A Novel Data Mining Scheme for Smartphone Activity Recognition by Accelerometer Sensor

Yajnaseni Dash, Sanjay Kumar and V.K. Patle

Abstract The prime objective of activity recognition is to recognize the actions performed by a person with the surrounding environment and forming different observation sets. It is necessary to choose the appropriate classifier for the data collected through accelerometer sensors incorporated in mobile phones, which have limited resources such as energy and computing power. In this paper, standard classification techniques of data mining like random forest (RF), multilayer perceptron (MLP), logistic regression, classification via regression, and J48 and RepTree have been implemented to compare the performance and accuracy of different classifiers by reducing the computational cost. In this experiment, it was found that RF required quite short time than MLP (0.64 vs. 270.07 s, respectively) to build the model and gives the better accuracy (92.6 % vs. 92.1 %, respectively). This study has concluded that RF has better performance score than other classification techniques applied in this study.

1 Introduction

The state of the user and its environment can be captured by computation of the recognized activity through heterogeneous sensors to facilitate adaptation to the external computing resources. Attachment of these sensors to the user's body allows continual monitoring of various physical activities in the form of signals. Activity recognition is one of the synergistic contexts between human and

Y. Dash (✉) · S. Kumar · V.K. Patle
School of Studies in Computer Science & IT, Pt. Ravishankar Shukla University, Raipur 492010, Chhattisgarh, India
e-mail: yajnasenidash@gmail.com

S. Kumar
e-mail: sanraipur@rediffmail.com

V.K. Patle
e-mail: patlevinod@gmail.com

S. Das et al. (eds.), *Proceedings of the 4th International Conference on Frontiers in Intelligent Computing: Theory and Applications (FICTA) 2015*, Advances in Intelligent Systems and Computing 404, DOI 10.1007/978-81-322-2695-6_12

computer. Activity means any physical activity of persons such as walking, jogging, seating, and standing. Activity recognition is a recent research field, where sensor containing mobile phones, i.e., smartphones can be used to record the physical activities. By applying classification techniques of data mining, we can find that a particular person is doing which activity more or less than a limit and accordingly the smartphone can form a signal. For example, if a person is performing less physical activity then he may become obese, thus an alarm can be send from smartphone to the user. Similarly it can send calls directly to voice mails when the user is exercising. Many more applications of activity recognition are there. Accelerometer senses the acceleration whenever there occurs a change in speed of any body part movement. A variety of researches on context-aware services have been focusing upon recognizing the individual activity based on minute wearable sensors because of the successful development of micro-electro-mechanical systems (MEMS) technology [1]. A context-aware system uses location as the main outline of context. However, addition of low-priced sensors (e.g., measurement of acceleration, audio, and light) to mobile and pervasive platforms, in combination with progresses in machine learning and data mining, facilitates systems for building a more affluent model of the user's context. For instance, body-mounted accelerometers can able to recognize various human activities, i.e., from common activities (walking or sitting) to higher-level activities (car driving or bus riding) [2]. Particularly, by combining numerous sensors for physical movements and bio-signals could spectacularly amplify the recognition accuracy through capturing details of users' current states [3]. At a particular instance of time, a person is busy in which particular activity that will be predicted by this research work. In this study, different data mining techniques were applied and a comparison of each algorithm was made to predict performance of the activities from the sensory input.

2 Related Work

Activity recognition (AR) is a fastest growing field, but AR with smartphone sensors is a difficult task owing to intrinsic noisy character of the input data and limited resource of the target platform. The rich features of smartphones like computing power, multi-tasking ability, and sensory inputs like tilt and acceleration of smartphones lends itself for studies of AR with imperative objective of identifying a number of activities, such as walking, jogging, sitting, and standing from the sensory inputs of the device.

Currently, activity recognition has been growing as a novel research area because of the increasing accessibility of accelerometers in mobile phones, and other prospective applications. Researchers have employed a combination of accelerometers and other sensors to accomplish activity recognition. Information can be extracted from variety of sources like environment [4] and body worn sensors [5, 6] to achieve the recognition process. Human AR has been studied by researchers since the last decade. Vision sensor, inertial sensor, and the mixture of both are used in the existing approaches. Machine learning-based algorithms are often applied for classification of the activities because of its reliable and correct outcomes. The earliest studies in accelerometer-based AR focused on the utilization of multiple accelerometers placed on different parts of the user's body. Bao and Intille [7] collected data from 20 users by 5 biaxial accelerometers and used different data mining techniques for classification. Authors [8] tested subjects by carrying the phone in the suitable location, i.e., in their pants pockets. Krishnan et al. [9] assembled data from 3 users using 2 accelerometers for recognizing five different activities. Authors claimed that data from a thigh accelerometer was not sufficient to classify various activities and hence several accelerometers were needed. The body activities were again monitored by 3 accelerometers and data gathered from 10 subjects [10]. Tapia et al. [11] implemented a real-time system to identify 30 gymnasium activities by gathering data from 5 accelerometers located on several body parts of 21 users. Performance was increased slightly by incorporating data from a heart monitor as well as the accelerometer data. Mannini and Sabitini [12] employed 5 triaxial accelerometers and recognized 20 activities from13 users. Foerster and Fahrenberg [13] collected data of 31 male subjects from 5 accelerometers. They built hierarchical classification model for differentiation of various postures. Parkka et al. [14] developed a system using 20 diverse types of sensors for recognition of activities. Another system was formed by Lee and Mase [15] for recognizing location of user and their activities by a wearable sensor module. Nishkam et al. [16] used sensors on wrist, chest, waist, and thighs to achieve better classification performance.

Some researchers used wearable sensors on different body parts as discussed above. However, the problem arises for common users to bear the uncomfortable situation as the sensor repositioning is required after dressing. Novel opportunities of AR research are coherent by the use smartphones where the user is a rich source of context information, and the phone is the sensing tool with embedded built in sensors such as dual cameras, microphones, gyroscopes, and accelerometers. Authors [17] presented an approach to utilize an Android smartphone for human AR employing its embedded triaxial accelerometers. Generally, researchers apply supervised classification algorithms for activity recognition. The algorithms are trained with labeled samples to generate classification model for the input data. As supervised classification algorithms require accurate computations for producing models from training data, so the implementations are being done in servers. Some implementations in smartphones were presented in [7, 18–22].

3 Classification of Wireless Sensor Data

Classification is one of the major tasks in data mining. It is the separation of one class of elements from other class of elements using different classifiers. We have employed three different classifier namely functions, meta and decision tree classifier. Logistic regression (LR), multilayer perceptron (MLP) known as function-based classifier, whereas classification via regression (CVR) comes under meta classifier. Decision trees such as J48, RepTree (RT), and random forest (RF) were also applied to evaluate the performance by classifying the sensor data. All these algorithms were explored in order to find the more appropriate algorithm based on its accuracy on the selected dataset.

A multimodal LR model was used for classification purpose with a ridge estimator. If there are k classes for n instances with m attributes, then the parameter matrix A to be calculated will be $m*(k-1)$ matrix. MLP is a classifier that uses back-propagation to classify instances. The network can be monitored and customized during training time. The nodes in this network are all sigmoid. CVR perform classification using regression methods with binary value and one regression model is built for each class value. J48 used to generate pruned or unpruned C4.5 decision tree. RT is fast decision tree learner that can builds a decision or regression tree using information gain or variance and prunes it using reduced error pruning (with backfitting). It can only one time sorts the values for numeric attributes, and the missing values are dealt with by splitting the consequent instances into pieces (i.e., as in C4.5). RF is used for constructing a forest of random trees.

4 Experimental Results

This section outlines our experimental analysis followed by presentation and discussion of our results for the activity recognition task. The dataset was collected from wireless sensor data mining (WISDM) Lab [23]. This WISDM Lab is concerned with collecting the sensor data from smartphones and other modern mobile devices (e.g., tablet computers, music players, etc.). Mining techniques can be applied to these sensor data for imperative knowledge discovery. After collection of data, we preprocessed and applied several classification techniques on it to predict the user activities using sensors. We have employed tenfold cross validation for execution of all the experiments in WEKA [24]. Here the total numbers of instances are 5418. The detailed result which is showing the confusion matrices associated with each of the six learning algorithms are presented in Tables 1, 2, 3, 4 and 5.

5 Performance Evaluation of Each Algorithm

The performance of various algorithms were evaluated and presented in Table 6 and Fig. 1. In Table 7, the training and simulation errors were represented. Percentage of correctly predicted records and accuracy of activity recognition of each class is summarized in Table 8. In Fig. 2a–c, comparisons between various parameters including percentage of instances, error score, and time required to execute different algorithms were shown.

Table 1 Confusion matrix for LR

Actual classes	Predicted classes					
	Walk	Jog	Up	Down	Sit	Stand
Walk	1980	9	57	34	0	1
Jog	18	1603	1	2	0	1
Up	177	6	317	128	4	0
Down	129	2	203	190	3	1
Sit	0	0	5	5	288	8
Stand	4	0	6	0	11	225

Table 2 Confusion matrix for CVR

Actual classes	Predicted classes					
	Walk	Jog	Up	Down	Sit	Stand
Walk	2009	11	33	28	0	0
Jog	15	1590	12	6	1	1
Up	81	20	432	95	2	2
Down	86	10	102	326	1	3
Sit	0	0	3	1	288	14
Stand	2	0	2	5	5	232

Table 3 Confusion matrix for J48 decision tree

Actual classes	Predicted classes					
	Walk	Jog	Up	Down	Sit	Stand
Walk	1988	19	37	34	2	1
Jog	1563	1563	31	13	0	1
Up	59	37	427	106	1	2
Down	53	14	126	334	1	0
Sit	3	1	2	1	295	4
Stand	2	3	1	0	0	240

Table 4 Confusion matrix for RT decision tree

Actual classes	Predicted classes					
	Walk	Jog	Up	Down	Sit	Stand
Walk	2053	9	12	6	1	0
Jog	38	1565	15	7	0	1
Up	9	11	479	133	0	0
Down	10	6	155	357	0	0
Sit	2	1	8	4	286	5
Stand	5	2	9	6	7	217

Table 5 Confusion matrix for RF decision tree

Actual classes	Predicted classes					
	Walk	Jog	Up	Down	Sit	Stand
Walk	2037	7	16	20	1	0
Jog	13	1596	8	7	0	1
Up	30	19	490	89	2	2
Down	39	8	118	360	2	1
Sit	0	1	1	1	300	3
Stand	2	0	4	3	3	234

Table 6 Simulation result of each algorithm

Algorithms used (total instances, 5418)		Correctly classified instances (% value)	Incorrectly classified instances (% value)	Time taken (in s)	Kappa statistics
Functions	LR	84.9575 (4603)	15.0425 (815)	133.68	0.7918
	MLP	92.1189 (4991)	7.8811 (427)	270.07	0.8926
Meta	CVR	90.0148 (4877)	9.9852 (541)	13.85	0.8629
Decision trees	J48	89.4611 (4847)	10.5389 (571)	0.89	0.8559
	RT	91.4913 (4957)	8.5087 (461)	0.6	0.8839
	RF	92.5987 (5017)	7.4013 (401)	0.64	0.8989

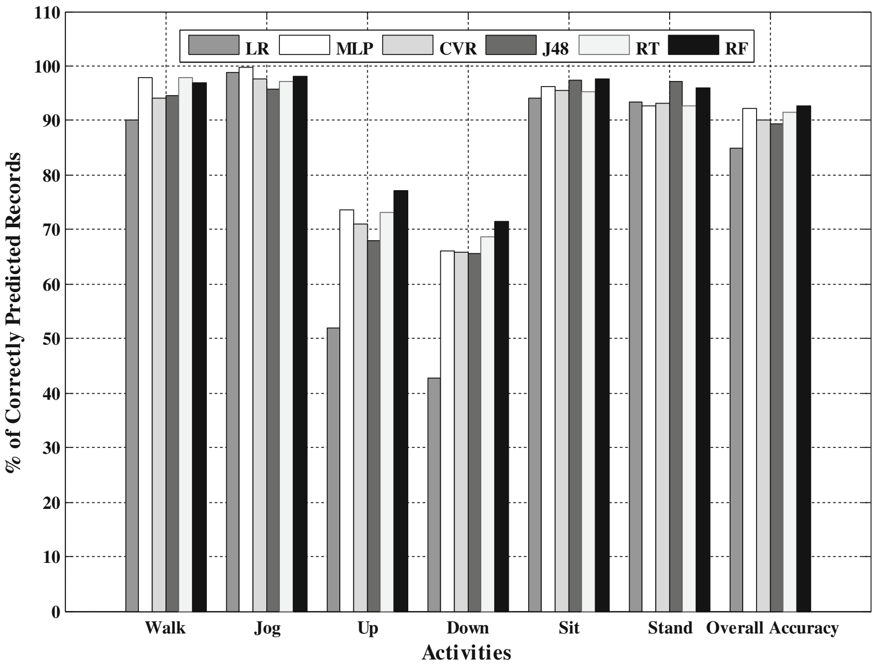

Fig. 1 Percentage of correctly classified records

Table 7 Training and simulation errors

Algorithms used (total instances, 5418)		Mean absolute error (MAE)	Root mean squared error (RMSE)
Functions	LR	0.0666	0.1893
	MLP	0.0285	0.1481
Meta	CVR	0.0563	0.1581
Decision trees	J48	0.0383	0.1741
	RT	0.0358	0.149
	RF	0.0505	0.1394

Table 8 Accuracy of activity prediction of each class

Activities	Percentage of correctly predicted records					
	LR	CVR	MLP	J48	RT	RF
Walk	90.2	94.0	**97.8**	94.6	**97.8**	**97**
Jog	**98.8**	**97.7**	**99.8**	95.8	97.2	**98**
Up	51.9	71.1	73.7	68.0	73.1	77.2
Down	42.8	65.9	66.1	65.7	68.6	71.4
Sit	94.1	95.5	96.3	**97.5**	95.3	97.7
Stand	93.4	93.2	92.6	97.2	92.7	96.1
Overall accuracy	84.9	90.0	**92.1**	89.5	91.4	**92.6**

6 Discussion

The abstract results for the AR experiments are represented in Tables 7 and 8. The predictive accuracy related to each of the activities specified in these tables for each of the six learning algorithms. Table 8 reveals that in most of cases higher levels of accuracy (above 90 %) can be achieved for the two common activities, walking, and jogging. Since jogging involves more intense alteration in acceleration, so it is easier to recognize than walking. It is very difficult to identify the two stair climbing activities as these two identical activities are often confused with each other. Sitting and standing activities were easily detected from the accelerometer data and can be well identified, as these two activities cause the device to modify its orientation.

Experimental results indicate that among the six learning algorithms RF (92.6 %) and MLP (92.1 %) are consistently perform best, but the MLP does not perform best overall as its time complexity is high. The performance of an algorithm is evaluated according to its time and space complexity. Hence, the total time taken to build the model is also a very influential parameter in comparing the classification algorithm.

In this experiment, the time required was shortest in case of RT (0.6 s) as compared to others, but the overall accuracy is 91.4 %. The next one after RT is RF which has taken 0.64 s to build the model and gives the highest accuracy of 92.6 %,

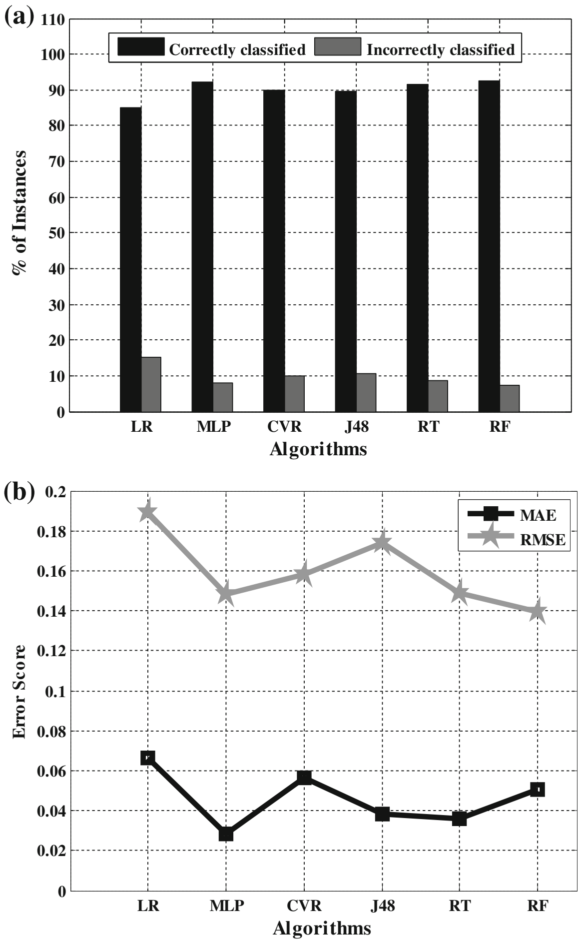

Fig. 2 **a** Comparision between algorithms on basis of % of instances, **b** comparison between algorithms on basis of error score, **c** comparison between algorithms on basis of time taken (s)

whereas MLP has taken 270.07 s to build the model with an accuracy of 92.1 %. In a previous experiment, authors [17] have shown the overall accuracy of MLP as 91.7 % but in our study it was 92.1 %. Authors [17] have applied J48, logistic regression, MLP, and straw man techniques for classification purpose. In the current study, we have applied other techniques too for better comparison purpose.

Kappa statistic is used to assess the accuracy of any particular measuring cases, it is usual to distinguish between the reliability of the data collected and their validity based on the kappa statistic criteria, the accuracy of this classification purposes is substantial [25]. The average kappa score of the RF algorithm is around 0.8989. The algorithm having a lower rate of error will be preferred as it has more powerful classification capability. We can study the errors resultant from the training of the six selected algorithms from Table 8. In this experiment, very common indicators for measuring error are employed namely mean absolute errors

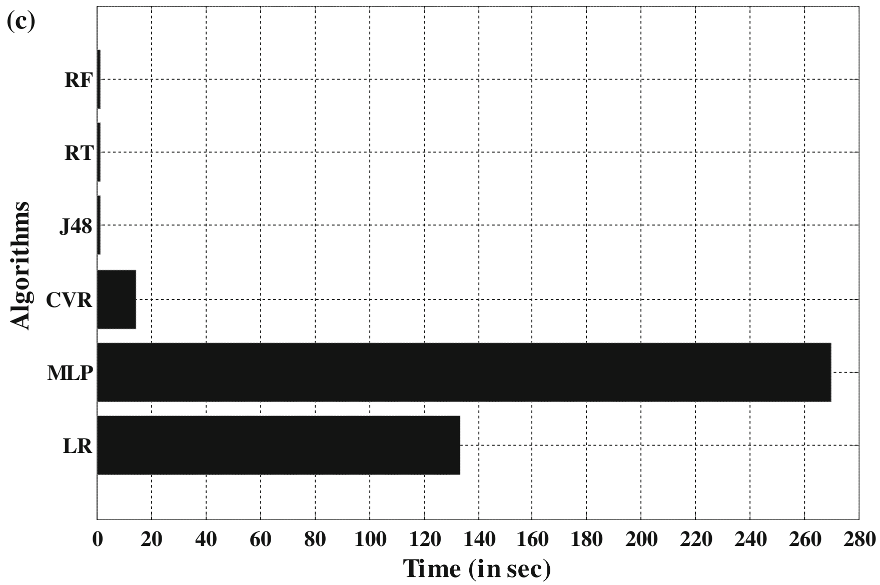

Fig. 2 (continued)

(MAE) and root mean squared errors (RMSE). In MLP, MAE is less as compared to RF, whereas in RF, RMSE is lowest as compared to MLP. So RF is a better option than MLP.

7 Conclusion

In this paper, a novel ensemble scheme was addressed to choose the appropriate classifier for the smartphone-based activity recognition system with wearable sensors. We have tested the activity recognition dataset using various classifiers. Thus, by observing accuracy, time complexity, kappa score, and error rate, we conclude that random forest decision tree results in better outcomes than other algorithms like MLP, RT, and CVR. Further investigation will be carried out with these issues as our future work.

References

1. Pantelopoulos, A., Bourbakis, N.G.: A survey on wearable sensor-based systems for health monitoring and prognosis. IEEE Trans. Syst. Man Cyber.-Part C: Appl. Rev. **40**, 1–12 (2010)
2. Davies, N., Siewiorek, D.P., Sukthankar, R.: Activity-based computing. IEEE Pervasive Comput. **7**, 20–21 (2008)

3. Krause, A., Smailagic, A., Siewiorek, D.: Context-aware mobile computing: learning context-dependent personal preferences from a wearable sensor array. IEEE Trans. Mobile Comput. **5**, 113–127 (2006)
4. Poppe, R.: Vision-based human motion analysis: an overview. Comput. Vis. Image Underst. **108**, 4–18 (2007)
5. Lukowicz, P., Ward, J.A., Junker, H., Stager, M., Troster, G., Atrash, A., Starner, T.: Recognizing workshop activity using body worn microphones and accelerometers. In: Proceedings of the 2nd International Conference on Pervasive Computing, pp. 18–22 (2004)
6. Karantonis, D.M., Narayanan, M.R., Mathie, M., Lovell, N.H., Celler, B.G.: Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Trans. Inf. Technol. Biomed. **10**, 156–167 (2006)
7. Bao, L., Intille, S.: Activity recognition from user-annotated acceleration data. Lect. Notes Comput. Sci. **3001**, 1–17 (2004)
8. Kwapisz, J.R., Weiss, G.M., Moore, S.A.: Activity recognition using cell phone accelerometers. In: Proceedings of the 4th International Workshop on Knoweldge Discovery from Sensor Data, Washington DC, pp. 10–18 (2010b)
9. Krishnan, N., Colbry, D., Juillard, C., Panchanathan, S.: Real time human activity recognition using tri-axial accelerometers. In: Sensors, Signals and Information Processing Workshop (2008)
10. Krishnan, N., Panchanathan, S.: Analysis of low resolution accelerometer data for continuous human activity recognition. In: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2008), pp. 3337–3340 (2008)
11. Tapia, E.M., Intille, S.S., et al.: Real-Time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor. In: Proceedings of the 11th IEEE International Symposium on Wearable Computers, pp. 1–4 (2007)
12. Mannini, A., Sabatini, A.M.: Machine learning methods for classifying human physical activity from on body accelerometers. Sensors **10**, 1154–1175 (2010)
13. Foerster, F., Fahrenberg, J.: Motion pattern and posture: correctly assessed by calibrated accelerometers. Behav. Res. Methods Instrum. Comput. **32** (2000)
14. Parkka, J., Ermes, M., Korpipaa, P., Mantyjarvi, J., Peltola, J., Korhonen, I.: Activity classification using realistic data from wearable sensors. IEEE Trans. Inf. Technol. Biomed. **10**, 119–128 (2006)
15. Lee, S.-W., Mase, K.: Activity and location recognition using wearable sensors. IEEE Pervasive Comput. **1**, 24–32 (2002)
16. Nishkam, R., Nikhil, D., Preetham, M., Littman, M.L.: Activity recognition from accelerometer data. In: Proceedings of the Seventeenth Conference on Innovative Applications of Artificial Intelligence, pp. 1541–1546 (2005)
17. Kwapisz, J.R., Weiss, G.M., Moore, S.A.: Activity recognition using cell phone accelerometers. SIGKDD Explor. Newslett. **12**, 74–82 (2011)
18. Cheverst, K., Davies, N., Mitchell, K., Friday, A., Efstratiou, C.: Developing a context-aware electronic tourist guide: some issues and experiences. **2**, 17–24 (2000)
19. Thurau, C., Hlavac, V.: Pose primitive based human action recognition in videos or still images. In: Proceedings of the 2008 IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–8 (2008)
20. Wu, O.W.H., Bui, A.T., Batalin, M., Au, L.K., Binney, J.D., Kaiser, W.J.: MEDIC: medical embedded device for individualized care. Artif. Intell. Med. **42**, 137–152 (2008)
21. Fahriddin, M., Song, M.G., Kim, J.Y., Na, S.Y.: Human Activity Recognition Using New Multi-Sensor Module in Mobile Environment (2011)
22. Deng, W.-Y., Zheng, Q.-H., Wang, Z.-M.: Cross-person activity recognition using reduced kernel extreme learning machine. Neural Netw. (2014)
23. http://www.cis.fordham.edu/wisdm
24. WEKA at http://www.cs.waikato.ac.nz/~ml/weka
25. Kappa: http://www.dmi.columbia.edu/homepages/chuangj/kappa