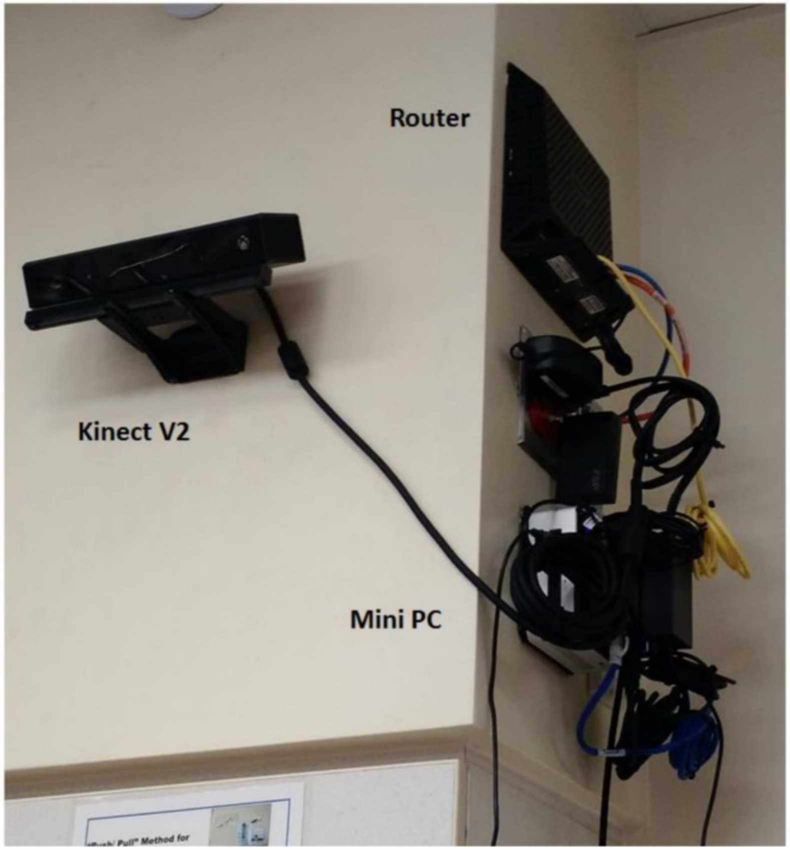
Experimental Results – Activity Recognition



Directly using object-use ground truth lead to roughly 20% better evaluation score when directly using ground truth data.

System Upgrade

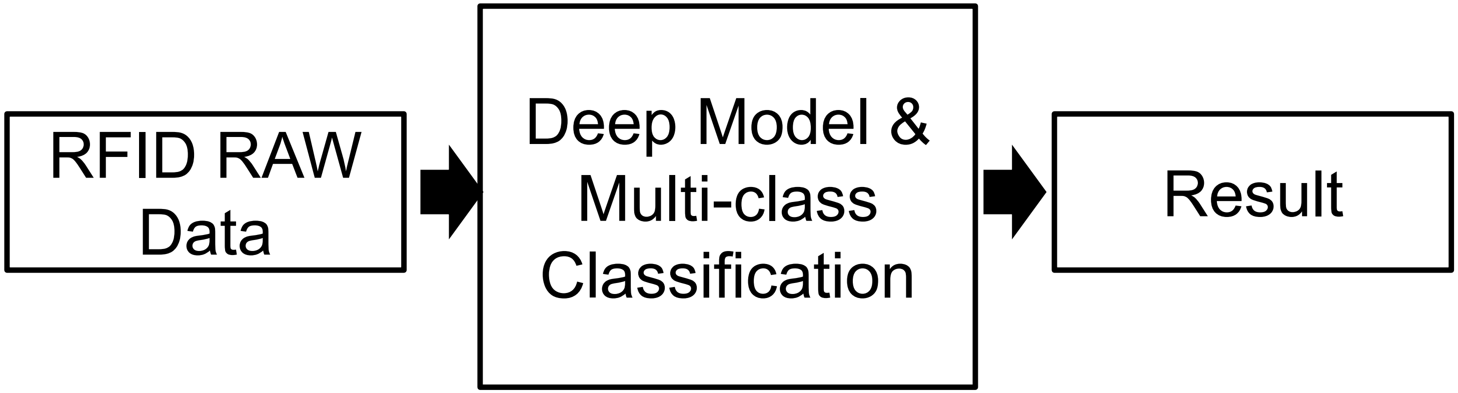




Limitation and Future Work

Limitations:

1. Error is pruning through the hierarchy of the model
2. Binary classification lead to generalization problems



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The End

Thank you

Questions?

Xinyu Li
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