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Supervised Feature Selection and Clustering for Equine Activity Recognition

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Abstract.
In this paper we introduce a novel supervised algorithm for equine activity recognition based on accelerometer data. By combining an approach of calculating a wide variety of time-series features with a supervised feature significance test we can obtain the best suited features using just 5 labeled samples per class and without requiring any expert domain knowledge. By using a simple cluster assignment algorithm with these obtained features, we get a classification algorithm that achieves a mean accuracy of 90+%. In this paper we will compare this approach to a state-of-the-art convolution neural network classifier both in terms of accuracy as well as in terms of number of labeled samples that were used to train the classifier.

Keywords.
Equine, activity recognition, accelerometer, time-series, feature selection, clustering

Introduction

As with humans, gaining insights into the day-to-day activities of horses is becoming increasingly important. Getting to know what your horse is doing is important not only for optimizing the training schedule of your Olympic level jumping horse but also for monitoring the health and welfare of your beloved equine companion.

The sensors that are most often used to perform this task are small 3-axis accelerometers as they are affordable, work in almost any environment and are very energy efficient. In terms of the algorithms used to interpret the data coming from these sensors, convolutional neural networks (CNN) that give average accuracies in the high 90% range are mostly used (Eerdekens, et al., 2020; Mao, et al., 2021). However, they require thousands of labeled samples to train. This would require capturing and labeling an entirely new dataset for each new scenario. To this end, lots of effort is being put into the development of more data efficient approaches. This can be achieved by combining manual feature extraction or feature learning through autoencoders with classical machine learning algorithms such as support vector machines (Casella, et al., 2019; Kamminga, et al., 2020). These algorithms achieved 80-90% accuracy whilst only requiring around 200 seconds of labeled training data. These models, however, are difficult to optimize or require expert domain knowledge.

We propose an algorithm that combines the benefits of manual feature extraction with the hands-off approach of automatic feature learning. By using a feature calculation phase using the tsfresh Python library followed by a supervised feature selection step we can automatically obtain the most relevant time-series features for the classification task at hand (Christ, et al., 2018). We then applied a simple cluster assignment algorithm that assigns samples to the closest activity centroid of the training data. This gave us a performant classification algorithm that only required a couple of seconds of labeled data. To evaluate the performance of our approach we compared it to a state-of-the-art convolutional neural network through a 3-fold cross validation on a dataset of 6 horses that were equipped with 2 leg-mounted accelerometers.

Methodology

Dataset

The data used during this study was captured at a local stable using 6 adult horses and consists of a mix of ridden and longed data. The average length of the dataset for each horse was 24 minutes, bringing the total dataset size to 144 minutes. Data was captured using 3-axis accelerometers (AX6, Axivity Ltd, Newcastle, United Kingdom) that were configured to capture data at 100 Hz with a range of ±16g. As previous research has shown that a sampling rate of 10 Hz is sufficient to accurately detect equine activities, and to reduce the computational cost of the models, we subsampled the datasets down from 100 Hz to just 10 Hz (Eerdekens, et al., 2021). We then divided the dataset into 5-second windows to perform the classification task.

Models

Feature selection algorithm

The features were calculated using the tsfresh Python library, this library contains a total of 794 different time-series feature calculators. For reducing the number of features to avoid the curse of dimensionality we used the Kendall-rank correlation coefficient to find the 100 most relevant features using 5 labeled samples per class (Abdi, 2007). Classification was then done by using the same labeled samples as for the feature significance test to calculate the centroid for each activity. When a new, unseen, sample needs to be classified it gets assigned to the class of the closest centroid.

Experimental setup

As a benchmark we used a state-of-the-art CNN classifier that has proven to achieve 99.5% classification accuracy (Eerdekens, et al., 2020). The dataset consisted of the 4 most common equine gates (stand, walk, trot and canter). To test the generalizability of each model we used 3-fold cross validation as well as running 10 iterations for each fold. For training the CNN we used the entire training fold. The feature selection model was trained using 5 randomly selected windows from this fold for each of the 4 classes, amounting to a total of 100 seconds of labeled data. Accuracies were averaged out over all 3 folds and all 10 iterations.

Results

The CNN model achieved a mean accuracy of 96.9% and an f1-score of 97%. The feature selection model achieved a mean accuracy of 92.1% and an f1-score of 88%. If we look at figure 1, we see that the CNN also has a more stable behavior over different folds and training iterations, with only a 5% difference between its highest accuracy value and its lowest value. For the feature selection model this spread is much larger, with almost 20% difference between its high and low accuracy values. However, the CNN was trained using more than 1.5 hours of training data whilst the feature selection algorithm only required 100 seconds of labeled data. Figure 2 shows us that both models perform similarly for classifying the stand and walk activities. For the trot activity the feature selection model achieved 8.5% less accuracy than the CNN, often misclassifying trotting for walking or cantering. For cantering the difference between the CNN and the feature selection algorithm increases to 20.5%.

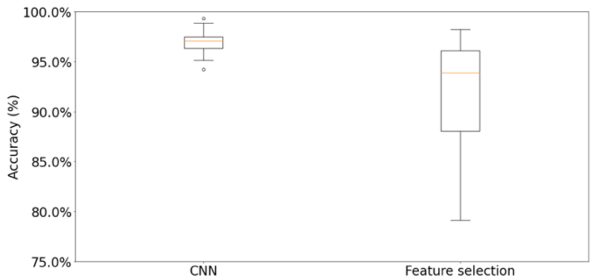

Figure 1: Boxplot of accuracies over all folds and iterations

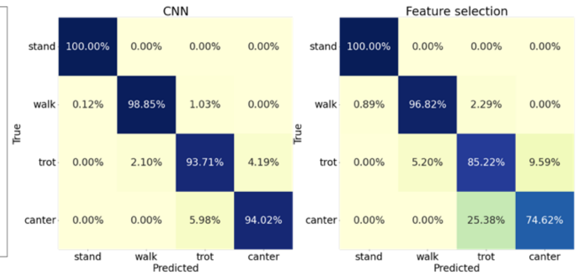

Figure 2: confusion matrix of the average accuracies

Conclusion

We can clearly see that whilst the feature selection algorithm requires 50 times as little labeled data than the CNN it can achieve accuracies that are just a couple of percentage points lower. However, this approach does not generalize as good as the CNN with accuracies dropping as low as 80% for some evaluation runs. It also proved challenging for the model to distinguish between the 2 high-energy activities of trotting and cantering. As this approach requires a lot less training data than more classical algorithms, we could improve the performance of this algorithm by either investigating different sensor configurations (more sensors, different sensor types, different locations), or by creation of a separate model per horse.

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