Hierarchical Decision Tree Model for Human Activity Recognition using Wearable Sensors

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Abstract. Motion related human activity recognition using wearable sensors can potentially enable various useful daily applications. In this study, we start from a deep analysis on natural physical properties of human motions, and then extract the implied commonly prior knowledge. With the prior knowledge, a hierarchical decision tree (H-DT) model has been proposed to recognize human motions and activities. H-DT has a multi-layer heuristic structure that is easy to understand. Support Vector Machine (SVM) has been selected as sub-classifier of each layer in H-DT. The experiment results indicate that the proposed H-DT methods performs superior to those adopted in related works, such as decision tree, k-NN, SVM, neural networks, and the H-DT has achieved a general classification rate of 96.4%±0.025.

Keywords: activity recognition, prior knowledge, decision tree

1 Introduction

Human activity recognition (HAR) is one of the most promising research topics for a variety UMAN motion related activity recognition (HAR) is of areas and has been drawing more and more researchers' attention. The maturity of Machine Learning and Ubiquitous Computing promotes the adhibition of various models and algorithms into human activity recognition. All these improvements enhance the advancement of HAR techniques with high precision, high real time capability, and has been widely used in a variety application areas, such as medical care [1], emergency rescue [2, 3], intelligent monitoring [4] and smart home surveillance [5, 6].

Due to the advantages of no need to deploy in advance, smaller data volume, lower cost and power consumption, sensors-based HAR stands out among various technologies and has been drawing tremendous attention and applied into many fields. The overall objective of HAR is, based on the given activity set and observation data, to pursue a certain classification model, aiming at a good generalization performance as far as possible. Thereinto, generalization performance refers to the capability of predicting unseen instances with the use of designed classifier given some training data under certain phenomenon (human activities in this study). Classifier's generalization performance are determined by two factors: data and prior knowledge [7-9].

In this paper, we present a conceptual model of human motions with which a new approach is put forward to recognize human motion related activities. By deeply mining commonly understanding of motions, a conceptual hierarchical decision tree model (H-DT) is proposed which intuitively presents the knowledge contained in motions. With applying this prior knowledge into motion classification and the integration of Support Vector Machine (SVM) using RBF Kernel, H-DT improves the performance of traditional decision tree method and makes up for the inadequacy of data itself. In this way, key features are extracted and the classification result shows that our proposed H-DT method works better than traditional methods such as C4.5, SVM, BP and has achieved a general true classification rate of 96.4% $\pm$0.025.

2 Hierarchical Decision Tree Model

Features used in the classifier present different activities' similarities and differences, and play a big part on the classification performance. To solve aforementioned problem, we try to bring more expert knowledge into the classifier to achieve the goal of extracting and using key features to improve classification performance in the motion recognition process. In this section, we present a new approach based on exploring rich domain knowledge for activity classification.

2.1 Conceptual Motion

As for activity recognition problems, prior knowledge is reflected in our understanding of motions. Unless we have already had a clearly definition and description on a certain activity, there is no chance we can tell if from the others. It's commonly believed that a human motion can be described from several attributes, such as intensity, orientation, velocity, and so on. These attributes, in some aspects, embody characteristics of motions and can be related with a series of key features that most eminently reflect the physical difference among activities. These key features may be used to group different kinds of activities into several subclasses as they have various distribution overlap on the same attribute. We model a human motion with attributes of intensity, orientation, velocity, body position and duration. Each attribute represents human motions in a side view from a particular angle.

2.2 Hierarchical Decision Tree Model

The proposed conceptual model above establish links between activities and conceptual information through activity-based attributes and make it possible to understand and distinguish different motions in finer perspectives. At the same time, multi-class classification could be done in steps one of which adopt one attribute as a basis. In this way, hierarchical relationships are constructed that link conceptual information with sensor observations through activity attributes. Above mentioned considerations similarly make decision tree classifier a first choice with the advantage of easier to build multi-level heuristic structure as decision tree is a set of if-then rules which are successively applied to the input data. Based on the analysis of activity attributes, we propose a fusion method, Hierarchical Decision Tree (H-DT), to achieve the goal of classification in a hierarchical way which at the same time avoid over-fitting and dimension disaster problems of traditional decision tree method and pursue a better generalization performance. The decision tree method is simple, easy to understand and has a clear hierarchy. However, it also suffers the drawback that may lead to serious over-fitting problem and have low generalization performance as the model construct process depends on the training data too much. Considering these problems, we take the advantage of proposed conceptual motion, to improve traditional decision tree method's performance.

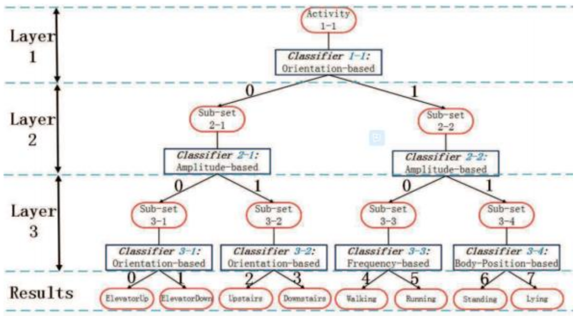

Fig. 1. Hierarchical Decision Tree. Global distinguished attributes (orientation and intensity) based sub-classifier are chosen as root node classifier, and local distinguished attributes (frequency and body-position) are distributed as leaf nodes.

Meanwhile, the conceptual activity model mentioned above is knowledge-based, so it may be feasible to replace the internal node in a decision tree structure with a specific classifier according to activity attributes. Taken these into consideration, we propose a Hierarchical Decision Tree (H-DT) method against activity model with the combination of decision tree and internal classifiers, shown in Fig. 1.

2.3 Classifier

As for the internal classifier, SVM stands out because it should work better in solving binary classification problems. Support Vector Machine is originally designed to solve binary classification problems and when it comes to multi-classification, usually several binary classifiers are constructed in methods of one-against-one or one-against-all. However, one-against-all method has seriously drawbacks as it chooses one kind of samples as a class and the rest as the other class. Then k classes will construct k SVMs. Under this condition, the training data set will lead to data bias problem and don't have much practical value. So one-against-one classifier is a better choice. Besides, in H-DT, all internal classifier view the input as two sub-classes so all work is binary classification which can to the most extent reflects SVM's advantage.

LibSVM [10] is a practical tool realized by one-against-one method. The classifier constructs k binary-classification rules where the m*th* function $\omega_m^T \phi(x) + b$ separates training vectors of the class m from the other vectors, where ω is the weighted coefficient vector that is normal to the hyper plane and b is the bias term [10]. Hence we obtain k decision functions but they are all used to solve the same problem. Thus it can be considered that the SVM solves the following problem:

$$\min_{\omega,b,\xi} \quad \frac{1}{2}\sum_{m=1}^{k}\omega_m^T\omega_m + C\sum_{i=1}^{l}\sum_{m\neq A_i}\xi_i^m\omega_{A_i}^T\phi(x_i)$$

$$subject\ \ to\ \ \omega_{A_i}^T\phi(x_i)+b_{A_i} \geq \omega_m^T\phi(x_i)+b_m+2-\xi_i^m$$

$$\xi_i^m \geq 0, i=1,...,n, m\in\{1,...,k\}-A_i$$

where the training data xi are mapped to a higher dimensional space by the function φ(•) when data are not linear separable, C is the penalty parameter and $C\sum_{i=1}^{l}\sum_{m\neq A_i}\xi_i^m\omega_{A_i}^T\phi(x_i)$ is a penalty term which can reduce the number of training errors. Equation (11) also means there need to be a balance between the regularization term $\frac{1}{2}\sum_{m=1}^{k}\omega_m^T\omega_m$ and the training errors.

3 RECOGNITION OF MOTION RELATED HUMAN ACTIVITIES USING H-DT

For the purpose of activity recognition listed in Activity case set, two most widely used sensors in related works are taken into consideration, namely a triaxial accelerometer, a triaxial gyroscope and in addition a barometer, which can be denoted by:

$$SensorUnit=\{Accelerometer, Gyroscope, Barometer\}$$

These sensors are mounted to several parts of human body and it can be defined as:

$$Location=\{Ankle, Knee, Waist, Shoulder, Wrist\}$$

On the basis of above considerations, our hierarchical decision tree is conducted through the process shown in Figure 7 and Figure 8 to classify an unknown activity by analyzing data collected by each sensor node. The entire process can be divided into two phases: modeling phase and prediction phase.

3.1 Experimental Setting

On the basis of above considerations, our hierarchical decision tree is conducted through the process shown in Figure 7 and Figure 8 to classify an unknown activity by analyzing data collected by each sensor node. The entire process can be divided into two phases: modeling phase and prediction phase.

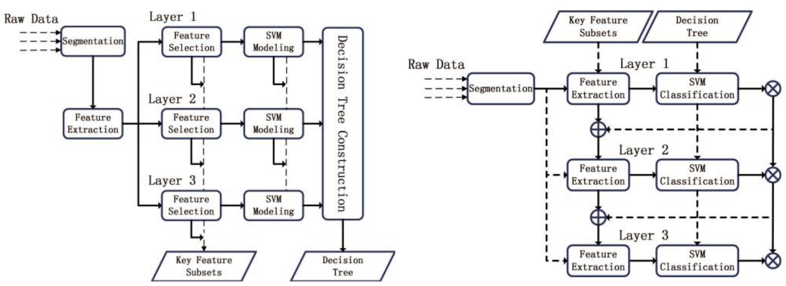

Fig. 3. Training phase and prediction phase.

3.2 Comparison with Existing Approaches

Our proposed Hierarchical Decision Tree (H-DT) method links conceptual information, namely common knowledge with activities through activity-based attributes and construct a hierarchical decision tree to simplify the classification process with exploring common knowledge to extract key features. To verify the validity of H-DT on HAR problem, we take decision trees (C4.5), support vector machine and BP neural work algorithms which are the most widely used four algorithms in the study of HAR to make a brute-force comparison. To compare the classifiers and to identify a principal classifier, we used the experimenter environment in the WEKA toolkit [36]. C4.5 is a most widely used decision tree algorithm providing good classification accuracy. We take a confidence factor of 0.25 to address the issue of tree pruning. Pruning of the decision tree is done by replacing a whole subtree by a leaf node as there may be anomalies due to noise or outliers in the training data. And a radial basis kernel (RBF) based SVM is adopted using LibSVM [10] with automatic parameter selection through grid searching techniques. For the BP neural work, we take the standard approach of recursively evaluating values for the learning rate and momentum using cross validation. A 10-folder cross validation is applied to each classifier independently and the experiment results are shown in the following table.

Table.1 Classification Accuracy and Variance

	C4.5	SVM	BP	H-DT
Standing	0.639±1.170	0.973±0.032	0.952±0.351	0.993±0.017
Lying	0.923±0.020	1±0	0.967±0.211	0.997±0.008
ElevatorUp	0.894±0.035	0.961±0.069	0.974±0.025	0.997±0.002
ElevatorDown	0.91±0.034	0.947±0.080	0.937±0.020	0.97±0.078
Upstairs	0.907±0.137	0.514±0.285	0.917±0.160	0.933±0.043
Downstairs	0.765±0.523	0.296±0.208	0.889±0.133	0.905±0.080
Walking	0.842±0.129	0.568±0.330	0.886±0.286	0.918±0.173
Running	0.931±0.089	1±0	0.967±0.075	0.998±0.001
Global Average	0.851±0.267	0.7824±0.126	0.936±0.131	0.964±0.025

From Table 1 we can see, the four algorithms show different classification accuracy and variance with the 10-folder experiments and according to the performance, the four can be sorted in the following order: H-DT > BP > SVM > C4.5. Furthermore, H-DT shows the highest global average accuracy and the lowest variance reflecting a high stability during the classification. And in each independent activity, H-DT also presents a better performance in classification accuracy and stability.

4 CONCLUSION

The major contribution of this work is the proposal of a knowledge-driven method to recognize motion related human activities. In this study, we construct a hierarchical decision tree (H-DT) is constructed. H-DT can be viewed as a recognition method with knowledge applied into the dealing of data which at the same time covers the advantages of data-driven methods. With a set of hierarchical rules successively applied to the recognition process, H-DT shows a better recognition accuracy (96.4% on average) and lower time consumption (0.02s on average) compared with most widely used methods such as decision tree, k-NN, SVM and neural networks.

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