Master of Science

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Exploring Use of Surface Electromyography during Horse Riding

An Animal-Computer Interaction Study Within the Equestrian World

A Master Thesis

Computer Science
Aalborg University

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Resume:

Animal-Computer Interaction (ACI) are the subfield under HCI which are focusing on animals as primary or partially users of technology. The field have grown in the last couple of years, with several research units around the world, and one annually congress. Research within the ACI field is important as it could influence our inter-species relationships by supporting or facilitating communication or lead to further insights into animal cognition. My research takes basis in equestrian sport.

I explore electromyography which is a technology that enables measurement of muscle activity. Within HCI research electromyography is very interesting as it enables new ways of interactions. By attaching electromyography sensors on the forearm, a person can control technology using simple gestures. Within an horse-rider setting it is even more interesting as it can provide us with information we do not have access to yet. I want to examine: 1) How and what we can measure using Surface Electromyography on a horse and 2) how we can design feedback systems based on muscle activity data.

I have designed and implemented two prototypes: MyoCollect and HindHelp. MyoCollect is a data-collection system that using surface electromyography measure and collect muscle activity data of a horse's hind legs. I perform three test session with two different equipages in the three gaits: walk, trot and canter. I analyze the collected data and show how gait recognition can be performed using statistics and graph analysis. I then propose HindHelp which built upon MyoCollect by applying muscle activity data and presenting it to the rider during jumping training.

My results shows that it is possibly to measure muscle activity data on horses using surface electromyography. However it is crucial that the horse is shaved and sensors are placed correctly on the attended muscles. Our analysis of the collected data shows that the three gaits are vary in average value, number of peaks, and distance between them. I show how these data can help perform gait recognition. An evaluation of HindHelp shows that electromyography is useful in a horse-rider setting as it can provide riders with previously inaccessible information but demands high accuracy of sensors and knowledge of the musculature of horses. Riders however is positive over the possibility for using technology together with their horses.

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Abstract:
We explore surface electromyography, which is a technology that enables measurement of muscle activity. This is very interesting within Horse-Rider Interaction as the technology enables riders to get information of their horse's which have yet not been accessible. We design and implement two prototypes: MyoCollect and HindHelp. MyoCollect is a data-collection system that using surface electromyography measure and collect muscle activity data of a horse's hind legs. We perform three test session with two different equipages and show how gait recognition can be performed using statistics and graph analysis. We then propose HindHelp which built upon MyoCollect by applying muscle activity data and presenting it to the rider during jumping training. Our results shows that it is possibly to measure muscle activity data on horses using surface electromyography. However it is crucial that the horse is shaved and sensors are placed correctly. Our analysis shows that the three gaits vary in average value, number of peaks, and distance between them. An evaluation of HindHelp shows that electromyography is useful in a horse-rider setting as it can provide riders with previously inaccessible information but demands high accuracy of sensors and knowledge of the musculature of horses.

Contents

1 Introduction

Performance analysis in sport is very useful for improving athletic performance. All athletes are focused on maintaining or bettering their physical form and training techniques or understanding for the gameplay. New training approaches continuously appears to optimize the athletes performances and pushing the limit for what their body can handle. When competing in sports with animals - which can only provide none or limited information of their well-being - the complexity of measurement, analysis and improvements are increased. Riders wants to push the horse to perform their best at competitions, but not more than their physic can handle. Equine performance analysis research aims to optimize the potential competition success of the horse (and rider) while concurrently promoting health and welfare.

Human-Computer Interaction investigate how people interact with technology in different contexts. This is interesting as new needs and usage patterns can be discovered. By introducing animals in the equation, interspecies relationships can be supported by technology. However this potentially defines many requirements which software designers and developers need to take into account. My work is focused on the case study with uses of Electromyography (EMG) as a quantitative tool for equine performance analysis. EMG is the study of the electrical signals that occur when muscles contract. By collecting these signals, we can get valuable information of when a muscle is used and to what extend. Comparing data from several muscles will set the basis for objective analysis of a horse movement. I explore what kind of data a rider can get from this technology during riding, and what the data can be used for.
The study is based upon the two research questions:

- How and what can we measure using Surface Electromyography on a horse?
- How can we design feedback systems based on muscle activity data?

This report will outline the motivation for the study. The next section is concerned with the research background. Section three summarize the research contributions of the paper. In the fourth section I discusses the results of the study and concludes on these in section five. The research paper can be find in Appendix.

2 Background

2.1 Animal-Computer Interaction

Animal-Computer Interaction (ACI) is a fairly new research area with big potential and a lot of issues to address. The field strives to improve animals daily lives and study their interaction with computing technology. This research can open up for new understanding of the animals we live together with and hopefully enrich their lives as well as our own. Clara Mancini defines ACI in her Manifesto from 2011 [3]: *"ACI aims to study the interaction between animals and computing technology within the animals' habitual contexts, design interactive technology that can support animals in their habitual tasks or daily lives, and that can foster the relationship between humans and animals, and develop a user-centred approach to the design of technology that is intended for animal* *use."* A number of ACI research groups exist world-wide, currently located at Georgia Institute of Technology, U.S.A., Open University, UK and Stockholm University, Sweden. Additionally, the congress *Internationale Congress on Animal Computer Interaction* is held annually since 2013. The research field also have its own website where guidelines and news are updated [5].

The subfield Animal-Human-Computer Interaction (AHCI) categorize technology used by humans in interplay with animals. This approach is useful as it can be difficult to design technology directly for animals to be used singularly by animals. My study centralize about the horse as the it-system is placed directly on its body and collects data for analysis. Further work would focus on the human-part of the case - as to what the rider could gain of the data, and how he would interact with the technology during interplay with the horse.

2.2 My Previous Work

I have previously work with ACI, concerning an literature review of the research field and a specific case of support rider-horse interaction.

On 9th semester I collected a snapshot of the relevant research in the ACI field in the period of 2010-2016 and classify the current themes of the papers. The results show a strong focus on dogs as either pets or working animals. Among other I classified the 38 papers in regarding to the animal they are concerned about. Research with canine users are clearly the most popular topic, as 22 of the 38 papers had canine users in focus. Half of these, 11 papers, was related to working dogs, where the other half were related to pet dogs or dogs in general. An example of a typical dog paper is the research by Cassim and colleagues [2]. The researchers examines possibilities for automatic recognizing dog activities though their collar-worn activity monitor. The purpose of the system is to monitor the welfare of animals that spend much time alone and support injury recovery. 18 dogs participated in the evaluation and the overall recognition accuracy ended up being of 68,6%. This system is a good illustrative example of a ACI project that provides the human with new information that can enrich the life of the animal and support the relationship of the dog and handler.

On 8th semester I developed BitHead which is a training tool for dressage riders. During dressage riding the horse's head needs to be in a vertical position, which can be challenging to determine from the back of the horse. BitHead consist of a sensor that measures the position of the horse's head relatively to the vertical line in degrees. Riders would receive a notification through a wireless headset if the degree measurement is above or below a chosen boundary in order to correct it. I conducted a field study with five equipages (rider and horse) and demonstrated that simple technology can help riders during training with keeping the horse's head in a correct position in order to prevent physically overload or injuries. The field study lead to the conclusion that riders do find computing technology useful in the interaction with their horse. BitHead was considered a small very specific product as riders expressed their wish for a system that would provide more information of their horse's movement. Participants considered BitHead most useful for experienced riders which are familiar with their horses.

These two presented projects showed that there is a big potential for developing software systems which can enriching the life of riders and horses in terms of improving riding skills by providing useful information and supporting the inter-specicies relationship.

3 Paper Contribution

I designed, implemented and tested two prototypes, which is described in the paper in the appendix. Below the highlights are summed up.

3.1 Purpose

Animal-Computer Interaction (ACI) are the subfield under HCI which are focusing on animals as primary or partially users of technology. The field have grown in the last couple of years, with several research units around the world, and one annually congress. Research with the ACI field is important as it could influence our inter-species relationships by supporting or facilitating communication or lead to further insights into animal cognition. Computing technology have improved the life of many people and are used multiple times on a daily basis. However, technology supporting inter-species relationship by improving quality time with our pets have yet to be developed.

In this paper, we explore electromyography which is a technology that enables measurement of muscle activity. Within HCI research electromyography is very interesting as it enables new ways of interactions. By attaching electromyography sensors on the forearm, a person can control technology using simple gestures [4] [1]. We want to examine: 1) How and what we can measure using Surface Electromyography on a horse and 2) How we can design feedback systems based on muscle activity data.

3.2 Method

We have designed and implemented two prototypes: MyoCollect and HindHelp. MyoCollect is a data-collection system that using surface electromyography measure and collect muscle activity data of a horse's hind legs. We perform three test session with two different equipages in the three gaits: walk, trot and canter. We analyze the collected data and show how gait recognition can be performed using statistics and graph analysis. We then propose HindHelp which built upon MyoCollect by applying muscle activity data and presenting it to the rider during jumping training.

3.3 Findings

Our results shows that it is possibly to measure muscle activity data on horses using surface electromyography. However it is crucial that the horse is shaved and sensors are placed correctly on the attended muscles. Our analysis of the collected data shows that muscle activity data values from the three gaits: walk, trot and canter have the average values of respectively 66.66%, 90.20% and 92.14%, where the values represent percentage measurable muscle activity. These data sets are proven significantly different with an ANOVA and post-hoc test. We present similar statistical analysis that likewise show how gait recognition can be performed using muscle activity data.

An evaluation of HindHelp shows that electromyography is useful in a horse-rider setting as it can provide riders with previously inaccessible information but demands high accuracy of sensors and knowledge of the musculature of horses.

4 Conclusion

I have worked within the research field of Animal-Computer Interaction, exploring the potential for use of data-collection technology of the horse's movement. I investigated the use of sensors for measuring muscle activity on horses during riding through the system . is a data-collection system which through two sensors measures and saves activity data from big muscles in the horse's two hind legs. We showed that this data can be used for detecting gait of the horse using graph analysis. Extending previous research on animal-computer interaction our experiments indicate that their is a potential for using IT-systems during interplay with horses, as it can provide us with so far unavailable information. However there exist some limitations to technology, which we will discuss below.

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Exploring Use of Surface Electromyography during Horse Riding

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ABSTRACT
Electromyography is an widely used technology within the medicine industry that enables measuring of muscle activity. The technology has big potential and many use case, but has yet to be applied in mainstream technology. We show how the technology can be useful in a Human-Horse setting.

We design and implement two prototypes: MyoCollect and HindHelp. MyoCollect is a data-collection system that using surface electromyography measure and collect muscle activity data of a horse's hind legs. We perform three test session with two different equipages in the three gaits: walk, trot and canter. We analyze the collected data and show how gait recognition can be performed using statistics and graph analysis. We then propose HindHelp which built upon MyoCollect by applying muscle activity data and presenting it to the rider during jumping training. An evaluation shows that electromyography is useful as it can provide riders with previously inaccessible information but demands high accurary of sensors and knowledge of the musculature of horses.

Author Keywords
Animal-Computer Interaction, Horse-Computer Interaction, Electromyography

INTRODUCTION
Computing technology have improved the life of many people and are used multiple times on a daily basis. However, technology supporting inter-species relationship by improving quality time with our pets have yet to be developed.

Animal-Computer Interaction (ACI) are the subfield under HCI which are focusing on animals as primary or partially users of technology. The last case with the human as link, referred to as Animal-Human-Computer Interaction (AHCI). The field have grown in the last couple of years, with several research units around the world, and one annually congress. Research with the ACI field is important as it could influence our inter-species relationships by supporting or facilitating communication or lead to further insights into animal cognition. As example it can improve the economic and ethical sustainability of food production and affords farm animals more freedom and autonomy, enabling them to live less unnatural lives [11]. Most research done within ACI are concerned with pets or helping animals such as assistance dogs. These animals represent a tiny part of all the living species, as being relatively small and living together with humans. Many bigger animals could be interesting to study, as their relation to technology could differ. One of these animals, is the horse. Humans have kept horses for thousand of years as either used for working, transportation, social companionship or sports. Horses even compete together with riders in several disciplines at the Olympic Games. For these reasons horses are an interesting animal to study in order to see if the human-horse relationships can be improved by technology. Horses are much bigger than normal pets and are are usually considered more a hobby animal, because of the main focus on sports.

Commercial technology products within equine sports are being developed. Several companies develop sensors for horses [5] [18] [7], which can measure heart rate, speed etc. during riding. In this paper, we explore electromyography which is a technology that enables measurement of muscle activity. Within HCI research electromyography is very interesting as it enables new ways of interactions. By attaching electromyography sensors on the forearm, a person can control technology using simple gestures [17] [9]. We wish to explore how electromyography can be used in a horse-rider interplay by collecting and analyzing muscle activity data from horses during riding. We design and develop two prototypes: MyoCollect and HindHelp. MyoCollect enables muscle data collection and show how gait recognition can be performed on the data using statistics and graph analysis. HindHelp illustrates an use case of electromyography during jumping training.

RELATED WORK
We examine previous work on ACI, Horse-Computer Interaction and electromyography with focus on horses.

Animal-Computer Interaction
Animal-Computer Interaction is a fairly new research area which is only considered by almost a handful of researchers throughout the world. We have earlier provided a snapshot of ACI research [1] in the period of 2010-2016. The results showed a strong focus on dogs both as pets and working animals. In relation to the last mentioned, over a quarter of

the 38 examined papers were concerned with the animal being a tool for a human to reach a goal, for example as cancer detection, rather than being in center of the research. An example of one of these papers, is the one by Robinson et. al. [16] concerned with diabetes alert dogs. These dogs are trained to warn their patient of an upcoming attack so the patient can take actions; calling for help etc. The researchers aims to investigate the development of a system that enables a dog to remotely call for help on their owner's behalf. They conducted a field study where they observed daily activities, interviewed dog trainers and handlers, and developed a prototype design for an alert system, which were trained and tested with two alert dogs and analyzed. The researchers developed a prototype consisting of an electronic base (just a piece of wood for the test), trigger and the bringsel which the dog should pull to trigger the alarm. The tests showed that the dogs were able to learn how to use the triggers, however the system could be improved by some feedback for the dogs when they have pulled (alarmed) correctly.

An example of an paper that takes basis in the animals well-being is one by Macini et. al [12]. The researchers wanted to investigate whether ubiquitous computing technology to enhance human well-being and daily experience could be used to improve the welfare of kenneled dogs. They performed a study on developing smart environments for kenneled dogs. The researchers visited the kennel 2 to 3 times (3 to 4 hours each time) weekly over a period of four months. The goal was to understand the canine carers and kenneled dogs lifes and work together and potential come up with smart solutions that could support them in their daily tasks. The results showed that through an intensive ethnography study the team was able to come up with multiple solutions which could add to the dogs' well-being and support the caretakers in their daily work. This included multiple tracking devices for the dogs' daily movement, heart and respiration rates, together with a smart kennel which for example automatically could change the information screens on a space based on the dog inside it.

These two above example shows the two main themes of ACI research: animals using IT-systems for support of human needs (etc. as cancer detection), and developing of technology that increase the well-being of the animal (etc. increasing well-being of kenneled dogs). Some papers are combining both themes. As an example, Noz et al. [14] created the human-animal interactive game: Cat Cat Revolution. The game can be played single player by the cat on an iPad or multiplayer where the human play on a connected iPhone. The goal is for the cat to catch the moving mouse on the tablet. The mouse is automated or controlled by the human. Seven owners and their cats participated in the evaluation of the game. Participants performed play tasks and answer questions about their gaming experience and interactions with their pets. The participants were happy about the multiplayer actions and the game, and one participants said his cat liked the multiplayer version better as the owner would move the mouse and as example let the mouse stay in one place for a while and the suddenly move. The single player version was also praised at the cat could play alone when the owner didn't have time. The paper suggest implications for future human-pet gaming systems and researchers have to explore new ways to include pets in the digital gaming experience.

Current ACI research are clustered around a low variety of animals and themes. In the future researchers should focus more on extending the studies related to kind of animals, study type etc. as this could lead to new discoveries and give an bigger overview. We will expand the field by exploring animal-computer interaction in a human-horse setting.

Horse-Computer Interaction

Thompson et al. have created an automated feedback system for amateur dressage riders, which based on four IMUs (inertial measurements units), one for each of the horses legs, recognize the gait and key performance attributes [23]. These attributes were (1) rhythm, (2) regularity, (3) impulsion (4) consistency of duty factor, and (5) smoothness of turns and straights. They conducted a deployment study with 23 horses and 21 riders, which participated in a total of 29 tests. Each of these 29 equipages was asked to perform a ridden test with the system equipped. Ridden tests were taped and annotated for gait, turns and movements. The system was able to predict the level of dressage test performed by the extracted performance attributes with $> 75\%$ accuracy. Additionally, it was observed that high level equipages were more consistent, as their standard deviation of key attributes as rhythm and smoothness for turns and straights were smaller than lower dressage level equipages.

Münz and colleagues have tested the correlation between riding skills and the interaction of the human pelvis with the horse [13]. 20 riders participated in the project and were split into two groups, beginners and professionals. They were measured riding on a straight-lined trackway of 30 meters in walk, sitting trot and right lead canter. Three inertial sensors were placed on the dorsal of the riders pelvis, centrally on the saddle girth beneath the horse's sternum and the last on the horse front leg to determine footfall. The results showed differences in kinematics between beginners and professionals. Beginners tilted their pelvis further to the right and more backwards. Professional riders kept their pelvis closer to the mid-position and further forward.

The research from Thompson and Münz are based on measuring the horse and rider during training for understanding their movement. With basis in this approach we also analysis the horse's movement by collecting and analyzing muscle activity data.

Electromyography on Horses

Electromyography (EMG) is a technique for recording of electric potential of muscles. Muscle recruitment are identified through the onset and offset of motor unit action potentials (MUAP). There are two kinds of electromyography referring to the way the electric potential are measured: surface EMG where electrodes are mounted on the horses skin, or intramuscular EMG where needles are placed in the muscle [15]. The electromyogram - the product of electromygraphy measurements - gives information on the motor neurons of the muscle at rest and in contraction [24]. EMG activity is measured in microvolt and illustrates the amount of muscle contraction. Due to the cognitive-behavioral processes of a living being, EMG activity will always be measurable without obvious actions from the patient [10].

Wessum et al. have examined different applications for EMG in horses for understanding of the pathology of the muscle and nerves [24]. They found that it can be useful for veterinarians making a diagnosis and especially for distinguishing whether the disorder is muscular or neurogenic in origin. EMG can also be useful as a research tool for assessing muscle activation patterns and force of contracting during locomotion in athletic horses.

Aoki and colleagues have examined the influence of the rider on a horse's shoulder muscles using electromyography [4]. They found that more muscle activity occur with a rider on top, rather when the horse moves freely alone. This was most clear in the swing phase of trot and canter, where muscle activity were recorded with the rider, but none without him. In 1995, Tokuriki and Aoki performed a similar study with focus on the horse hindlimb [3]. They examined the activity in two of the horse's big hindlimb muscle, with and without rider in all three gaits. Their results indicated different purpose for the muscles, as the two would be active in different phases of the horse's locomotion. Other research are also concerned with the movement of the rider as for example investigating the muscle activity in riders upper-body during trot [22] and head movement of different level riders in all gaits [21].

As shown by this small overview, multiple research have been done with electromyography on horses, primarily within veterinary research. They all have in common that the user of the systems and results of the research are for vets or scientists. Most papers are concerned with investigating the horse body, and not on possible solutions. None provides the electromyogram data directly to the riders or horse owners. In this paper, we strive to make a simple system which can be attached on a horse and provide useful information about the horse' hind legs to the rider during training.

HORSE MOVEMENT

In this section we will elaborate on how horses move around. Understanding horse movement is crucial when working with electromyography as the knowledge will set the basis for correct sensor placement and analysis of the collected data.

Typical competition horses have three gaits: walk, trot and canter, which are shown on Figure 1. First row illustrates walk, which is a four-beat gait, where 2 or 3 legs always will touch the ground. As show on the illustration the horse will move its legs one at a time in the sequence: left hind leg, left front leg, right hind leg, right front leg.

Trot is a two-beat gait where the horse will have two diagonal hooves in the ground alternately. Between the strides the horse will not touch the ground and be in a swing phase. Trot can come in various of forms: Dressage riders distinguish between four types: collected, working, medium and extended trot, differing in stride length and collecting etc., here sorted in stride length, ascending. Trotting racehorse compete in the fastest trot they can with very long strides.

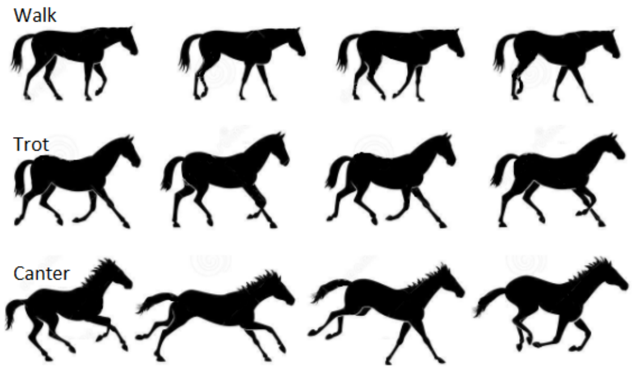


Figure 1: The horse's three main gaits; walk, trot, and canter.

Canter is a three-beat gait that come in two version: left or right, referring to which front leg being the forward leg. In the illustration the horse is in right canter. At first the left hind leg will touch the ground. Following up is the second beat with the diagonal pair of the right hind leg and the left front leg. Last beat is right front leg, which demonstrates why it is called right canter, as the right front leg always will show most forward. After the three-beat stride, the horse will be in a flight phase with no hooves on the ground. Right canter is used when riding right around, as the horse will lean slightly inwards and right front leg will support the horse. The opposite is valid for left canter.

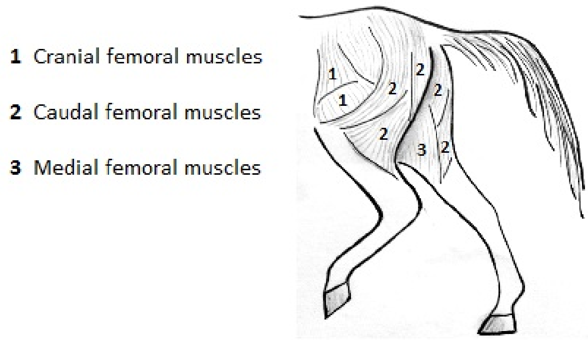


Figure 2: Simplified illustration of muscles in the horse's thigh.

The hindlimb which are the primary motor behind horse movement, consist of several important muscle as shown in Figure 2. The muscles surrounding the thigh are categorized in three groups according to their location and role [6]: Cranial femoral muscles work primarily as flexors of the hip. The big caudal femoral muscles are important for locomotion and their complex actions vary according to the gait and phase of the stride. The medial femoral muscles are adductors, as contraction of these results in a pulling of the limb forward.

We will test our prototypes on the caudal femoral muscles (group 2 in Figure 2) as these takes the biggest part in the horse movement. Furthermore the muscles are big and flat, which makes the sensor placement and attachment easier.

MYOCOLLECT

To explore the potential of wearable technology for horses, we introduce MyoCollect, a data-collection system that measures muscle activity using surface electromyography. In our prototype system we choose to focus on the horse's hind (back) legs, but the technique could be applied elsewhere. This is an attractive area for measurements as the hind are considered the motor-units of the horse, as described in the previous section. Furthermore, the hind legs consist of big muscles that makes it easier for placing sensors on specific muscle groups.

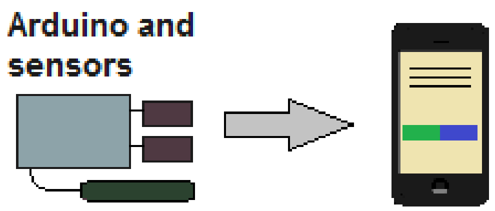


Figure 3: Conceptual illustration of MyoCollect. On the left: an Arduino, two sensors and a power bank. On the right: Mobile phone with an android application.

MyoCollect is a combination of two parts: a sensor system and an android app which is illustrated in Figure 3. In this section, we describe the two parts in detail.

Sensing

Overall the sensor system consist of two MyoWare Muscle Sensors, an Arduino 101 and the necessary wires for connections. The MyoWare Muscle Sensors measures the activity of a muscle by detecting its electric potential [19]. It acts by measuring the filtered and rectified electrical activity of a muscle; outputting 0-Vs Volts depending of the amount of activity in the selected muscle, where Vs signifies the voltage of the power source. Our setup gives the sensor a 5V input, and they thereby outputs 0-5V. The higher measured muscle activity, the higher output voltage.

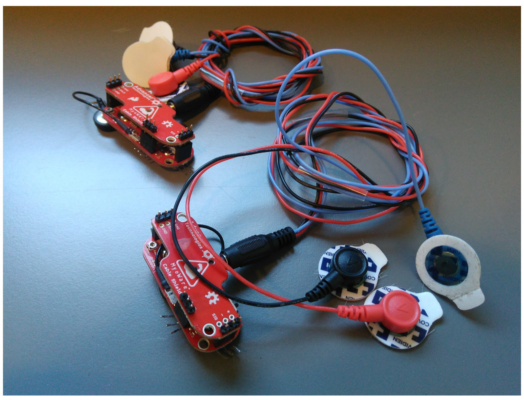


Figure 4: Two MyoWare Muscle Sensors with the Myoware Cable Shield attach, which makes it easy for attaching the electrode cables. At the end of each there is an electrode, where we have attached electrode pads.

An electromyogram can be obtain using either needle or surface electrode pads. We use surface electrodes as these are non-invasive and safer to use by non-ventenarians. Each sensor have three cables and electrodes in the end - these are shown in Figure 4. The Myoware sensor are usable without cables as electrodes pads can be attach directly on the sensor. We however attach a Cable Shield and cables for a greater range between the electrodes. The electrode pads can easily be attached on the cables using the clip-on system. An electrode pad contains (blue) electrode gel in the middle, which helps the electricity transfer from the muscle to the electrodes. Around the gel the pad have clue that helps sticking to the skin.

Interface and Processing

The arduino continuously receive muscle activity voltage from the sensors and sends the sensor data values through the built-in Bluetooth LE component with the CurieBLE library to a smartphone with the android app.

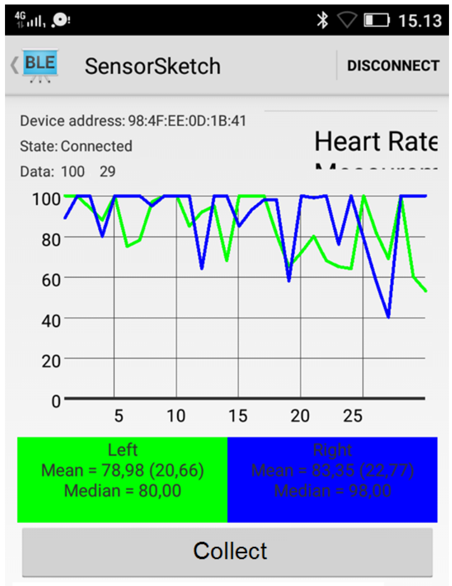
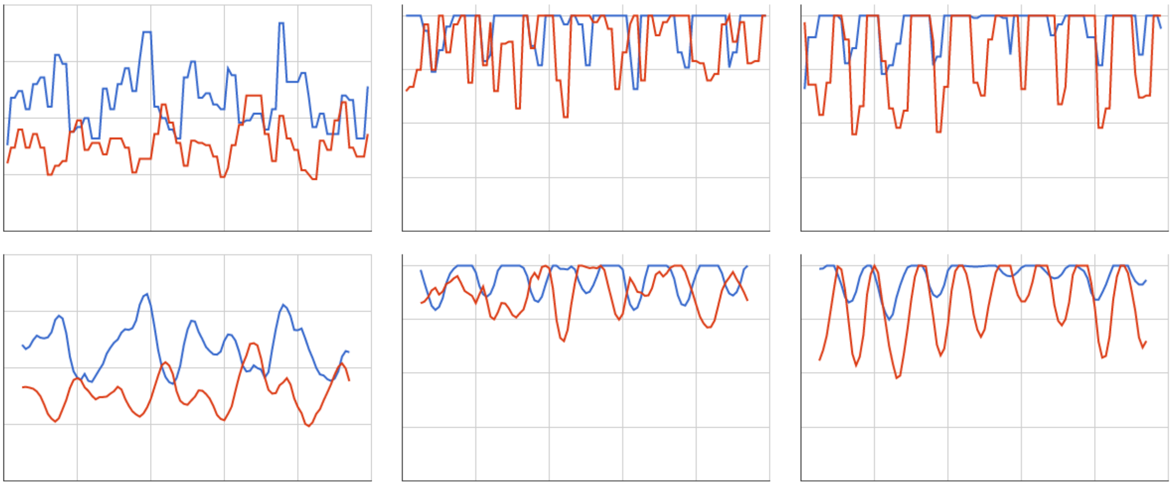


Figure 5: Snapshot of our android application which enable communication with the sensor system and saves 5-seconds data bits when pushing the big button.

The android application is build upon the official android BluetoothLeGatt example [2], which already support pairing of devices and retrieving data from the different characteristic of a Bluetooth LE connection. Figure 5 shows a screenshot of the android interface. Our android app continuously shows the sensor data from both sensors and draw a graphical representation, which is very useful for debugging as one can see if sensor data change as the horse moves or if the mobile phone looses the contact with the arduino.



a) Walk b) Trot c) Canter

Figure 6: Application of Savitzky-Golay filter on three data set from walk, trot and canter. First row shows raw data, and second row shows the same data after application of the filter. The X-axis on each graph denotes seconds and the Y-axis the % percentage of measurable muscle activity.

EXPERIMENT

We test MyoCollect using an explorative field study, where the goal is to understand which data the system can provide.

Participants and Settings

We recruited two equipages (horse and rider) through our network. The first equipage consist of the 9 year old mare Kallisto and her 23 year old rider Sofie. Kallisto have a height of 155cm and is very slim. Second equipage is the 12 year old mare Tanzania and her 24 year old owner Michelle. Tanzania have a height of 165cm and sturdy. Riders and horses are used to training together. We have performed three session with the two different equipages, as summed up in Table 1. Two sessions with sensors placed on each hind leg, and one on the same muscles on same side.

Session	Horse	Sensor Placement	Shaved
1	Kallisto	Left and Right	Yes
2	Kallisto	Same side	Yes
3	Tanzania	Left and Right	Yes

Table 1: Overview of test sessions.

Procedure

Test sessions were executed at the stables were the horses live. First we explained the riders about the purpose of the experiment, the agenda of the day and collected personal information about the rider and horse, eg. name, age, familiarity of each other etc. Next the rider would prepare the horse with equipment, while we would attach MyoCollect. The horses was equipped as normally with sadle and bridle (head piece). Riders wore helmets and there regular riding clothing and boots. Figure 8 shows how MyoCollect is attached and placed on a horse.

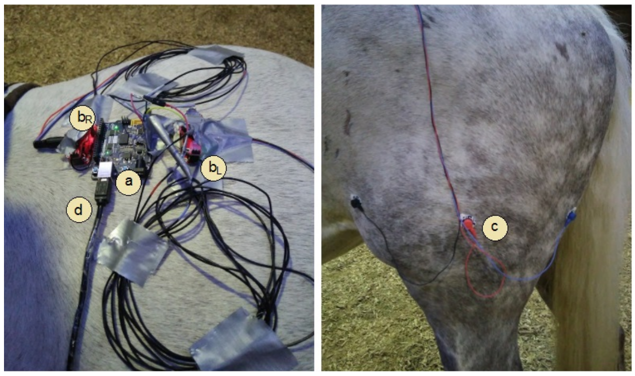


Figure 8: MyoCollect seen on a horse. The following can be seen: a) the Arduino microcontroller board, b_L) the myoware muscle sensor measuring the left hind leg, b_V) the myoware muscle sensor measuring the right hind leg, c) electrodes for left hind leg, d) wire for the power supply that would be placed in the pocket of the rider.

The experiment took place in the associated riding hall of each stable. The rider would warm up the horse in walk for 5-10 minutes before the test started. Riders was asked to ride in a big circle at approximately 20 meters in diameter. This approach were chosen due to the Bluetooth LE signal and similarity of the sensor data. The test monitor would stand in the middle and push the button in MyoCollect, as shown earlier in Figure 5, when the equipage was moving in the desired gait. For each session the muscle activity was measured in the following sequence: walking right around, walking left around, trotting right around, trotting left around, cantering right around, and cantering left around. For each of these, 10 data sets of 5 seconds each was captured and saved; containing sensor data for both left and right sensor. Sensor

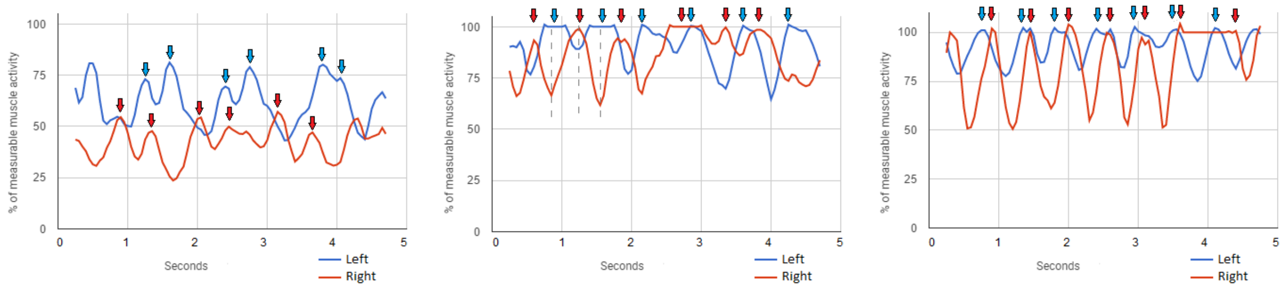


Figure 7: Graphical representations of three data sets from walk, trot and canter. Peaks of each graph are illustrated with arrows.

data were measured every 5 milliseconds, giving 2x100 data points per 5 seconds. We chose to capture data in these 5 seconds slots as it is long enough to have several strides but easier to handle than bigger data sets.

Data Collection and Analysis

For each session we collect 60 data sets - 5-seconds data bits - distributed over the three different gaits. One data set consist of 100 data points for each sensor; left or right. The raw sensor data can be very noisy or too detailed. When measuring horse movements, small fluctuations can be dismissed as we are primarily interesting in big peaks or troughs that determine strides and the characteristics of these.

We use the Savitzky-Golay filter which minimize noise by smoothen data. Visualization of the data transformation can be seen in Figure 6, where first row shows raw data, and second shows same data after alternation with the filter. The filter gently smoothing the data by fitting successive sub-sets of adjacent data points with a low-degree polynomial by the method of linear least squares. This means that the filter will generate a new data point based on raw data and the surrounding data points. Thereby will small peaks and noise disappear. The window size of the filter determines how many surrounding points there will be considered. We have demonstrated window size of 9, which mean that four datapoints before and four after will be weighing in on the smoothing.

RESULTS

We have analyzed the collected data using several kinds of graph analysis methods. We show clear differences in data sets and how the muscle activity data can be used for gait detection. In addition, we describe observations regarding sensor placement and skin preparation.

Gait Recognition

Gait is the pattern of movement of the legs of an animal. As mentioned earlier, a typical riding horse have three kinds of gaits: walk, trot and canter, where walk and trot corresponds to human walk and running. Canter is the horse's fastest gait which follows a round three beat flow.

Stride delimitation can be performed using graph peak and trough analysis, where a peak will symbolize a high muscle activity - caused by a movement or weight-bearing of the leg. Just by looking at the graphs in Figure 6 it is clear that there is a difference between walk and the two faster gaits; trot and canter. Below we will describe the differences in detail. We will start with an visual analysis of what the graphical representations can tell us of the three gaits. Figure 7 consist of three good examples of the gaits. Note that these are different from the ones of Figure 6. The x-asis denotes seconds, and the y-axis shows percentage of measurable muscle activity. Blue and red arrows states peaks of the data. First illustration show measurements for walk. Each graph follows a pattern with two peaks close located followed by a big drop. Due to the symmetrically of the four-beat gait, the data for the left hind leg will peak when the one for the right hind leg will drop.

Second illustration shows an example of muscle activity measured for trot. Trot will follow the same pattern as for walk, as the peaks for one graph will be simultaneously with the troughs of the other. We have shown this on the figure with dotted lines for the three first occasions. Peaks also appear sharpener and longer away from the median of the data than for walk. The horse moves its legs faster in trot, and will thereby use more muscle power and have a higher frequency of the strides. Arrows on top of the graph indicates peaks, and illustrates that peaks occurs alternately, all though the data seems irregularly for the last half part.

Canter is a asymmetrically three-beat gait where the two hind legs will move right after each other. This can be seen in the third illustration, as the two graphs will follow same pattern, just with the red for the right hind leg following slightly behind. The peaks of the two graphs will be very close as illustrated on the figure with arrows. We call an occurrence of two close peaks of each data set for a peak-pair and will introduce these further later on.

	Walk	Trot	Canter
Avg. muscle activity:	66.66%	90.20%	92.14%
Standard deviation:	24.13	13.74	13.11

Table 2: Average data values from the two sensors combined in the three gaits walk, trot and canter.

We present average data values - muscle activity in % - from both sensors combined, together with the standard derivation in Table 2. The values show what we also can see on the graphical representations: the muscle activity in walk is lower than trot and canter. We perform an ANOVA test to define if the difference in average values are significant. All data points - 4000 points - for each gait was compared. The p-value corresponding to the F-statistic of one-way ANOVA is lower than 0.05, suggesting that the one or more treatments are significantly different. We perform the post-hoc test, Tukey HSD test, to identify which of the pairs of treatments are significantly different from each other. The results show that all three pairs are significantly with $p < 0.01$. We can thereby conclude that our measurements for walk, trot, and canter with the respectively averages at 58,5%, 85% and 88.5% are significantly different. Despite this, it is clear that the difference between trot (90.20%) and canter (92.14%) are smaller than the one between the two and walk (66.66%). We will thereby look further into how these can be differentiated.

Peaks

Above we touched upon the difference in the patterns of the graphical representations of the data. Now we will look at the data from a more statistical point of view, by analyzing the occurrences of peaks.

Table 3 summarize the average of peaks and distance between peaks for both left and right sensor in the three gaits. Each number in the table is an average of 40 5-seconds data bits from session 1. First row indicates that the number of peaks increases with a faster gait, as walk have the lowest number of peaks - 7.95 in average - and canter have the highest - 11.15 in average.

	Walk	Trot	Canter
Avg. number of peaks:	7.95	9.03	11.15
Standard deviation:	3.28	3.17	2.97

	Walk	Trot	Canter
Avg. dist. between peaks:	0.56s	0.48s	0.58s
Standard deviation:	5.17	4.06	3.72

Table 3: First table summarize average number of peaks in total in the three gaits. Beneath the average distance between the peaks are stated in seconds.

Comparing the two tables, we see there is a clear correlation between the number of peaks and the avg. distance between peaks; the more peaks, the lower average distance between these. This makes sense as the more peaks the less space for distance between them.

We perform an ANOVA test to check if the distance between peaks are significantly different. The compared data consist of respectively 261, 300 and 255 data points for walk, trot and canter. The p-value corresponding to the F-statistic of one-way ANOVA is lower than 0.05, suggesting that the one or more treatments are significantly different. The post-hoc Tukey HSD test shows that the difference between walk and trot are insignificantly. On the other hand, the pairs walk and canter, and trot and canter are significantly different with $p < 0.01$.

Detecting Peak-Pairs for Canter recognition

We introduce peak-pair as a term for two nearby peaks from each data set. We distinguish between two kind: left-right and right-left peak-pairs, where the name indicates the order of the peaks. Figure 9 illustrates the two definitions. For categorizing as a left-right peak-pair, the right peak should be categorized within the range of the decreasing phase of the left data. Peak-pairs can be seen in Figure 7. There are several left-right peak pairs - where the data set representing the left hind leg will peak first, just followed by the data of the right leg. For the data on this figure the horse were in right canter; for left canter the order of would be switched, which in theory give us right-left peaks pairs instead.

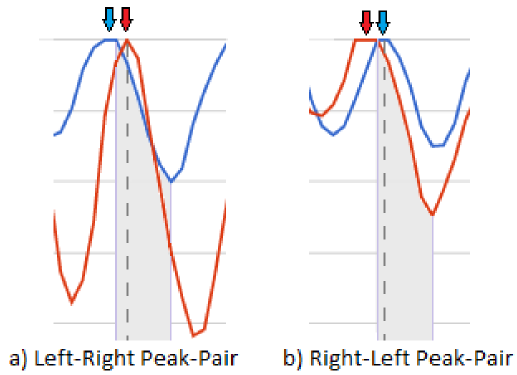


Figure 9: Detecting of peak-pairs. Two data points from two distinguished data sets categorize as a peak-pair if the second peak occurs within the range (gree area) of the following drop of the first peak.

Peak Pairs	Left-Right	Right-Left
Walk (Right Around)	29% (2,70)	34% (3,20)
Walk (Left Around)	25% (2,10)	27% (2,10)
Trot (Right Around)	59% (5,20)	48% (4,60)
Trot (Left Around)	26% (2,50)	29% (2,80)
Right Canter (Rigth Around)	53% (3,50)	3% (0,20)
Left Canter (Left Around)	5% (0,40)	16% (1,30)

Table 4: Average occurrences of left-right and right-left peak pairs in the three gaits; walk, trot and canter. Percentage indicates peak pairs occurrences in relation to all peaks. Actual average of peaks shown in parenthesis. Note that peaks can be part of both left-right and right-left peaks, and a row can thereby accumulate to more than 100%.

Detecting peak-pairs becomes very interesting in relation to canter. Peak-pairs give information of order of leg movement. As mentioned beforehand, a left-right peak-pair indicates that the data for the left hind leg will peak first, followed by the data for the right hind leg, as shown in Figure 1. We can use this information to determine from a dataset if the horse is in right or left canter. The two last rows in Table 4 shows an higher occurrences (53%) of left-right peak-pears in right canter that right-left peak-pairs (3%). For left canter, the difference is not as significant, but present as right-left peak-pairs occurs oftener (16%) than left-right peak pairs. By calculating peak-pairs, we can find out whether the horse is right or left canter. With the highest occurrences of left-right peak-pairs, the horse will with high accuracy be in right canter. An opposite for left canter.

Sensor Placement

We performed an additional test session (Session 2 in Table 1) with our shaved test horse having both sensors measuring the same muscle. This test shows us how precise the sensors are, as we would expect somehow similar data from both. By comparing statistical analysis of the data from both sensors we found that one sensor consistently returns higher voltage than the other. By inspecting graphical illustrations of the data we however find that the sensor data to some extent follow the same pattern.

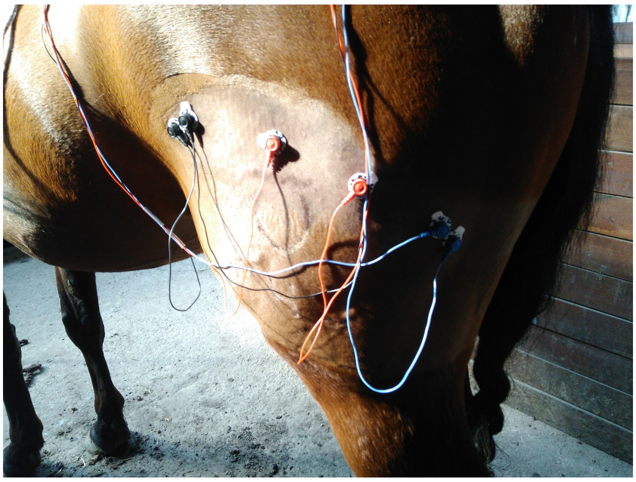


Figure 10: Sensor placement of the the electrodes on same hindleg. The left-most black, red and blue sensor are connected to sensor 1, and the right-most electrodes are connected to sensor 2.

	Walk	Trot	Canter
Sensor 1	67.95% (SD=13.97)	96.01% (SD=3.78)	92.51% (SD=8.25)
Sensor 2	54.85% (SD=15.44)	86.15% (SD=6.17)	70.20% (SD=11.96)

Table 5: Average muscle activity measured with sensors placed on same muscles.

Table 5 shows average values of sensor data from the session. As an example, the first column of data in the table shows average data values for the two sensors in walk: Sensor 1 had an average of 67,95% and sensor 2 had 54,85%. By comparing the average values for both sensors, we discover that Sensor 1 have consistently higher values which could be a result of multiple things: high different of voltage in the different location of the muscle, electrodes not probably placed, uneven calibration of sensors etc. We will discuss these limitations later.

Hair-coat vs. shaved skin

Our third session (see Table 1 was performed with a different horse, Tanzania, a 12 year old mare. Figure 8 shows MyoCollect on her. The focus of this session was to examine if MyoCollect could be used on non-shaved horse skin. The results shows that it is crucial that the horse is shaved, so the electrodes can be placed directly on the skin and measure muscle activity correctly. Figure 11 illustrates which data we got from the session. On the right a snippet of the data is shown, on the left a graphical representation of all data points. Independent of Tanzania's movement, we got similar output to the one shown in the figure. Sensor 1 would consistently output a muscle activity of value 50% and sensor 2 constantly 100%.

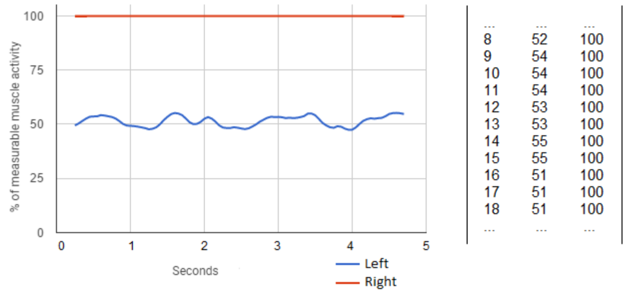


Figure 11: A graphical illustration of one dataset obtained with the non-shaved horse Tanzania during session 2 of our experiment. On the right a snippet of the data is shown. First column is the number of datapoint (each dataset containing 100 datapoints), column two is of the left sensor (blue) and the third column is the right sensor (red).

Horses do have a natural coat of hair, some longer and with higher density than others. Tanzania have a thin and short coat, but it is still too much to measure muscle activity compared to the patterns we saw in session 1 with our shaved horse Kallisto.

HINDHELP

We have developed MyoCollect which is a system for measuring and collecting muscle activity data of a horse during riding. We performed three test sessions and showed how the collected data can be used for gait recognition. In addition, we also showed some limitations to the technology as sensor placement and preparation in the form of shaving is crucial. We now present HindHelp, which is an extension to MyoCollect that apply the muscle activity data in a simple application that can help riders understand their horse's move patterns and potentially discover uneven movement.

The Case: Take-off During Jumping Training

Our case is concerned with horse jumping. Jumping is a very technical discipline. Professional jumping competitions takes the equipages through a course of 10-13 obstacles with a height up to 160 centimeters [8]. Horses often need to jump their own height and length, which require a lot of technique to succeed. To reach the necessary height the horse needs to get an optimal take-off into the air over the jump (see Picture 12). We will now demonstrate how surface electromyography can provide useful muscle activity information to support training of jumping horse.

We show the phases of a jump in Figure 12. Just before an obstacle the horse will lengthened its forelimb to facilitate the transformation of a horizontal movement to a vertical [6].

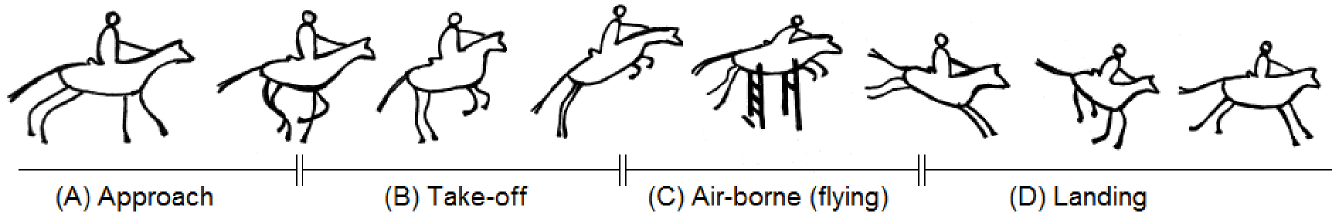


Figure 12: A jump consists of four phases: approach, take-off, flying and landing as shown in Figure 12. In the first phase (A) the equipage will approach the obstacle in a energetic canter with round strives. During take-off (B) the energy will be used to push the equipage away from the ground. The rider will rise from the saddle and lean forward to give the horse possibility for bending in the back. The air-borne phase (C) is where the horse fly over the obstacle. In this phase the horse will lift its legs to avoid hitting a bar. To prepare for the landing (D) the horse will stretch its forelegs and gently bend them when touching the ground to absorb the shock. When all legs are on the ground again, the equipage will continue in canter.

The limbs are engaged and pulled up just behind the front legs. Propulsion are achieved by straightening of the hind limbs. The upwards impulsion pushes the horse's body over the obstacle. To achieve the best jump, the horse are supposed to place its back legs right next to each other and push equally with both. An electromyogram of the back legs in the take-off phase can tell if the legs are equally bearing. If not, the rider can focus the training on strengthening the weak hind leg.

Technical Setup

To illustrate how sEMG can be used during jumping training, we introduce the partly developed system HindHelp. HindHelp built-upon our data-collection system MyoCollect. Instead of collecting and saving data, the system analysis a 5-second data bit and returns data analysis to the rider. The data analysis can be executed in multiple ways, we choose a simple method by presenting the rider for average values of both data sets; the left sensor data set, and the right sensor data set - see Figure 13. This will provide the rider with an number between 0-100 for each hind leg, symbolizing its average muscle activity.

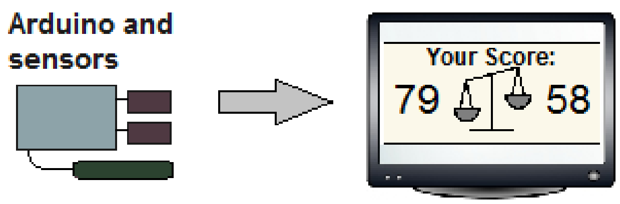


Figure 13: The sensing part of HindHelp is equally to the one of MyoCollectas shown before, consisting of an arduino, two MyoWare Muscle Sensors and a power supply. The output feedback of HindHelp is presented to the rider on a big screen located in the end of the riding hall. It contains a simple interface with the average of the two sensor data sets shown. Between them an old scaling weight is added for visualization of which side of the horse is most weight-bearing.

Imaging the use scenario: A rider attach HindHelp to the horse before a jumping training session. When approaching a jump, HindHelp will start collecting muscle data and save data for 5 seconds covering the take-off. Shortly after the jump, the rider can look at the screen in the riding hall and see

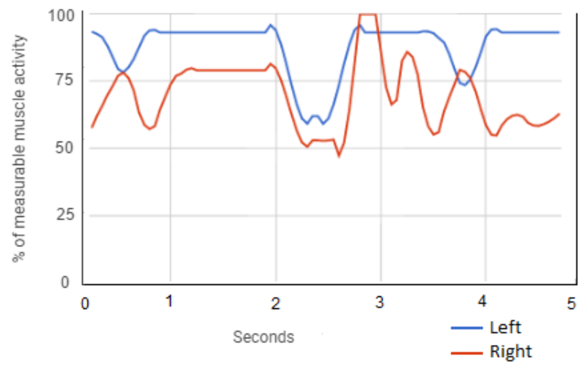


Figure 14: An example of a data set collected during jumping.

his score, as demonstrated in Figure 13. The score helps the riders to reflect over there technique and continuously uneven scores can indicate that the horse needs to go through specific exercise for strengthening its hind legs. Figure 14 shows an example of a data set collected during jumping. Both graphs drop in the middle of the figure illustrating the flying phase of jump. Average of this example is respectively 87,64% for the left sensor and 69,58%, which shows that the last mentioned have an overall lower muscle activity.

Evaluation

We evaluated our conceptual use case scenarios with three riders using informal interviews. All evaluations was performed at the farms were the participants had their horse stabled and had a length of 10-20 minutes. Participants were females in the age of range 21-27 years. We presented the idea by showing them HindHelp and examples of output feedback. The purpose was to get comments on the use case of surface EMG during horse-rider interaction.

All three riders were overall exited about HindHelp. They haven't used similar technology during riding beforehand and liked the idea of achieving information that they - or a trainer - can not see. Camilla, the youngest and most inexperienced participant, said *"I think it is very cool - but I would never imaging something like this by myself."*.

We presented the riders with the raw prototype and it was clear that they became a bit overwhelmed by all the different electronic pieces and wires. Michala, who works with product development, claimed that the setup needed to simplified so you only needed some small sensor components and a smartphone. She also stated that attaching HindHelp correctly on the attended muscle groups might be to difficult compared to the size of information that the rider would get about their horse. Camilla expressed same concerns as she said that she wasn't familiar with the different muscles of the horse. The last participant, Emilie was through her job as a veterinarian familiar with electromyography. She had in connection with her education worked with needle EMG in a laboratory setting. She liked the idea of using EMG in a training setting, but expressed doubt about the precision of the surface electrodes. Elaborating that *"I wouldn't change my way of riding because of small variation in the data provided by HindHelp"*.

Our evaluation shows that systems like HindHelp have a potential for providing useful information to riders, that haven't been available beforehand. The riders however express concerns about the usability of the prototype as it may be too complex, require knowledge of the horse's musculature and sensor data be incorrect or untrustworthy.

DISCUSSION

We investigated the use of sensors for measuring muscle activity on horses during riding through the system MyoCollect. MyoCollectis a data-collection system which through two sensors measures and saves activity data from big muscles in the horse's two hind legs. We showed that this data can be used for detecting gait of the horse using graph analysis. Extending previous research on animal-computer interaction our experiments indicate that their is a potential for using IT-systems during interplay with horses, as it can provide us with so far unavailable information. However there exist some limitations to technology, which we will discuss below.

Electromyography on Horses

Most electromyography research performed with horses are needle EMG used in laboratory settings. Surface EMG is noninvasive and can easily be used in the field by non-scientist users to assess muscle activity [25]. It is uncertain how the two kinds vary in accuracy, but more noise and errors would possible occur with surface EMG.

We performed a test session with a horse without remove its hair on the target muscles. The setup gave unreliable data as the sensors would simply just continuously output their maximal value, as it also was the case of test session 3. It is clear that attaching sensors to a non-shaved skin can be challenging. Horses frequently roll around in the field for pleasure, grooming or discomfort [20]. Thereby the horse' coat can contains a lot of dirt, which can be difficult to remove with everyday brushing or washing. Electrode pads will have trouble sticking to the dirty coat and furthermore can dense hair be in the way of the electrode reaching the skin and thereby the sEMG signal of the muscle, resulting in wrong or none output. We considered it a big limitations that shaving is necessary for using the electrodes, as this will potential frighten riders from using the technology. Some will say it is ugly to have shaved spots, and other would be afraid to mess with the horse's natural fur coat generation. However most riding horses have their coat cutting during winter and instead wears a rug, due to not having to be wet of sweat in the cold temperatures. During this period, the horse owner could consider cutting the hair fully of and thereby creating possibility for using a wearable system as HindHelp. It could be interesting to investigate further if sEMG sensors can be used through the coat, to use on non-shaved horses or potentially other animals with fur.

Limitations of Sensors

During test sessions it was noticed that sensors would stay in maximal value for some time, even though it seems like the horse was relaxing the muscles again. As an example, when the horse would stand still the sensors would output values around 20% muscle activity. Then a fly would land on one of the hind legs resulting in a rapidly muscle contraction do spook the fly. Measured muscle activity would raise to 100% and stay there for several seconds. The used sensors are developed to humans and all examples of their use are with humans. Potential error measurements can be expected as we use the sensors on a horse which have larger muscles and not as linear orientated as humans. Myoware recommend that their sensor are placed on the middle of a muscle with the reference electrode on an adjacent muscle. To achieve this we extended the sensors with electrode cables.

CONCLUSION

We have implemented and tested MyoCollect, which is a data-collection system used on horse during riding for measuring muscle activity using surface electromyography. consist of two sensors, an arduino and a mobile application. The arduino and sensors are attached to a horse's back legs and measures the voltage they produce, eg. their muscle activity. We present the data and show how this can be used for gait recognition using different kinds of peak analysis. We extend the data-collection case by presenting the use case of show jumping training. The paper contributes to the ACI research field by presenting a new use context of surface electromyography and setting a basis for further investigations of the technology.

Future Work

This paper contributes to the ACI and equine research field by taking an exploratory approach to facilitating existing technology in a new context. The work can be used as a basic for further investigation of the use of sEMG or other sensory systems in a human-horse relationship. Future work could include building and testing HindHelpor similarly systems that provides riders with informations they are not use to getting. Studies like these would not only create further understanding of the potential of the technology but also investigate how riders can and will interact with it in specific contexts.

Standardization of sEMG on animals would be useful to develop in the future, as the technology can be very useful in multiple cases. Imagine a commercial version of a sEMG sensor that animal owners can use on their pets during recovery from illness. Attaching the muscle sensors to a horse overnight can give the owner detailed information about its wellbeing - as potential tensions can be recognized and cured.

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