Gait and Jump Classification in Modern Equestrian Sports

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ABSTRACT
In modern showjumping and cross-country riding, the success of the horse-rider-pair is measured by the ability to finish a given course of obstacles without penalties within a given time. A horse performs a successful (penalty-free) jump, if no element of the fence falls during the jump. The success of each jump is determined by the correct take-off point of the horse in front of the fence and the amount of strides a horse does between fences. This paper proposes a solution for tracking gaits and jumps using a smartphone attached to the horse's saddle. We propose an event detection algorithm based on Discrete Wavelet Transform and a peak detection to detect jumps and canter strides between fences. We segment the signal to find gait and jump sections, evaluate statistical and heuristic features and classify the segments using different machine learning algorithms. We show that horse jumps and canter strides are detected with a precision of 94.6% and 89.8% recall. All gaits and jumps are further classified with an accuracy of up to 95.4% and a Kappa coefficient (KC) of up to 93%.

ACM Classification Keywords
I.5.4 Pattern Recognition: Applications: Signal Processing

Author Keywords
Activity Recognition; Wearable Sensing; Showjumping

INTRODUCTION
Horse riding was officially included in the 1900 Olympic games in Paris, and since then equestrian activities gained popularity in the private and professional sector. Showjumping as well cross-country riding are sports that require a rider and a horse to jump over a course of fences in a specific order within a given time. Depending on the course and type of competition, horses have to jump different kinds of fences: upright fences (e.g. verticals), high and wide fences (e.g. oxers, triple bars, tree trunks), wide and flat fences (e.g. moats). Inside the course, fences are placed separately or in close distance to each other. The horse has to perform a specific amount of strides between fences in order to execute a successful jump.

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A typical sport horse is able to move in three different gaits - walk, trot and canter, which differ in the intensity of speed, frequency and vertical swing. Walk, trot and transitions between the two gaits are ridden for warming up the horse, keeping it warm and cooling it down before and after the jumping course. A balanced warm-up is essential for a responsive horse inside the jumping course and the foundation of every successful jump. A sport horse typically jumps all fences in a course running towards them in canter. It is possible to jump fences when trotting, but not common in competition scenarios. The amount of strides between two jumps have to be chosen by the rider and depend on the individual stride length and training experience of the horse. Riders usually walk around the course before a competition to measure distances between the fences and calculate how many strides to make with their horse. The ability to determine the optimal amount of strides to perform before each fence is critical for a successful jump. However, the stride length and canter pattern of every horse are different and not always visually predictable, and depend on the rider's experience. Failing to jump a wooden fence can cause injury to the horse and rider. Currently, human trainers provide feedback to riders for each jump in training sessions. However, not every rider can afford a human trainer. Video feedback is used for short jump sequences, but it might be impractical to replay an entire training or competition. We propose a method to classify horse gait types and detect canter strides and jumps performed by a horse-rider-pair using a smartphone attached to the horse's saddle. Our method aims at generating a training report that can be used by riders to analyse and keep track of their training performance by generating a list of jumps and strides made before each jump. This solution supports the

Figure 1. Three horses performing jump sequences over different fence types such as a a tree trunk, an oxer and a vertical (from top to bottom).

rider in making strategic decisions on how to ride a course and can prevent accidents due to a miscalculation of canter strides in between fences.

Related Work

Wearable sensors have been used in a variety of sport applications. In the field of wearable technologies for animals, research was done with dogs and the respective dog-human interaction using wearable sensors [5]. Ladha et al. [6] focused on activity recognition for dogs, and classified jumping and walking for measuring the dogs' well being. Haladjian et al. [2] developed an approach to detect anomalies in the gait of cows that might be caused by a lameness-related disease. Previous work on equestrian applications includes using wearable sensors both for the kinematic analysis of horses as well as for tracking the rider's posture. Low et al. [8] studied how to prevent lamenesses in racehorses using a wireless sensor system attached to the horse's limbs. Thompson et al. [10] developed a system for automated feedback for dressage riders using sensors on the horse's limbs to classify different gaits and specific exercises in the domain of dressage. Green et al. [4] provided a system for tracking positions, velocity and physiological data of horses using wearable sensors in equestrian training. Barrey and Galloux studied the kinematics of a horse's gait and found that the penalty rate increased if the horse was ridden in a low stride frequency and suddenly reduced its stride frequency at take off [1]. Other studies track the rider's behaviour and posture. Li et al. [7] investigated on how to correct an equestrians posture using a wearable sensor system. A similar study quantifies the horse-rider-expertise using inertial sensors in show jumping to classify their performance level [9].

METHODS

Our data set was collected using the accelerometer and gyroscope of an Apple iPhone 7 with a sampling rate of 100 Hz. We placed the smartphone in a tightly fitted bag attached to the right side of the saddle pad, its display facing the horse's body. We mounted the bag on the horse's torso to capture its vertical and horizontal body movement. We gathered the movement of 9 horses in 4 different riding arenas, containing movements from 2 indoor and 2 outdoor arenas. Outdoor arenas enable horses to gain more speed and lead to an increased stride length. We monitored all horse-rider-pairs during their usual jumping or cross-country training. Our recordings include gait motion such as walking and trotting before and after the actual execution of the course. The horse-rider-pairs jumped different fences in different heights, widths and shapes depending on the experience of the pair (Figure 1). All pairs jumped in their levels of expertise, some being able to jump 100 cm (± 5 cm) fences and others jumped 125 cm (± 5 cm) fences during our study. We chose horses of different heights to include different stride lengths to our data set (Table 2). We video recorded the horse-rider-pairs and annotated the beginning and ending of each walk and trot section as well as canter stride and jump peaks according to the video protocol. In total, 49.24 minutes of data were recorded, including 25.38 minutes of canter, 12.48 minutes of trot, 9.61 minutes of walk and 1.77 minutes of jumps.

FH[cm]	*RA[y]*	*HH[cm]*	*FH[cm]*	*RA[y]*	*HH[cm]*
110	> 35	145-165	100	> 35	145-165
110	26-35	145-165	100	> 35	> 165
110	< 15	< 145	115	15-25	> 165
110	15-25	< 145	120	15-25	> 165
			125	> 35	> 165

Table 1. Overview of the participants including horse height (HH), fence height (FH) of the course (± 5 cm) and rider age (RA) in years indicating experience of cross-country (left) and showjumping (right) riders.

Stride and Jump Detection

To find and further classify gait and jump segments, we use two methods: we first perform an event detection to detect canter strides and jumps. If no event is detected, we determine walk and trot segments, where we do not detect single steps. Detecting canter strides is particularly challenging because most trot strides have a comparable acceleration. We decided to detect canter strides and jumps on the acceleration along the x-axis, based on our observation that most walk strides and some trot strides have less acceleration than canter strides along this axis (Figure 2 (a)).

We designed a filter based on Maximal Overlap Discrete Wavelet Transform (MODWT) to reduce noise and attenuate the frequencies dominant in most trot strides. We found the seventh level MODWT using the 'Sym2' symlet mother wavelet to produce the desired effect based on a visual comparison of the raw and filtered signal for the different gait types. The raw signal $S_{1_{raw}}$ is transformed to wavelet components $M_1(x_i)$ within the signal length m ($1 \leq i \leq m$).

$$M_1(x_i) = MODWT(S_{1_{raw}}(x_i)) \tag{1}$$

By retaining levels six and seven for the signal reconstruction $S_{1_{MODWT}}(x_i)$, we discard narrower frequencies of the trot sections, while keeping the wider frequencies from canter strides/jumps (Figure 2 (b)).

$$S_{1_{MODWT}}(x_i) = IMODWT_{6:7}(M_1(x_i)) \tag{2}$$

We run a peak detector on $S_{1_{MODWT}}(x_i)$ using a minimal peak height h and a minimal peak distance r (Figure 2). The threshold h and minimal peak distance r were evaluated experimentally and set to 1.25 and 30. We detect peaks for canter strides and jumps as follows:

$$P_j(x_i) = \begin{cases} 1, & \text{if } S_1(x_i) \geq h \wedge P_{j-1}(x_{i-r}) = 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

All peaks detected by our peak detector are further used for signal segmentation and feature extraction.

Gait, Stride and Jump Segmentation

We segment the signal using two different segment sizes depending on the output of the peak detection: we define peak-centered segments k_p, aiming at describing canter strides and jumps, to ensure that one exact canter stride/jump is evaluated and further classified at a time. We process gaps between peaks using duration-dependent segments k_d, intending to describe a walk or trot interval rather than the single strides made in this interval (Figure 3). We determine segments k_p for every

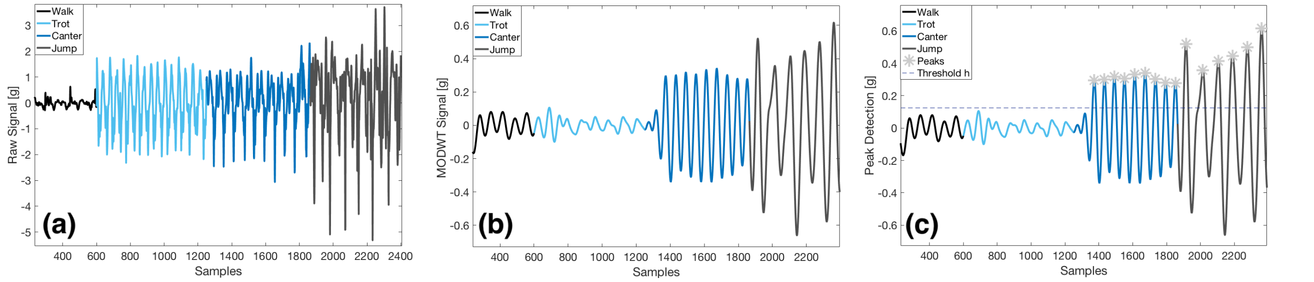

Figure 2. Raw data stream of the x-axis accelerometer data for different movements walk, trot, canter and jumps (a). Processed data stream using MODWT (b). Peak detection based on threshold h on the processed data (c).

detected peak $P_j(x_i) = 1$ using a fixed frame located around the peaks. We set the segment size for detected peaks to 100 ms based on the observation that most jumps last around 100 ms. We use the duration-dependent method if there is no peak detected within the last 150 ms. Based on our observation that jumps and canter strides have a wider length than walk or trot, we define a smaller window size of 50 ms to process duration-dependent segments. We define our peak-based segments k_p and duration-based segments $k_d = [x_{i-a}, x_{i+b}]$ with:

$$a, b = \begin{cases} 50, & \text{if } P_j(x_i) = 1 \\ 25, & \text{otherwise} \end{cases} \tag{4}$$

Feature Extraction and Selection

We calculate 268 different features for each determined segment for all axes of the accelerometer and gyroscope as well as for their general magnitude and normalise them between $[0;1]$. We calculate standard statistical as well as heuristic features for our specific problem. To find a feature set that describes our data set as precisely as possible, we studied features in the time and frequency domain, similar to [3]. We use the Minimum Redundancy Maximum Relevance algorithm (mRMR) to select 20 more relevant features for our entire data set.

Classification

We classified all feature vectors based on all peak-centered and duration-dependent segments using 22 different machine learning algorithms. Support Vector Machines (SVM) with linear, quadratic and cubic and a fine, medium and coarse gaussian kernel were tested. The gaussian SVM kernel with a number of predictors P were set to $\sqrt{P}/4$ for the fine, $\sqrt{P}$ for the medium and $\sqrt{P} * 4$ for the coarse gaussian SVM. We tested the K-Nearest Neighbours (KNN) algorithm with a fine (1 neighbour), coarse (100 neighbours), medium, cosine, cubic and weighted (10 neighbours) kernel. Trees were computed with a maximum number of splits of 100 for fine, 20 for medium and 4 for coarse trees. We processed ensembles using boosted, bagged, RUSBoosted trees, subspace discriminants, subspace KNN, linear and quadratic discriminant algorithms. We computed a 9-fold cross validation to test and train all machine learning algorithms. All classifiers are compared by accuracy and KC to comprise the imbalance of the jump class in comparison to the gait classes to find a suitable classifier for our problem.

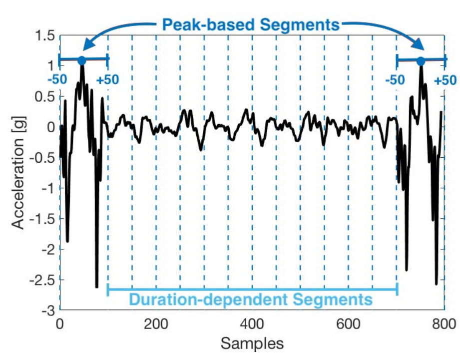

Figure 3. Segmentation explained by the acceleration of a horse performing a transition from canter to walk to canter.

RESULTS

A canter stride or jump was detected correctly and marked as a True Positive (TP) if the maximum deviation d of the detected to the labeled peak is $d \leq 50$ ms. Detected strides or jumps were marked as False Positives (FP), if no label was found within range d. Labeled, but undetected strides or jumps were marked as False Negatives (FN). Correctly undetected instances were referred to as True Negatives (TN).

Stride and Jump Detection Results

We evaluated the threshold h and minimal peak distance r to optimise the f-measure for our peak detector based on our entire data set. This lead to an optimised threshold $h = 0.125$ and minimum peak distance $r = 30$ for our data set. We labeled 2687 canter strides and 137 jumps the ground truth. Our final peak detector based on threshold h and minimal peak distance r detected 2535 correct instances in total, including 107 jumps and 2428 canter strides. The peak detector detected 144 false positives, whereof 102 were walk and 40 trot, as well as one misdetected canter stride and one jump (Table 3). It showed 289 false negatives (259 missed canter strides and 30 jumps) (Table 2).

Type	*#TP*	*%*	*#FP*	*%*	*#FN*	*%*
Canter	2428	90.4	141	5.3	259	9.6
Jump	107	78.1	3	2.2	3	21.9
Total	2535	89.8	144	5.1	289	10.2

Table 2. Performance of our detection method.

Class	# FP	%	#FN	%	Prec.	Rec.	F-M.
Walk	102	70.8	-	-	-	-	-
Trot	40	27.8	-	-	-	-	-
Canter	1	0.7	259	89.6	94.5	90.4	92.4
Jump	1	0.7	30	10.4	97.3	78.1	86.6

Table 3. Misdetection rate of our detection method per motion type. E.g. 70.8% of all incorrectly detected instances were walk (left). Precision, Recall and F-Measure of the detection in % (right).

	Walk	Trot	Canter	Jump	Prec. [%]	Rec. [%]
Walk	**1068**	13	30	0	91	96
Trot	72	**1273**	56	1	95	91
Canter	31	55	**2429**	4	96	96
Jump	0	2	9	**107**	91	96

Table 4. Confusion matrix of the linear SVM classifier. Rows indicate the ground truth, columns indicate predicted labels (left). Precision and Recall of the classifier in % (right).

Classification Results

All gaits and jumps could be classified with an accuracy between 90.2% (coarse tree) and 95.4% (cubic SVM). The KC ranged between 84.2% and 93.0%. For a detailed analysis, we proceeded using the linear SVM with an accuracy of 94.7% and a KC of 91.7%. Due to its lower computational costs, we accept the loss in accuracy of 0.7% and KC of 1.3%. The linear SVM algorithm classified canter strides and jumps with a precision of 96% and 91% and a recall of 96%. Jumps were misclassified as canter strides in most cases. If canter strides were misclassified, most of them were misclassified as trot steps. For walk and trot, the precision is 91% and 95%. The confusion matrix is shown in Table 4. Canter strides were mistaken by jumps in 2 cases (0.1% of all annotated canter strides), whereas jumps were mistaken by canter strides in 9 cases (7.8% of all annotated jumps). Walk was mistaken as canter strides in most cases, whereas trot was misclassified as walk in the majority of all misclassified trot instances.

CONCLUSION

This paper provides a solution for gait and jump classification in modern showjumping and cross-country riding. Data streams of a smartphone were evaluated to detect and classify gaits and jumps in the training of modern sport horses. We used the MODWT to remove gait-specific frequencies and a peak detector to extract features. Our canter stride and jump (peak-based) approach detects single strides and jumps with a precision of 94.6% and 89.8%. We showed that our method classifies gaits using machine learning algorithms with an accuracy of up to 95.4% and a Kappa coefficient of up to 91.7%.

Our study was conducted for the specific purpose of detecting jumps and strides in a given training session. The achieved accuracy of the detection and classification is applicable and it's degree of error acceptable to support the rider in decisions regarding the amount of canter strides to make between fences. Our approach can thus increase the probability of performing a successful jump and potentially prevent accidents due to the rider's miscalculation of canter strides between fences. Our work can be used to generate an evaluation of warm-up and cool-down phases which can be used by riders to analyse and keep track of their training performance. In the future, the computational costs and energy consumption should be assessed and the peak detection and feature selection parameters should be recalculated on a larger data set using an inner cross-validation.

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