RTagCare:deep human activity recognition powered by passive computational RFID sensors

Guibing Hu, Xuesong Qiu, Luoming Meng
State Key Laboratory of Networking and Switching Technology
Beijing University of Posts and Telecommunications
Beijing, China
E-mail: hugb@bupt.edu.cn

Abstract—**Activity recognition is a hot topic of research that is widely adopted by many applications such as fall detection of elderly people. Emerging passive RFID (radio-frequency identification) is creating huge opportunity for wearable devices to achieve activity recognition. However, performance of activity recognition is constrained by RFID localization accuracy and low quality of data streams characterized by sparsity and noise. In this paper, we present a novel activity recognition system, called RTagCare, which is a low-cost, unobtrusive and lightweight RFID based system. The RTagCare system leverage RFID localization technology, 3D-accelerometer base human activity identification and data mining algorithm to overcome traditional activity recognition system issues. RTagCare has been implemented and deployed in a test environment. As a result, RTagCare generally performs well to recognize human activity with high performance (F-score >94%).**

Keywords- RTagCare; Passive RFID; activity recognition; Accelerometer; Feature Representation;

I. INTRODUCTION

The aging of population is a problem that is facing in many countries in recent years due to increasing life expectancy and low birth rate. With rapid developments in low-cost sensor and networking technologies, it has become possible to develop a wide range of valuable applications such as the remote health monitoring and intervention. These applications offer the potential to enhance the quality of life for the elderly, afford them a greater sense of security, and facilitate independent living [1]. The key to realizing these applications is activity recognition, which is emerging research area in recent years [2].

In this paper, we propose a novel activity recognition system called RTagCare which combined RFID based localization, 3D-accelerometer base human activity identification and data mining algorithms using a passive computational RFID tag-Moo tag [3]. The three main contributions of our work are summarized below:

1) We propose a data stream segmentation algorithm from both sensor data streams and human's localization information, Compared to the existing activity recognition segmentation method, It is innovatively involve human localization information based on passive RFID tag's RSSI and phase to data set and mixed with accelerometer sensor data. our method achieves good accuracy for data partitioning and also is flexible to apply to other use cases by adjusting parameter.

2) We propose a lightweight and effective feature selection method to extract information patterns. We particularly consider the inadequate sensor observations (sparsity) to directly recognize activity (bed-entry, chair-exit and walking).

3) We implemented an end to end experiments using data collection from sixteen volunteers to verify our system. As a result we observe the precision is around 95% during identification of the three activities (i.e. bed-entry, chair-exit and walking).

II. RELATED WORK

There are different types of approaches to address issues of activity recognition: camera based approaches, binary sensors approaches, RFID based approaches and electrical load analysis approaches. We describe briefly each class.

A. Camera based approaches

Many researchers used camera base approaches to do activity recognition and some of those get good result. However, the main limit for this approach is that camera is generally considered to be intrusive to people's privacy and also depend on light conditions.

B. Electrical load signature approaches

Non-intrusive appliance load monitoring (NIALM) is a method by detecting the state of power fluctuations to a building or a house. This approach is limited by the amount of information it provides. This approach only works on activities involving electrical appliance and can't do activities recognition without power consumption.

C. Binary sensors approaches

In this approach, Cook et al. [4] have gotten good results with this type of sensor. In fact, the binary data collection system is composed of an array of motion sensors, which acquire information by devices and sensor network. However, they are still limited to recognize specific scenarios and complexed deployment because of a significant number of sensors.

D. RFID based approaches

The RFID is very popular in activity recognition in recent years. Many researchers used passive RFID to do indoor localization and activity recognition, the main issue for passive

RFID only solution is the low precision of localization and frequently result in failure in a crowded indoor environment.

III. PROBLEM DEFINITION AND OVERVIEW

In this section, we discuss two key problem definitions for human activity recognition, before that, we brief passive computational tag for proposed RTagCare.

A. Passive computational tag

In this paper, we use a Moo tag, which is a passive computational RFID equipped with a 3-Axis accelerometer (ADXL330). The Moo not only act as common passive tag, but also provides a RFID-scale, fully programmable, battery less sensing platform. The programs execute on an MSP430 microcontroller.

Moo tag send a raw data represented by 5-tuple $[a_x, a_y, a_z, RSSI, ID]$ to reader where a_x , a_y and a_z are defined as frontal, lateral and vertical accelerations measured by acceleration sensor embedded in Moo tag, RSSI(Received Signal Strength Indicator) represent the RF signal power measured by reader and ID is unique identifier of each tag.

B. Passive RFID tag based Localization

In recent years, many literatures introduced indoor localization based on passive RFID tag, Two RF features, *RSSI* and *phase*, are available for passive tag based indoor localization for readers.

RSSI: Lots of state of art on RSSI to distance transformation, the following is indoor propagation path loss model as (1) and its simplified derivation transformation as (2) for the simple solution to do transformation

$$P(d)_{dBm} = P(d_0)_{dBm} - 10n\log(\frac{d}{d_0}) + X_{dBm} \tag{1}$$

$$\Rightarrow d = 10^{\frac{P(d_0)_{dBm} - P(d)_{dBm}}{10n}} \text{; if } d_0 = 1 \text{ and } X_{dBm} = 0 \tag{2}$$

Where $P(d)_{dBm}$ is the received power, along the propagation path of relative distance d, and $P(d_0)_{dBm}$ is the received power along the propagation path of reference distance d_0 (1 m).

Phase: Another RF feature phase is also frequently used to do indoor localization[5], since RF backscatter, the signal across a total distance of 2d outbound and inbound. The following formula defined the relationship among antenna phase rotation, tag phase rotation and distance

$$\theta = (2\pi\frac{2d}{\lambda} + \theta_{Ant} + \theta_{Tag}) \bmod (2\pi)\lambda \tag{3}$$

Where θ_{Ant} and θ_{Tag} is defined as antenna and tag phase rotation respectively. The phase is a periodic function with 2π radians which every $\lambda/2$ in the distance of RF communication.

C. Data driven activity recognition

The data driven approach for activity recognition mainly includes learning of new activities to provide flexibility. This approach has the key component in identifying the context of a user for providing services based on the application. In this paper, We study four typical patient states(Lying on bed, sitting on chair, walking and standing) in hospital ward and focus on eight related correlative activities(entry bed, exit bed, entry chair, exit chair, start walking, stop walking, start standing, stop standing)[6]. As we aforementioned, Lots of literatures adopted passive RFID tag based data driven approach to achieve activity recognition[7]. However, in actual world situation, since passive tag is powered by reader, data collected from senses are sparse and affected by noises due to nature of RF, such as distance between antenna and tag, signal multipath propagation, etc. RTagcare based on Moo tag is designed to address the proposed to identify eight activities with high precision .

IV. THE SYSTEM AND ALGORITHM

Our system – RTagcare is composed of four main stages:

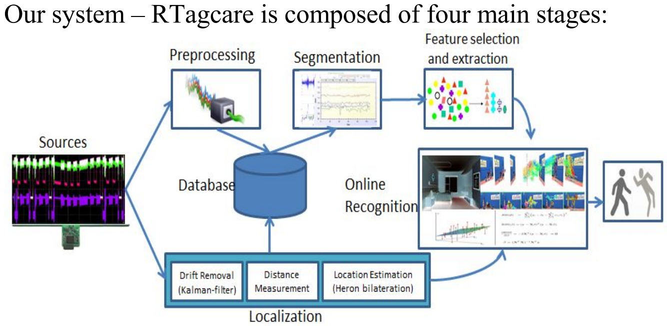

Fig. 2 The architecture of proposed RTagcare system

1) Preprocessing stage is the first stage of processing the raw signal streaming data from various Moo tag, the main purpose of this stage is smooth the data by applying signal process filter methods and focus on a certain frequency spectrum. RTagcare use Kalman filter to do pre-processing.
2) Segmentation stage is to split the continuous data stream into a set of unique segment, the various segment maps to corresponding activity (e.g. lying, sitting, walking, standing, etc.).
3) Feature selection and extraction stage is selecting and extracting activity features from individual segmentation.
4) Online recognition stage is applying machine learning algorithm to data set and get best approximates answer for testing sample.

A. Preprocessing

The raw sense data get through a preprocessing stage to process the data for further steps. The survey of Figo et al. [8] describes preprocessing techniques in detail.

In this paper, according to RSSI and accelerometer data feature, we use inertial filter to do preprocessing for data filter and partial noisy removal. The mathematical defined as below.

$$T_f\frac{y(k) - y(k-1)}{T} + y(k) = x(k) \tag{9}$$

$$\Rightarrow \quad y(k)=\frac{T}{T_f+T}x(k)+\frac{T_f}{T_f+T}y(k-1)=ax(k)+(1-a)y(k-1) \qquad (10)$$

Where $y(k)$ is defined as the kth output of filter, $x(k)$ is the kth input value of filter. $a=T/(T_f+T)$ is the filter coefficient, T_f is the parameter we define,

B. Segmentation

We propose a real-time segmentation method, which can detect activity exit/entry based on 3-axis and localization data. We leverage 3-axis sense data to detect the human truck change and define two angels to represent the 3-axis changes, As is showed in Fig 3, θ represent human trunk inclination angel on sagittal plane and ϕ means inclination angel on frontal plane. According to mathematical coordination conversion, we can get $\theta=arctan(\sqrt{a_x^2+a_y^2}\,)/a_z)$ and $\phi=arctan(a_y/a_x)$.

Besides 3-axis sense data, we also use location info which is calculated by RSSI to improve the system perform. We can get a 5 tuples sense data S_i at I time, we define $S_i=[a_x, a_y, a_z, RSSI, ID]$. We also define a new variable Activity Change Indicator (ACI) which represent indicator of activity change. When ACI exceed ACI_{thres} you set, it represent the human activity changed

$$ACI = w_1\frac{\theta_{sd}}{\theta_{max}} + w_2\frac{\phi_{sd}}{\phi_{max}} + w_3\frac{L_{sd}}{L_{max}} \qquad (11)$$

$$\text{s.t.} \quad \begin{cases} w_i > 0 & i=1,2,3 \\ \sum_{i=1}^{3} w_i = 1 \end{cases}$$

Where θ_{max}, ϕ_{max}, L_{max} represent the maximum value respectively. w_i is the weighting coefficient of object. θ_{sd}, ϕ_{sd} and L_{sd} is standard deviation for θ, ϕ and *location* respectively during eclipsed time Δt, w_i and Δt can be adjusted to reflect your actual circumstance, apparently, the performance of the RTagcare is closely related to value with larger weighting coefficient as you set.

The segmentation algorithm is described as Algorithm 1.

Algorithm 1: Segmentation

Inputs: S_i, θ_{max}, ϕ_{max}, L_{max}, Δt
Outputs: segmentations

```
Temp.initialization()
For i=0 to T do
   If isEmpty(temp) then    // judge if it is a new segmentation
     t 0= ti
   end if
   temp.add(Si ,location)
   if isACI (ti, θmax , φmax , Lmax ) and (ti – t0 > Δt ) then
      segi = temp
      temp.clear()
   output segi and continue
   end if
end for
```

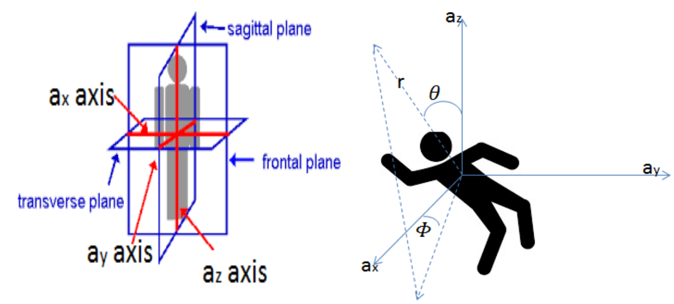

Fig. 3 (a) The 3-axis and planes with human body, (b) Angel θ and ϕ

C. Feature extraction and selection

In many previous literatures, features from acceleration signals and RFID RSSI have been features from acceleration signals have been extracted by considering signals in the time-domain [9] and frequency-domain [10] as well as studies in biomechanics [11]. By reason of the sparse data, frequency domain features isn't suitable. So we extract time domain features considering biomechanical movements analysis as described in Table I.

TABLE I. FEATURES EXTRACTED FROM MOO TAG

No.	*Feature*	*Description*
1	3-axis (a_x, a_y, a_z)	Acceleration signals from accelerometer
2	$L(x,y)$	Human localization from RSSI
3	θ	Angel on sagittal plane
4	ϕ	Angel on frontal plane
5	θ_{sd}, ϕ_{sd} and L_{sd}	Standard deviation for θ, ϕ and L

D. Online recognition

After last extracting features, we select feature vectors $X=(t_i, x_i)_{i=1}^{T}$, where $x_i \in \mathbb{R}^n$, t_i is the time of x_i and T is the size of sequence. we leverage machine learning algorithm based to do online recognition prediction , we define activity prediction sequence $Y=(t_i, y_i)_{i=1}^{T}$ where y_i represented by X.

We construct training data set $TD=(X_i, Y_i)_{i=1}^{n}$ for machine learning classification algorithm.

V. IMPLEMENTATION AND RESULTS

A. Implementation configuration

1)*Hardware*: We carry out a prototype of RTagcare by using Impinj Speedway R220 with two directional antennas. The reader works at the frequency of 916 MHz , 2)*Software*: we download *Impinj MultiReader Software* from impinj website(impinj.com) and use it for testing. All soft wares are running at my laptop. Software connects to the RFID reader with Low Level Reader Protocol(LLRP)

3)*Parameter setting*: We set the initial parameters and adjust those parameters based on different activities and algorithms. The initial parameter setting is listed in TABLE II

TABLE II. EXPERIMENTAL PARAMETERS

Parameter	*value*	*Parameter*	*value*
Δt	3	w_1	0.4
θ_{max}	90	w_2	0.3
ϕ_{max}	90	w_3	0.3
L_{max}	0.5	ACI_{thres}	0.5

B. *Implementation*

We recruited sixteen volunteers whose age is between 25 and 40 years old. The data acquisition is placed in 5m*5m room that simulated the real hospital ward with equipped with one bed, one chair and one table.

C. *Implementation result*

the initial parameters and adjust those parameters based on different activities and algorithms. From our experiments, we observed that a volunteer took approximately 60s to complete a set activities. We also use F-score, TP, TN, FP and FN to evaluate the performance of RTagcare.

Initially, we find out a suitable value for the ACI threshold parameter ACI_{thres} for three different algorithms, As result is shown, Even the different classification algorithm have different performance, but when ACI_{thres} value is around 0.5, the performance(F-score) for each algorithm nearly achieve the best. So we set values of ACI_{thres} to 0.5 in the experiment.

As result shown, the classification algorithm achieve the highest performance when Δt is around 3s. comparing with NB, the results in Fig 5 show that RF and CRF clearly outperformance the NB classifiers, By detailed observation on data, RF and CRF results in less false activity transitions, according decreasing the activity recognition of false movement predictions.

Result shows the performance for each activity considered using the prediction models for RF and CRF. The RF based approach clearly provides the highest mean F-score for all movements. RTagCare system can capture over 94% of the activity recorded in the data stream and means less than 6% of activities were missed on average.

Compared with previous literatures[11], RTagCare has some advantages on the following aspects: i) we the use Moo Tag that is lightweight, battery less, low cost and maintenance free tag with sense; ii) Combined with Passive RFID tag based localization to improve performance of activity recognition with low misses and false alarms; and iii) high performance segmentation algorithm with low latency. A series of activity recognition generate a comprehensive falls prevention mechanism and help caregivers monitor patients and lower the fall risk.

VI. CONCLUSION AND FUTURE WORKS

We present RTagCare, which is a lightweight, battery less, unobtrusive human activity recognition system. RTagCare has the potential to assist independent living of older people and patient monitoring. We particularly involve localization information to system for sparse, noisy and unstable RFID sensor signals. Our RTagCare specially consider the system flexibility to adapt different use cases by simply adjusting parameter. Our future work will evaluate our system on larger areas and see if we need to optimize system.

VII. ACKNOWLEDGMENT

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References

[1] M. Chan, D. Esteve, and C. Escriba, “A Review of Smart Homes-Present State and Future Challenges,” Computer Methods and Programs in Biomedicine, vol. 91, no. 1, pp. 55-81, 2008.

[2] A. Iosifidis, A. Tefas, and I. Pitas, "Multi-view action recognition based on action volumes, fuzzy distances and cluster discriminant analysis," Signal Processing, vol. 93, no. 6, pp. 1445-1457, Jun. 2013.

[3] E. Hoque and J. A. Stankovic, “Monitoring quantity and quality of sleeping using WISPs,” in Proc. 9th ACM/IEEE Int. Conf. Inf. Process. Sensor Netw. (IPSN), Apr. 2010, pp. 370–371.

[4] V. Jakkula and D. J. Cook, "Mining Sensor Data in Smart Environment for Temporal Activity Prediction," Poster session at the ACM SIGKDD,San Jose, CA, 2007.

[5] M. Scherhaufl, M. Pichler and A. Stelzer, "UHF RFID localization based on phase evaluation of passive tag arrays", IEEE Trans. Instrum. Meas., vol. 64, no. 4, pp. 913-922, 2015.

[6] D. C. Ranasinghe, R. L. Shinmoto Torres, K. Hill, and R. Visvanathan,“Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions,” Gait Posture, vol. 39, no. 1, pp. 118–123, 2014.

[7] J. Hilbe, E. Schulc, et al , “Development and alarm threshold evaluation of a side rail integrated sensor technology for the prevention of falls,” Int. J. Med. Inform., vol. 79, no. 3, pp. 173–180,2010.

[8] D. Figo, P. C. Diniz, D. R. Ferreira, and J. M. Cardoso, “Preprocessing techniques for context recognition from accelerometer data,” Pers. Ubiq. Comput., vol. 14, no. 7, pp. 645–662, 2010

[9] L. Bao and S. S. Intille, “Activity recognition from user-annotated acceleration data,” in Pervasive Computing (Lecture Notes in Computer Science). Berlin, Germany: Springer-Verlag, 2004, pp. 1–17.

[10] D. C. Ranasinghe, R. L. Shinmoto Torres, K. Hill, and R. Visvanathan, “Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions,” Gait Posture, vol. 39, no. 1, pp. 118–123, 2014.

[11] A. Godfrey, A. K. Bourke, G. M. Ólaighin, P. van de Ven, and J. Nelson, “Activity classification using a single chest mounted tri-axial accelerometer” Med. Eng. Phys., vol. 33, no. 9, pp. 1127–1135, 2011