ADL Classification Using Triaxial Accelerometers and RFID

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Abstract: A robust recognition of ADL(Activities of Daily Living) based on human motion and object identification has proposed. Two wireless accelerometers are used for the classification of 5 human body states using decision tree, and detection of RFID tagged objects with hand movement provides additional object related hand motion information. To do this, we develop zigbee based wireless triaxial accelerometers and glove type RFID reader. The fusion of these recognition results provides overall recognition rate of over 90% over 12 ADLs, which can be applicable to a real environment with strong confidence.

1. Introduction

We propose a novel method to infer a user's activities of dailyvliving(ADL) with RFID and accelerometers. ADL is a way to describe the functional status of a person[1]. Therefore the recognition of ADL is a significant problem in human caring system, especially in elder care. Due to the advance in sensor technology, people have an interest in the development of systems for monitoring human subjects over long period of time using wearable monitoring units.
Recently, a number of researchers have investigated ADL inference with accelerometers.

Accelerometers can provide quantitative measurements and respond to both acceleration for gravity and acceleration for body movement. This makes them suitable for measuring postural orientations as well as body movements.
Using these accelerometers, many researchers have proposed different approaches to classification, including fixed-threshold classification[2], pattern matching based classification[3] and neural network based classification[4]. Kiani et al.[5] presented a more systematic approach to classification based on a decision tree(DT). Each node of the tree had multiple branches leading to all of the movements of interest at the next level of the hierarchy.
The decision at each node was obtained by the measurement of parameters such as average, norm and standard deviation and then classification on the basis of these parameters. Bao and Intille[6] calculated mean, energy and frequency domain entropy of acceleration data and tested several classifiers, such as decision table, IBL, decision tree and naïve bayes, using these features.
Among them, they showed DT classifiers had the best performance in recognizing activities of daily living. Although DT classifiers had been used, recognition accuracy on a variety of activities is around 80%, the accuracy does not satisfactory so that it must be increased for the general uses, especially under a natural and out-of-lab environment.
Some researchers tried to infer the human activities by detecting human-object interactions[7]. To do this, they used RFID technology that facilitates applications that are triggered by handling tagged physical objects. This approach has the advantage of very high accuracy. There are little false negatives. However, these approaches have a weakness that false positive may occur when the object is detected without being truly used. In this paper, a novel and robust recognition of ADL based on human motion and object identification has proposed. By combining the recognition of body states using low body motion sensors with the human-object interaction detected by the RFID-tagged object grasps, the recognition rate of ADL can be improved significantly in a real usage environment.

2. Analysis using wireless motion sensors

To detect the physical activities of the user, three triaxial accelerometers were worn on thigh, waist and wrist. We made our motion sensors with Zigbee module so that wireless connection is possible. Figure 2 shows our motion unit. The feature values of mean, energy, entropy and correlation in frequency-domain are calculated from acceleration data with 256 sample window. The way of extracting each feature is as follows. To extract features, we apply FFT transform in advance. For the mean feature, we can get easily by extracting DC component of sample window. It means average acceleration value for the duration of sample window. For the energy feature, we multiply every magnitute after FFT except DC component by itself and add it all together. Then, we normalize the value by dividing with window length.

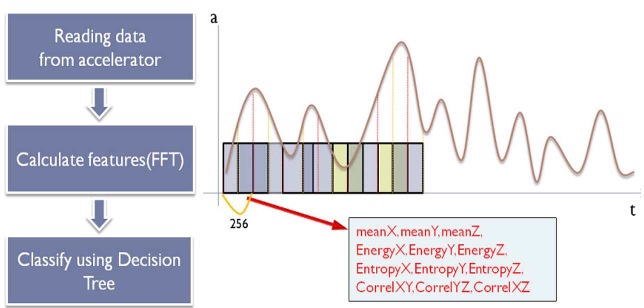

Figure 1 Feature extraction process

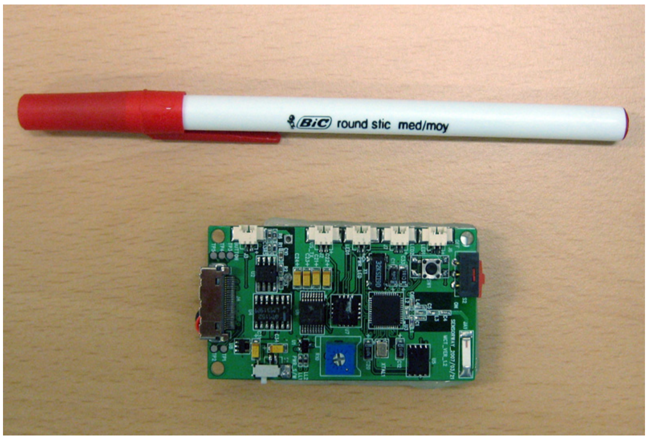

Figure 2 Zigbee based triaxial accelerometers

For the entropy, we calculate the normaized information entropy of every magnitude except the DC component. The following equation is for getting information entropy.

$$\text{Info. Entropy} = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i) \qquad (1)$$

We can get the probability *p(x)* by counting the number of magnitude in a specific bin after dividing the range of magnitude into several bins. Becauase we used triaxial accelerometers to get motion information, we can get the correlation information by calculation the normalized cross product between each axis value. The figure 1 shows the overview of extracting features.

Consecutive sample windows are overlapped with 128 samples and each sample window represents 4 seconds. Overlapped sampling window of 4 seconds was used to capture the cycles in activities such as walking, running, or brushing. Activity recognition based on these features was performed using DT classifiers[6]. Two triaxial accelerometers worn on ankle and waist are used to classify 5 states of current body states of standing, lying, sitting, walking and running. One accelerometer worn on wrist is used to decide hand motion with object ID. Even though DT method is slow to train, a pre-trained DT enables the classification of user activities in real-time.

3. RFID Module

RFID systems have been widely applied over recent years for the identification and tracking applications [7]. Passive RFID tags do not need battery and are small enough to be attach on the small objects like screw driver and tooth brush. List of the RFID tagged objects used for the ADL is shown in figure 3. The RFID tagged objects are detected by the glove which integrates the HF RFID reader of 13.56 Mhz [Figure 3]. The reader is also small enough so that can be embedded in a wearable glove similar to that of Philipose et al.[7]. The designed glove can only read object ID within 50mm range from the palm of the hand and only the object taken by the hand can be detected. The reader samples three times per second.

Figure 3 Our glove type RFID reader and RFID tagged object

4. Sensor Fusion

Figure 4 shows the flow chart of the proposed method to classify the ADL. We observed that most people stay in one of the five body states of standing, lying, sitting, walking and running, and may act some kind of hand activity with different object, called instrumental activity, under each body state. For example, people may brush his/her teeth in standing position, sitting position or walking position. Previous works based on motion data only have less recognition accuracy under real environment because they did not differentiate these body states with hand activities. Proposed method classifies the current state of user body using DT over lower body motion information from waist and lag. After classification of user's body state, the results are combined with instrumental activities. For instrumental activities, we examine the movement of hand and object ID to infer the more detailed intension of the user. For the hand movement analysis, we categorize the movement of hand as three categories, such as rotating, vertical movement and lateral movement. If the movement of hand is detected, then we try to detect the object ID taken by the hand using our RFID reader. If an object is detected, we can infer user's activity from the detected object ID in a classified body state. To get rid of false positive cases of hand activity recognition, we use the categorized hand motion information. For example, if we are to drink something, the hand movement will be vertical movement. In this case, we can classify the activity as drink activity if we detect cup by RFID reader and detect the movement as vertical movement. However, the classified hand movement is lateral motion or circular motion while the detected object is cup by RFID reader, we cannot call it drink activity.

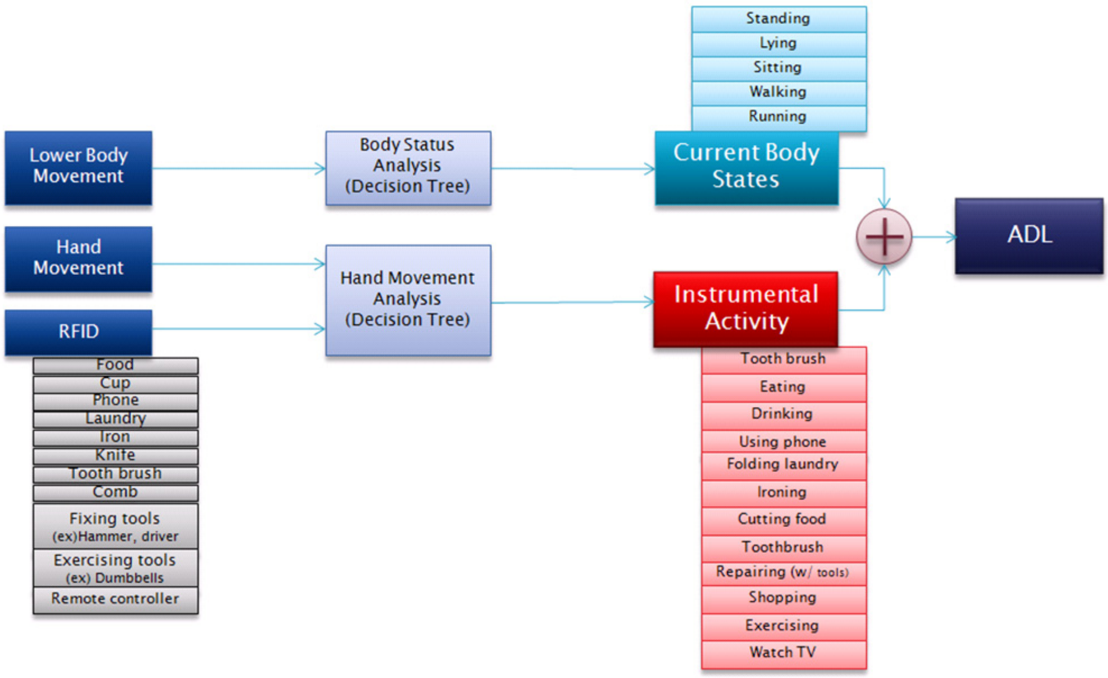

Figure 4 Flow chart of the 2-stage ADL inference

5. Experimental Result

We have collected acceleration data from 18 subjects of 11 males and 7 females using 3 triaxial accelerometers. The average age of subjects is 25.6. Each subject was asked to repeat the performance of predefined sequence of 12 activities[Table 1] for two minutes for each activity to record the training data set. Acceleration data collected were marked with the start and stop times, and labeled with the name of each activity. Mean, energy, entropy and correlation features were extracted from acceleration data.

Table 1 List of activities for our experiment

Activities	Definition
Sitting	One of periods when a user is just sitting still on chair
Standing	One of periods when a user is just stand still
Walking	Walk with empty-handed
Lying	Lie down on his/her back
Running	Jogging with empty-handed
Sitting+Drinking	Drink something while being seated
Standing+Drinking	Drink something while standing
Walking+Drinking	Drink something while walking
Ironing+Standing	Ironing while standing
Cutting+Standing	Cut something while standing
Brush hair+Standing	Brush hair with comb while standing
Repairing+Standing	Using a screw driver while standing

Table 2 Recognition Results

Activities	Accuracy % (motion only)	Accuracy % (motion + RFID)
Sitting	97.64	100.0
Standing	96.72	100.0
Walking	90.92	96.91
Lying	95.94	94.02
Running	94.68	97.91
Sitting+Drinking	94.57	94.38
Standing+Drinking	62.86	97.68
Walking+Drinking	88.19	94.86
Ironing+Standing	69.23	97.94
Cutting+Standing	56.35	98.67
Brush hair+Standing	84.16	98.34
Repairing+Standing	55.02	94.98
Overall	82.26	97.16

To show the comparison of the activity recognition accuracy, the proposed classification method was compared with the conventional classification method of DT classifier using only motion data from three accelerometers.
For the generalization of the results, we tested only subject left out of the training data set. This leave-one-subject-out validation process was repeated for all 18 subjects. The summary of the classification accuracy is shown in table 2. The result shows that our proposed method is strongly confident especially for the object related hand activities.
We also showed the confusion matrix based on the leave-one-subject-out method for 18 subjects in figure 5. This figure will help to understand the recognition results in table 2.

6. Conclusions

A novel and robust recognition method for ADL inference based on human motion and object identification has proposed. The suggested system uses sensor fusion of 3 accelerometers and RFID reader. Two accelerometers are used for the classification of 5 human body states using decision tree, and detection of RFID tagged objects with hand movement provide object related instrumental activities. This hierarchical approach of recognition of human body state instrumental activities provide robust and high accuracy recognition rate. The overall recognition rate of 12 ADL is over 97%, which can be applicable to a real environment with strong confidence.

7. Acknowlegement

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None + Sitting	Drinking + Sitting	Drinking + Standing	Drinking + Walking	None + Standing	Ironing + Standing	Cutting + Standing	Brush_hair + Standing	Repairing + Standing	None + Walking	None + Running	None + Lying	Ironing + Sitting	Cutting + Sitting	Brush_hair + Sitting	Repairing + Sitting	Ironing + Walking	Cutting + Walking	Brush_hair + Walking	Repairing + Walking	Drinking + Running	Ironing + Running	Cutting + Running	Brush_hair + Running	Repairing + Running	Drinking + Lying	Ironing + Lying	Cutting + Lying	Brush_hair + Lying	Repairing + Lying	total	Activity	Accuracy (%)
510	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	510	None + Sitting	100
12	504	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	534	Drinking + Sitting	94.38202
0	0	505	8	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	517	Drinking + Standing	97.67892
0	0	22	498	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	525	Drinking + Walking	94.85714
0	0	0	0	519	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	519	None + Standing	100
0	0	0	0	8	522	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	533	Ironing + Standing	97.93621
0	0	0	0	1	0	520	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	527	Cutting + Standing	98.67173
0	0	0	0	0	0	0	534	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	543	Brush_hair + Standing	98.34255
0	0	0	0	11	0	0	0	473	1	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	498	Repairing + Standing	94.97992
0	0	0	0	11	0	0	0	0	502	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	518	None + Walking	96.91119
0	0	0	0	0	0	0	0	0	11	516	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	527	None + Running	97.91271
23	0	0	0	0	0	0	0	0	0	7	488	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	518	None + Lying	94.2085
545	504	527	506	554	522	520	534	473	514	528	489	0	0	0	0	3	6	9	13	5	0	0	0	0	17	0	0	0	0	6269	total	97.16063

Figure 5 The confusion matrix based on leave-one-subject-out method for 18 subjects