Dressage Horse Pattern Recognition and Analysis

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ABSTRACT

This paper describes an approach of combining wearable sensors and machine learning for automatic recognition of dressage horse gaits and movements. Data are collected from tri-axial (3D) accelerometers and gyroscopes instrumented on horse and rider. Our methods can achieve an accuracy of 97.4373% for 10-class classification by using the sensor on the horse's bridle, and accuracy of 97.4052% of 4-class leave-one-out classification by using the smartphone in the rider's pocket. The result confirms that our method is not only effective but also robust and user-independent. We also get an insight by using techniques of data analytics and visualization. Our work can be further applied to self-improvement, automatic judging, horse fitness monitoring, and lameness detection.

Author Keywords

Horse; dressage; wearable; pattern recognition; data analytics; accelerometer; gyroscope.

INTRODUCTION

Dressage is an international sport where horse and rider are expected to perform from memory a series of predetermined movements [1]. In its most basic stages dressage includes movements such as walk, trot, and canter, which help the horse and rider communicate with each other and develop balance, strength, flexibility and accuracy. As horse and rider become more proficient in dressage, they begin to perform the more spectacular movements, such as the collected and extended gaits, lateral movements, and collected work such as the pirouettes, passages and piaffes [2]. It is important for riders to review their dressage and know the quality of the movements performed in order to improve.

In this paper, we introduce a way of combining wearable sensors and machine learning to automatically recognize dressage gaits and movements. The wearable sensors are tri-axial (3D) accelerometers and gyroscopes instrumented on both horse and rider to gather information of movements during horse dressage. The data acquired by the sensor are processed and used to train machine learning models for automatic pattern recognition. Apart from pattern recognition, we also get an insight by using techniques of data analytics and visualization.

RELATED WORK

There are several papers that use sensors instrumented on horse, rider, or both to acquire data for analysis. [3] uses two 3D accelerometers on a kidney belt worn by the rider and attached to a girth strap of the saddle to gather data during endurance races. Patterns of horse-rider coordination are analyzed by Lissajous plots and statistical analysis. [4] instruments single-axis sensors on the horse's head (accelerometer), pelvis (accelerometer) and right forelimb (gyroscope), and performs statistical analysis to evaluate lameness. [5-8] instruments 3D accelerometer on the trotting horse's hooves to discriminate the track surfaces or to analyze the horse movement patterns. However, there is little similar work has been done in dressage sports and no machine learning techniques for automatic pattern recognition have been researched.

METHODS

We put wearable 3D accelerometer and/or gyroscope sensors on both the horse and the rider for data acquisition. Different dressage movements and gaits are performed with the sensors, during which videos are recorded for data labeling. The collected data are analyzed, segmented, and labelled into different groups. Feature extractions are then performed on each segment. Finally, machine learning models are trained with features for automatic classification.

Data Acquisition

We put different kinds of sensors on the horse and the rider for data acquisition. We use the commercially available Axivity AX3 as the sensor on the horse because of its light weight and small volume. The AX3 is a wearable data logger a 3-axis electronic accelerometer along with NAND flash memory, real time clock and lithium polymer power source. It weighs 16g, has a size of 6mm x 21.5mm x 31.5mm, and its accelerometer data sampling rate can be up to 2 kHz.

We pick one of the commercially available smartphones with accelerometer and gyroscope to put on the rider. Here we use LG G2, which has a 3-axis accelerometer and a 3-axis gyroscope. It weighs 143 g, has a size of 138.5mm x 70.9mm x 8.9mm, and an Android System of version 4.4.2.

Figure 1. The wearable sensor (left) to be put on the horse and the smartphone (right) to be put on the rider.

We mount the wearable sensor on the horse's bridle, and put the smartphone in the rider's pocket. The wearable sensor is small and light-weighted enough so as not to affect the movement of the horse, and the smartphone can be put the rider's pocket without moving much.

The sampling rates of all sensors are set to be 80Hz. Data recording is started before the dressage and stopped after the end of the dressage. The whole dressage process lasts about 30 minutes, in which several movements and gaits are performed including walk, halt, trot, extended trot, collected trot, canter, extended canter, collected canter, 2-, 3-, 4-tempi flying changes, half-pass, rein back, pirouettes, and circles. The rider and the horse are both international level. The rider has riding experience of 40+ years and dressage experience for 14+ years as a USDF Silver Medalist.

Data Analytics and Visualization

We label and visualize the collected data as in Figure 3. The top bar are color representations of the movements performed where the color mapping is to the right. The lower three graphs are collected 3D accelerometer and gyroscope data: the first is the accelerometer data on the horse's bridle, the second and the third are from the smartphone accelerometer and gyroscope in the rider's pocket. All the four graphs are vertically aligned.

Figure 2. The instrumentation of sensors on the rider and the horse.

In general, although data of different axis of the same sensor vary in magnitudes and offsets, they follow the same trend in magnitudes. Comparing data of the rider and the horse we can see they are largely alike, which means this is a skilled rider who can keep close and in pace with the horse.

The variation of the magnitudes match with the dressage movements, and can thus serve as a good indicator: halt produces the minimum magnitude from the horse's head, walk small magnitude, trot bigger, and canter biggest. However, trot can lead to bigger magnitude from the rider than canter, as trot can be "bumpier" than canter. Also, advanced movements are similar in magnitudes to their corresponding base movements, such as half-pass and trot, pirouette and canter, etc.

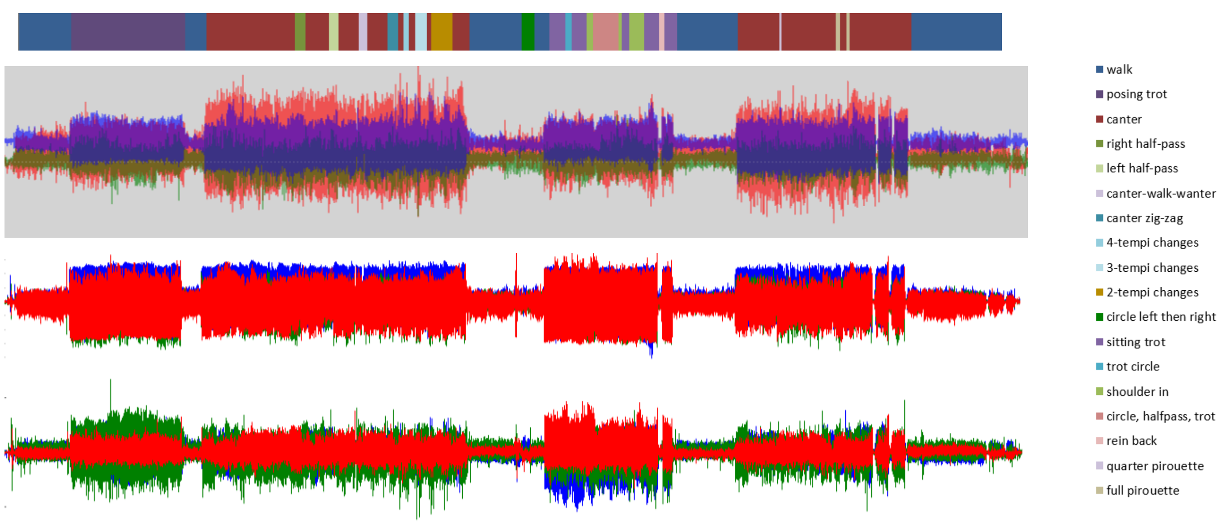

Figure 3. 3-axis sensor data acquired during the whole dressage process: accelerometer on the horse's bridle, accelerometer and gyroscope in the rider's pocket.

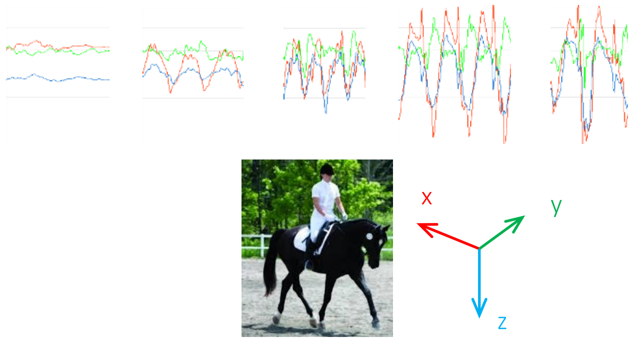

Figure 4. A close look at different gaits from the sensor on horse's bridle. From left to right: halt, walk, trot, canter, flying change

Figure 4 is a closer look at some of the different gaits from the sensor on horse. Different axis of data represent different directions relative to the horse's bridle. X axis represents the longitudinal (anterior-posterior) direction, Y axis is the lateral (side to side) direction, and Z axis is the vertical (dorsal-ventral) direction. When the horse is standing straight, Z axis is approximately the direction of gravity.

We average each movement by over 300 strides, as is shown in Figure 5. A stride is defined as a full cycle of limb motion. In walk and trot the horse's head shake twice in one stride, while in canter the horse's head shake once in one stride. We can see that walk is both small in magnitude and frequency. Trot has the highest frequency, while canter has the shortest stride duration. Flying change can be also distinguished by its unique pattern from normal canter.

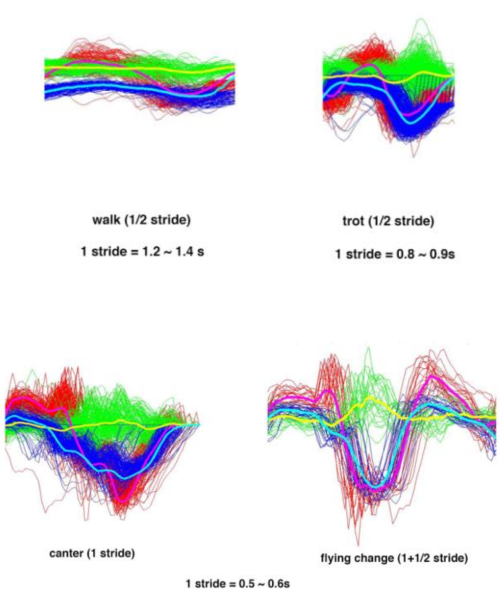

Figure 5. Averaged movements of many strides.

Also in Figure 4 we can see that in the most of time, the magnitudes of vertical and longitudinal coordinates are greater than those of lateral coordinate, reflecting the horse's head movements are more vertical and longitudinal than lateral. To validate this we scatter-plot the data of whole dressage in X-Y, Z-Y, and X-Z plane as is shown in Figure 5. As we can see from X-Y and Z-Y plots, points are scattered along and symmetrically aside the Y axis. X-Z plot shows the patterns of horse head movements as observed from left of the horse.

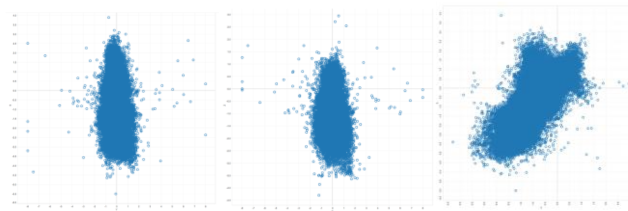

Figure 6. Scatter plot of sensor data on horse's bridel. From left to right: X-Y, Z-Y, X-Z.

Stride Count

We have been using step-counting devices such as Fitbit and Nike Fuelband for health monitoring, which can be applied to horse stride count. To do this, we firstly calculate the scalar magnitude of the accelerometer data. Then we apply a Gaussian filter with $\sigma = 5$, length = 1000 on the magnitude to smooth it from noises. Finally we apply a peak detection function with a threshold of 0.0005. The result can be seen in Figure 7.

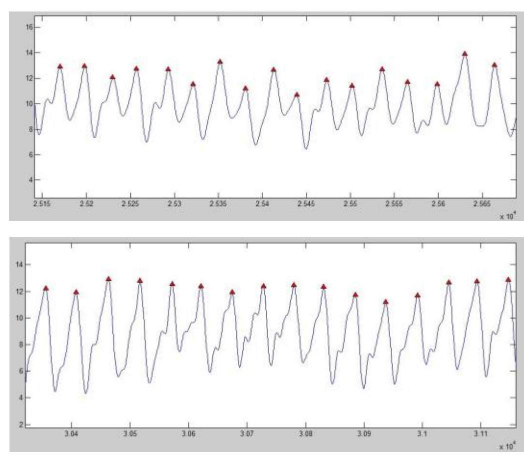

Figure 7. Peak detection on smoothed scalar accelerometer data of trot and canter.

Since a stride is consist of two peaks in trot or walk and one in canter, stride count cannot be done yet, but can be done after pattern recognition when which type of movement is detected.

Pattern Recognition

The automatic pattern recognition of horse movements are consist of 5 steps: preprocessing, feature extraction, feature reduction, model training, and testing. The flowchart is shown in Figure 8. We start with the accelerometer data on the horse's bridle.

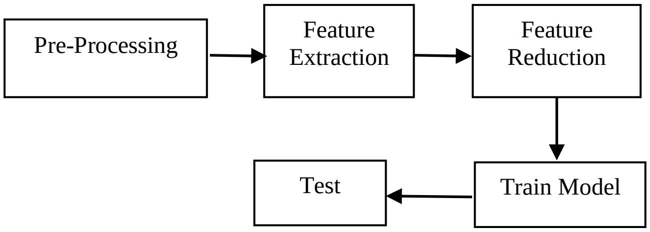

Figure 8. Pattern recognition process.

In the Pre-Processing phase, we apply a Gaussian filter with $\sigma = 5$, length = 100 on the data to reduce the noises. Then we normalize the data by dividing the maximum magnitude. After that, we apply a sliding window with a length of 40, overlapping of 20 to cut the data into segments, and group them according to their labels, as is shown in Table 1. Note that we discard the transition between two consecutive movements to reduce ambiguity.

Group	Label	Number
Walk	Walk	1731
Trot	Sitting Trot	115
	Posing Trot	735
	Left Half-Pass	57
	Right Half-Pass	65
	Shoulder In	90
	Trot Circle	33
Canter	Canter	693
	Pirouette	121
	Tempi Change	67

Table 1. Number of segments.

In the Feature Extraction phase, we extract both temporal and spectral feature on the data. The feature we extracted are shown in Table 2.

In the Feature Reduction phase, we use Principal Components Analysis in Weka software (version 3.7.10), with R=0.95, A=5, M=-1to reduce the dimension of features from 37 to 20.

In the model training phase, we pass these features to a use Support Vector Machine library LibSVM in Weka, with C=1, E=0.001, P=0.1. The kernel of SVM we choose is radial basis function (RBF). The design parameters of SVM are selected using training data via a grid search on a base-2 logarithmic scale. In general, the RBF kernel is suitable because its ability to model the non-linear relation between attributes and target and less numerical difficulties compared to polynomial and sigmoid kernels.

Category	Feature Name	Dimension
Temporal	Max, Min, Average, Standard Deviation	16
	Pearson Linear Correlation Coefficient	3
	Energy Entropy	3
	Short-Time Energy	3
	Zero Crossing Rate	3
Spectral	Spectral Rolloff	3
	Spectral Centroid	3
	Spectral Flux	3
All		37

Table 2. Extracted features.

In the testing phase, we use 10-cross validation for all the segments. The data partitioning is based on random sampling of files from a pool wherein all gaits are mixed.

Overall, the classification accuracy of 10 classes is 97.4373%. The confusion matrix is shown in Table 3.

From the confusion matrix we can see that there is a clear margin between 3 groups of Walk, Trot, and Canter. Within the Trot group, Circle and Shoulder In are sometimes mixed, as the horse is turning its body in both movements. Within the Canter group, while Left and Right Half-Pass are discriminated quite well, they are sometimes misclassified as Canter. Tempi-Change are sometimes misclassified as Canter and Half-Pass. Overall, the classification model has done a good job as some of the differences between within-group movements data are so subtle that they cannot be spotted by human eye, like Half-Pass and Canter, Circle and Trot, etc.

Applied to the Data from the Phone

We apply the same pattern recognition process to the accelerometer and gyroscope data from the phone in the rider's pocket. We have only classified 4 kinds of movements here: Halt, Walk, Trot, and Canter. The overall classification accuracy is 96.7051%. As can be seen from confusion matrix in Table 4, Trot and Canter are sometimes mixed.

User Test

We gathered data from a dressage performed by an intermediate level rider, where only Halt, Walk, and Trot are performed. To test if our model is user-independent, we use our international level rider's data to train the classification model, and then use the model to test the

	Sitting Trot	Walk	Circle	Shoulder In	Canter	Posing Trot	Pirouette	Tempi Change	Left Half-Pass	Right Half-Pass
Sitting Trot	108	0	0	0	3	4	0	0	0	0
Walk	0	1731	0	0	0	0	0	0	0	0
Circle	0	0	10	21	0	0	1	1	0	0
Shoulder In	0	0	4	84	0	0	2	0	0	0
Canter	0	0	0	0	689	3	0	0	0	1
Posing Trot	0	1	0	0	2	732	0	0	0	0
Pirouette	0	0	2	1	0	0	116	0	2	0
Tempi	3	0	0	0	5	0	2	51	4	2
Left Half-Pass	0	0	0	0	14	0	0	0	37	6
Right Half-Pass	0	0	0	0	9	0	0	0	2	54

Table 3: Confusion matrix of sensor data.

intermediate level rider's data. The overall classification accuracy is 97.4052%, and the confusion matrix is shown in Table 5.

	Halt	Walk	Trot	Canter
Halt	36	0	0	0
Walk	0	155	0	0
Trot	0	0	286	4
Canter	0	0	16	110

Table 4: Confusion matrix of phone data.

	Halt	Walk	Trot	Canter
Halt	153	0	0	0
Walk	0	161	13	0
Trot	0	0	174	0
Canter	0	0	0	0

Table 5: Confusion matrix of user test.

CONCLUSION

We have demonstrated the feasibility of using wearable sensors instrumented on dressage horse and rider to do pattern recognition of dressage gaits and movements. We can achieve an accuracy of 97.4373% for 10-class classification with 10-fold cross validation by solely using the sensor on the horse's bridle, and accuracy of 97.4052% of 4-class leave-one-out classification by solely using the smartphone in the rider's pocket. The result confirms that our method is not only effective but also robust and user-independent. Combining pattern recognition and data analytics we can do automatic horse stride count and monitoring.

FUTURE WORK

We plan to use phone data to perform a 10-class classification. Also, we plan to combine the data from the sensor and the smartphone to perform pattern recognition. As the sensor is measuring horse movements, and the phone is measuring rider movements, investigating the relationship between them will reveal more information about the horse and the rider. For example, we can use the method described in [3] to measure the rider's coordination with the horse and we can do automatic judging. Also, we can gather data from riding healthy horse and lame horse to do automatic lameness detection. We can also develop mobile applications on smartphone to help riders review their dressage and monitor their horses.

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REFERENCES

1. About Dressage, International Equestrian Federation, retrieved August 26, 2011 http://www.fei.org/disciplines/dressage/about-dressage.
2. What is Dressage? University of New Hampshire, retrieved April 28, 2014 http://www.equine.unh.edu/dressage
3. Viry, Sylvain, et al. "Patterns of Horse-Rider Coordination during Endurance Race: A Dynamical System Approach." *PloS one* 8.8 (2013): e71804.
4. Marshall, J. F., D. G. Lund, and L. C. Voute. "Use of a wireless, inertial sensor-based system to objectively evaluate flexion tests in the horse." *Equine veterinary journal* 44.S43 (2012): 8-11.
5. Chateau, H., et al. "Effects of a synthetic all-weather waxed track versus a crushed sand track on 3D

acceleration of the front hoof in three horses trotting at high speed." *Equine veterinary journal* 41.3 (2009): 247-251.

6. Gustås, P., et al. "Relationships between fore-and hindlimb ground reaction force and hoof deceleration patterns in trotting horses." *Equine veterinary journal*36.8 (2004): 737-742.
7. Schaer, BL Dallap, et al. "The horse-racetrack interface: a preliminary study on the effect of shoeing on impact trauma using a novel wireless data acquisition system." *Equine veterinary journal* 38.7 (2006): 664-670.
8. Ryan, C. T., BL Dallap Schaer, and D. M. Nunamaker. "A novel wireless data acquisition system for the measurement of hoof accelerations in the exercising horse." *Equine veterinary journal* 38.7 (2006): 671-674.