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HUMAN ACTIVITY RECOGNITION BASED ON ADABOOST ENSEMBLE CLASSIFIER

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Abstract. Human activity recognition (HAR) has been widely applied in the field and has good application prospects. Various classifiers in machine learning have shown excellent performance in their own fields. In this paper, AdaBoost ensemble classifier for human activity recognition is proposed to improve the performance of human activity recognition technology by using a weighted combination of multiple classifiers. The experimental results of HAR data were evaluated, and the total classification accuracy and receiver operating characteristic (ROC) area were calculated. The results show that the AdaBoost ensemble classifier framework proposed in this paper can accurately identify six kinds of human activities, and the AdaBoost ensemble classifier algorithm can significantly improve the HAR recognition accuracy.

Keywords: human activity recognition, AdaBoost, ensemble classifier.

Introduction

Human activity recognition (HAR) refers to the automatic detection of various physical activities that people perform in their daily lives. The system helps identify the activities that people perform and provides information feedback for intervention. Human activity recognition technology aims to perceive the external performance of human behavior and identify its categories according to the perception results. As a key technology that enables computers to provide services to people in a more active and natural way, human activity recognition has attracted the interest of researchers for its wide range of potential applications in recent years. Human activity recognition is widely used in surveillance [1], security [2], education [3], sports [4], medical [5] and other fields.

In recent years, with the intelligent mobile devices (such as smart phones and wearable devices) and related sensors (such as motion sensor, and skin conductance sensor) such as the rapid development of technology, user activity recognition technology research focus is from the method based on computer vision to the user to carry the intelligent recognition method based on other sensors on a mobile device [6]. These emerging user activity recognition technologies based on intelligent mobile devices do not rely on external devices and are more in line with the requirements of contemporary people for portable activity recognition. Machine learning classifiers are often used to evaluate the prediction accuracy of human activity recognition.

This research aims to introduce the basic process of human activity recognition and evaluate the performance of different classifiers. The smart phone-based accelerometer has a sampling frequency of 50 Hz and collects daily life data of human activities, including walking, walking upstairs, walking downstairs, siting, standing, and lying. Use k-nearest neighbor (kNN) [7], Naïve Bayes (NB) [8], support vector machine (SVM) [9] and random forest (RF) [10] to evaluate the data set. The research results show that RF has the highest accuracy for human activity recognition.

This paper uses AdaBoost ensemble classifier to identify human activity data collected by human body sensor. The traditional classification method is to find a classifier closest to the actual classification function in a space composed of various possible functions, and the classification accuracy is often not ideal [11]. Ensemble classifier builds a group of base classifiers from training data (base classifiers mainly include RF, NB, SVM，kNN, etc.) and then classifies by voting the prediction of each base classifier. By aggregating the prediction results of multiple classifiers, the classification accuracy of the classifier can be improved, and the weighted combination of multiple classifier models can achieve better performance, which has been well promoted and applied in practice.

In this paper, the AdaBoost ensemble classifier framework for human activity recognition is proposed, it shows in Figure 1.

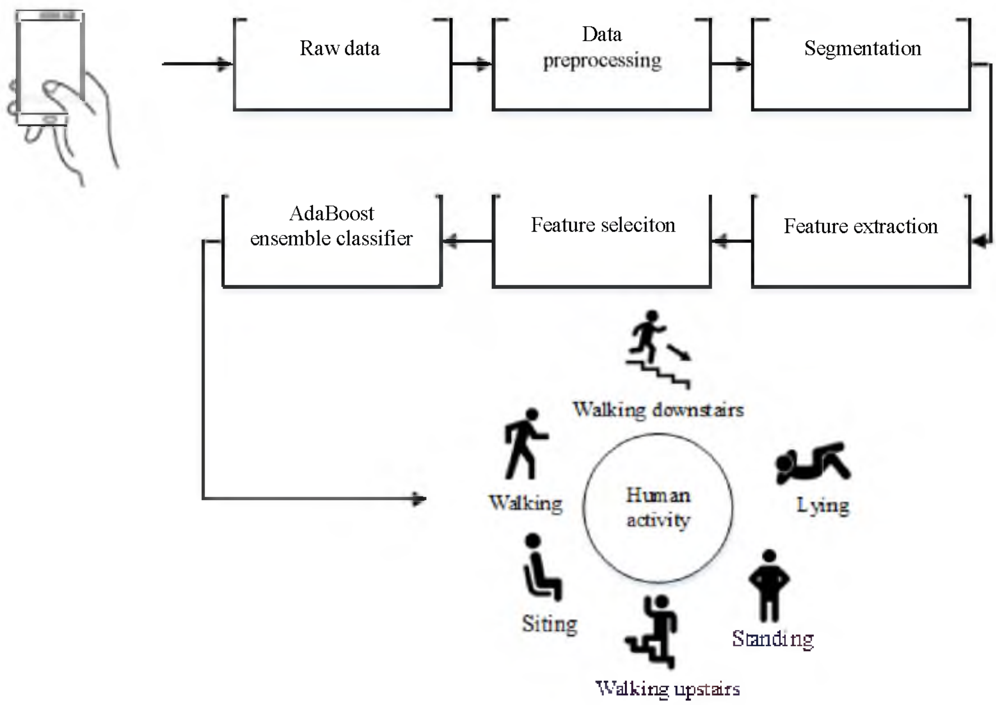

Figure 1. Human activity recognition based on AdaBoost ensemble classifier

Different base classifiers (RF, NB, SVM, and kNN) are compared to study the performance evaluation of base classifier and AdaBoost ensemble classifier. Experimental results show that the ensemble classifier based on AdaBoost algorithm is feasible in practical problems. Significantly improved automatic HAR performance. The search for local extrema is a basic operation for many image processing tasks.

Classification methods

AdaBoost algorithm can be applied to a variety of base classifiers to form a variety of combined classifiers. This paper mainly selects RF, NB, SVM, KNN and decision tree C4.5 as base classifiers for research.

Random forest is an ensemble classifier based on multiple base classifiers [10]. The construction process of the random forest is as follows: Firstly, bootstrap sampling is used to extract K samples from the original training set, and the sample size of each sample is required to be consistent with the original training set. Secondly, a decision tree model is constructed for each sub-sample, and K decision trees are trained. The last K decision trees are voted for the final classification. The random forest algorithm constructs a decision tree for each training subset and generates N decision trees. Node splitting is the core of the algorithm. Only through node splitting can a complete decision tree be generated. Each tree selects attributes based on the Gini index.

Naïve Bayes classifier is based on the assumption that each attribute of the sample is independent from each other, requiring fewer parameters to be estimated and smaller error rate than other classifiers [8]. When the correlation between attributes is small, NB classifier can achieve better performance.

Support vector machine (SVM) is a classifier for linear and nonlinear data, which is characterized by simultaneously minimizing empirical error and maximizing geometric edge regions [9]. It uses nonlinear mapping to transform original training data into high dimensional data. In this new dimension, the linear optimal separation hyperplane is studied. By appropriately nonlinear mapping to an efficient high-dimensional hyperplane, the maximum spacing hyperplane is established, which is discovered by support vector machines using support vectors and boundaries. It is assumed that the larger the distance or gap between parallel hyperplanes, the smaller the total error of the classifier. Then the covering theorem can be used to achieve linear separation in the result feature space.

k-Nearest-Neighbor (kNN), as one of the classical classification methods, is a non-parametric classification method based on comparison learning, which has the characteristics of simple implementation and high robustness [7]. It is used to store all available cases into multiple categories and predict the classification of new cases based on the nearest k-nearest neighbor. kNN algorithm uses distance measure functions (such as Euclidean distance) to find k-nearest neighbors. Most of k nearest texts belong to a certain category, so the samples also belong to this category.

C4.5 is an extension of ID3 [8] and classifies samples by generating decision trees. Decision tree is an inductive learning algorithm, which extrapolates classifiers in the form of decision tree from training sample sets and uses top-down recursive method. C4.5 uses the information gain rate function as the classification standard, and uses the value of "classification information" to standardize the information gain, avoiding the disadvantage of using the information gain to select attributes with more values. Compared with ID3, it can discretize continuous attributes, process incomplete data, and prune trees in the process of tree construction.

AdaBoost is an iterative algorithm [11]. Firstly, different training subsets are sampled from the same training sample set, and then different base classifiers are trained with these different training subsets. Finally, these base classifiers are combined to form a strong classifier. In AdaBoost algorithm, each sample in the training sample set is assigned a weight, which represents the probability that this sample is selected into the training subset by a base classifier. The AdaBoost process is shown in Figure 2 and Figure 3.

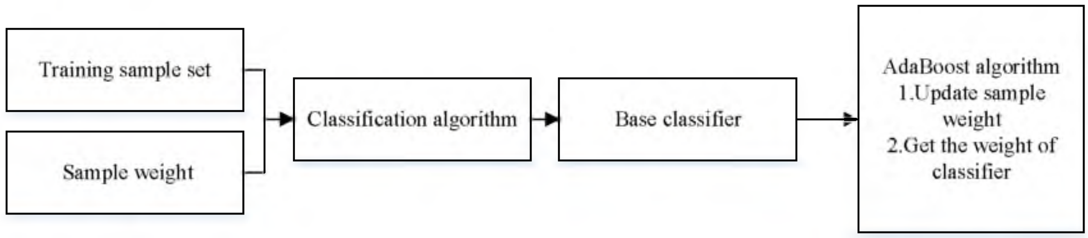

Figure 2. AdaBoost iterative training process

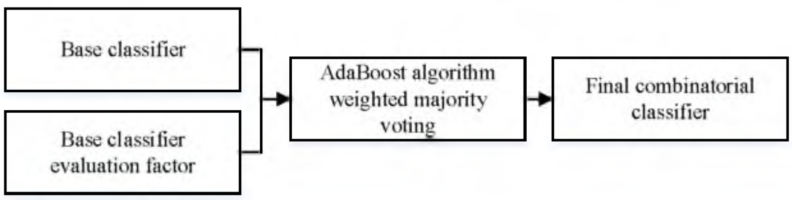

Figure 3. The block diagram of the generation of combined classifier (AdaBoost with single algorithms)

In each iteration, the weight of the sample is updated according to whether the classification of the sample is correct or not and the classification accuracy of the whole training sample set last time. Then, according to these weights, sample points are selected to obtain a new training subset and train the next base classifier. If a sample is correctly classified, its weight will increase and its probability of being selected into the next training subset will increase, while if a sample is incorrectly classified, its probability of being selected into the next training subset will decrease, thus making the AdaBoost method focus on those relatively difficult samples.

In the concrete implementation process, first of all, the weight of all samples in the initial seasonal training sample set is equal. Secondly, in the t iteration, sample points are selected according to the sample weight to form a training subset, and the training base classifier H_t is trained. All samples are classified to improve the weight of incorrectly classified samples and reduce the weight of correctly classified samples; the updated weighted sample set is used to generate the next training subset and train the next base classifier H_{i+1}. Finally, multiple base classifiers generated by iteration are used to classify the samples, and weighted majority voting is carried out on the classification results to obtain the final result.

Final classifier: As shown in Figure 3, a set of base classifier $h_1, h_2, ..., h_t$ generated by iteration is used first sample X is classified to get the classification result $h_1(x), h_2(x), ..., h_r(x)$, and then they are voted with weight $\alpha_1, \alpha_2, ..., \alpha_t$ to get the classification result.

Experimental results

Through accelerometer and gyroscope embedded in smart phone to collect speed and gyroscope sensor data, sensor data collection of mobile phone data collection application matlab@mobile is opened, and placed in the pants pocket of the activity, when the activity is completed, take out the mobile phone to close the application. In the process of data collection, the scene mode of normal life was simulated. Six basic physical activities were completed: 1. Walking, 2. Walking upstairs, 3. Walking downstairs, 4. Siting, 5. Standing and 6. Lying. The 66 time features extracted from ACC data and related to 6 physical activities are used in the analyzed HAR system.

Figure 4 shows the original ACC data distribution point diagram based on two features in the time domain (TotalAccYMean and TotalAccXMean). It follows from the figure recognizing 6 classes of activities requires design of a new feature space by mean of the classifier proposed in the paper.

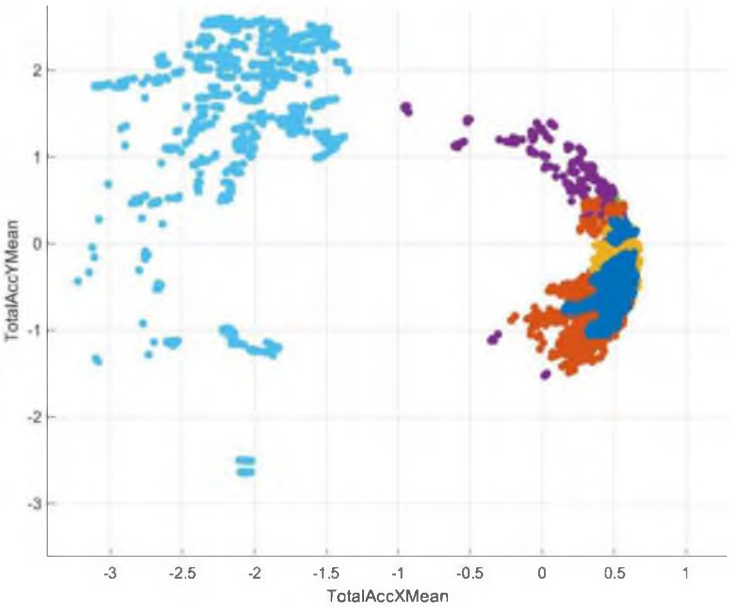

Figure 4. Distribution of ACC data activity classes in two dimensional feature space

Performance evaluation measures

In this paper, experiments are set up to evaluate the classifier to achieve consistency evaluation of model quality and quantitative study of prediction performance of the model. Accuracy measures are often used to evaluate the performance of classifiers. In fact, this metric measures the percentage of correctly classified examples. In the case of binary classification, the classification accuracy can be expressed as:

$$Accuracy = \frac{T_N + T_P}{F_P + F_N + T_N + T_P}, \quad (1)$$

where T_N (True negatives) represents the correct classifications of negative examples, T_P (True positives) represents the correct classifications of positive examples, F_N (False negatives) and

F_p (False positives) represent, respectively the positive examples incorrectly classified into the negative classes and the negative examples incorrectly classified into the positive classes.

In the process of training, the training model can match the training data, but cannot match the test set well. In order to better deal with the evaluation method of bias and variance tradeoff, this study adopts the 10-fold cross-validation method to randomly divide the data set into 10 parts, ensuring that each part takes turns as a test set, and the remaining 9 parts as a training set, so as to select more appropriate parameters for the model.

Area under curve (AUC) is the area under the ROC curve. We often use AUC value as the evaluation standard of the model, because in many cases, the ROC curve cannot clearly explain which classifier has a better effect. As a value, the classifier with a larger AUC has a better effect. Due to the complexity of human movement and the changeable environment, there are still many problems in human movement pattern recognition. For example, detailed classification of different motion modes requires more effective feature extraction and more efficient classification algorithms. In this study, we focus on how to obtain a more efficient classification algorithm, and propose the ensemble classifier AdaBoost algorithm. In order to suggest the feasibility of the algorithm, different base classifiers (RF, NB, SVM, kNN, C4.5) were adopted, with the same parameters for each classifier.

The experiment divided the data set into training set and test set, and adopted the method of 10-fold cross-validation to prevent over-fitting. The tables 1 and 2 show the Classification results of single classifier and AdaBoost ensemble classifier on activities. The total accuracy of single classifier and AdaBoost classifier was compared.

Table 1. **Multiclass classification accuracy estimation of single classifier and AdaBoost ensemble classifier**

Algorithm	Accuracy (%)						Roc Area
	Walking	Walking upstairs	Walking downstairs	Sitting	Standing	Laying	AUC
RF (single)	93,4	93,5	92,9	91,3	93,8	96,8	0,99
RF (AdaBoost)	96,6	97,0	93,0	93,7	90,0	99,9	1,00
NB (single)	90,2	72,1	82,7	42,6	66,1	89,9	0,92
NB (AdaBoost)	91,7	72,9	82,5	80,0	71,6	97,2	0,96
SVM (single)	94,7	93,4	91,2	83,2	88,5	100,0	0,95
SVM (AdaBoost)	96,1	95,5	96,8	85,7	83,6	99,9	1,00
KNN (single)	84,9	86,8	93,9	82,5	65,9	96,7	0,99
KNN (AdaBoost)	93,8	94,1	94,9	66,4	68,9	98,4	0,98
C4.5(single)	91,3	88,3	87,8	91,6	89,9	99,7	0,97
C4.5 (AdaBoost)	91,8	91,1	89,8	91,2	92,5	100,0	0,97

Table 2. **The total accuracy of single classifier and AdaBoost classifier**

Classification Method	Single accuracy (%)	AdaBoost accuracy (%)
RF	93,60	95,03
NB	73,90	82,65
SVM	91,80	92,90
kNN	85,10	86,08
C4.5	91,40	92,07

Table 1 shows the classification results of single classifier and AdaBoost ensemble classifier, and Table 2 shows the total accuracy of single classifier and AdaBoost ensemble classifier. According to the analysis in Table 1 and Table 2, among the single classifiers, the random forest classifier performed best, with the accuracy rate of all six kinds of activities higher than 90 % and the total classification accuracy rate of 93,6 %. SVM and C4.5 also performed well, and the total classification accuracy of single classifier reached 91,8 % and 91,4. However, their shortcoming lies in the uneven prediction accuracy and the large difference of recognition effect among different activities. NB is the worst performer overall.

As can be seen from the tables, the AdaBoost ensemble classifier has improved the recognition of each activity and the whole model to a certain extent. After the AdaBoost integrated classifier, RF, NB, SVM, KNN and C4.5 were increased by 1,7 %, 8,75 %, 1,1 %, 0,98 % and 1,3 % respectively. The data show that all the classifiers mentioned in this paper have improved the classification accuracy, especially the accuracy of weak classifiers has been significantly improved. After using the AdaBoost ensemble learning method, the area under the ROC curve of RF and SVM was increased to 1.

Conclusion

Human activity recognition has developed rapidly in recent years. The main steps include data preprocessing and feature extraction, feature selection, training of classifier and implementation of classification algorithm. Starting from classifier training and classification algorithm, this paper proposes AdaBoost ensemble classifier for human activity recognition. In HAR, AdaBoost ensemble classifier is combined with k-nearest neighbor, naive Bayes network, C4.5, SVM and random forest. This class uses a weighted combination of multiple classifiers to improve the performance of human activity recognition technology. The experimental results show that the proposed AdaBoost ensemble classifier framework can enough accurately (95 % total accuracy) identify simple human activities, including walking, walking upstairs, walking downstairs, and site selection, standing and lying down. The AdaBoost ensemble classifier algorithm significantly improves HAR recognition accuracy.

References

1. Hsu Y., Yang S. // IEEE access. 2008. Vol. 1. P. 11–15.
2. Tao D., Guo Y. // IEEE Trans Image Process .2016. Vol. 11. P. 25–31.
3. Kim Y., Son Y. // Classification of Children's sitting postures using machine learning algorithms. 2018. Vol. 2. P. 8–12.
4. Ermes M., Pärkkä J. // IEEE transactions on information technology in biomedicine. 2008. Vol. 13. P. 20–26.
5. Nazabal A., Ghahramani Z. // IEEE journal of biomedical and health informatics .2015. Vol. 20. P. 1342–1351.
6. Ahad M. // Intelligent Systems. 2017. P. 119–128.
7. Theodoridis S., Pikrakis A. Introduction to Pattern Recognition. Academic Press. 2010.
8. Maswadi K. // Multimedia Tools and Applications. 2021. Vol. 14. P. 9–26.
9. Vapnik V. The Nature of Statistical Learning Theory. Springer. 2000.
10. Breiman L., Friedman J. Classification and Regression Trees. CRC press. 1984.
11. Kondratieff Y. Introduction to machine learning. Morgan Kaufmann Press. 2018.