

Position-independent Human activity recognition using smartphone sensors

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1. Introduction:

The purpose of Human Activity Recognition (HAR) is to distinguish human daily physical behaviors through the analysis of relevant data obtained from various methods (e.g., video-based and sensor-based approach). Compared with other systems, smartphone-based sensor system has significant advantages in terms of computing power, portability, ubiquity and cost [1][2]. This system has been widely used in many fields, such as health care, smart home, game entertainment, Robot R&D, surveillance, sport and fitness [3][4][5][6]. However, previous work mainly focuses on several specific on-body positions, such as hand, trouser pocket, jacket pocket, hand, armband [7][8][9][10][11]. In fact, people also carry their smartphones in other locations. Moreover, the position of smartphone influences the performance of human activity recognition [12][13][14]. For example, data collected from waist produces different signal patterns from hand. Therefore, it is meaningful to develop a HAR system with considering of various locations where the phone is placed. In general, there are 4 fundamental steps in sensor-based HAR: data pre-processing, segmentation, feature extraction and classification. In this paper, the data is collected from 11 positions including hand, front trouser pocket, back trouser pocket, jacket pocket, upper arm, forearm, backpack front pocket, satchel handbag pocket, tote bag pocket, cross bag pocket, and fanny bag pocket. The main purpose of this paper is to present an effective system which is capable of identifying 6 types of human daily activities including walking, jogging, going upstairs, going downstairs, biking and standing, by using accessible signals collected from 9 subjects' smartphones platform. To eliminate the effect of smartphone's orientation, reduce calculation cost and speed up activity identification, the experiment investigates whether it is possible to successfully recognize human activity through the acceleration data in only one direction (gravity direction in earth coordinate system) instead of 3-axis acceleration and 3-axis gyroscope data from smartphone's local coordinate system. After feature extraction and selection in time domain and frequency domain, 7 classification techniques including Naïve Bayes, K-Nearest Neighbors, Linear Regression, Decision Tree, Support Vector Machine, Random Forest, and Deep Neural Network, are applied to conduct activity recognition tasks.

The contributions of this paper are as follow:

- A new dataset with some new positions of smartphone is presented.
- A model related to acceleration data in only one direction (calculated from 3-axis acceleration and 3-axis gyroscope data) achieves 93% accuracy of HAR with time and frequency domain features under 7 classification methods.
- Data from hand and thigh produces relatively low accuracy using our method.

2. Related Work:

The position of smartphone sensors is a factor which greatly influence the quality of data collection and the accuracy of classification algorithms. Table 1 shows a list of papers separated by the position of smartphones.

Position	Papers
Any position	[20][22][26][27][28][29][34][35][37][42][43]
Waist	[2][11][15][23][30][31][36][40][41][44][45][46]
Trouser pocket	[2][8][9][10][16][17][18][19][21][23][25][32][33][38][39][40][44][45][46]
Coat pocket	[2][16][18][19][21][24]
Hand	[2][17][18][19][25][32][40][46]
Arm	[2][11][33][36][40]
Chest	[11][19][25][33][36][45][46]
Head	[11][36]
Backpack	[18][33]
Shin	[11][36]
Thigh	[11][36]

Table 1. List of papers separated by the position of smartphones

It is meaningful to develop a HAR system without considering the position of the smartphone [47]. To tackle down this problem, one solution is to extract activity-sensitive and position-invariant features which are greatly altered by various human activities but free from different positions under the identical behavior [48][49]. But few satisfactory handcrafted features extracted from domain experts limits this approach. Also, those shallow features cannot be generalized for diverse scenarios. Another method is to firstly determine the specific position of smartphone before the classification of human activity for this position [50][51][52]. The limitation of this way is the uncertainty of position in real application and the requirement of high computing power and long computing time since the model is required to identify the position first and then the activity for each instance. Neither of these two solutions achieves very ideal performance on human activity recognition.

The classification algorithms for generating models to recognize human activities are divided into two groups: conventional machine learning algorithm and deep learning algorithm. The former is relatively shallower and requires feature extraction which is limited by domain knowledge [53]. However, the simpler structure of conventional machine learning (e.g., Support Vector Machine, K-Nearest Neighbors) is more suitable for fast calculation and small database calculation [18][25][54]. The most common deep learning algorithms on HAR, such as Convolutional Neural Network, Recurrent neural network, Long Short-Term Memory and Stacked Autoencoder, provide benefits to generate high-level features that effectively represent the attributes of data [55][56][57][58][59][60]. However, there is a trade-off between HAR model performance and data processing time [61].

3. Database:

The collection of data is carried out in a group of 9 volunteers. The dataset consists of smartphones (iPhone 8/X/11) located at 11 different positions: hand, front trouser pocket, back trouser pocket, jacket pocket, upper arm, forearm, backpack front pocket, satchel handbag pocket,

tote bag pocket, cross bag pocket, and fanny bag pocket. Each person performs 6 human daily activities: walking, jogging, going upstairs, going downstairs, standing and biking. Accelerometer and gyroscope data are recorded at a constant rate of 16 Hz. An important feature of dataset is that gravity and device motion acceleration signals can be directly obtained from iPhone Operation System (iOS) Core Motion System without the separation of gravitational and body motion components from sensor acceleration signal [62]. Previous studies tested different window size and features [63][64][65]. Overlapping windows have been proved to be more suitable because they expand dataset and handle transitions more accurately. The accuracy of human activity recognition from window lengths of one to two seconds are larger than those from other windows [61]. Based on those results, the collection of sensor signals is divided into segments with the identical 2-second window length and 50% overlapping. The dataset is randomly partitioned into 70% as training set and 30% as test set.

4. Coordinate Transformation:

3-axis accelerometer and gyroscope data, which are related to smartphone's local coordinate system, are recorded from iOS Core Motion System during the process of data collection. *User Acceleration* \vec{A}_u attempts to define the 3-axis acceleration vector that the user imparts to the device rather than gravity force. *Gravity* \vec{A}_g represents 3-axis gravity acceleration vector in the smartphone's local coordinate. A_{gx}, A_{gy}, A_{gz} are the three components of resultant gravity acceleration whose magnitude is supposed to be 1.000g.

In order to recognize human activities with uncertainty in different orientation, coordinate transformation from smartphone's reference frame to earth's coordinate system are required. This conversion can be interpreted in terms of Eulerian angle differences of two frames [66]. Although it is meaningless to determine whether the smartphone is back-to-front during human activity recognition process, the absolute value of horizontal component of acceleration can be derived. The vertical acceleration (A_v) and horizontal acceleration (A_h) can be formulated as

$$A_v = \frac{\vec{A}_g \cdot \vec{A}_u}{\|\vec{A}_g\|_2}$$

$$|A_h| = \|\vec{A}_u\|_2 \times \sqrt{1 - \left(\frac{\vec{A}_g \cdot \vec{A}_u}{\|\vec{A}_g\|_2 \times \|\vec{A}_u\|_2}\right)^2}$$

where $\|\vec{A}_g\|_2$, $\|\vec{A}_u\|_2$ represents Euclidean norm of A_g and A_u .

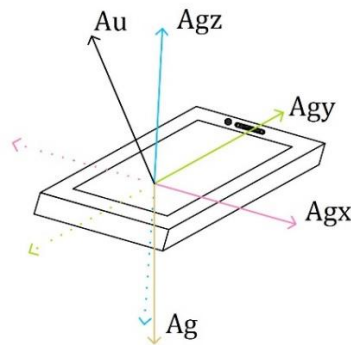


Figure 1. Smartphone's local coordinate system and transformation

5. Feature Extraction and Selection:

The basic idea of feature extraction is the computation of feature vector from signal windows. To avoid the influence of smartphone orientation, the most common features based on A_v have been extracted in time domain and frequency domain. Frequency-based features are transformed from time-based features through Fast Fourier Transform. In fact, due to different aims and settings, it is difficult to compare different but overlapping feature sets from preceding studies [67]. However, some features, such as frequency-based features and autoregression coefficients in time domain, have been proved to be a good factor in activity recognition improvement [68]. Those special features are capable of mitigating the variation in motion data of identical activity in different positions. There are 29 features have been used to recognize human activities in this research:

Domain	Feature
Time domain	Mean, Max, Min, Median, Mad, Std, Interquartile Range, Entropy, Zero Crossing Rate, Signal Magnitude Area, Root Mean Square, Energy, Skewness, Kurtosis, 1 st – 4 th Autoregression Coefficient
Frequency domain	1 st – 8 th Fast Fourier Transforms Coefficients, Skewness, Kurtosis, Entropy

Table 2. Summary of extracted features

Feature extraction can sometimes generate irrelevant features which causes the negative impact on the performance of classification algorithms. To improve the performance of models and reduce the computational cost, feature selection is a vital process to select those features which contributes most to the result. In this research, High Correlation Filter method is used to remove features that are highly correlated with others and provide redundant information through the calculation of the correlation between independent numerical variables.

6. Classification:

In this study, 7 classifiers are used for the classification of human activity. Naïve Bayes (NB) simplifies learning based on Bayes' theorem with strong independence assumptions between the features. K-Nearest Neighbors (KNN) is a non-parametric classification method, which classifies data by finding the training data with a minimal Euclidean distance to the samples in the test set. Linear Regression (LR) is a linear approach to modelling the relationship between a scalar response and one or more explanatory variables. Decision Tree (DT) classifies data by constructing a flowchart-like structure which consists of internal nodes (test on an attribute), branches (outcome of the test) and leaves (class label after computing all attributes). Support Vector Machine (SVM) separates data by finding hyperplanes that effectively differentiate the classes. The map of data from input space into a higher dimensional feature space improve the classification performance. Random Forest (RnF) is an ensemble learning method for classification which operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees. Deep neural network (DNN) is a network of neurons organized in a sequence of multiple layers, where neurons receive as input the neuron activations from the previous

layer, perform a simple computation and output a result. Hyperparameters are the variables which determines the network model and the network result. Generally, there are many different approaches to find the best hyper-parameter values in deep neural network. In this paper, a randomized search over parameters is implemented, where each setting is sampled from a distribution over possible parameter value. This has two main benefits over an exhaustive search: ①A budget can be chosen independent of the number of parameters and possible values. ②Adding parameters that do not influence the performance does not decrease efficiency. Three gradient descent optimization algorithms including traditional stochastic gradient descent (SGD), RMSprop, and Adam, are used to tune network weights iteratively. SGD is adapted as it revealed higher performance. The best performance of model is achieved when dropout rate was 0.20. The optimal number of fully-connected layers is determined to be 6 layers after spanning a range of 0 to 10 layers. For the number of neurons in each layer, 300 neurons are selected after testing values from 150 to 500 neurons. Rectified Linear Unit (ReLU) activation function, which computes efficiently and performs better than other methods (e.g., linear function, tanh function and sigmoid function), is used in deep neural network.

7. Result and analysis:

The activity recognition performance of 7 classifiers is shown in Table 2. The best result from DNN algorithm shows an overall accuracy of 93% for the test data consists of 14644 samples. A comparison of the results demonstrates that different classification methods significantly affect accuracy. DNN outperforms the other classifiers. In contrast, SVM and RnF achieves reasonable results. Among six activities, bike, jog and stand exhibit better performance with the recognition accuracy higher than 95%. The classification performance also shows that go upstairs and downstairs have relatively low identification accuracy which is close to 80%. In particular, there is a noticeable misclassification overlap between these two activities and walk. From signal windows, the characteristics of walking, going upstairs and going downstairs are distinguishable for just one subject but similar between different users. Those suggests that the vertical component of device motion acceleration in global coordinate system do not sufficiently represent all human activities and advanced experiment is required to improve classification performance. However, if we only consider two basic activities: dynamic activities (e.g., walk, bike) and static activities (e.g., stand), the model can easily recognize. More detailed results are presented in appendix.

F-Score	NB	KNN	LR	DT	SVM	RnF	DNN
Bike	0.93	0.94	0.95	0.96	0.97	0.97	0.98
Go downstairs	0.55	0.70	0.64	0.65	0.77	0.76	0.81
Jog	0.86	0.93	0.92	0.90	0.95	0.95	0.96
Stand	0.98	0.97	0.99	0.99	0.99	0.99	0.99
Go upstairs	0.50	0.65	0.62	0.61	0.75	0.74	0.78
Walk	0.74	0.86	0.80	0.82	0.90	0.89	0.92
Weighted avg.	0.79	0.87	0.86	0.85	0.92	0.91	0.93

Table 3. F-score of the proposed models for human activity recognition

To further analyze HAR accuracy in each location, the number of mislabeled cases is calculated and shows in Table 4. In this paper, the worse recognition performance (error rate > 8%) exists in four positions including hand, satchel handbag, front trouser pocket and back trouser pocket. Human activities are complex procedures. Data collected from smartphone sensors reflect the movement pattern of the part where the phone is placed. One part of motion data (e.g., data from hand or thigh) at a time makes HAR a difficult task. It is difficult to extract information related to body movement using data from hand or thigh. The result shows the impact of the difference in flexibility of hands, thighs and body during the specific activity.

Mislabeled cases	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Overall cases	Error Percent
hand	0	24	6	5	27	5	610	11%
front trouser pocket	2	31	0	0	23	12	791	9%
back trouser pocket	0	21	1	1	43	18	860	10%
jacket pocket	7	19	0	3	20	3	872	6%
upper arm	0	11	0	2	26	6	878	5%
forearm	0	17	0	0	17	5	801	5%
backpack	0	35	10	1	47	9	1855	5%
satchel handbag	5	89	30	3	120	49	3082	10%
tote bag	7	45	0	1	47	4	1626	6%
fanny bag	10	31	0	2	47	22	1543	7%
cross bag	9	27	4	1	50	31	1726	7%

Table 4. Mislabel cases on each position

8. Conclusion and future work:

This paper introduces a new dataset including several new possible positions for HAR of 9 subjects through smartphone sensors and acknowledge some results using 7 classification methods. The result shows that the best performance of classification algorithm is achieved with Deep Neural Network technique. In this paper, the overall human activity recognition accuracy is 93%. However, the vertical acceleration on gravity direction (A_v), which can eliminate the impact of smartphone's orientation, is not very ideal to recognize highly similar activities (e.g., go upstairs and go downstairs) based on the existing work in this paper. Subsequently, mislabeled cases show that hand, satchel handbag, front trouser pocket and back trouser pocket are the worst positions for human activity recognition due to high flexibility of hand and thigh during human activity process. To continue this research, there are several straightforward improvements: (1) applying more complex deep learning models, such as CNN, RNN and LSTM, to improve the HAR performance using acceleration signals in only one direction. (2) generating more sophisticated but meaningful features (e.g., features in wavelet domain). (3) using some advanced feature selection techniques (e.g., Recursive Feature Elimination) or dimensionality reduction methods (e.g., PCA, t-SNE, ICA). (4) making full use of more data (i.e., 3-axis acceleration and 3-axis gyroscope data collected in this paper). (5) collecting data from more subjects and more potential positions of smartphone. (6) investigating and eliminating the impact of smartphone's orientation on human activity recognition using another method.

9. Appendix:

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2597	15	0	0	21	163	0.93
Go downstairs	5	850	148	0	272	374	0.52
Jog	3	155	1520	0	82	121	0.81
Stand	47	2	0	3152	0	0	0.98
Go upstairs	38	134	47	0	769	839	0.42
Walk	98	232	23	0	187	2750	0.84
Precision	0.93	0.61	0.87	1.00	0.58	0.65	

Table 1. Confusion matrix of classification results on test data using Naïve Bayes

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2602	8	3	124	15	44	0.93
Go downstairs	13	1088	117	0	214	217	0.66
Jog	7	41	1787	0	14	32	0.95
Stand	11	0	0	3190	0	0	0.99
Go upstairs	70	196	33	0	1039	489	0.57
Walk	31	97	11	1	116	3034	0.92
Precision	0.95	0.76	0.92	0.96	0.74	0.80	

Table 2. Confusion matrix of classification results on test data using K-Nearest Neighbors

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2696	3	0	14	24	59	0.96
Go downstairs	7	978	124	0	256	284	0.59
Jog	16	65	1724	0	11	65	0.92
Stand	10	0	0	3191	0	0	0.99
Go upstairs	47	114	25	0	1102	539	0.60
Walk	68	151	16	0	223	2832	0.86
Precision	0.95	0.75	0.91	0.99	0.68	0.75	

Table 3. Confusion matrix of classification results on test data using Linear Regression

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2656	5	4	3	37	91	0.95
Go downstairs	4	1033	111	0	245	256	0.63
Jog	9	93	1655	0	23	101	0.88
Stand	13	0	0	3188	0	0	0.99
Go upstairs	33	178	26	0	969	621	0.53
Walk	34	136	14	0	179	2927	0.89
Precision	0.97	0.71	0.91	0.99	0.67	0.73	

Table 4. Confusion matrix of classification results on test data using Decision Tree

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2741	6	2	3	20	24	0.98
Go downstairs	12	1239	70	0	199	129	0.75
Jog	3	53	1797	0	15	13	0.96
Stand	6	0	0	3195	0	0	0.99
Go upstairs	47	116	25	0	1352	287	0.74
Walk	27	62	8	0	112	3081	0.94
Precision	0.97	0.84	0.94	0.99	0.80	0.87	

Table 5. Confusion matrix of classification results on test data using Support Vector Machine

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2733	5	0	1	23	34	0.98
Go downstairs	4	1183	98	0	217	147	0.72
Jog	4	21	1824	0	7	25	0.97
Stand	12	0	0	3189	0	0	0.99
Go upstairs	41	106	26	0	1287	367	0.70
Walk	18	59	3	0	112	3098	0.94
Precision	0.97	0.86	0.93	0.99	0.78	0.84	

Table 6. Confusion matrix of classification results on test data using Random Forest

Activity	Bike	Go downstairs	Jog	Stand	Go upstairs	Walk	Recall
Bike	2756	3	1	0	22	14	0.99
Go downstairs	5	1299	67	0	168	110	0.79
Jog	1	30	1830	0	9	11	0.97
Stand	18	0	0	3183	0	0	0.99
Go upstairs	37	159	21	0	1360	250	0.74
Walk	14	48	4	0	98	3126	0.95
Precision	0.97	0.84	0.95	0.99	0.82	0.89	

Table 7. Confusion matrix of classification results on test data using Deep Neural Network

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