Enhanced Human Activity Recognition on Smartphone by Using Linear Discrimination Analysis Recursive Feature Elimination Algorithm

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Abstract. Human Activity Recognition (HAR) is a challenging research topic in tracking a person's state of motion and interaction with the surroundings. HAR plays an important role in developing many applications helping improve quality of life. Applications based on HAR could be used in checking the state of health, identifying a mobile phone's context, keeping track of user's physical activities, etc. In this research, we applied Recursive Feature Elimination based on Linear Discrimination Analysis (RFELDA) to (http://topepo.github.io/caret/rfe.html#rfe) reduce the dimensionality of dataset before applying classification algorithms to assign subject's activities. The experiment results on dataset showed that RFELDA improved performance and reduced processor time better than original dataset did.

Keywords: Feature Selection · Smartphones · Human Activity Recognition

1 Introduction

In recent years, Human Activity Recognition (HAR) is a special branch of research in tracking the state of motion. It attracted many researchers' as well as technology companies' special interest. This shows that research in HAR is of great importance. Firstly, the intelligent application systems are based on the identification of human activities and the surroundings. Secondly, HAR somewhat helps identify human being's psychological complexity. Thirdly, in the era of Internet of Things, the applications based on HAR are developed to focus primarily on supporting human beings. Therefore, human activity recognition needs to be studied to develop the system of applications related to human activity.

Applications based on human activity recognition could be used in: checking the state of health [1], detecting the fall status of patients [2], recognizing outdoor contexts, keeping track of individual's daily activities [3–5], recognizing terrorists or crimes in the crowd, etc.

HAR would be based on various devices including camera, mobile devices (smartphones, smartwatches, glasses, etc.) and home sensors. However, human activity recognition is primarily based on smartphone. Firstly, a smartphone is normally equipped with many sensors such as acceleration, gyroscope, GPS, image, audio, light,

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temperature, etc. Secondly, the smartphone is one of the intelligent devices which are used most in our society because of their small size, wearability and modern functions like computing power. Thirdly, in recent years, research in human activity recognition based on sensor-embedded smartphones has been conducted by organizations and companies, and has stimulated the great interest among researchers [4].

For these reasons, in our research, we deployed the Human Activity Recognition System (HARS) on Androi-based cell phones which are equipped with two popular sensors: three-dimensional acceleration sensor-xyz, and gyroscope-xyz. Data collection and application development are conducted on Android because its operating system is free, open-source, easy to program. The system we developed helps identify and classify a user's daily activities including: walking, going upstairs, going downstairs, sitting, standing, and lying.

We apply RFELDA to select features and reduce dimensionality of dataset. Machine learning algorithms (Naïve Bayes, k-nearest – neighbor (KNN), Random Forest) are used to identify user's activities. The results of our experimental research are very positive and promising. The accuracy of Random Forest method is 91.89%, k-nearest neighbor is 85.81%, and Naïve Bayes is 69.69%.

This paper is structured in the following way: Related work is depicted in Sect. 2; The Human Activity Recognition System is presented in Sect. 3; The Evaluation Method is described in Sect. 4; the experiment results are showed in Sect. 5; The Conclusion is described in Sect. 6.

2 Related Work

Human activity recognition is a fundamental step in building the intelligent application systems. In general, stages of processing information in the intelligent systems include: data collection, data analysis, decisive orientation and response to the surrounding context. Human activity recognition is conducted in two first stages. The goal is to classify the simple-to-complex activities. In order to reach this goal, researchers used different instruments to monitor a user's activity level. However, two most common instruments are cameras (image sensors) and wearable devices. Through these instruments, human activities can be divided into five main groups (see Table 1).

Table 1. Activities and applications based on human activity recognition

Application	Example
Daily activity	Watching television, ironing, eating, bathing, cleaning, and watering
Locomotion	Cycling, driving, drop, falling, standing, and sitting
Community	Calling, chatting, and talking
Security	Detecting terrorism and crime
Sports/Fitness	Jumping, weightlifting, swimming, and skiing

Yet, using cameras to monitor a user's activity level is most likely limited and has some disadvantages. For example, cameras equipped in rooms where the user stays must be high-resolution. Additionally, using cameras is able to cause the user's feelings of be uncomfortable. Thus, the use of wearable devices may be more effective because they are equipped with various sensors and easy to carry. For this reason, many research projects have been conducted on mobile devices, like cell phone, in order to build applications which are used in the elderly's healthcare [6, 7] and the falling state detection [8, 9]. Activities recognized from sensors associated with the surroundings are also analyzed in order to avoid the situation in which the user's cell phone is falling onto the floor. Additionally, applications based on HAR to keep track of a person's daily exercise and measure the level of energy consumption [10, 11] have also been developed to give users the necessary advice for fitness.

In another research project, N. Ravi [12] used acceleration sensors to identify human activities. He left them on the participant's pelvic to identify seven actions including: standing, walking, jogging, climbing stairs, going downstairs, vacuuming, and sitting upright. He used decision trees, k-Nearest Neighbors, SVM, Naïve Bayes to evaluate the accuracy.

In 2013, Guiry et al. [13] used algorithms including C4.5, CART, SVM, Multi-Layer Perceptrons, Naïve Bayes to collect data from sensor-based cell phones. A total of 24 volunteers participated in the experimental research. The sensors were placed inside the participants' chest. And, the results showed that the accuracy of recognizing activities including lying, sitting, standing, walking, jogging and cycling was 98%. Additionally, in 2015, Capela et al. [14] proposed a method to increase the capability for classifying human activities including sitting, standing and lying. The experimental research was conducted on Blackberry Z10 smartphone with two sensors: acceleration and gyroscopes with a view to collecting 16 daily activities. The total of 30 people of different ages participated in the study. The Blackberry Z10 smartphone was placed on the participants' right-front hip. The researchers focused on recognizing the transitioning-into and transitioning-out state of a sitting to evaluate accurately the sitting activity. Sang et al. [15] also used smartphone devices with two common sensors (accelerometer and gyroscope) to collect data on human activities including: going downstairs, going upstairs, sitting with the phone in a pocket, driving and putting the phone on the table. They used two algorithms including k-Nearest Neighbors (kNN) and Artificial Neural Network (ANN) to classify user's activities. The result showed that the accuracy of recognizing five activities was 74% for kNN and 75.3% for ANN.

Differing from other researchers, several groups of researchers primarily focus on the preprocessing stages: feature extraction and selection to reduce the dimensionality of data, selection of the optimal feature subsets. For example, Tuan Dinh and Chung Van [16] applied Correlation-based Feature Selection method and the Instance-Based Learning Algorithms Family (IB3) to remove redundant instances and irrelevant features.

Therefore, for the classification to be better, we applied RFELDA method to our research. This method helps reduce the redundant features and the processor time better than using the original dataset.

3 The Human Activity Recognition System

The human activity recognition system consists of four components: data collection, feature extraction, dimensionality reduction and classification labels (Fig. 1).

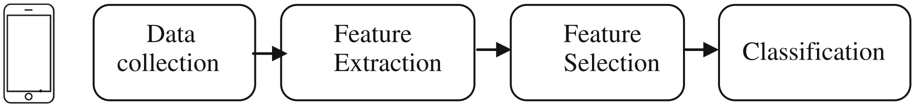

Fig. 1. The process of activity recognition

3.1 Data Collection

Dataset was collected from the smartphone with accelerometer and gyroscope sensors. The smartphones were placed on the left of the participants' waist. The acceleration and gyroscope signals have proved to be effective for human activity recognition. Because accelerometer sensor is used to determine acceleration though a three-axis accelerometer identifying the changes of the cell phone's direction, whereas gyroscope plays as a rotation sensor to determine the rotation of the phone.

3.2 Feature Extraction

The collected signals with noise will be pre-processed to eliminate some unwanted features. The unwanted features will be eliminated by applying noise filters and then divided into small sliding windows of 2.56 s and 50% overlap (128 readings/window). Feature extraction will be carried out with the time domain and frequency domain. For each row in the dataset, it is 561 feature vectors with time domain and frequency domain, user's activity labels and the subject in the experiment.

3.3 Feature Selection

We included a correlation matrix to remove redundant features with threshold 0.95 before using the backward recursive feature elimination selection. This is a method which starts with all features, and then removes redundant features based on ranking criteria until satisfied with a stop condition. For Linear Discrimination Analysis, it is an application of RFE using LDA criteria for ranking. The goal is to project a dataset onto a lower-dimensional space with good subset of features. The LDA algorithm and cross validation method are used repeatedly to evaluate the model. It is configured to explore good subset of the features. The RFELDA would give a good rank variables and the error prediction would be lowered.

Linear Discrimination Analysis was performed on the basis of the minimum total error of classification model. The observation is assigned to the class label with the highest probability. It is also called Bayes rule. According to Bayes' rule, if there are n classes, observation x will be assigned to class i:

$$\mathrm{P(i} \mid x) > \mathrm{P(j} \mid x),\ \forall j \neq i$$

Formula in Bayes theory describes the relationship between two conditional probabilities P(i|x), P(x|i):

$$P(i \mid x) = \frac{P(x \mid i) * P(i)}{\sum_{\forall j} P(x \mid j) * (P(j)} \tag{1}$$

To make it convenient for the calculation, statisticians have found equivalent conversion formula called discrimination Analysis.

$$\mathrm{f_i} = \mu_i C^{-1} \boldsymbol{x}_k^T - 1/2\, \mu_i C^{-1} \mu_i^T + \ln(p_i) \tag{2}$$

To assign an observation to the ith class label if the probability f_i is the highest. In the formula (2), the component $\mu_i C^{-1} \mu_i^T$ is Mahalanobis distance to measure the distance discrimination among groups.

LDARFE Algorithm following steps:

Inputs:

Step 1: Initalize

Training examples F = $\{f_1, f_2, \ldots f_k, \ldots f_n\}$

Set p=n // p: number of features, p=152 features

Class labels : y = [walking, walking up,walking down, sitting,standing, lying]

Feature ranked list r **= { }**

Step 2: Train data the classifier LDA

Step 3: Calculate discriminant coefficients of eigen vector from LDA classifier to evaluate the relevancy of each feature for activity classification by using k-cross validation

Step 4: Find the feature f_i with the smallest F-value ranking which is removed

Step 5: Update feature ranked list

r **=** ***{****r* U *[F(fi), r]****}***

F={F-fi} and set p=p-1
Go to step 2 unitl p=1 or F={ }

Output: Feature ranked list r.

3.4 Classification Algorithms

The Machine Learning algorithms are applied to classify user's activities after reducing original dataset. In this system, we were recommended to use Random Forest, Naïve

Bayes, KNN because they help us obtain good performances better than other classifications do. To evaluate classifications, we used k-cross validation to estimate the performance models.

4 Evaluation Method

To evaluate the performance system, we use confusion matrixes, precision (P), recall (R), F-measure (F) and the accuracy metrics.

The accuracy was calculated by the following formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where,

TP (True Positives): The number of positive observations was assigned to positive class label.

TN (True Negatives): The number of negative observations was assigned to negative class label.

FP (False Positives): The number of negative observations was assigned to positive class label.

FN (False Negatives): The number of positive observations was assigned to negative class label.

Precision (P) is positive predictive value:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall (R) is true positive rate:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F-measure (F) is a value to be derived from recall and precision

$$\text{F - measure} = \frac{2 * \text{P*R}}{\text{P} + \text{R}}$$

5 Experiment Results

5.1 Experiment Design

Dataset was collected from 30 participants of the age between 19 and 49. Each participant wore Samsung Galaxy II cell phone on the waist and then performed six physical activities including: walking, going upstairs, going downstairs, sitting, standing, and lying down. The Samsung Galaxy smartphone was equipped with two sensors: accelerometer and gyroscope. The former is to determine 3-axial linear acceleration and the latter is to determine 3-axial angular velocity at a constant rate of 50 Hz.

Dataset was divided into two sets, 70% for training the classifier and 30% for testing. Noise signals in datasets will be eliminated by applying noise filters and then divided into small sliding windows of 2.56 s and 50% overlap (128 readings/window) for feature extraction from the time domain and frequency domain. Each row in dataset has 561 feature time and frequency domain. We used parallel computing using R tool and caret package. The Human Activity Recognition Dataset (UCIHAR) was downloaded from UCI's website.

We included a correlation matrix to remove redundant features with threshold 0.95 and obtained 277 features before applying RFELDA algorithms to reduce dimensionality of dataset from 277 features to only 152 features. Finally, we used algorithms to classify users' activities.

5.2 Feature Selection Result

LDA recursive feature elimination algorithm selected important features from the 277 features in the dataset. We plot the result of RFELDA algorithm and choose features which have greater value than threshold 0.9. We obtained 152 features compared to 561 features of original dataset (Fig. 2).

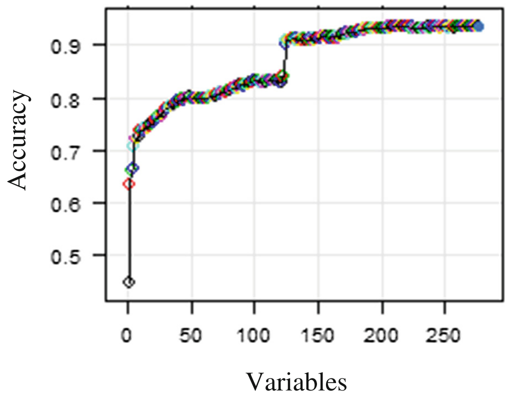

Fig. 2. The variable importance chart

5.3 Result of Classification

Confusion Matrix. The results are presented in Tables 2, 3 and 4. We observed the Precision, the Recall and The F-Measure of classifications. We found that the results of random forest are better than others. Particularly in the case of lying state, using random forest algorithm obtained the highest precision (100%).

Table 2. Confusion matrix of kNN results on testing data

	Walking	Upstairs	Downstairs	Sitting	Standing	Lying	Recall %
Walking	473	67	105	0	0	0	0.733
Upstairs	14	401	65	2	0	0	0.832
Downstairs	9	3	250	0	0	0	0.954
Sitting	0	0	0	336	41	0	0.891
Standing	0	0	0	153	491	20	0.739
Lying	0	0	0	0	0	517	1
Precision %	0.954	0.851	0.595	0.684	0.923	0.963	
F-measure %	0.829	0.842	0.733	0.744	0.821	0.981	

Table 3. Confusion matrix of Naïve Bayes results on testing data

	Walking	Upstairs	Downstairs	Sitting	Standing	Lying	Recall %
Walking	365	45	76	0	0	0	0.751
Upstairs	58	401	61	5	12	7	0.747
Downstairs	73	25	283	0	0	0	0.743
Sitting	0	0	0	356	267	0	0.571
Standing	0	0	0	25	120	1	0.822
Lying	0	0	0	105	133	529	0.69
Precision %	0.736	0.851	0.674	0.725	0.226	0.985	
F-measure %	0.743	0.796	0.707	0.639	0.354	0.811	

Table 4. Confusion matrix of random forest results on testing data

	Walking	Upstairs	Downstairs	Sitting	Standing	Lying	Recall %
Walking	462	28	25	0	0	0	0.897
Upstairs	26	437	50	1	0	0	0.85
Downstairs	8	6	345	0	0	0	0.961
Sitting	0	0	0	408	13	0	0.969
Standing	0	0	0	77	519	0	0.871
Lying	0	0	0	5	0	537	0.991
Precision %	0.931	0.928	0.821	0.831	0.976	1	
F-measure %	0.914	0.887	0.886	0.895	0.92	0.995	

Activities in the same group could be missing classification against different group. Static activity compared to dynamic activity. For example, sitting, standing and lying in the same group is difficult and missing classification. However, activities in different group could be clearly classified.

Accuracy. With regard to the accuracy of classifications by using kNN, Naïve Bayes, and Random forest classifiers, Table 5 shows that the accuracy of Random forest model was 91.89% higher than Naïve Bayes (69.69%) and KNN model (85.8%). This indicates that Random forest model is the best approach and should be chosen. The calculation of the error of Random forest model is 1.00 – accuracy (0.0811).

Table 5. The accuracy of testing classifications

Method	Accuracy %
KNN	85.81
Naïve Bayes	69.69
Random forest	91.89

Sensitivity (Recall), Specificity. We plot the sensitivity and specificity rate of our results in Fig. 3. We found that Random forest is better in both aspects.

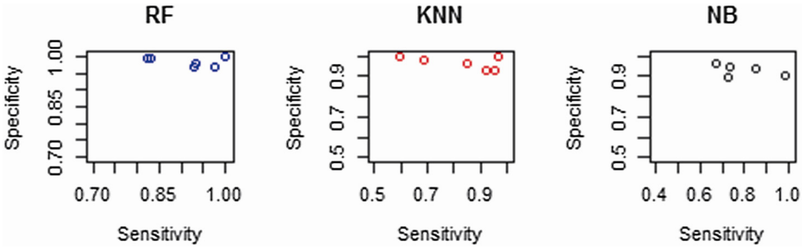

Fig. 3. The sensitivity (recall) and specificity models

6 Conclusion

In this paper, we proposed a new method for reducing irrelevant features. Our experimental results show that the system improved processor time and enhanced the accuracy of recognizing the user's activities better than original UCI dataset did. However, this approach could be further improved in several aspects. In the future, we are investigating feature subsets with higher classification and obtaining a small size with other classifications such as Support Vector Machine (SVMRFE), Principle Component Analysis (PCA). It is able to further improve the model performance by tuning the model parameters and collecting more users' activities.

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