Energy Efficient Activity Recognition Based on Low Resolution Accelerometer in Smart Phones

Yunji Liang, Xingshe Zhou, Zhiwen Yu, Bin Guo, and Yue Yang

School of Computer Science, Northwestern Polytechnical University,
Shaanxi, Xi'an, China, 710129
lemonliang@mail.nwpu.edu.cn,
{zhouxs,zhiwenyu,guob}@nwpu.edu.cn, nwpu.yangyue@gmail.com

Abstract. Smart phone is becoming an ideal platform for continuous and transparent sensing with lots of built-in sensors. Activity recognition on smart phones is still a challenge due to the constraints of resources, such as battery lifetime, computational workload. Keeping in view the demand of low energy activity recognition for mobile devices, we propose an energy-efficient method to recognize user activities based on a single low resolution tri-axial accelerometer in smart phones. This paper presents a hierarchical recognition scheme with variable step size, which reduces the cost of time consuming frequency domain features for low energy consumption and adjusts the size of sliding window to improve the recognition accuracy. Experimental results demonstrate the effectiveness of the proposed algorithm with more than 85% recognition accuracy for 11 activities and 3.2 hours extended battery life for mobile phones.

Keywords: energy efficient, hierarchical recognition, low resolution, activity recognition, tri-axial accelerometer.

1 Introduction

Activity is one of the most important contexts in pervasive computing. User activity has been used to evaluate the metabolic energy expenditure; to explore the activity patterns; and to enhance interactions in social groups [1-4]. To recognize user activity continuously, we need a nonintrusive, light weight, and real-time recognition scheme. Fortunately, the mobility, commercial built-in sensors, and nonintrusive detection make smart phones an ideal platform for monitoring user activities. However, activity recognition on smart phones is still a challenge due to constraints of low battery capacity and computational workload.

The sampling rate to assess daily physical activities should be no less than 20 Hz [5-7]. However, the long-term sensing with the full working load of sensors is energy-consuming. For example, the battery life of Samsung i909 reaches up to over 30 hours when all applications and sensors are turned off. But the battery life declines to 5.5 hours (50 Hz) and 8 hours (20 Hz) respectively, when the accelerometer is monitored.

R. Li, J. Cao, and J. Bourgeois (Eds.): GPC 2012, LNCS 7296, pp. 122–136, 2012.

Toward the energy efficiency of activity recognition based on the single accelerometer in the smart phone, it is feasible to reduce the energy consumption by adopting a lower sampling frequency. Lower sampling frequency means less work time for the heavy-duty sensors. However, low sampling frequency may result in the loss of important sampling data, reducing the recognition rate with low resolution sensory data [8]. In addition, many classification algorithms are heavy weight and time consuming for mobile devices. In general, the size of sliding window in most classification algorithms is constant. The fixed-step algorithm deteriorates the recognition rate to some extent, which not only reduces the ability to detect short-duration movements, but also occupies lots of resources with the consumption of battery power.

To overcome above issues, we consider two factors - sampling frequency and computational load - in the design of the activity recognition algorithm. Specifically, we propose an energy-efficient method to recognize user activities based on a single low resolution tri-axial accelerometer in the smart phone. The hierarchical recognition scheme reduces the cost of the time consuming frequency domain features for lower computational complexity and adjusts the size of sliding window according to similarity to enhance the recognition accuracy.

The rest of this paper is organized as follows: in Section 2, the related work about activity recognition based on accelerometer is summarized. Then Section 3 describes the process of data collection. Section 4 presents the details of our solution, including the framework of activity recognition, feature extraction, and the hierarchical recognition scheme. The evaluation is given in Section 5. Finally we conclude this paper in Section 6.

2 Related Work

2.1 Activity Recognition

Numerous studies have been conducted about the activity recognition based on accelerometers. The work toward the activity recognition based on the accelerometer is divided into three types roughly.

First, the activity recognition based on multi-accelerometer sensors is conducted [9-12]. Norbert et al. [9] implemented an activity recognition system by using a wristwatch-like device, named MotionBand. Three MontionBand devices are attached to the wrist, hip and ankle to collect the sensory data of user activities. Then all those sensory data is sent to a mobile phone by Bluetooth and is classified using the feed-forward back-propagation neural networks. Although lots of sensors are employed to benefit the recognition, sensors fixed on human body are barriers for users. On one hand, users are confined to the laboratory environment due to constraints of wearable sensors, which reduces the practicability of the prototype in daily life. On the other hand, users are distracted from their tasks. This is contradicted with the vision of pervasive computing for less attention taken from users.

Second, single accelerometer sensor is utilized to benefit the activity recognition [6, 13-15]. A. M. Khan et al. [6] carried out experiments to monitor physical activities based on a tri-axial accelerometer. A hierarchical recognition scheme was proposed to recognize 15 kinds of activities. Activity recognition based on a single accelerometer sensor relies on the design of specialized sensors. Those specialized sensors are not off-the-shelf items and just research-only devices confined to the laboratory. Meanwhile, those specialized sensors are power-consuming due to the wireless communication and the high sampling frequency.

Nowadays, with the advent of smart phones, the sensing abilities of smart phones are strengthened with lots of built-in sensors. Different from most previous work, the daily activity recognition on smart phones uses a commercial mass-marked device rather than a research-only device, and employs a single device conveniently kept in the user's pocket rather than multiple devices distributed across the body [7, 15]. In [7] J. R. Kwapisz et al. employed the accelerometer in the smart phone to recognize 6 categories of activities. However, the power consumption of recognition scheme is not considered in the previous work. Smart phones are resource-limited, the power consumption and the computational workload pose challenges to the activity recognition on smart phones. The classic recognition algorithms are time-consuming and heavyweight for the mobile phone [7].

2.2 Energy Conservation

Energy is a vital resource for mobile devices. The battery limitations pose a challenge to the success of the activity recognition on mobile devices. Y. Wang et al. [16] designed a scalable framework of energy efficient mobile sensing system (EEMSS) for automatic user state recognition. The core component of EEMSS is a sensor management scheme which defines user states and state transition rules by an XML configuration. The sensor management scheme allocates the minimum set of sensors and invokes new sensors when state transitions happen. P. Zappi et al. [17] selected the minimum set of sensors according to their contribution to classification accuracy during data training process and tested this solution by recognizing manipulative activities of assembly-line workers in a car production environment. X. Li et al. [18] applied machine learning technologies to infer the status of heavy-duty sensors for energy efficient context sensing. They tried to infer the status of high energy consuming sensors according to the outputs of light weight sensors. The existing solutions extend the battery life by the collaboration of multi-sensors and the reduction of sensor work time. Different from the above studies, we try to recognize user activity by a single accelerometer. The collaboration of multi sensors is infeasible in our solution.

Different from the previous work, we intend to address the energy consumption issue in accelerometer-based physical activity recognition. The sampling frequency has a dominating effect on the density of raw sampled data. To reduce the computational workload and the work time of sensors, the lower sampling frequency should be adopted to capture less raw data. On the other hand, features are important for the computational complexity as well. The frequency domain features, which need to transform the signal into frequency domain, is time consuming. Therefore, we try to reduce the cost of the frequency-domain feature extraction. Additionally, Algorithms involved in the previous work are time-consuming. Those algorithms usually are performed on PC or workstation. The computational complexity is overwhelming for the resource-limited devices.

3 Data Acquisition

Human activities consist of some basic movements, such as walking, sitting, standing, running etc. The exploration of basic activities contributes to the far-reaching understanding of user activities with semantic information. We select the most common activities recognized in previous work as target activities. Target activities of our study are shown in Table 1.

Table 1. Defination of target activities

Activity Type	Activity
Static	Standing, Sitting, Lying(prone), Lying (supine), Driving
Repetitive	Walking, Running, Ascending stairs, Descending stairs, Cycling, Jumping

A total of 24 subjects, 16 males and 8 females with age ranging from 22 to 35, were involved. All of them were recruited from the school of computer science, Northwestern Polytechnical University, China including students and staff in exchange for the use of a high-end smart phone for the duration of the experiment. Each subject was assigned with a smart phone, including HTC G11, Samsung i909. The range of the tri-axial accelerometer outputs is $\pm 2g$. The orientations of the tri-axial accelerometer in the smart phone (HTC) are presented in Fig. 1a. An android application was developed and pre-installed to record the real-time outputs of the accelerometer (See Fig. 1b).

(a) Orientations of accelerometer (b) Interfaces on mobile phones

Fig. 1. Experimental interfaces on mobile phones

The subjects manually label their activities and set the sampling frequency in advance through the application as shown in Fig. 1b. The optional frequencies are: 0.5 Hz, 2 Hz, 10 Hz, and 20 Hz. All subjects are divided into four groups equally and each group utilizes the same sampling frequency. They launched the application when they began to perform the activities, selected the setups and put phones into their front pant pockets. When subjects started to perform an activity, a log file whose name contains information about the activity type and sampling frequency was produced with the contents of timestamps and accelerometer outputs on each axis. When activities were finished, they took out the phone and stopped the application. This process was repeated for daily activities. We monitored the user activities during two weeks. To rule out the dirty data of each log file, we cut off the data at the beginning and the end of the log files.

4 Activity Recognition

4.1 The Framework of Activity Recognition

As shown in Fig. 2, the framework of activity recognition consists of two parts: the offline data training and the online classification. The offline data training extracts features from the sampled data and constructs template for each activity respectively. The online classification extracts features of the sliding window, calculates the similarity between the target activity and templates, and selects a suitable class as the label of the sampled data in the sliding window.

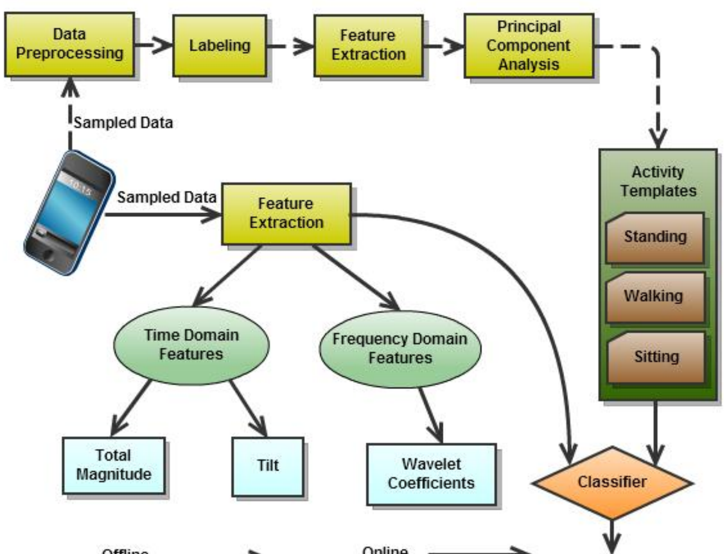

Fig. 2. The Framework of Activity Recognition

The offline data training consists of four steps. The data preprocessing takes charge of the data cleaning and the data representation. The labeling defines the class of each sampled data using all the target activities. The feature extraction captures characteristics of each activity. Principal Component Analysis (PCA) is introduced to select the most discriminative features. Finally, a template will be generated for each activity. To reduce the time consumption, the offline training is performed on the PC or workstation. Only those results are transplanted into the smart phone to serve as templates of user activities.

For the online process, we design a light weight, hierarchical recognition algorithm with variable steps. First, time-domain features are utilized to classify user activities based on the template-based classification. However, some activities are indistinguishable when only the time-domain features are taken into consideration. Then the frequency-domain features are introduced and the size of sliding window is segmented. For each such small section, the decision tree algorithm is performed based on the combined features.

4.2 Feature Extraction

Features play important roles for activity recognition. As mentioned above, the feature extraction is performed in two phases. The time-domain features are extracted from samples directly. Only when those time-domain features are unable to discriminate user activities, the frequency-domain features are introduced. The following presents the related features and their number.

- Mean of each axis (3): The acceleration signals of human activities on three axes are different as illustrated in Fig. 3.
- Deviation of each axis (3): The deviation indicates the fluctuation of signal magnitude on each axis.
- Mean of Total Magnitude (1): The intensity of user activity is a significantly important metric to discriminate activities. Based on the sampled data on each axis, Total Magnitude (TM) is calculated to according to Equation (1).

$$TM = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

- Deviation of Total Magnitude (1): Like the deviation on each axis, the deviation of TM cues the fluctuations of TM.
- Tilt (1): Tilt is employed to calculate the angle between the gravity and the y-axis. The tilt gives a cue of body posture, e.g. forwardness or backwardness. The tilt is evaluated based on Equation (2).

$$\theta = \arccos \frac{y}{g} \tag{2}$$

- Linear regressive coefficients (4): To reveal the relationship among the TM and the magnitudes on three axes, we calculate the coefficients based on the linear regression. Those coefficients enclose the contributions of each axis to the total magnitude. Linear regressive coefficients are calculated according to Equation (3), where $\boldsymbol{S}$ is the matrix of linear regressive coefficients, $\boldsymbol{W}$ represents the matrix of magnitudes on each axis and the $\boldsymbol{Q}$ is the matrix of total magnitudes.

$$\boldsymbol{S} = (\boldsymbol{W}^T\boldsymbol{W})^{-1}\boldsymbol{W}^T\boldsymbol{Q} \tag{3}$$

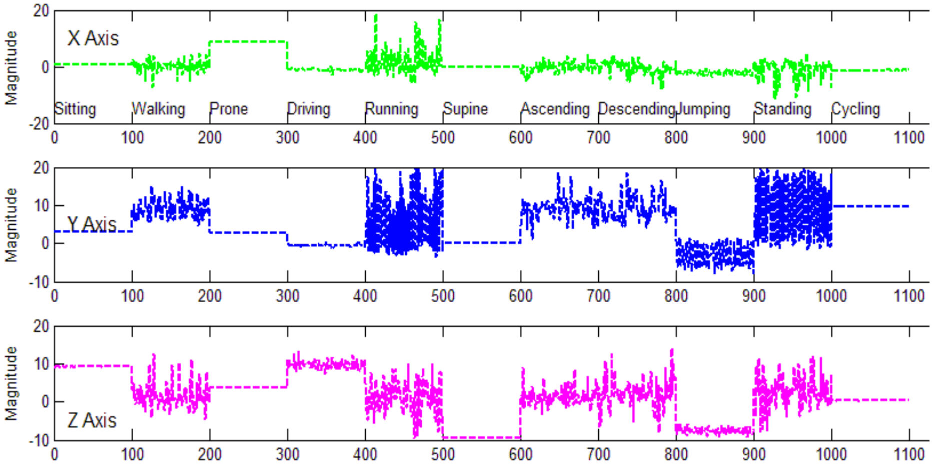

Fig. 3. Acceleration signals of target activities on three axes

- Wavelet coefficients: Different activities have discriminative frequency features, especially for repetitive activities. Meanwhile the frequency of human activities is low, thus we extract the low frequency features based on the wavelet analysis.

Different from the previous work, the feature extraction is performed in two steps. At first the time-domain features are extracted as the basic features. As the extraction of frequency domain features is time consuming, thus we try to reduce the opportunity of utilization of the frequency-domain features with the introduction of the two-step feature extraction.

4.3 Hierarchical Recognition Scheme

In general, the size of sliding window in classical classification algorithms such as Decision Tree (DT), Support Vector Machine (SVM) is constant (See Fig. 4a). The fixed-step algorithm deteriorates the recognition rate. The dynamics of activities enlighten the introduction of a hierarchical recognition scheme with variable step size, which is suitable for both static and repetitive activities.

The comparison of the classic classification algorithms with our proposed hierarchical recognition scheme is illustrated in Fig 4. As shown in Fig. 4b, differences of our proposed algorithm are in two aspects. Firstly, the feature extraction is completed in two steps, which reduces the opportunity of utilization of the time-consuming frequency-domain features. Secondly, the size of sliding window is adjusted according to the similarity. When it is indiscriminative, the sliding window is split into small segments equally. Otherwise frequency-domain features are introduced to classify user activities based on decision tree. The hierarchical recognition scheme consists of the following three steps.

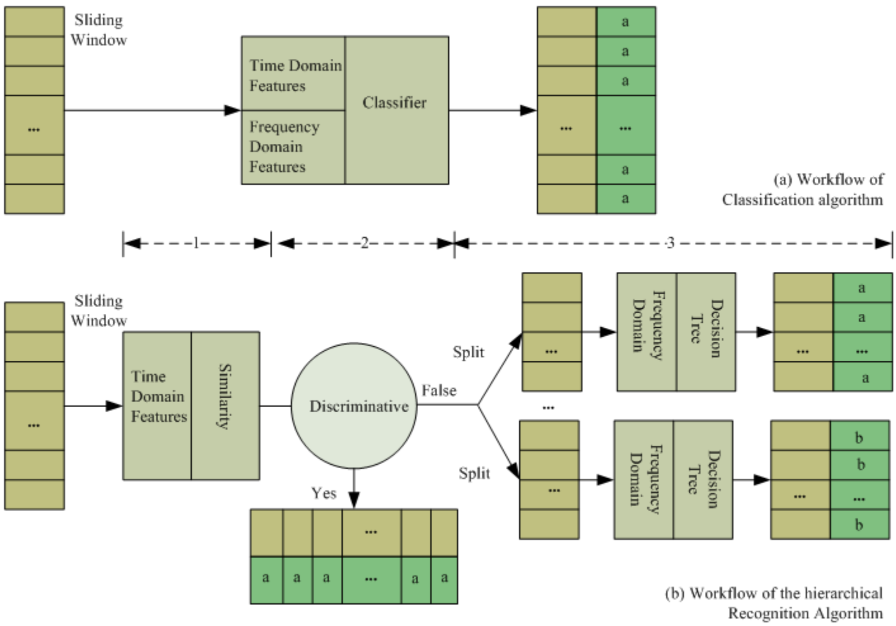

Fig. 4. Comparison of classical classification algorithms and the hierarchical algorithm

Similarity Measurement of Time-Domain Features: Similarity is utilized to demonstrate the likelihood of current inputs to the activity templates. For the sliding window, the time-domain features are calculated and represented with vector ***X***. Then every activity template compares its characteristic parameter vector ***Y*** with the vector ***X*** according to Equation (4). Here, ***Y*** is the vector of time-domain features, which is obtained in the offline data training process. After the similarity measurement with each activity templates, a vector ***C*** is generated. The size of ***C*** is $1\times M$, where M is the number of predefined activities and $c_i \in [0,1]$, $1 \le i \le M$. Each element c_i in the vector ***C*** denotes the extent to which a feature vector belongs to a given class.

$$c_i = \cos(X,Y) = \frac{X}{\| X \|} \cdot \frac{Y}{\| Y \|} \tag{4}$$

Evaluation of Similarity Discrete Degree: Occasionally differences among those similarities are indiscriminative, e.g. the difference of c_i and c_j is tiny. Under such condition, it is not convincing to classify the user activity into the class with the highest similarity. Thus, we need to evaluate the discrete degree of the vector ***C***.

A vector ***C*** is indistinguishable, if it satisfies one of the following two constraints (See Equation (5) and (6)).

$$\sqrt{\frac{\sum (c_i - \bar{c})^2}{M}} \le \delta \tag{5}$$

According to Equation (5), the standard deviation of vector ***C*** is calculated. If the standard deviation of vector ***C*** is smaller than a threshold δ, ***C*** is indistinguishable, where δ is a constant and belongs to [0.1, 0.2]. In our experiments, δ equals to 0.15.

For the vector ***C***, elements are sorted in ascending order, represented with $c_{(1)}$, $c_{(2)}$,.., $c_{(M)}$ respectively. Then the differences are calculated according to $d_j = c_{(j+1)} - c_{(j)}$, $1 \le j \le M-1$. In Equation (6) letter E represents the expectation. According to (6), if the difference of $c_{(M)}$ and $c_{(M-1)}$ is smaller than the expectation, the vector ***C*** is indiscriminative.

$$c_{(M)} - c_{(M-1)} \le E(\{d_j\}) \qquad 1 \le j \le M-1 \tag{6}$$

Based on Equation (5) and (6), we are able to judge whether the similarity vector ***C*** is indistinguishable. If the similarity vector ***C*** is differentiable, it means that those time-domain features are capable of explicitly differentiating those activities. Thus, we should classify the current activity into the corresponding activity with the largest similarity in the vector ***C***. On the contrary, if the vector ***C*** is indiscriminate, the frequency domain features are introduced to classify user activities.

Table 2. Hierarchical recognition alogrithm

Inputs: accelerometer signals
Outputs: classification results for accelerometer signals

1: Set the size of the sliding window with **N**.
2: **For each sliding window**
3: Extract time-domain features, including the mean of magnitude on each axis etc.
4: Calculate the similarity vector ***C*** among the sliding window and the predefined activity templates based on (4).
5: Justify whether the vector ***C*** is discriminative based on (5) and (6).
6: **IF** vector ***C*** is discriminative
7: User Activity = $\max\{c_1,...,c_i,...,c_M\}$
8: **ELSE**
9: Divide the sliding window into K small sections equally, length of each section is L = **N**/K;
10: **For each small section**
11: Obtain low-frequency wavelet coefficients and time-domain features;
12: Based on those combined features, classify those data using the decision tree algorithm.
13: **End For**
14: **End IF**
15: **End For**

Hierarchical Recognition Algorithm: For the recognition algorithms with fixed step size, it is crucial for the recognition rate to select a reasonable step length. If the step length is long, it is prone to the ignorance of short-duration activities; if the step length is short, it leads to lots of redundant computational workload. Thus, we propose a fine-grain recognition algorithm with variable step size, which adjusts the size of sliding window according to similarities to enhance the recognition accuracy. The details of the proposed algorithm are presented in Table 2. For combined features decision tree (C4.5) algorithm is utilized as it provides a good balance between accuracy and computational complexity [8, 19].

As elaborated above, the hierarchical algorithm extracts fewer features and those features are calculated in different phases, which benefit the decline of the computational load. Furthermore, the size of sliding window is adjusted according to the similarities, which contributes to the recognition of short-duration activities with the increase of recognition rate.

5 Experiment and Evaluation

To evaluate the proposed algorithm on mobile devices, we perform person-independent experiment in terms of recognition accuracy, power consumption and computational load.

5.1 Activity Recognition Rate

Our hierarchical recognition algorithm includes two phases. We analyze the proportion of the two phases where inputs are classified and the recognition rate of the hierarchical scheme. The 5-folder cross-validation is used to evaluate the hierarchical recognition scheme with 2 Hz sampling frequency.

First, the average recognition rate reaches up to 89.1% (See Table 3). The recognition rate demonstrates the activity recognition based on the low resolution accelerometer with low sampling frequencies is feasible. Although activity recognition with low resolution sensory data is inconsistent with the previous work [5, 6], it is reasonable due to features of user activities including the repeatability, the symmetry and the normality. Regardless of static activities and repetitive activities, the features are repeated periodically.

Second, majority of target activities are recognized in the first phase based on time-domain features, especially for static activities. This demonstrates that those selected time-domain features are very useful to discriminate user activities. And this benefits the decrease of computational load. On one hand, opportunities of the time-consuming frequency-domain feature extraction and the heavyweight decision tree algorithm are minimized, which contributes to the reduction of computational workload. On the other hand, the introduction of classification based on combined features benefits the improvements of recognition rates, during which complex activities such as Ascending and Descending are discriminated based on frequency domain features.

Table 3. Activity Recognition Rates

Activity	Percentage of Records Correctly Recognized		
	Time Domain Features (%)	*Frequency Domain Features (%)*	*Total (%)*
Standing	98.98	1.02	98
Sitting	100	0	100
Lying (prone)	100	0	100
Lying (supine)	99.28	0.72	100
Walking	0	100	80
Jumping	0	100	82
Running	56.76	43.24	86
Ascending	0	100	88
Descending	0	100	82
Cycling	97.50	2.50	84
Driving	37.69	62.31	80
Average	53.66	46.34	89.1

5.2 Power Consumption

To test the battery life under different sampling frequencies, we measured the time spans and the recognition accuracy with changes of sampling frequencies when 90% of battery power is consumed (Fig. 5).

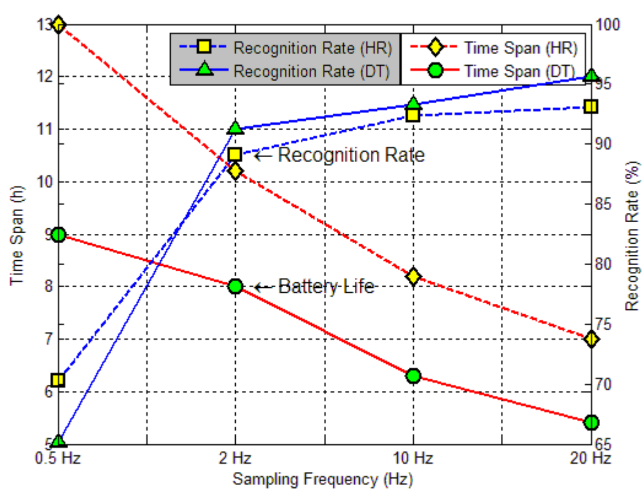

Fig. 5. Time Span and Recognition rate with changes of sampling frequencies

It is obvious that the battery life declines with the increase of sampling frequencies. For a resource-constraint device, the high sampling frequency leads to the rapid depletion of power. Also, it demonstrates that the recognition rates increase with the growth of the sampling frequencies. Although those sampled data indicate more features of user activities and benefits the increase of the recognition rate, it promotes the rapid increase of the power consumption. Additionally, the hierarchical recognition scheme (HR) and decision tree (DT) are compared in terms of time span and the recognition accuracy. As shown in Fig. 5, although the decision tree outperforms the proposed algorithm in recognition accuracy, the battery life is longer in our solution.

To reduce the power consumption and achieve better recognition accuracy, we adopt a reasonable sampling frequency. It is a tradeoff between the power consumption and the recognition rate. Compared with the battery life of 20Hz, the battery life of 2 Hz is lengthened by 3.2 hours and the average recognition rate of the proposed algorithm is over 85%. Thus, it is considered that the 2 Hz is a suitable frequency for the user activity recognition based on the tri-axial accelerometer.

5.3 Computational Load

We aim to provide a model to evaluate the computational workload of the proposed algorithm using the time complexity and compare our proposed recognition algorithm with decision tree in term of time complexity.

As elaborated in the previous section, the proposed algorithm consists of two steps: the recognition based on time-domain features and the recognition based on combined features, denoted with P_1 and P_2 respectively. As the time domain features extraction and the template-based similarity measurement are contained in the P_1, the time consumption of P_1, $T(P_1)$ is constant. By contrast, the time consumption of P_2, $T(P_2)$ is variable due to the variability of the frequency domain features and the classification process.

To evaluate the time complexity of the recognition scheme, the probabilities of user activities are taken into consideration. The probability set ϕ of user activities is presented by $\phi=\{p_1, p_2,..., p_i,...p_n\}, 0 \le p_i \le 1$, where n is the type of user activities, p_i is the probability of the i^{th} activity, and all the elements in ϕ satisfy $\sum_i^n p_i = 1$. Due to the repeatability of user daily activities, the probability of each activity is calculated by the statistical method.

Meanwhile, the percentages of the two recognition stages, which mean how many sampled data of a particular activity are correctly discriminated by each phase, are important factors to evaluate the time complexity as well. Here, the percentages of the two phases for a specified activity are denoted with u_i and v_i respectively. As shown in Table 3, the percentages of the two phases verify for different activities. The time complexity of the i^{th} activity is measured according to Equation (7), where $T_i(P_2)$ is the time consumption in the second step for the i^{th} activity.

$$\begin{aligned} t_i &= u_i \times T(P_1) + v_i \times (T(P_1) + T_i(P_2)) \\ 0 &\le u_i \le 1 \\ 0 &\le v_i \le 1 \\ u_i &+ v_i = 1 \end{aligned} \tag{7}$$

Average Time Complexity (ATC) is presented in Equation (8), where n is the types of target activities. As p_i in Equation (8) is measured by analyzing the daily activities with statistical method, u_i, v_i are demonstrated in Table 3, and $T(P_1)$ is constant due to the fixed time consumptions of the time domain feature extraction and that of the similarity measurement in phase one. Thus, $T_i(P_2)$ is the only variable in Equation (8).

$$ATC = \sum_{i=1}^{n} p_i t_i = \sum_{i=1}^{n} p_i \times (T(P_1) + v_i \times T_i(P_2)) \tag{8}$$

To evaluate the accuracy of Equation (8), we extract 500 sample data from each activity and construct a new test set to calculate the time consumption. To simplify the computation, here we use the mean of $T_i(P_2)$ as a substitution of $T_i(P_2)$. As the size of target activity set is 11, n = 11. For this test set, the p_i is same for each activity and equals to 1/11. And the pair of $<u_i,v_i>$ for every activity is presented in Table 3. Thus, the value of ATC is 4.81 ms.

We measured the execution time of the hierarchical recognition scheme. Compared with the ATC, the execution time is approximate to the theoretical value as shown in Fig. 6. Meanwhile, our experimental results demonstrate that our proposed

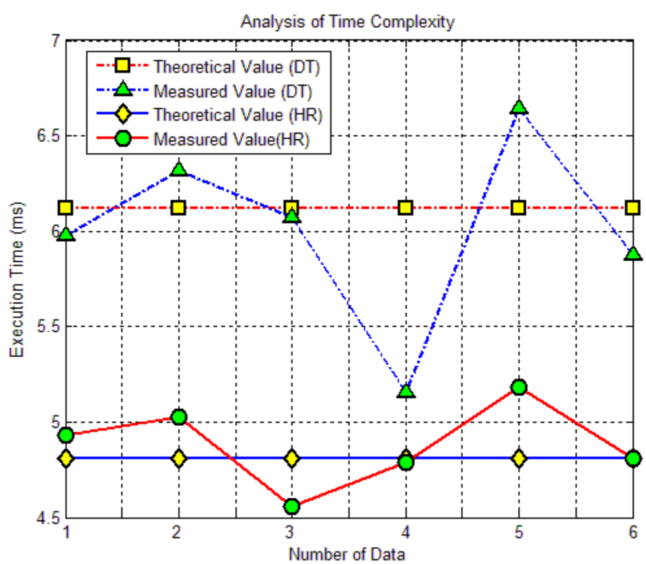

Fig. 6. Comparison of the theoretical value and the measured value

hierarchical recognition scheme outperforms the decision tree. As shown in Fig. 6, the average execution time of DT is longer than that of the HR, which confirms that HR benefits the decline of the time complexity and the computational complexity.

6 Conclusion

With the popularity of the smart phone, it is becoming an ideal platform for activity recognition based on the built-in accelerometer sensor. The constraints of mobile phones such as power consumption, computational load raise a challenge to the activity recognition. In this paper, we presented an approach for activity recognition with a hierarchical scheme for low resolution accelerometer data on the mobile phone. To achieve the goal of energy efficient activity recognition on the cell phone, we propose a hierarchical scheme with variable step size. To evaluate the validation of the method, total 24 healthy subjects are recruited to perform the 11 activities in their daily life. The average recognition rate of the proposed algorithm is over 85%, and the battery lifetime is extended by 3.2 hours. The experimental results demonstrate that the proposed hierarchical scheme not only reduces the power consumption with low resolution sensor data, but also classifies activities with good recognition rate.

Acknowledgments. This work was partially supported by the National Basic Research Program of China (No. 2012CB316400), the National Natural Science Foundation of China (No. 60903125, 61103063), the Program for New Century Excellent Talents in University (No. NCET-09-0079), Microsoft and the Doctorate Foundation of Northwestern Polytechnical University.

References

1. Kawahara, Y., Ryu, N., Asami, T.: Monitoring Daily Energy Expenditure Using a 3-Axis Accelerometer with a Low-Power Microprocessor. International Journal on Human-Computer Interaction 1(5), 145–154 (2009)
2. Kim, E., Helal, S., Cook, D.: Human Activity Recognition and Pattern Discovery. IEEE Pervasive Computing 9(1), 48–53 (2010)
3. Gu, T., Wang, L., Wu, Z., Tao, X., Lu, J.: A Pattern Mining Approach to Sensor-Based Human Activity Recognition. IEEE Transactions on Knowledge and Data Engineering 23(9), 1359–1372 (2011)
4. Nijholt, A., Zwiers, J., Peciva, J.: Mixed reality participants in smart meeting rooms and smart home environments. Personal and Ubiquitous Computing 13(1), 85–94 (2009)
5. Bouten, C., Koekkoek, K., Verduin, M., Kodde, R., Janssen, J.D.: A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. IEEE Transactions on Biomedical Engineering 44(3), 136–147 (1997)
6. Khan, A.M., Lee, Y., Lee, S.Y., Kim, T.: A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. IEEE Transactions on Information Technology in Biomedicine 14(5), 1166–1172 (2010)
7. Kwapisz, J.R., Weiss, G.M., Moore, S.A.: Activity Recognition using Cell phone Accelerometers. ACM SIGKDD Explorations 12(2), 74–82 (2010)

8. Maurer, U., Smailagic, A., Siewiorek, D.P., Deisher, M.: Activity Recognition and Monitoring Using Multiple Sensors on Different Body Positions. In: Proc. of International Workshop on Wearable and Implantable Body Sensor Networks, pp. 113–116 (2006)
9. Győrbíró, N., Fábián, Á., Hományi, G.: An Activity Recognition System for Mobile Phones. Mobile Networks and Applications 14(1), 82–91 (2009)
10. Mannini, A., Sabatini, A.M.: Machine Learning Methods for classifying Human physical activity from on-body accelerometers. Sensor 10(2), 1154–1175 (2010)
11. Krishnan, N.C., Juillard, C., Colbry, D.: Recognition of hand movements using wearable accelerometers. Journal of Ambient Intelligence and Smart Environments 1, 143–155 (2009)
12. Ruch, N., Rumo, M., Mader, U.: Recognition of activities in children by two uniaxial accelerometers in free-living conditions. European Journal of Applied Physiology 111(8), 1917–1927 (2011)
13. Lee, M., Khan, A.M., Kim, J., Cho, Y., Kim, T.: A Single Tri-axial Accelerometer-based Real-time Personal Life Log System Capable of Activity Classification and Exercise Information Generation. In: Proc. of 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 1390–1393 (2010)
14. He, Z., Liu, Z., Jin, L., Zhen, L., Huang, J.: Light weightness Feature – A Novel Feature for single Tri-axial accelerometer based Activity Recognition. In: Proc. of 19th International Conference on Pattern Recognition, pp. 1–4 (2008)
15. Ravi, N., Dander, N., Mysore, P., Littman, M.L.: Activity Recognition from Accelerometer Data. In: Proc. of the 20th National Conference on Artificial Intelligence and the 17th Innovative Applications of Artificial Intelligence Conference, pp. 1541–1546 (2005)
16. Wang, Y., Lin, J., Annavaram, M., Quinn, J.A., Jason, H., Bhaskar, K., Sadeh, N.: A Framework of Energy Efficient Mobile Sensing for Automatic User State Recognition. In: Proc. of the 7th ACM International Conference on Mobile Systems, Applications, and Services, pp. 179–192 (2009)
17. Zappi, P., Lombriser, C., Stiefmeier, T., Farella, E., Roggen, D., Benini, L., Tröster, G.: Activity Recognition from On-Body Sensors: Accuracy-Power Trade-Off by Dynamic Sensor Selection. In: Verdone, R. (ed.) EWSN 2008. LNCS, vol. 4913, pp. 17–33. Springer, Heidelberg (2008)
18. Li, X., Cao, H., Chen, E., Tian, J.: Learning to Infer the Status of Heavy-Duty Sensors for Energy Efficient Context-Sensing. ACM Transactions on Intelligent Systems and Technology (unpublished)
19. Bao, L., Intille, S.S.: Activity Recognition from User-Annotated Acceleration Data. In: Ferscha, A., Mattern, F. (eds.) PERVASIVE 2004. LNCS, vol. 3001, pp. 1–17. Springer, Heidelberg (2004)