Activity Recognition Using Wrist-Worn Sensors for Human Performance Evaluation

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***Abstract*—Recent development of wearable technology has opened up great opportunities for human performance evaluation applications in various domains. In order to measure the physical activities of an individual, wrist-worn sensors embedded in smart-watches, fitness bands, and clip-on devices can be used to collect various types of data, as the subject performs regular daily activities. In this paper, we propose using the acceleration data generated by wrist-worn sensors to recognize ambulation activities for performance evaluation purposes. Twelve features are extracted from the raw accelerometer data, then feed into individual classifiers as well as their combinations for training and validation. The classifiers we consider in this paper are Naive Bayes, Support Vector Machines, Decision Tree, k-Nearest Neighbors, Multilayer Perceptron, and Random Forest, as they have been reported effective by a few previous works. We evaluate the set of selected classifiers with real-world data sets generated by three subjects, including data from both left and right wrists. The best accuracy performance is the combination of classifiers which is above 90%. The result shows that data generated by wrist-worn accelerometer sensor is sufficient for ambulation activity recognition and can be used for human performance evaluation applications.**

Keywords*—*Activity Recognition, Wrist-Worn Sensor, Human Performance Evaluation.

I. Introduction

Recent development of wearable technology has gained increasing popularity among individual users, especially wrist-worn devices, such as smart watches and fitness trackers, for compactness and convenience. Various types of sensors embedded in those devices, including accelerometer, gyrometer, heart rate sensor, GPS, and etc., greatly facilitate the acquisition of individually generated data. This data can then be analyzed by fitness apps, for example, to recognize movement types and to calculate calories burned.

While wrist-worn electronic devices provide many primary services, such as fitness tracking and other mobile apps, the continuous collection of individual movement data will also open up unprecedented opportunities for human performance evaluation applications in a variety of domains, such as sports and rehabilitation. In particular, in the medical domain, the physical abilities of individual patients are of great value to doctors and researchers to assess how a patient's disease is progressing and to determine appropriate treatment and prognosis. The ECOG performance status [1], a widely used criteria for patient evaluation, assigns a numeric grade, between 0 to 4, to each patient based on whether he/she is confined to bed or chair more than 50% of waking hours, capable of ambulation activities, or capable of complex and physically strenuous activities. However, many clinical studies have shown a very low agreement between patient's self-assessed performance score and that of his/her oncologist, i.e., 50% of cases agree as in [2].

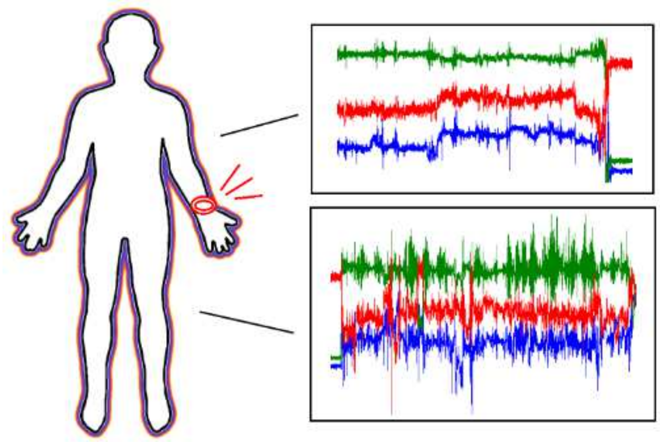

Fig. 1. Wrist-Worn Sensor and Generated Acceleration Data

The high chance of disagreement in performance scores can be inflicted by several facts: doctors have limited time and observations for each patient in the traditional setting, i.e., during the patient's visit; on the other hand, the patient's self-assessment may not be accurate due to different interpretations and pessimism [3]. Clearly, data collected outside the doctor's office can help truly understand the patient's physical abilities and improve the current evaluation process of the ECOG performance score. Wrist-worn devices can be used in this setting as they impose minimum impact and constraints on a subject's daily living, thus providing a unaltered view of his/her physical abilities.

Although activity recognition has been extensively studies [4] [5] [6] [7], the majority research works rely on a set of sensors deployed at multiple body locations, e.g., wrists, chest, hip, ankles. Although those studies report highly accurate recognition of activities, e.g., above 90% accuracy, by combining sensor data from multiple body locations, this deployment is not applicable in our setting due to its inconvenience and potential discomfort to patients. A few works considered deploying one device/sensor on each user, such as [5] and [8]. However, the performance rate in these work is still limited. Moreover, the work use the accelerometer of mobile phone, which is not always worn or brought along with users.

In this paper, we investigate the problem of activity recognition with 3-axis accelerometer data generated from wrist-worn devices. We focus on the recognition of ambulation activities, which will enable various human performance evaluation applications. We extract 12 features from the raw sensor data and adopt 6 classifiers which have been reported effective, as well as their combinations. Empirical evaluations are conducted with real-world data sets and the results show the recognition accuracy of more than 90%.

The organization of the paper is as follows: First, we have a quick survey of previous works of human activity recognition field in Section II. In Section III, we show our system design, including three parts as Data Collection & Activity Labels, Data Preprocessing & Feature Extraction and Classification. We report the empirical evaluation of the proposed methods using real-world datasets in Section IV. Finally, Section V concludes this paper and states future work directions.

II. Related Work

The majority of existing works on Human Activity Recognition proposed to used multiple sensors of different types, such as accelerometer, environmental sensors, physiological sensors, GPS, and etc., deployed at various body locations. The authors in [9] proposed using multiple sensors to recognize 7 classes of activities: Lying, Rowing, Biking, Sitting/Standing (one class), Running, Nordic Walking and Walking. The data used were acceleration data, vital signs from physiological sensors, environmental attributes (light intensity, temperature) and location from Global Positioning System (GPS). The best accuracy was 86% for using Automatic Decision Tree classifier. Another work using context information, such as light intensity, temperature and GPS location, in physical activity recognition is [7] in which a hybrid reasoning system with the accuracy rate of 93.44% was built. In [6], Lara and Labrador presented an system using mobile phone's accelerometer and Zephyr's BioHarness^{TM} chest strap sensors. Applying the Additive Logistic Regression algorithm, the system achieved the overall accuracy of 95.7% in recognizing of Running, Walking, Ascending, Descending, and Sitting. Although those works were reported to be highly accurate, the collection of context information and locations would raise user privacy concerns in our setting.

A few works [4] [10] [11] [12] proposed to use only accelerometers in mobile phones or wearable devices, and they have shown that acceleration data is sufficient to recognize ambulation actitivities, such as walking, standing still, running, and etc. Bao's system [4] included 5 accelerometers placed on 5 positions of user's body. The system achieved over 80% of accuracy. In [10], 3 sensors placed on user's hip, thigh and wrist were used to recognize 6 different activities of daily living which resulted in 84.3% accuracy. While [10] applied Dynamic Time Warping classifier, the authors in [11] proposed using Semi-Markov conditional random fields. Only two accelerometers were used in this work (one on the wrist and the other in the right pocket). Furthermore, multiple accelerometers were considered in the application of human activity recognition in robot-assisted living. Zhu and Sheng [12] presented proposed to use hidden Markov models with data extracted from two sensors: on wrist and on foot. However, deploying two or more sensors on each individual user can cause obtrusiveness [13] which may affect the quality and truthfulness of the collected data.

In order to enable activity recognition in a wider range of applications, a few studies focused on data generated by only one accelerometer. This includes mobile phone, smart watch or fitness band sensor. Mobile phone's acceleration data with k-Nearest Neighbors classifier was studied in [5] and was shown to be accurate from 70% to 90% recognizing Walking, Climbing Stairs, Sitting Down, Standing Up and Falling. Moreover, [8] showed that wrist-worn sensor performed the best in comparison to other body positions, such as: in trousers pocket, in shirt pocket, in bag, on belt, or around the neck. The authors of [8] proposed eWatch system and evaluated: Decision Tree, Naive Bayes and k-Nearest Neighbors with 5-fold cross validation. The accuracy ranged from 55% to 87.1% depending on the chosen method/features. In this work, we adopt a similar setting as in [8], i.e., one wrist-worn accelerometer per subject, and consider a wider range of classifiers and features.

III. System Design

In this section, we describe the workflow of our system. As in Figure 2, acceleration data is collected from the subject's wrist, left or right. The raw sensor data goes through a pre-processing step, followed by feature extraction. The extracted features are then used by various classifiers for training models and validating.

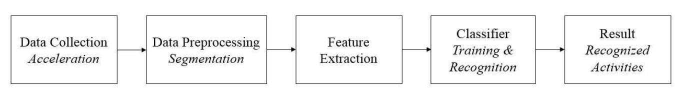

Fig. 2. Workflow of Activity Recognition

A. Data Collection & Activity Labels

In the field of activity recognition, four groups of data are often collected [13]: environmental attributes, acceleration data, location and physiological signals.

For human performance monitoring applications, we do not consider the collection of location or contextual data due to privacy concerns as well as high energy consumptions [13]. To reduce the obtrusiveness of the design, only wrist-worn devices are considered in our study. Our study takes acceleration data as input, since it has been shown effective for activity recognition and accelerometer is widely available on wearable devices.

The accelerometers capture subject's movement along the x-axis, y-axis and z-axis. In our study, we focus on four ambulation activities: Walking, Standing, Sitting and Lying they are essential to defining the performance status [1]. Figure 3, Figure 4, Figure 5, and Figure 6 show the triaxial acceleration data in the dataset of Activity Recognition Challenge [16], corresponding to the four activities, which was collected from a wrist-worn device in 5.5 seconds. Note that the device in this field can be a smart watch, a fitness band or a clip-on sensor. The x-axis and y-axis in the figures,respectively, represent the acceleration record indexing numbers and the raw acceleration value. From these figures, it can be seen that the acceleration for each activity has quite distinct properties. As can be seen, Figure 3 - Walking shows more fluctuation than Figure 4 - Standing, Figure 5 - Sitting and Figure 6 - Lying. The reason is that walking involves a lot of arm movements, especially movement along the y-axis, while there is fewer arm movements in standing, sitting and lying. Moreover, in walking and sitting, the y-axis acceleration value is higher than x-axis and z-axis because the subject swings/moves his or her arm while walking/standing doing activities.

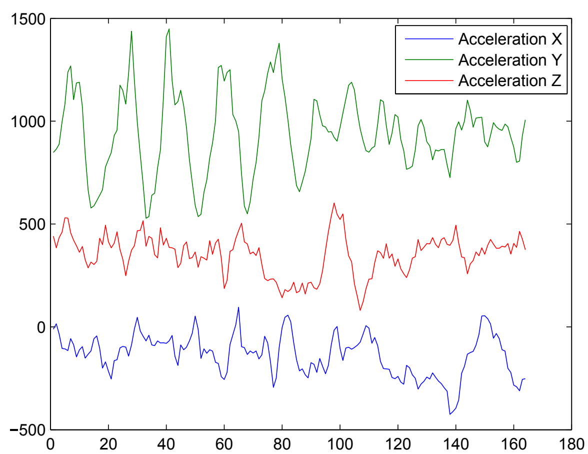

Fig. 3. Acceleration for Walking

B. Data Preprocessing & Feature Extraction

1) Preprocessing: We first process the raw acceleration data samples into windows. Given the sampling frequency of 30Hz, we consider windows containing 128 samples, each represents approximately 4.2 seconds. There is a 64 samples overlapping between two consecutive windows similar to [4].

2) Feature Extraction: In this study, we extract a total of 12 features for each window. These features are mean, energy values, frequency-domain entropy for each of three axes data and correlation between two axes in three pairwise combination of axes. Use of these features has been shown to result in accurate recognition in [4], [8], [9] and [14]. The details of feature extraction are listed below for a given signal X = $\{x_1, x_2, ..., x_{n-1}, x_n\}$

Mean value along each axis: $\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$

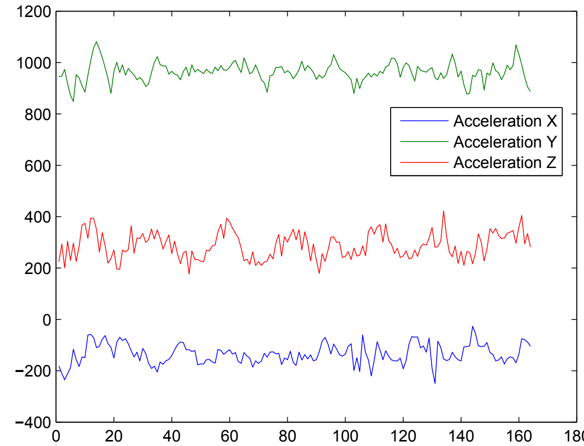

Fig. 4. Acceleration for Standing

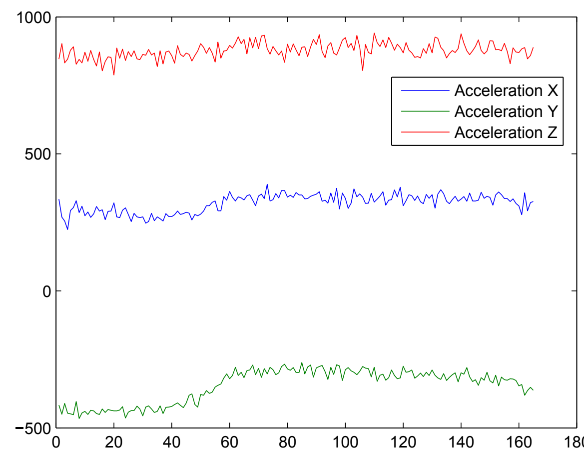

Fig. 5. Acceleration for Sitting

Energy value along each axis: To compute energy value, first, Fast Fourier Transform (FFT) is applied to each window. Direct Current (DC) component is also removed in this step. Then, energy values are calculated as the sum of the square FFT component (F_i):

$$\text{Energy(X)} = \frac{\sum_{i=1}^{n} F_i^2}{n}$$

In order to distinguish between activities with the same energy value, frequency-domain entropy is extracted. First, the FFT components are put in normalized function. Then, frequency-domain entropy H is computed from normalized values (p_i) as:

$$p_i = \frac{F_i}{\sum_{i=1}^{n} F_i}$$

$$\text{H} = -\sum_{i=1}^{n} p_i \ln p_i$$

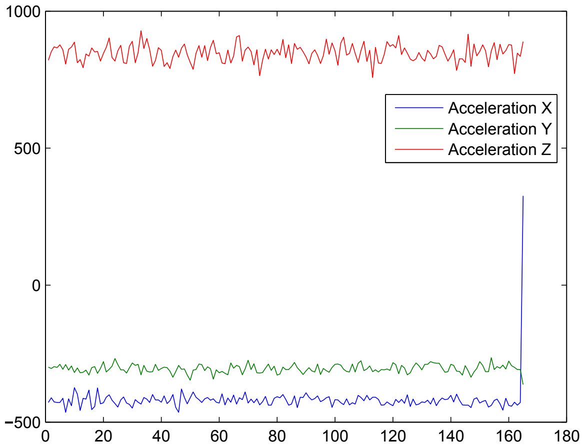

Fig. 6. Acceleration for Lying

Features measuring correlation between two axes are used in this work. Correlation is calculated between the x-axis and y-axis, y-axis and z-axis, x-axis and z-axis. Below is the calculation of X - Y correlation $\rho(X,Y)$ given σ_X and σ_Y is the standard deviations:

$$\rho(X,Y) = \frac{covariance(X,Y)}{\sigma_X \sigma_Y}$$

C. Classification

Extracted features are put into classifiers to learn models and validate for activity recognition. Some previous works have shown success using individual classifiers, such as Decision Tree C4.5 in [19], [4], k-NN in [5], Naive Bayes in [4]. However, in these studies, multiple sensors are put on user's body, which cause obtrusiveness and might not be applicable in human reality performance evaluation. In this work, we also consider Multilayer Perceptron and Random Forest which have been shown to be effective for data generated by smartphone sensors [14]. We will evaluate the performance of these classifiers on acceleration data generated from wrist-worn sensors.

Naive Bayes is a widely used, simple probabilistic classifier. Regarding SVM, the classifier constructs a hyperplane which separates the two classes with the largest distance to the nearest class point. To solve the multi-class problem in setting, our work considers one-versus-one multiclass SVM in which each pairwise classes group is chosen as a two-class SVM each time. Another wide used classifier is Decision Tree. Decision Tree builds a tree-like model of decisions, then validates the final class through the conditions of each tree node. k-Nearest Neighbors classifier decides an object's label by its neighbors. The object is classified as the class which is the most common among its k nearest neighbors. Multilayer Perceptron builds a feedforward artificial neural network model which maps the input acceleration data to the output classes. Random Forest builds an ensemble of Decision Trees at training step. Subset of features is put into the classifier to construct each tree.

Combining classifiers is shown in [14] which can improve recognition accuracy. Our work considers two types of combination: Majority Voting and Average of Probabilities. In Majority Voting, individual classifier gives a vote for its classification result. The label that has the most votes is the final result in activity recognition. Average of Probabilities computes the mean of the probability distributions for every individual classifiers. All the classifiers accuracy and confusion matrices are evaluated in the next section IV.

IV. Evaluation

A. Dataset

In this work, we use the dataset of Activity Recognition Challenge [16] (also used in [17] and [18]) to evaluate the accuracy. In the challenge dataset, acceleration data was captured from 3 subjects performing their morning activities. Sensors were deployed at various body locations. Timestamps and data labels of 4 activities (Walking, Standing, Sitting and Lying) are also provided. In our evaluation, we only consider wrist sensors. A sensor was deployed on each wrist of the subject. We evaluate the accuracy of data recorded by each wrist sensor. The sampling frequency is 30Hz. In summary, there are over 300,000 records or 2300 windows (window length is 128) for each wrist of a subject.

B. One Classifier

Table I presents the accuracy results of different classifiers. We evaluate the performance of the following classifiers: Naive Bayes, SVM, Decision Tree, k-NN, Multilayer Perceptron and Random Forest. In k-NN approach, 5 is used as the value of k since this value gives the best result. With Random Forest, the maximum of tree depth is 10 and the number of features in random selection for each tree is 3 as this setting produces good accuracy. 10-fold cross validation approach is applied. Also, we use WEKA toolkit [15] to do evaluation of classifiers.

It can be seen from Table I that all classifiers achieve over 70% of accuracy in recognition. Naive Bayes provides the lowest accuracy among all classifiers, which is consistent with existing work [4]. The best result of all classifiers and all subjects is 91.92% which is achieved by Random Forest method for subject 1 on right wrist. Random Forest has the highest overall accuracy of 85.95% and 87.70% for left wrist and right wrist respectively. Also, the tree models in Random Forest show that the mean value along x-axis, y-axis and z-axis are the most influential features. Both k-NN and Multilayer Perceptron produce above 80% accuracy in all cases. When looking at individual classifiers, we observe most of them perform better on average for the right wrist of subjects, except for Naive Bayes. We believe this is due to the fact that the right hand is the dominant hand for the subjects included in the dataset.

In conclusion, the result shows that one wrist-worn sensor is sufficient for activity recognition. We further present the confusion matrices of Random Forest for all subjects in the datasets. From table II, it can be seen that Random Forest does not distinguish well between two classes: Standing and Walking. The reason is the data was collected while subjects were performing morning activities, such as making coffee or preparing breakfast. As a result, a lot of hand movements took

TABLE I. ACTIVITY RECOGNITION ACCURACY OF INDIVIDUAL CLASSIFIERS

Classifier	Left Wrist				Right Wrist			
	S1	S2	S3	Average	S1	S2	S3	Average
Naive Bayes	63.48%	71.09%	76.60%	70.39%	80.46%	67.43%	57.18%	68.36%
SVM (one-vs-one)	75.68%	75.48%	79.13%	76.76%	83.19%	74.89%	81.76%	79.95%
Decision Tree	77.84%	79.06%	81.31%	79.40%	88.30%	79.58%	83.43%	83.77%
Multilayer Perceptron	81.38%	82.52%	83.42%	82.44%	87.65%	80.63%	83.97%	84.08%
k-NN	82.94%	82.71%	84.58%	83.41%	89.31%	81.74%	83.57%	84.87%
Random Forest	84.26%	84.99%	85.95%	85.07%	91.92%	84.70%	86.77%	87.80%

place when the subjects were in “standing” position.

TABLE II. CONFUSION MATRICES OF RANDOM FOREST

SUBJECT 1					
Ground Truth	a	b	c	d	Classified As
Left Wrist	**652**	70	43	1	a = Standing
	96	**192**	12	0	b = Walking
	13	0	**510**	0	c = Sitting
	22	5	0	**49**	d = Lying
Right Wrist	**733**	33	7	0	a = Standing
	73	**226**	3	0	b = Walking
	7	0	**521**	3	c = Sitting
	0	0	10	**68**	d = Lying

SUBJECT 2					
Ground Truth	a	b	c	d	Classified As
Left Wrist	**545**	72	13	1	a = Standing
	104	**212**	14	0	b = Walking
	26	6	**566**	2	c = Sitting
	2	0	3	**53**	d = Lying
Right Wrist	**570**	59	8	0	a = Standing
	131	**192**	5	0	b = Walking
	20	3	**571**	4	c = Sitting
	1	0	17	**40**	d = Lying

SUBJECT 3					
Ground Truth	a	b	c	d	Classified As
Left Wrist	**590**	49	21	0	a = Standing
	95	**255**	10	0	b = Walking
	29	2	**302**	0	c = Sitting
	0	0	0	**113**	d = Lying
Right Wrist	**559**	45	10	3	a = Standing
	100	**318**	3	0	b = Walking
	32	2	**296**	2	c = Sitting
	0	0	1	**126**	d = Lying

C. Multiple Classifiers

We combine the best classifiers in the previous section using Majority Voting and Average of Probabilities fusion method. The right wrist data from subject 1 is used in this experiment. Each combination is evaluated with 10-fold cross validation. Table III provides the accuracy results for all combinations.

From Table III, it can be seen that both fusion methods achieve high accuracy, i.e., above 89%. The best performance is the combination of Random Forest and k-NN using Average of Probabilities approach. The reported human activity recognition accuracy is 91.98%. Note that the combination of classifiers may outperform individual classifiers. For example, the combination of k-NN, Decision Tree, and SVM outperforms each of them individually. But the single best classifier, i.e., Random Forest, is hard to beat by either fusion method. We also investigate the confusion matrices of the best combination, which is Random Forest combined with k-NN, using the Average of Probabilities fusion approach (Table IV). Compared to Table II, this combination slightly improves over Random Forest for classification between Walking and Standing. However, the incorporation of k-NN also introduced errors, such as misclassification between Sitting and Lying for right wrist in Table IV.

TABLE III. HUMAN ACTIVITY RECOGNITION ACCURACY OF COMBINATION OF CLASSIFIERS

Combination of Classifiers	Avg. of Pro.	Major. Voting
k-NN, Decision Tree, SVM	89.96%	89.79%
Random Forest, Decision Tree, SVM	89.13%	90.56%
k-NN, Multilayer Perceptron, Decision Tree	90.32%	89.55%
Random Forest, kNN, Multilayer Perceptron, SVM	90.86%	89.79%
Random Forest, k-NN, NB	90.20%	90.38%
Random Forest, k-NN, Decision Tree	90.62%	91.27%
Random Forest, kNN, Multilayer Perceptron, Decision Tree	90.97%	90.56%
Random Forest, k-NN, SVM	91.63%	90.38%
Random Forest, k-NN, Multilayer Perceptron	91.15%	91.03%
Random Forest, k-NN	91.98%	90.20%

TABLE IV. CONFUSION MATRICES OF THE COMBINATION OF RANDOM FOREST AND K-NN USING AVERAGE OF PROBABILITIES

SUBJECT 1					
Ground Truth	a	b	c	d	Classified As
Left Wrist	**651**	69	45	1	a = Standing
	89	**196**	12	3	b = Walking
	14	0	**509**	0	c = Sitting
	18	5	0	**53**	d = Lying
Right Wrist	**731**	34	7	1	a = Standing
	65	**236**	1	0	b = Walking
	8	0	**517**	6	c = Sitting
	0	0	13	**65**	d = Lying

V. CONCLUSION AND FUTURE WORK

A. Conclusion

We have proposed to use the acceleration data generated by one wrist-worn sensor to recognize ambulation activities. To enable human performance evaluation applications, we focus on four primary activity types: Walking, Standing, Sitting and Lying. We described the extraction of 12 different features and evaluated 6 widely used classifiers for our task as well as their combinations. The empirical evaluation was conducted with real-world activity data generated by three subjects. On average, the classification accuracy by individual classifiers range from 68.36% to 87.80% for both wrist sensors. In general, the right wrist yields higher accuracy than the left wrist. The results show that Random Forest achieves the highest accuracy among individual classifiers, up to 91.92%, and the combination of Random Forest and k-NN using Average Probability can further improve the performance. We believe that acceleration data generated by only one wrist-worn sensor is sufficient for ambulation activity recognition and can enable various human performance evaluation applications.

B. Future Work

One direction of future work is to improve the accuracy of the selected classifiers. Recall that the confusion matrices in in Table II and Table IV show that most misclassification happens between class Walking and class Standing. Therefore, we plan to extend our work by studying other potential features that may help distinguish better between these two activities.

In addition, various human performance evaluation applications require to recognize complex activities, such as performing housework, which can be a composite of simple ambulation activities. We will extend our work and investigate the recognition of complex activities.

Another important future work is to collect data from more subjects in realistic settings, especially to simulate performance evaluation scenarios, such as during workouts and daily living environment.

Last but not least, we can also investigate an automatic sensor data generator based on historical data. It often occurs that the wearable devices are out of battery or out-of-sync. In those cases, the activity data cannot be collected in real time. We suggest to build a prediction model based on the user's historical data to predict possible movements and activities for real-time human performance monitoring applications.

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