An Empirical Evaluation of Activities and Classifiers for User Identification on Smartphones

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Abstract

In the past few years, smart mobile devices have become ubiquitous. Most of these devices have embedded sensors such as GPS, accelerometer, gyroscope, etc. There is a growing trend to use these sensors for user identification and activity recognition. Most prior work, however, contains results on a small number of classifiers, data, or activities.

We present a comprehensive evaluation of ten representative classifiers used in identification on two publicly available data sets (thus our work is reproducible). Our results include data obtained from dynamic activities, such as walking and running; static postures such as sitting and standing; and an aggregate of activities that combine dynamic, static, and postural transitions, such as sit-to-stand or stand-to-sit. Our identification results on aggregate data include both labelled and unlabeled activities. Our results show that the k-Nearest Neighbors algorithm consistently outperforms other classifiers. We also show that by extracting appropriate features and using appropriate classifiers, static and aggregate activities can be used for user identification.

We posit that this work will serve as a resource and a benchmark for the selection and evaluation of classification algorithms for activity based identification on smartphones.

1. Introduction

With the development of mobile technology, in recent years, mobile devices have become ubiquitous and embedded different kinds of sensors, such as GPS, acceletometer, gyroscope, fingerprint reader, etc. Because of the small size and high computation capability of smartphones that have these embedded sensors, there is a growing research interest to identify an individual from his or her ordinary activities, such as walking, running, etc. [7, 18, 11, 5, 13, 4, 15, 8, 10, 6, 17]

Most of the reported work has some shortcomings. For example, in [8] and [11], only three and two classification algorithms were evaluated respectively. We present a comprehensive evaluation on ten classifiers, which are Random Forest, Support Vector Machine, Naive Bayes, J48, Neural Network, k-Nearest Neighbors, Rpart, JRip, Bagging and AdaBoost. Another deficiency of previous work is that it addressed a limited number of activities, such as walking and running. Some recent work [8] extended the activities to jogging, climbing, etc. However, all of the reported results only consider dynamic activities. We test and compare ten classification algorithms on a plethora of activities; these include dynamic activities, such as walking and running; static postures, such as sitting and standing; and an aggregate of activities that combine dynamic, static, and postural transitions, such as sit-to-stand or stand-to-sit. Our identification results on aggregate data include both labelled and unlabeled activities.

We test our approach on two different public data sets, available from the UCI Machine Learning Repository. The first data set, *User Identification from Walking activity Data Set* [1], consists of accelerometer readings of walking patterns from 22 participants. The second data set, *Smartphone-Based Recognition of Human Activities and Postural Transitions Data Set* [12], contains activity and postural transition data from 30 volunteers, collected from accelerometer and gyroscope.

Specifically, our work makes the following contributions:

1. We provide insights and a comprehensive evaluation of ten different classifiers on various human activities. To our knowledge, of the ten classifiers, Rpart, JRip, Bagging, and AdaBoost, have never been studied in user identification with wearable sensors. For evaluation of the classifiers, we not only compute overall accuracy, but also sensitivity and specificity of every user.

2. To our knowledge, static postures for user identification have never been studied before. We propose

that by selecting features and classifiers appropriately, static postures (sitting, standing and lying) can also be utilized to identify a user accurately. Further, we consider postural transitions in our classification. We combine all activities and transitions together, remove the activity labels, and find that it is still possible to identify every user accurately. We believe that this result adds a significant contribution to research findings in user identification with wearable sensors.

3. We find that k-Nearest Neighbors achieves high performance in all of the tests in the two data sets. Not only does the classifier work well for different activities and transitions, but the algorithm can be highly accurate with a small set of features.

4. All of our work is based on two different *publicly accessible* activity data sets, downloaded from the UCI Machine Learning Repository. Thus, our results can be easily reproduced. We post all of our work, including the data processing scripts, onto GitHub [1].

The remainder of this paper is organized as follows. We discuss related work in Section 2, describe the data transformation and experimental design of two different data sets in Section 3, demonstrate the evaluation results in Section 4, give a discussion on results of two data sets in Section 5, and summarize our conclusions in Section 6.

2. Related Work and Our Work

2.1. Related Work

Traditional gait recognition mainly concerns identifying or authenticating an individual from his or her style of walking. According to a survey of biometric gait recognition presented by Gafurov [3], gait recognition could be categorized into three types of approaches: machine vision-based, floor sensor-based, and wearable sensor-based. The machine vision-based approach is related to using cameras to capture and record gait information. The silhouette information of a user is extracted for comparison and analysis. For example, Yam et al. [18] identified a person using walking and running patterns recorded by cameras. Recently, with the development of virtual games, some researchers are trying to use Microsoft Kinect for user recognition. Kinect can provide information of gait through its sensors. For example, Preis et al. [11] claimed they obtained promising results in gait recognition with the help of Kinect. The second category of gait recognition is related to collecting data of activities through sensors installed on the floor. This approach could offer footstep profiles of users. For instance, Middleton et al. [9] designed a sensor consisting of 1,536 individual sensors for gait recognition. They extracted features of stride length, stride cadence, and time on toe to time on heel ratio, and achieved a recognition rate of 80%. In the last type, the wearable sensor-based approach, data is collected from sensors worn on user's body. This is the area we concentrate on in this paper.

[1] https://github.com/UserIdentificationBTAS/btas-2016

In previous work, there are some studies on the sensors for user identification. Currently, accelerometers and gyroscopes are widely used in this area. Gafurov et al. [5] performed experiments on a data set comprised of 300 walking sequences from 50 subjects, collected by an accelerometer sensor placed in the trousers pocket. Another work by Trung et al. [17] was related to user recognition with walking patterns on a large data set which contained data from 736 subjects, recorded by an accelerometer and gyroscope. More recently, Zhong et al. [19] presented a novel representation of walking activity data collected from accelerometers and gyroscopes. Additionally, considering the influence of orientation of devices, Subramanian et al. [16] proposed an orientation invariant gait matching algorithm, and achieved high performance.

There is some work discussing the approaches to processing data. For example, recently, Sprager et al. [14] gave a review of approaches used in sensor-based gait recognition. Considering that raw data collected from sensors is mainly time series data, most of previous work uses time series data processing techniques to analyze the sensor-based data. Kale et al. [7] extracted features from width vectors and performed the dynamic time-warping (DTW) approach on three different gait data sets. Chen et al. [2] extended the algorithm to the dynamic time-warping-delta approach, and they tested their method on unlabeled data sets. Nickel et al. [10] implemented the hidden markov model for biometric gait recognition. They claimed that their approach obtained a false non match rate (FNMR) of 10.42%, and a false match rate (FMR) of 10.29%. In recent years, some researchers utilized other machine learning algorithms to analyze the time series data. Kwapisz et al. [8] proposed an approach to divide the time series data into 10-second segments, and to generate feature vectors from every interval.

2.2. How Our Work Differs From Previous Work

The previous work provides insights in the area of user identification with wearable sensors. However, our work differs in multiple perspectives. Table 1 shows experimental conditions and identification approaches from three papers that are similar to our work. In [15] and [11], only the walking pattern was considered for user identification. [8] augmented the activities to walking, jogging, walking upstairs and walking downstairs. But the activities were still limited to dynamic activities. While, in our work, we identify an individual from six basic activities. Not only

Study	# of users	# of features	sensor(s)	sensor location	pattern(s)	methods(s)
Sprager et al. [15]	6	65	accelerometer	hip	slow walking	SVM
					normal walking	
					fast walking	
Preis et al. [11]	8	13	Kinect	off-body	walking	1R
						C4.5
						Naive Bayes
Kwapisz et al. [8]	36	43	accelerometer	leg	walking	J48
					jogging	
					upstairs	Neural Network
					downstairs	
Our work	30	24	accelerometer	waist	six activities (sitting, walking, etc.)	ten classifiers (kNN, AdaBoost, etc.)*
			gyroscope			
	18	9	accelerometer	chest	walking	ten classifiers*

Table 1. Summary of experimental conditions and evaluation of three studies similar to our work. For the Walking Pattern Data Set, we only use samples of 18 users from 22 participants because other four have too few samples. *: The ten classifiers are listed in Figure 1.

dynamic activities are considered, but static postures like sitting, standing, and lying are also included. More importantly, we also combine the activity data and transition data such as stand-to-sit, sit-to-lie together to recognize users. It is more accurate to utilize this approach to simulate a user's daily routine, and is easier to be deployed in practice for user identification and authentication, because the method does not require recognition of a specific activity.

Another significant difference is the methods utilized to train models. In [15], only support vector machine was exploited. And in [8], the authors performed J48 and Neural Network. Even though [11] had more classifiers, still only three algorithms were tested. In contrast, in our work, we use ten different classification algorithms to identify users, and we also provide insights and comparative evaluation of the algorithms. This can be beneficial for other people to select appropriate approaches for user identification.

One interesting result of our work is that we find that k-Nearest Neighbors algorithm achieves high accuracy in all of our tests, and in most of the tests, the accuracy is as high as 100%. To the best of our knowledge, previous research has not obtained such accuracy in user identification with wearable sensors.

3. Data Transformation and Experimental Design

3.1. High Level Design

In this paper, we perform user identification experiments on two activity data sets. The high level design of our experiment is shown in Figure 1. The Walking Pattern Data Set was gathered from the accelerometer of an Android smartphone in a chest pocket, and the Human Activities and Postural Tranisitons Data Set was collected from accelerometer and gyroscope embedded in a smartphone on waist. Usually, the raw sensor signals are presented in a time series format, and our approach is to partition them into fixed-width windows. And for every window, we extract necessary features to construct a feature vector. The samples are then partitioned into a training data set and testing data set for classification.

3.2. Descriptions of Data Sets

The first data set we performed experiments on is the Walking Pattern Data Set [1], which could be accessed from the UCI Machine Learning Repository. This data set contains accelerometer time series data from 22 participants. The sensor is embedded in an Android smartphone, put in the chest pocket. The data set only has data of walking patterns, sampled at 52 Hz. We plot graphs of information from four users in Figure 2. From the figure, we observe that every user has a unique pattern of walking.

The second data set we studied is the Human Activities and Postural Transitions Data Set [12], which consists of six basic activities: three dynamic activities (walking, walking upstairs, and walking downstairs) and three static postures (standing, sitting, and lying). The data set also includes transitions between the static postures, which are stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie and lie-to-stand. The data is from 30 volunteers, collected by embedded accelerometer and gyroscope worn on every subject's waist.

3.3. Data Transformation and Feature Extraction

After the two data sets were obtained, we need to implement data transformation for our experiment. Usually, the raw data collected from accelerometer and gyroscope is time series data, making it difficult to directly apply machine learning algorithms. Our approach is to partition the data into fixed-width sliding windows. For the Walking Pattern Data Set, we partition data into fixed-width (100 samples) sliding windows with a 50% overlap. For the Human

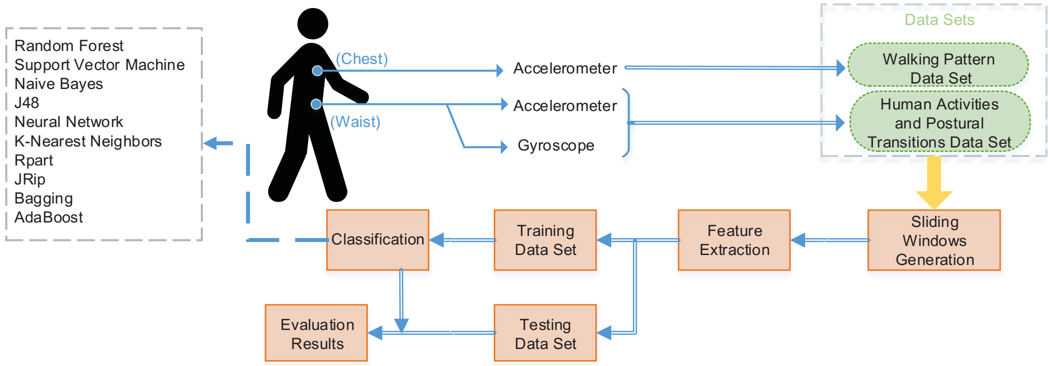

Figure 1. High level design of our experiment.

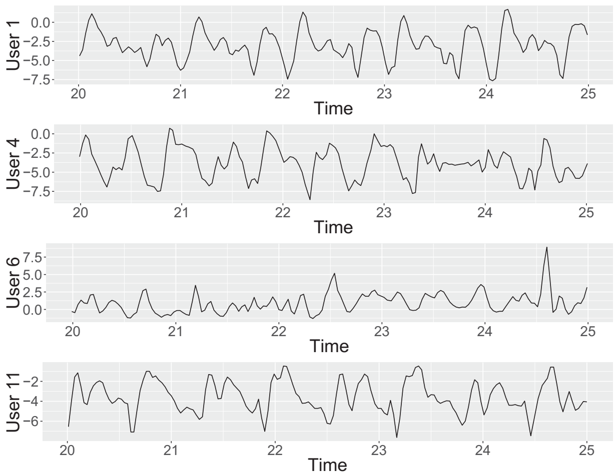

Figure 2. X axis accelerometer data in 20 - 25s from four users in the Walking Pattern Data Set.

Activity and Postural Transitions Data Set, the original contributors have already pre-processed the sensor signals by noise filter and partitioned the data into fixed-width sliding windows with a 50% overlap.

After the partition, we extract features from every sliding window. For the Walking Pattern Data Set, we extract 9 features from every window and scale the features to [-1, 1]. The 9 features are the mean values, standard deviations and median absolute deviations of x, y, and z axis of acceleration signals. After the pre-process, we notice that there are some users having too few samples. For example, User 3 only has 23 samples. Because we have little information about the users, we remove subjects 3, 5, 16, and 19 from the data set. So finally, our cleaned data set has samples from 18 participants. We demonstrate the number of samples per user in Table 2. Note that the numbers of samples vary greatly between the individuals. For instance, User 21 only has 62 samples, while, by contrast, User 17 has 440 samples.

ID	Count	ID	Count
1	101	12	96
2	78	13	134
4	140	14	241
6	99	15	74
7	75	17	440
8	70	18	416
9	160	20	339
10	62	21	62
11	113	22	194

Table 2. Number of samples per user in the Walking Pattern Data Set.

For the Human Activities and Postural Transitions Data Set, the original contributors constructed a 561-feature vector for every window. From the features, we extract 24 features which are related to mean and standard deviation:

- tBodyAccMean (3): Mean values of x, y, and z axis of body acceleration signals.
- tBodyAccSTD (3): Standard deviations of x, y, and z axis of body acceleration signals.
- tGravityAccMean (3): Mean values of x, y and z axis of gravity acceleration signals.
- tGravityAccSTD (3): Standard deviations of x, y and z axis of gravity acceleration signals.
- tBodyAccJerkMean (3): Mean values of x, y and z axis of jerk signals of body acceleration.
- tBodyGyroMean (3): Mean values of x, y, and z axis of angular velocity.
- tBodyGyroSTD (3): Standard deviations of x, y and z axis of angular velocity.
- tBodyGyroJerkMean (3): Mean values of x, y and z axis of jerk signals of angular velocity.

ID	Walk	Up	Down	Sit	Stand	Lie	Total
1	95	53	49	47	55	48	347
2	59	48	47	46	55	49	304
3	58	59	49	52	63	63	344
4	60	52	45	49	56	52	314
5	56	47	47	43	57	51	301
6	57	51	48	56	58	56	326
7	57	51	47	47	54	50	306
8	48	41	38	45	57	55	284
9	52	49	42	53	49	54	299
10	53	47	38	55	46	59	298
11	59	54	46	54	50	58	321
12	50	52	46	56	62	61	327
13	57	55	47	49	60	60	328
14	59	54	45	53	62	48	321
15	54	48	42	61	55	74	334

Table 3. Number of samples of first 15 users for six activities in the Human Activities and Postural Transitions Data Set.

Activity	Count	Transition	Count
walk	1722	stand-to-sit	70
up	1544	sit-to-stand	33
down	1407	sit-to-lie	107
sit	1801	lie-to-sit	85
stand	1979	stand-to-lie	139
lie	1958	lie-to-stand	84
Total	10411	Total	518

Table 4. Numbers of samples of the activities and transitions in the Human Activities and Postural Transitions Data Set.

We present an overall description of the number of samples in every activity in Table 3. Because of space limitations, we only present information from the first 15 users. Additionally, we give a summary of the samples of every activity and transition in Table 4. In total, the post-processed data set has 10,411 samples of activities and 518 samples of transitions. It is normal that the transitions have a much smaller number of samples than that of activities, because a transition usually lasts for a very short time.

3.4. Experimental Design

After preparing the data sets, we perform and compare ten classification algorithms, and most of them are widely used in user identification research. Our motivation is that even though there has been some work using the algorithms in user recognition, there is a lack of work to compare performance of the classifiers. The ten classification algorithms are: Random Forest (RF), Support Vector Machine (SVM), Naive Bayes (NB), J48, Neural Network (NN), k-Nearest Neighbors (kNN), Rpart, JRip, Bagging (Bag) and AdaBoost (AB). We use functions in R packages for the classification. For the Neural Network, we set the number of units in the hidden layer to 9, the parameter for weight decay to 5e-4, and the maximum number of iterations to 1,000. For k-Nearest Neighbors, we configure k to 5. For all the other classifiers, we utilize the default settings. We partition the cleaned data set into 70% training and 30% testing data, according to every user. And we train the models by the training data set and test them on testing data set.

For the Human Activities and Postural Transitions Data Set, we perform more experiments because it contains more activities. We partition it into six segments, with each corresponding to a specific activity (walking, walking upstairs, walking downstairs, sitting, standing or lying). With the six sub data sets, we perform the experiments to explore the performance of different classifiers on various activities. While, these experiments are only related to one specific activity which has been known beforehand. The next series of experiments we conduct is to integrate the samples of all the six activities. This idea was first presented in [8]. In this case, we obtain a large data set with six different activities mixed together. There is a divergence as to whether or not the labels of activities should be removed. It is more similar to a real scenario if we remove all the labels, because in practice, we may not have precise information about the activity a user is performing. In our work, we compare the results of the two approaches. We first keep the labels and apply the classifiers; afterwards, we eliminate the labels and conduct the experiment again.

One important experiment is performed afterwards. Because the data set also contains the transitions between static postures, we append the transition data to the aggregated data set without any activity labels. In our opinion, this case achieves the most accurate simulation of a human subject's activities. It is also beneficial for continuous identification and authentication because in practice, an activity may not be recognized if the recognition system is only trained for some specific activities.

4. Evaluation Results

4.1. Evaluation Results of Walking Pattern Data Set

To compare the classifiers, we calculate the overall accuracies for every experiment, and we also compute the sensitivity and specificity of every user for each classification algorithm. In our work, *sensitivity* is defined as the proportion of positive cases identified correctly by a classifier. And *specificity* is defined as the proportion of negative cases identified correctly by a classifier. The reason for computation of sensitivity and specificity is that even though a classifier can obtain a reasonably high overall accuracy, it may not identify some specific users well. This problem may influence the usage of the classifier in practice. So, for each classifier, it is also crucial to evaluate the identification performance for every user.

Classifier	Accuracy	Classifier	Accuracy
RF	85.7	kNN	**99.8**
SVM	77.2	Rpart	64.0
NB	48.3	JRip	72.6
J48	78.0	Bag	69.9
NN	76.3	AB	71.9

Table 5. Accuracies (%) of ten classifiers on the Walking Pattern Data Set. Accuracies higher than 90% are bold. RF: Random Forest. SVM: Support Vector Machine. NB: Naive Bayes. NN: Neural Network. kNN: K-Nearest Neighbors. Bag: Bagging. AB: AdaBoost.

ID	RF		kNN	
	Sensitivity	Specificity	Sensitivity	Specificity
1	76.7	99.8	100.0	100.0
2	39.1	99.8	100.0	100.0
4	81.0	99.5	100.0	100.0
6	86.2	99.8	96.6	100.0
7	95.5	99.3	100.0	99.8
8	47.6	99.8	95.2	100.0
9	79.2	98.3	100.0	100.0
10	83.3	99.9	100.0	100.0
11	84.8	99.6	100.0	100.0
12	85.7	99.9	100.0	100.0
13	97.5	98.9	100.0	100.0
14	94.4	99.6	100.0	100.0
15	81.8	99.6	100.0	100.0
17	87.1	97.4	100.0	100.0
18	91.1	95.7	100.0	100.0
20	96.0	99.3	100.0	100.0
21	88.9	99.5	100.0	100.0
22	77.6	98.6	100.0	100.0

Table 6. Sensitivity and specificity per user of Random Forest and k-Nearest Neighbors in the Walking Pattern Data Set.

We first compute the overall accuracy of each classification algorithm. The result is illustrated in Table 5. From the table, we observe that only Random Forest and k-Nearest Neighbors could achieve accuracies higher than 80%. Particularly, k-Nearest Neighbors gives an excellent result, as the identification accuracy is nearly 100%. Remember that the data set is not pre-processed by noise filters, and only nine very basic features related to mean, standard deviation and median absolute deviation are extracted, it is surprising that k-Nearest Neighbors achieves such a good performance.

To check more details of user identification of the two classifiers, we present Table 6 to provide sensitivity and specificity of every user. The table indicates a promising result that k-Nearest Neighbors has 100% identification accuracies for almost all of the users. For Random Forest, the specificities are very high, though for some users (User 2 for example), the sensitivities are relatively low.

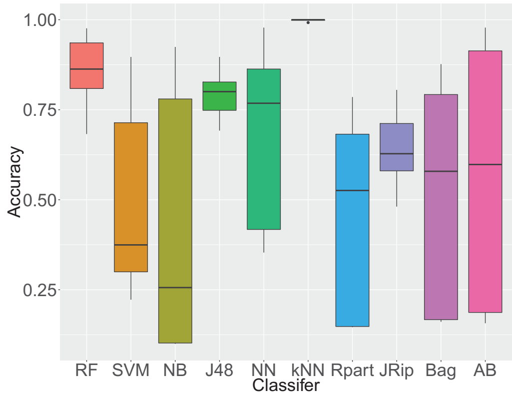

Figure 3. Comparison of box plots of ten classifiers on the Human Activities and Postural Transitions Data Set. Note that kNN's performance is so high that in the figure it is almost just a line.

4.2. Evaluation Results of Human Activities and Postural Transitions Data Set

Details of the overall accuracy of every classifier is reported in Table 7. From the table, we observe that five classifiers (Random Forest, Naive Bayes, Neural Network, k-Nearest Neighbors, and AdaBoost) can achieve more than 90% accuracy in user identification with the walking pattern. Regarding the six different activities, the table indicates that for the three dynamic activities (walking, walking upstairs, and walking downstairs), there are some classifiers that can accurately identify users. Random Forest, k-Nearest Neighbors and AdaBoost are the three best algorithms which obtain more than 90% accuracy in each of the three dynamic activities. While, from the perspective of static postures, the performance is different. All the classifiers except k-Nearest Neighbors cannot work well for the recognition. We notice that, on average, the classifiers obviously gain a higher performance in dynamic patterns than that of static patterns. And walking achieves highest identification accuracy in the six activities.

A very important part of our work is that we aggregate all the samples together. In the last three rows of Table 7, we consider three additional scenarios: aggregated data with activity labels, aggregated data without activity labels, aggregated data without activity labels and containing transitions. For these three experiments, almost all of the classifiers' performance deteriorates. For Naive Bayes, Rpart, Bagging and AdaBoost, the accuracies for these experiments are even lower than 20%. It seems that Random Forest's accuracies can still be higher than 80%, which is tolerable. Additionally, k-Nearest Neighbors's accuracies are more than 99%. Actually, k-Nearest Neighbors obtains very high accuracies (nearly 100%) in all of the tests. This indicates that even when the data is from static postures or aggregated data with various activities, k-Nearest

Type	Activity	RF	SVM	NB	J48	NN	kNN	Rpart	JRip	Bag	AB	Average
Dynamic	Walk	**97.6**	89.7	**92.4**	89.7	**97.8**	**100.0**	78.5	80.5	87.7	**97.8**	**91.2**
	Upstairs	**93.6**	79.6	82.9	82.7	**90.5**	**100.0**	71.4	71.2	80.9	**91.4**	84.4
	Downstairs	**94.6**	71.4	78.0	80.2	86.3	**100.0**	68.2	67.2	79.2	**95.6**	82.1
Static	Sit	68.3	22.2	12.9	69.2	62.9	**99.8**	33.7	48.1	44.3	46.4	50.8
	Stand	72.2	37.5	25.6	74.1	76.8	**100.0**	52.6	60.7	57.9	59.8	61.7
	Lie	86.6	46.9	34.7	84.1	80.6	**99.8**	58.8	72.4	66.5	84.5	71.5
Aggregated	Aggregate	86.3	30.6	10.1	80.0	40.2	**100.0**	14.8	62.8	16.1	18.5	45.9
	Aggregate*	83.4	30.0	10.0	77.1	41.7	**100.0**	14.8	58.0	16.7	18.7	45.0
	Aggregate**	80.9	29.2	10.2	74.8	35.3	**99.2**	14.6	57.0	16.4	15.7	43.3

Table 7. Accuracies (%) of ten classifiers on the Human Activities and Postural Transitions Data Set. Accuracies higher than 90% are bold. Aggregate: Aggregated activity data with activity labels. Aggregate*: Aggregated activity data without activity labels. Aggregate**: Aggregated activity data without activity labels but containing transitions. kNN achieves high accuracies in all of the tests.

ID	NN		kNN		AB	
	Sens	Spec	Sens	Spec	Sens	Spec
1	96.4	100.0	100.0	100.0	100.0	100.0
2	100.0	100.0	100.0	100.0	100.0	100.0
3	94.1	99.8	100.0	100.0	94.1	100.0
4	100.0	100.0	100.0	100.0	100.0	100.0
5	100.0	99.8	100.0	100.0	100.0	100.0
6	100.0	100.0	100.0	100.0	94.1	99.8
7	94.1	100.0	100.0	100.0	94.1	100.0
8	100.0	99.8	100.0	100.0	100.0	100.0
9	86.7	100.0	100.0	100.0	100.0	100.0
10	100.0	100.0	100.0	100.0	80.0	100.0
11	100.0	100.0	100.0	100.0	100.0	99.8
12	93.3	99.8	100.0	100.0	80.0	100.0
13	100.0	100.0	100.0	100.0	100.0	100.0
14	100.0	100.0	100.0	100.0	100.0	100.0
15	100.0	100.0	100.0	100.0	100.0	99.8

Table 8. Sensitivity and specificity of first 15 users under walking in the Human Activities and Postural Transitions Data Set. Sens: Sensitivity. Spec: Specificity.

Neighbors could still identify users accurately. This is very promising, because it indicates that for user identification with various activities, we do not need to recognize the activity first, but can directly feed the models with activity data. Overall, we put the comparison of the ten classification algorithms in a boxplot, in Figure 3. From the plot, we observe that k-Nearest Neighbors is the most stable classifier of the ten. And Random Forest also has a relatively high and stable performance in all of the nine experiments. Some classifiers, such as Naive Bayes and AdaBoost, have a large difference between various activities. For example, Naive Bayes achieves 92.4% accuracy in the walking pattern, but can only identify 12.9% samples correctly in the sitting pattern.

In Table 8, we also provide additional information about sensitivity and specificity of first 15 users for Neural Network, k-Nearest Neighbors and AdaBoost, with respect to walking activity. It illustrates that the three algorithms work well for almost all of the users. More importantly, k-Nearest Neighbors achieves 100% accuracy for identifying every user.

5. Discussion

After the analysis of two activity data sets, we summarize what we have found in this section. In Figure 4, we illustrate the overall comparison of the ten classification algorithms based on the evaluation results of the two data sets. We compute the rankings in three categories: aggregated, dynamic and static activities. Because the figure is about rankings, the lower, the better. K-Nearest Neighbors is obviously the best classifier of the ten, and it ranks first in all of the three categories. Additionally, Random Forest is another classifier which ranks high in all of the three kinds of activities.

6. Conclusions

In this paper, we evaluated ten classifiers on two publicly available activity data sets for user identification. We considered data sets obtained from dynamic activities, static postures, and postural transitions. Our results included analysis on individual activities and labelled and unlabeled aggregate of activities. In our experiments, the k-Nearest Neighbors algorithm outperformed all other classifiers. We plan to extend our analysis on data obtained from additional sensors, such as EEG obtained from Brain Computer Interface devices. We posit that this work will serve as a resource and a benchmark for selection and evaluation of classification algorithms for activity based identification on smartphones.

7. Acknowledgement

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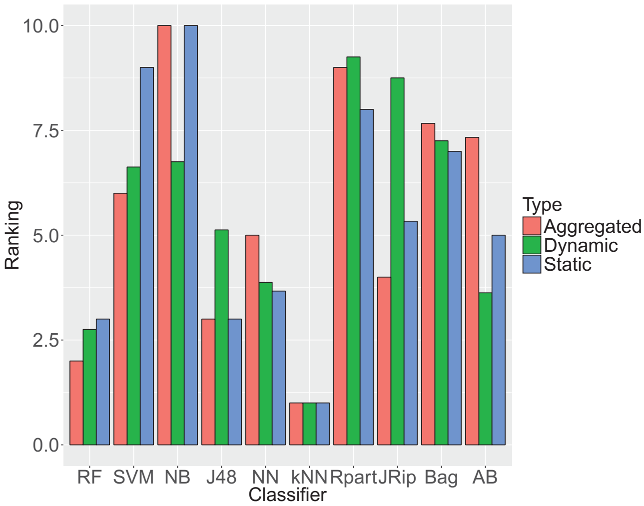

Figure 4. Rankings of each classifier for aggregated, dynamic and static data sets. The rankings of dynamic activities are from analysis of Walking Pattern Data Set and Human Activities and Postural Transitions Data Set. The rankings of aggregated and static activities are solely from Human Activities and Postural Transitions Data Set.

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