Human daily activities recognition using decision tree

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Abstract. Decision tree is a supervised classifier that is easy to understand. There are various decision tree methods. This study aimed to compare the performance of decision tree methods in human activity recognition using acceleration and jerk data. The subjects performed human activity daily living, namely walking on a flat surface, walking upstairs, walking downstairs, sitting, standing, and lying down. The features were grouped into three categories: acceleration features, jerk features, and combined features of acceleration and jerk. The evaluation was done using Random Forest, J48, Logistic Model Tree, Reduced Error Pruning Tree, Decision Stump, Random Tree, and Hoeffding Tree. The results showed that Random Forest outperformed the other classifiers with acceleration features performed better than the jerk features. However, the combined acceleration and jerk features yielded the highest accuracy. In conclusion, Random Forest is the best decision tree technique in recognizing the pattern in human activity.

1. Introduction

One of the common techniques to understand human movement in daily lives is through machine learning. There are many machine learning techniques with their advantages and drawbacks. The decision tree is one of the most common machine learning approaches because of its ability to classify dependent variables into different groups [1]. By considering several possible variables to make predictions, it explores the data and recognizes major independent variables [1, 2]. For large datasets, the decision tree saves time in making a model time since it does not require a lengthy training process. Most significantly, it is easy to grasp the classification and the nature of the data is not presumed a priori.

Decision Tree is a supervised classification approach. It is a basic structure with non-terminal nodes to display checks on one or more attributes, and terminal nodes reflect judgment results [2]. The use of decision tree classifiers [3-6] in human activity recognition has shown positive results in past research. The most popular decision tree technique in human activity recognition is the Random Forest (RF). It is an ensemble decision tree that, by combining the method of bootstrap aggregation and randomization in the selection of data node segmentation, will increase classification efficiency [5, 7]. For the regression of the ensemble, a prediction is made by majority voting or averaging. RF yields a generalization error rate, but the noise [2] is more robust. The RF outperformed the other classifiers in a comparative analysis for human activity recognition [5].

Another popular method is the J48, which is the enhanced C4.5 and was developed to create a pruned or unpruned C4.5 decision tree [6, 8]. It selects the feature of the data that separates the set of samples into subsets with the normalized gain of information as the splitting criterion. If all samples in the list are in the same class [4], it creates a node leaf to assign a class for the decision tree. For discrete
attributes, the number of distinct values is considered. Binary tests are considered in the case of continuous attributes with all different values of the attribute [2]. The training dataset under consideration is sorted for the values of the continuous attribute and the binary cut's entropy gains depending on the separate value are computed in a scan [2].

The Logistic Model Tree (LMT) is a promising technique considering its robustness in estimating the probability of the class explicitly [9, 10]. It is a mixture of a decision tree and logistic regression functions. Logistic regression functions are found in the leaves. Each leaf has two branches to the left and the right with the left branch is the one with a lower value than the threshold, while the right branch is the one with a higher value than the threshold [9].

Other decision tree techniques are namely Reduced Error Pruning Tree (RepT), Decision Stump (DS), Random Tree (RT), and Hoeffding Tree (HT). The RepT is a method that constructs a decision tree from information gain as the splitting criterion, then reduces the errors using pruning [2]. This method filters numeric attribute values and then uses the C4.5 technique's fractional instances to search for missed values. The DS is a one-stage decision tree where the division at the root level is the subject of a special attribute pair. In this process, a tree with one internal node (root) is bound to the terminal node. A projection based on a single input feature [11] facilitates this strategy. Whereas, the RT is a decision tree drawn at random from a collection of possible trees (RT). In this algorithm, each tree has an equal probability of being sampled. The RT is possible to be generated in an effective manner, and using a combination of RT with large sets usually improves accuracy [2]. Lastly, the HT is a method that uses the Hoeffding Bound to construct and analyze the decision tree to determine the number of instances to be run. This method suggests that distribution-generating samples remain the same over time. The HT is able to compare attributes better than the other algorithms while using less memory. However, it takes a longer time to inspect if links exist [12].

The purpose of this current research was to assess the performance of several decision tree classifiers namely RF, J48, RepT, DS, RT, and HT in understanding human activities in everyday lives. Additionally, we compared the performance of acceleration and jerk-based datasets as well. This article is arranged as follows. In section 2, the methods of collecting data are defined. In section 3, the results and discussion are explained. Finally, in section 4, the conclusion is provided.

2. Methodology

To assess the usefulness of decision tree approaches using the acceleration and jerk dataset, the public domain dataset obtained by Anguita et al. [13] was used. The data was collected by using the built-in triaxial accelerometer of the smartphone with a 50 Hz sampling frequency. The handset was fixed around each subject's waist. Thirty subjects between nineteen and forty-eight years of age were asked to walk, walk upstairs, walk downstairs, lay down, sit down, and stand. In between each assignment, the subjects were allowed to have 5 seconds of rest. While the experiment was performed in the laboratory, the subjects were requested to carry out the activities freely in order to establish the most natural atmosphere possible. The overlapping window was used to pre-process the collected dataset. In this analysis, the features in frequency-domain and time-domain of acceleration and jerk were all extracted. The extracted dataset was then further analyzed using each decision tree technique to assess the accuracy of each technique in each category of the dataset in classifying the activities.

3. Results and Discussion

This study evaluated the performance of the decision tree methods using acceleration and jerk datasets: RF, J48, LMT, RepT, DS, RT, and HT to evaluate which method is best to recognize the human movement in everyday activities. In addition, in detecting the activities, we also measured jerk sensitivity relative to acceleration. We categorized the datasets into three categories: a combination of acceleration and jerk, acceleration, and jerk. Then, as presented in Table 1, the decision tree methods mentioned above were used to evaluate these three different categories. Except for the jerk category, the
RF has the highest accuracy compared to the other classifiers (Figure 1). However, the LMT had the highest accuracy for the jerk category. Overall, the RF and LMT outperformed the other decision tree techniques in terms of accuracy. Whereas, the DS is the worst classifier in this research. It is evident that the RF is an efficient method for determining the value of variables. Different from the other decision tree classifiers, the tree in the RF is only able to pick a subset of features randomly that allows the variance between the trees in the model to be increased. Therefore, given the low correlation across trees [5, 14], the classification would result in higher precision.

Table 1. Classification accuracy of the decision tree methods (in %).

| Category               | RF      | J48     | LMT     | RepT    | DS      | RT      | HT      |
|------------------------|---------|---------|---------|---------|---------|---------|---------|
| Acceleration and Jerk Combined | 89.32   | 84.52   | 88.38   | 87.51   | 78.51   | 86.39   | 84.52   |
| Acceleration           | 87.45   | 82.65   | 87.00   | 85.80   | 78.47   | 85.72   | 82.65   |
| Jerk                   | 83.52   | 82.30   | 83.71   | 83.03   | 78.51   | 81.64   | 81.43   |

The performance of both acceleration and jerk combinations resulted in the highest accuracy. Acceleration resulted in greater precision than jerk when the acceleration and jerk were measured as a separate group. As the derivative of the acceleration, the jerk was expected to be able in detecting slight differences in the activity [15]. In this study, however, the acceleration yielded higher accuracy than the jerk. This may occur due to, with less-to-no instructions from the experimenters, the previous study used jerk to test the recognition of behavior in animals.

Figure 1. Comparative evaluation of the decision tree methods

Next, the focus of the comparative measurement of acceleration and jerk is on the RF with respect to the efficiency of the RF. Table 2 and Table 3 display the acceleration and jerk confusion matrix of the RF. In general, static postures such as lying, sitting, and standing are misclassified. Acceleration-based features, however, yielded better classification than the jerk-based features. The jerk did not yield higher accuracy in detecting human movement in this study. This result is contradictory to the results of past research [15]. This could be caused by there were only small changes in forces during the static postural
tasks. As the derivative of acceleration, jerk could be felt when there is a change of direction in the acceleration itself [16].

Table 2. Random Forest matrix for acceleration data.

| Label       | Walk | Downstairs | Upstairs | Lay down | Sit | Stand |
|-------------|------|------------|----------|----------|-----|-------|
| Walk        | 508  | 14         | 81       | 0        | 0   | 0     |
| Downstairs  | 25   | 431        | 37       | 0        | 0   | 0     |
| Upstairs    | 106  | 24         | 410      | 1        | 0   | 0     |
| Lay down    | 0    | 1          | 1        | 328      | 151 | 200   |
| Sit         | 0    | 0          | 0        | 174      | 218 | 231   |
| Stand       | 0    | 0          | 0        | 171      | 174 | 323   |

For walking activities, jerk also performed worse than the acceleration-based features. Walking activities can be distinguished better when the acceleration features are used. However, there are still several walking activities that are misclassified with one another. This could be caused by the fact that the participants in this study were all healthy young adults with better postural stability in compensating for the challenges of a more difficult walking task such as walking upstairs and walking downstairs [17].

Table 3. Random Forest matrix for jerk data.

| Label       | Walk | Downstairs | Upstairs | Lay down | Sit | Stand |
|-------------|------|------------|----------|----------|-----|-------|
| Walk        | 369  | 146        | 88       | 0        | 0   | 0     |
| Downstairs  | 114  | 329        | 50       | 0        | 0   | 0     |
| Upstairs    | 96   | 20         | 424      | 1        | 0   | 0     |
| Lay down    | 0    | 0          | 2        | 265      | 196 | 218   |
| Sit         | 0    | 0          | 0        | 199      | 198 | 226   |
| Stand       | 0    | 0          | 0        | 231      | 197 | 240   |

On the basis of the findings in this research, it is evident that RF is the decision tree classifier with the highest accuracy among the other decision tree classifiers. Furthermore, we also found that where the shift in force in the operations is negligible, acceleration is the better option in recognizing human daily activities than jerk. A clearer explanation of this problem may be provided by future research utilizing human movement with an explicit shift of force since the activities in this research were not too different from one another.

4. Conclusion

The comparison of the performance of the decision tree methods in terms of their accuracies in recognizing human movement in daily activities was assessed in this paper. The methods used were all supervised machine learning techniques, namely the Random Forest (RF), J48, Logistic Model Tree (LMT), Reduced Error Pruning Tree (RepT), Decision Stump (DS), and Hoeffding Tree (HT). With regard to the results of the calculation in this research, it can be concluded that the RF exceeded the other decision tree methods in terms of accuracy, and jerk did not yield higher accuracy than acceleration in detecting the changes in human movement data. This may happen due to only minor force variations of acceleration in both static and dynamic movement being measured in this study. Further works analyzing more different activities are needed to assess the performance of jerk in detecting human activities in daily lives.
5. References

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