# Monitoring local muscle load in football

Use leg acceleration, processed with a big data analysis approach, as an indication of the local muscle load to accurately represent the players' experienced load.

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Delft University of Technology

> Research project



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## Preface

During the bachelor Mechanical Engineering, I became quite fascinated by applying a mechanical approach to human movement and healthcare issues. The curriculum allowed me to learn more about how to approach the human body from a mechanical engineering perspective. By choosing the minor Sport, Movement, and Health at the VU University Amsterdam and a BSc thesis on meniscus tissue, my academic path became more and more clear.

From a very young age, I practised various sports at a high recreational level, ball sports in particular being my favourite. I have experienced the effects of intensive movement on my own body, suffering sore muscles and pain regularly, recovering by training wisely. A specialisation in Sports Engineering within the MSc BioMechanical Design and studying Biomaterials and Tissue Engineering at University College London appeared to be both logical and very interesting steps.

These main themes led to the thesis project of monitoring local muscle load in football, in close collaboration with the Dutch Football Association. The Sports Engineering Institute became my playground and provided a research area within the analysis of sports. At top-level sports and technology, I had the opportunity to acquire more knowledge, investigate human movement, and design solutions to healthcare issues. What a great chance to contribute to research and development at an elite athlete level. I became convinced that anyone performing recreational sports and health, and moving conditions in general, can benefit from this approach and the results.

From the start, this subject was quite an appealing challenge. Combining my competences as a sports-loving academic in an operational setting and finding answers by using a systematic big data analysis approach, suited me perfectly. This big data analysis approach formed the basis of developing a widely applicable, sustainable method, not only to use in top-level sports with elite football athletes but in other sports and levels as well, thereby reaching larger groups of consumers. Being a user-friendly method and a true cost saver, I strongly believe in further research. It could then be an excellent and widely used indicative muscle prevention system, focussed on improving performance and physical condition.

I would like to thank Daan Bregman – TU Delft – and Edwin Goedhart – KNVB – for their perpetual enthusiasm in daily supervising me during the project. Their non-stop support and knowledge in this field made it possible to apply an academic perspective to a highly relevant topic in practice. Furthermore, I would like to thank the entire graduation committee for evaluating and discussing my thesis.

To my dear family and friends, I say 'thank you' with a big smile. You were all at my side throughout the process of my studies. In many ways you stimulated and supported me to pursue my possibilities and dreams for which I am truly grateful.

Enjoy reading my thesis,

Rozemarijn Schotel 20.06.2019

## Abstract

In football, a lot of hip and thigh muscle injuries occur as a result of high muscular loads due to accelerative leg movements. To prevent muscle damage and optimise performance, it is essential to continuously identify when and how frequent local hip and thigh muscular loads develop in the explosive and dynamic football environment. The currently used method is an acceleration index based on two-dimensional position data of the whole global body measured by the Local Positioning Measurement system. The problem is that this system does not correspond with the experienced load of players because leg movements are excluded. Therefore, this study introduces a new local concept of gathering local three-dimensional leg acceleration data by inertial measurement units.

This pilot study aims to use a big data analysis approach to translate leg acceleration data into a measure to indicate local muscle load and compare this new local and the current global method to the players' experienced load. Five participants performed specific football drills with an intensity increase from jogging to sprinting and by adding a pass and shot. Measures are developed, based on the pelvis, upper leg, and lower leg accelerations, by a peak and cumulative data analysis approach.

By evaluating trend percentages of the intensity increase, it is obtained that a local acceleration measure is comparable to the players' experienced load if it considers the sum of normal or peak data points weighted per zone and per travelled distance. Furthermore, a similar result is obtained when only the upper leg or lower leg accelerations are considered.

It can be concluded that local three-dimensional acceleration of the lower extremities, processed with a big data analysis approach, represent the football players' experienced muscular load more accurate than the current global method. Further research, including a higher number of participants, should prove the significance.

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# Introduction 1

In football or - alternatively - soccer a lot of muscle injuries occur. 31% of all injuries consist of muscle injuries and cause 27% of the total injury absence of players (Ekstrand et al., 2011). Muscle injuries will be defined as: "a traumatic distraction or overuse injury to the muscle leading to a player being unable to fully participate in training or match play" (Ekstrand et al., 2011). Ekstrand et al. (2011) investigated muscle injuries in elite football teams, finding an average of 0.6 muscle injuries per player per season, which lead to missing 15 days, 10 practices, and 2.5 matches per muscle injury. Furthermore, professional football players' physical performance - based on whole body motion profiles and conducted passes - has increased over the past decade (Barnes et al., 2014). Barnes et al., 2014 showed that high-intensity running distance and actions increased by 30% and 50%, respectively. The sprint distance and number of sprints increased by 35%. Additionally, the study shows substantial growth in the number of - successful - passes. Therefore, muscle injury risk increases as an effect of the physical performance raise. A growing rate of 4% per annum is visible with regards to training-related hamstring injuries in elite male football players (Ekstrand et al., 2016). The high - increasing - rate of muscle injuries is a big problem among players and teams since it leads to absence and high costs in professional football (Eirale, 2015, Corazza et al., 2013, and Ekstrand et al., 2011). A one-month injured elite football player costs around €500,000 (Ekstrand, 2013). Thus, the importance of muscle injury prevention from an economic point of view becomes clear. Bearing the massive impact on a player's health as well as the significant financial implications in mind, the need for early injury detection and minimising the injury rate through continuous monitoring of the muscle load becomes apparent and is of high relevance (Woods et al., 2004).

Muscle injuries mostly arise at the end of a match half and during explosive movements. First, fatigue influences the muscles, which lead to a decline in maximal force or power output (Halson, 2014, Fitts, 1994, and Edwards, 1983). Fatigue is easy to observe, but it is a complex phenomenon (Halson, 2014). Neuromuscular and mechanical factors are key in developing fatigue (Özkaya et al., 2017, Boyas and Guével, 2011, Enoka and Duchateau, 2008, and Noakes and St Clair Gibson, 2004). Many football movements consist of repetitive and short high-intensity activities, and different contraction and stimulus types are needed, which lead to muscle fatigue. A study by Mohr et al. (2003) shows that high-intensity running distance - 35-45% – and sprinting distance – 43% – in elite players decline towards the end of each match half, i.e. fatigue starts to play a role. Furthermore, players experience temporary fatigue after short highintensity activities. Muscle injuries happen about equally during matches and practices - 53% and 47% respectively. However, the injury incidence rate is about six times higher in matches (Ekstrand et al., 2011). During matches, injuries were found to happen more towards the end of each half (Ekstrand et al., 2011 and Woods et al., 2004). Second, football is an interval-based team sport with high physical demands: elite football players perform both high- and lowerintensity activities during practices and matches. The high-intensity activities consist of acceleration and deceleration movements (Varley and Aughey, 2013), which are physically much more demanding than constant velocity, confronting players with large local musculoskeletal loads (Osgnach et al., 2010). Typical football movements are fast and explosive like sprinting, turning, shooting, sliding, and jumping (Mueller-Wohlfahrt et al., 2013, Varley and Aughey, 2013, Andersson et al., 2008, and Järvinen et al., 2005). Summarising, football players have a higher incident rate to get muscle injuries towards the end of each match half, which could be due to fatigue in the muscle fibres and the neuromuscular system as a result of the high-intensity nature.

Explosive movements increase the risk of acute and chronic muscle damage and cause muscle injuries as a result of powerful eccentric muscle stretching (Nédélec et al., 2012 and Andersson et al., 2008). First, according to a study by Ekstrand et al. (2011), acute trauma causes 2 out of 3 football muscle injuries, and 42% of the groin, 30% of the hamstring, and 26% of the quadriceps muscle injuries were due to overuse. Furthermore, distinguishing direct and indirect muscle trauma within acute muscle injuries (Maffulli et al., 2015 and Mueller-Wohlfahrt et al., 2013), most muscle injuries occurred during situations without any contact: 96% hamstrings, 96% quadriceps, and 92% adductors (Ekstrand et al., 2011). Second, muscle injuries mostly happen during excessive lengthening or stretching of an actively contracting muscle - i.e. eccentric contraction -, which can lead to muscle pain and weakness (Maffulli et al., 2015, Allen, 2001, and Garrett, 1999). Elite football players conduct a lot of explosive movements, which result in numerous powerful eccentric contraction. There is no external force in these situations, and muscle damage can evolve (Nédélec et al., 2012). Two initial events cause this indirect muscle damage: disruption of the sarcomeres - structural damage - and a failing excitation-contraction coupling system - nonstructural damage (Maffulli et al., 2015, Mueller-Wohlfahrt et al., 2013, Allen, 2001, and Proske and Morgan, 2001). The latter, overexertion, intra-/intermuscular and intersegmental coordination are prone to faults during the fast and explosive movements, (neuro-)muscular fatigue could play a role. Concluding, football players have a high chance to obtain exercise-induced skeletal muscle injuries, primary by an acute indirect muscle trauma or overuse, as a result of repetitive or excessive lengthening of muscle fibres or stretching of an active muscle (Askling et al., 2008 and Slavotinek et al., 2002).

Hip and thigh muscles have the highest injury risk due to the type of movements in football and their specific muscle characteristics. First, acute indirect trauma and overuse are the most common types of muscle injuries in football. In both cases, there is no impact involved and can be divided into structural and non-structural injuries with different levels of severity (Mueller-Wohlfahrt et al., 2013), respectively to the two initial events named above. Second, muscles involved in indirect traumas are mostly muscles crossing two joints with a pennate architecture and a high percentage of type II fibres (Maffulli et al., 2015, Mueller-Wohlfahrt et al., 2013, Järvinen et al., 2005, and Woods et al., 2004). Bi-articular muscles are more involved in getting injured than muscles spanning one joint, due to the increased chance of getting lengthened excessively and the complex intersegmental coordination system. Furthermore, pennate muscles have a muscle fibre angle relative to the long muscle axis, and therefore, have more but shorter muscle fibres, which makes it possible to powerfully contract with a small range of motion. Additionally, type II muscle fibres are mostly damaged (Clarkson and Hubal, 2002 and Friden et al., 1983), due to their non-fatigue resistant character (Schiaffino and Reggiani, 2011 and Kelly, 2004). Last, the most muscle injuries - 79% of all muscle injuries and 25% of all injuries - in professional football occur in three major muscle groups in the hip and thigh region: 37% in the hamstrings, 23% in the adductors, and 19% in the quadriceps (Ekstrand et al., 2011). So, overuse and acute non-contact situations can cause structural and non-structural damage, specifically biarticular muscles with a nonfatigue resistant and pennate fibre composition are prone to get injured, which are seen in the hip and thigh muscles.

To date, there is a high need to continuously know the muscular load of the most injury-sensitive muscle groups in real-life football situations and on an individual level. A quote by Halson (2014) emphasises the importance of monitoring: "Appropriate

monitoring of training load can provide important information to athletes and coaches; however, monitoring systems should be intuitive, provide efficient data analysis and interpretation, and enable efficient reporting of simple, yet scientifically valid, feedback". Currently, limited knowledge exists on the local muscle level, and it is challenging for players, technical staff, and medical staff to track and identify when the load on the thigh musculoskeletal system becomes too high, which could lead to muscle injuries. To adjust the training load, optimise performance, and prevent muscle injuries, it is essential to know when and how many high local muscle loads occur (Halson, 2014). Two main approaches are used to determine the physical load. First, subjective measurement methods like questionnaires exist. A questionnaire is not a very accurate method but can be conducted very efficiently without spending a lot of money (Halson, 2014) to obtain the players' experienced load for a specific activity or duration. Second, three objective systems exist to track the players' whole body - i.e. global - activity throughout an entire practice or match. Video cameras, Global Positioning Systems, and Local Position Measurements are available to obtain the whole-body motion profile in two dimensions based on positional information in time (Buchheit et al., 2014 and Carling et al., 2008). These systems provide global data regarding the players' travelled distance, speed, acceleration, and change in direction (e.g. Varley and Aughey, 2013 and Mathie et al., 2004). Currently, the total travelled distance and travelled high-speed metres are used as an indicator of physical load and performance (Vigh-Larsen et al., 2018). But, football is a dynamic sport with many accelerations, which are eliminated by this approach (Polglaze et al., 2016). The Dutch Football Association recently started to include these in an acceleration index - i.e. acceleration count. However, this measure excludes specific information about local limb motion patterns. There do exist measurement systems which consider the local movements. Indoor three-dimensional motion analysis methods are available, such as VICON and Kinect (Afrouzian et al., 2016, Dupré et al., 2016, and van den Bogert et al., 2013). 3D motion analysis systems combine the kinematics and kinetics of the musculoskeletal system in a human body model. These commercially available systems measure a variety of local variables during one movement under controlled environmental conditions. This does not represent the dynamic football environment. Concluding, the problem is that the currently available monitoring systems do not provide accurate information about leg movements to predict the local load in real-life football situation, and therefore, it is necessary to develop new methods.

The literature background of muscle injuries and current measurement system leads to the measurement requirements of this study. (i) Obtain the muscle load by objective measurement methods and use subjective data to support objective findings. (ii) Gain valuable local muscular load information of the hip and thigh muscles, due to the high muscle injury rate in the upper legs. (iii) Minimum and maximum peaks indicate low and high-intensity movements, respectively. The magnitude and number of peaks provide insight into heavy and easy drills. As stated before, acute non-contact trauma has a high occurrence rate and temporary fatigue arises during short highintensity activities. Therefore, monitor peaks above a certain threshold to decrease muscle injury risk. (iv) Use cumulative values to reveal the load of multiple drills, practices, or matches. Muscle injuries often happen as a result of overuse and most muscle injuries occur during the end of a match half, when fatigue starts to play a role. Therefore, local cumulative values of all performed movements could provide information and give a better understanding of muscle injuries in time. (v) Measure these peak and cumulative values in a timeframe of an entire practice or match. (vii) Obtain the data outside on the entire pitch in the normal environment to get a good view of all the repetitive dynamic activities (James, 2006). (viii) Use a non-invasive and safe to use measurement method which does not restrict the player when executing any movement (Fleming and Beynnon, 2004). In summary, the new method requires to obtain objective local data by capturing peak and cumulative values during an entire match or practice on the pitch, without restricting the players' movement.

Use accelerations of the lower extremities, measured by inertial measurement units, to indicate local muscle load. Eccentric contractions are the primary cause of high muscular loads in the hipand thigh-related muscle groups. These occur during the physically very demanding explosive high-intensity movements, like sprinting, shooting, and turning, which include many high and repetitive accelerations and decelerations. Therefore, monitoring the accelerations of the lower extremities has excellent potential to indicate hip and thigh muscle load. Many studies investigate the application of inertial measurement units - IMUs for short - attached to the body segments to perform accurate and reliable human motion analyses in health monitoring, rehabilitation, and sports, due to the technical developments of the recent decade (Tao et al., 2012, Tao et al., 2012, Cuesta-Vargas et al., 2010, Saber-Sheikh et al., 2010, and Omkar et al., 2009, and Mathie et al., 2004). An IMU consists of a 3D magnetometer, gyroscope, and accelerometer module, which measure the magnetic field, angular rate, and acceleration, respectively (Tao et al., 2012, Yun et al., 2007, Zhu and Zhou, 2004, and Bachmann et al., 2004). This provides a sourceless, small, light, low-cost, onboard data-logging, optional wireless, and easy to use sensor, which can be used in any area without restricting the football player and in any environment to provide valuable objective kinematic information to evaluate the musculoskeletal system during movement (Tao et al., 2012, Cuesta-Vargas et al., 2010, Saber-Sheikh et al., 2010, Yun et al., 2007, James, 2006, Channells et al., 2005, Mathie et al., 2004, Zhu and Zhou, 2004, and Mayagoitia et al., 2002). Most studies use all three or a combination of two of the IMU modules to obtain the position and orientation to analyse joint angles (El-Gohary et al., 2017, He et al., 2015, Seel et al. 2014, Kitamura and Sagawa, 2012, Saber-Sheikh et al., 2010, Bonnet and Héliot, 2007) and are compared to 3D motion analysis methods (Channells et al., 2005) like VICON (Schiefer et al., 2011 and Mayagoitia et al., 2002). These studies were conducted using one or two IMUs during short and straightforward movements: around one joint, one segment, one movement, as a whole-body, in one direction or one plane, at constant speeds, low speeds, and repetitive motions. However, football is a dynamic sport with long durations (James, 2006). Concluding, further investigate the use of IMUs to obtain the local leg acceleration profile in a fast and dynamic realistic football setting, as this has not vet been studied.

Two different data processing approaches can be distinguished to translate leg acceleration data into a measure to predict muscle load during football activities: a biomechanical segmental model of the legs and a big data analysis. Previous studies used IMUs to obtain the orientation, relative position, and direction and magnitude of displacement of a segment to analyse joint angles by a variety of methods: single and double integration, Euler angles, rotation matrix, quaternions, Kalman filter, and extended Kalman filter (He et al., 2015, Seel et al., 2014, Schiefer et al., 2011, Saber-Sheikh et al., 2010, Yun et al., 2007, James, 2006, Yun and Bachmann, 2006, Luinge and Veltink, 2005, Sabatini et al., 2005, Mathie et al., 2004, and Zhu and Zhou, 2004). Most of these algorithms use the integration of the angular rates to estimate the orientation or by integrating the acceleration twice to obtain the position, a downside of this method is drifting of the signal (Yun et al., 2007, and Sabatini et al., 2005). This drift will increase extensively due to the long measurement times, fast movements, and many directional changes in football. Furthermore, IMUs have an internal coordinate system. Obtain the segmental orientation by integrating the angular rate to separate the gravitational and kinematic acceleration components. However, some fast football movements will result in high leg angular rates, which exceed the gyroscope range in commercially available IMUs - see Appendix H.1. Complex biomechanical models of the trunk and lower extremities, which are time-consuming and need high computational load due to the constantly changing dynamic situations in football, are needed to make this approach sufficient. The biomechanical segmental model is not possible with the set requirements. These examples show the complexity and error sensitiveness of double integration of acceleration to obtain position

and single integration of angular rate to obtain orientation (He et al., 2015 and James, 2006). The quote by James (2006) explains this very accurately: "A purely technology based approach using accelerometers for sporting applications has yielded little success, whereas informed signal processing of the data through the use of sport specific knowledge and involvement of sport scientists has allowed the extraction key features in the data which can then be interpreted in a useful manner". A second approach to express muscle load in local acceleration data of the lower extremities could be using big data analysis. A less accurate and precise approach, but collecting a lot of data, of extensive periods of measuring time, and in the real football environment, could provide a manner to predict local muscle load by developing measures based on a peak and cumulative analysis, and eventually optimise performance and prevent muscle injuries. This approach will allow wide applicability, within elite football athletes, but also has the potential to be used in other sports, in entire teams - i.e. on a big scale -, and on a recreational level. This could be achieved due to the affordable, easy to use, and low computational load of using accelerometers and a big data analysis approach. Using big data analysis is interesting to investigate, as this approach has not yet been researched. This study has been done to elaborate on the whole new concept of integrating commercially available IMUs in a sports legging and perform football drills with increased intensity on the pitch to obtain leg accelerations. The focus should be on translating the data into an easy to use and intuitive measure for players, medical staff, and technical staff.

This pilot study aims to use a big data analysis approach to translate leg acceleration data into a measure to indicate local muscle load and compare this new local and the current global method to the players' experienced load. Therefore, the research question of this exploratory research is: could local three-dimensional acceleration of the lower extremities, processed with a big data analysis approach, represent the football players' experienced muscular load more accurate than the current global method? The current method is an acceleration index based on two-dimensional position data of the whole body obtained by the Local Positioning Measurement system -LPM for short - and the new local method gathers local acceleration data of the lower extremities in three dimensions by using the acceleration module of Shimmer3 IMUs. The expectations are that the local data is a more accurate representation of the experienced load than the current global measure, i.e. increasing the drill intensity in football will be visible in the local three-dimensional acceleration pattern of the lower extremities, but not in the current global indication of load. This research tests the hypothesis "the intensity increase of a football drill will increase the local load similarly as the experienced load, but not global, based on acceleration" to show this.

# Method 12

#### 2.1 Experiment design

Develop an experiment with representative football drills, including significant intensity contrasts, and compare the local and global accelerations to the experienced load. Perform two drills – including specific football movements: jog/sprint, turn, and pass/shoot – on the pitch by 5 participants: (A) back/forth and (B) zigzag. Increase the intensity of these drills from jogging to sprinting and adding a pass/shot. The participants wear a set of sensors to measure the movements. The measurement methods are (I) questionnaire: subjective method to obtain the experienced load, (II) 2D LPM: current objective method to obtain the global acceleration index of the whole body, with the sensor location between the shoulder blades, and (III) 3D accelerometers: new objective method to obtain the local acceleration of the lower extremities, with sensor locations at the middle of the pelvis, upper legs, and lower legs.

### 2.1.1 Participants

Five participants perform the experiment. The information letter of Appendix A informs the participants by explaining the reason for the study, the experiment, and what will happen with their data. The participant profile: male in the age of 20–29 with a length between 168–185cm, and three of them left-footed and the other two rightfooted. Furthermore, the participants' sports background: one professional forward football player at the end of his revalidation, one indoor goalkeeper, two endurance players, and a field hockey player, all of them with plenty of experience in ball sports. All participants were able to complete the experiment. The participants are men, able to shoot a ball, and can physically finish the experiment – i.e. to have a moderate fitness level –, because this is a pilot study.

### 2.1.2 Measurement methods

This study considers three measurement methods. The objective is to test the hypothesis with off-the-shelf accelerometers – Shimmer3 IMUs – available at the Delft University of Technology and the current global method – LPM system – of the Dutch Football Association to indicate muscle load in comparison to a questionnaire on experienced load. The study intends to explore acceleration measures. This paragraph elaborates on the use of these measurement methods and the attachment to the body without restricting the participant in any way while performing the experiment.

Method I: Questionnaire. Obtain the experienced load on a scale of 1 - easy - to 10 - hard - per situation via a questionnaire by asking the participant directly after each part of the experiment. This results in subjective data and is the benchmark in this study. See Appendix B for the experienced load questionnaire.

Method II: Local Positioning Measurement system. This is the current global objective method to obtain two-dimensional motion data of the whole body. LPM is a real-time radio-frequency identification technology based Local Positioning Measurement system and uses *inmotio* analysis software (Ogris et al., 2012, Frencken et al., 2010, Barris and Button, 2008, and Carling et al., 2008). The system uses multiple passive base stations around the pitch and an active transponder worn by the football player to measure position in time, which can be used for an individual player or track a team (Buchheit et al., 2014, Ogris et al., 2012, Frencken et al., 2010, and Stelzer et al., 2004). The location of the sensor is in a small shoulder harness – Figure 2.1A –, which sticks to a special tight t-shirt with velcro fastener. See Figure 2.1D and E for a schematic visualisation and a participant picture of the global sensor location on the body, respectively. Additional features of the LPM system are cameras to film the participant and a heart rate monitor. The experiment protocol in Appendix C describes step-by-step how to operate the system.

The current global acceleration measure to evaluate the players' physical load and performance by medical and technical staff during practice and matches is an acceleration index. *Inmotio* is the software to calculate this by differentiating the position-time data twice to obtain whole body acceleration in the direction of movement and export this data in a .csv format with a sampling rate of 200Hz. The acceleration index is a cumulative value defined as the count of accelerations which meet the condition of at least 0.5s above 1.6 m/s<sup>2</sup> and lead to >10 km/h<sup>2</sup>.

Method III: Shimmer3 Inertial Measurement Units. The accelerometer modules of the Shimmer3 IMUs - Figure 2.1B measure the acceleration profile of the lower extremities. This is a local objective measurement method. There are two different accelerometer modules integrated: low-noise and wide-range, with a range of  $\pm 2g$  and  $\pm 16g$ , respectively. The protocol trial results exceed the low-noise range. The acceleration magnitudes of the legs will be the highest of the body, especially in the forward direction (Bhattacharya et al., 1980), but the other directions should be taken in consideration (Lafortuna, 1991), and will depend on the type of movement (Mathie et al., 2004). The highest accelerations occur around the ankle during sprinting: ±8.1-12.0g (Woodward and Cunningham 1993, Lafortune 1991, and Bhattacharya et al., 1980). A study by Channells et al. (2005) used accelerometers of ±18g to test constant running with different speeds. So, the three-dimensional wide-range accelerometers will include all the fast leg accelerations.

Use five accelerometers to obtain a complete 3D acceleration profile of the lower extremities. The focus is on the three most occurring muscle injuries in football: hamstring, adductors, and quadriceps. Due to the bi-articular nature of the hamstrings and quadriceps, which cross the hip and knee joint, the acceleration profile of the pelvis and lower legs are relevant. The adductor muscle group cross the hip, therefore, consider the pelvis accelerations. So, the locations of the IMUs are in the middle of the pelvis, the right upper and lower leg, and the left upper and lower leg to include all leg movements (El-Gohary et al., 2017, Kitamura and Sagawa, 2012, Schiefer et al., 2011, and Namal et al., 2006), see Figure 2.1D.

Integrate the five IMUs into a tight sports legging, which will not hinder or limitate movement of the participant, see Figure 2.1E. The middle of the leg might vary between the participants due to different segmental lengths. Therefore, the sensor locations in the legging are adjustable to customise to the participant. The sensors stay in place by safety pins. Be consistent and position the sensors roughly at the same location for each participant. Measure the sensor distance relative to each other and specific body features. A visualisation of the method to measure this distance is on the information participant form - Appendix B - and the protocol - Appendix C. Note the measured distance during the experiment in the information participant form. The position of the sensors will vary a bit between the participants, and some displacement will occur during movement. However, these small deviations are not of significance in this exploratory study, and by using a big data analysis approach, not of high relevance. Furthermore, IMUs have a local coordination system, see Figure 2.1C. Therefore, position the sensors in the legging with the same orientation. Concluding, the local measurement method is a sensor legging with adjustable IMU locations to fit the participants, with IMUs in the same orientation and location throughout all experiments.

IMUs have an internal timeline, and therefore, start at a different moment in time. Create a mark in the angular rate signal – measured by the gyroscope module – by simultaneously rotating the IMUs around the z-axis. The synchronisation of the internal timelines occurs in the data processing phase – Paragraph 2.2.1 – by using this mark. The maximum gyroscope range –  $\pm$ 2000dps – is sufficient. Furthermore, attach a reference IMU – sixth local sensor – at the location of the LPM sensor to obtain a similar acceleration profile – see Figure 2.1A – to synchronise the timelines of the global and local measurement methods. The discovery of using a reference sensor was during the protocol trial. So, use the gyroscope module of the IMUs and a reference IMU to synchronise the global and local data.

*ConsensysBasic* is the software to operate the Shimmer3 IMUs, see Figure 2.1F. There does exist a *ConsensysPro* version with more options, however, to make it easier to reproduce the experiment by others, use *ConsensysBasic* for convenience. The experiment protocol in Appendix C describes step-by-step how to operate the system in great detail. Varying the sampling rate during a local sensor trial resulted in 199.8Hz. Export the local calibrated data from this software in a *.m* file, to be processed.



Figure 2.1 – A: LPM sensor including a reference IMU; B: All Shimmer3 IMUs C: Internal coordinate system of Shimmer3 IMUs; D-E: Schematic representation and a picture of a participant with all measurement methods, respectively; F: Preparation and configuration of the IMUs.

#### 2.1.3 Experiment drills

Base the drill design on previous literature studies, the disadvantages of the LPM system, and the expertise of football staff. First, injuries mostly occur for hamstrings during multi-directional acceleration, changing of direction, stretching, high-speed running,

shooting, and sliding (Melegati and Tornese, 2015, Heiderscheit et al., 2010, Askling et al., 2007, Askling et al., 2006, and Woods et al., 2004), for adductors during turning, twisting, shooting, stretching, jumping, quick accelerating, and side-to-side movement (Loureiro et al., 2017, Barreira et al., 2017, Dupré et al., 2016, and Maffulli et al., 2015), and quadriceps during sprinting/running and shooting (Barreira et al., 2017 and Orchard, 2002). Second, global data represents the whole body movement measured at the upper back in 2D, while the movement pattern of the legs will be different and in 3D. Therefore, global data is expected to be insufficient to include all movement, whereas a local system will measure all leg movement. For example, LPM does not register when a player shoots a ball – Appendix H.2 –, while this has an impact on the thigh muscles. Last, discussing this knowledge with football experts, the chosen elements are jog/sprint, turn, and pass/shoot. So, when performing specific football movements, differences will show between the local and global data, and it is likely that sprinting, shooting, and high-speed turning - highintensity elements - will cause higher local muscular loads than jogging, passing, and low-speed turning – low-intensity elements.

Process these elements into two drills, each including all movements in a slightly different form to add some variety. The drills are designed in collaboration with the medical football staff of the Dutch Football Association. Conduct two easy to perform drills to compare the different measurement methods and analyse if they structurally differentiate in both variations. Moreover, performing multiple drills per experiment increases the comparability with a real practice setting to evaluate if the new local method also works if muscle fatigue occurs. Performing multiple situations of each drill with an intensity increase will allow the comparison of the global and local measurements to the subjective method to predict load. So, the variable factor is the intensity increase per situation. Intensity can be adjusted by frequency, load, and duration (Halson, 2014). In this study, increase the intensity by changing the load while keeping the frequency and distance constant. Note that the duration will be shorter if speed is increased and longer by adding a shot, while travelled distance remains the same. The repetitions per situation are the same throughout the experiment, meaning that the distance is constant and the time it takes to complete every situation is dependent. Furthermore, use short distances to simulate the many short accelerative movements in football correctly and focus on performing the movements in a normal manner. Therefore, standardise the drills with as little constraints as possible and perform these on the pitch. Design the drills with large intensity contrasts and include elements which the global measurement method does not detect, but players experience as high load.

**Drill A.** This drill is a simple back and forth exercise. The first situation includes two jogs of five meter and two turns – situation 1a – with a repetition rate of 10 times. The intensity increases by adding a pass – situation 1b – and a shot – situation 1c – at one side, aiming at a target. The second situation is similar, but sprinting replaces the jogging element, which also increases the turning intensity. See Figure 2.2A for a schematic representation, drill dimensions, and situation description. Figure 2.2C shows a picture of a participant performing drill A on the pitch during the experiment.

**Drill B.** This drill is a zigzag exercise. The third situation includes three zigzags and seven turns – situation 3a –, with a repetition rate of 5 times. After each repetition, the participant walks or slowly jogs back to the start. The intensity increases by adding a shot – situation 3b – at the end, aiming at a target. The fourth situation is similar, but sprinting replaces the jogging element, which also increases the turning intensity. See Figure 2.2B and D for a schematic representation of drill B, including the dimensions and the situation description, and a picture of the drill during the experiment.

**Execution of the drills.** The drill location on the pitch is for every experiment the same. Place one cone on the penalty spot, this is the start point of drill A, and the end point of drill B. Figure 2.2C and D show a picture of drill A and drill B on the pitch with a participant, respectively. As mentioned before, the focus is to conduct a study in the most natural environment of football players – i.e. out of lab

settings and on the pitch - while performing normal football drills. However, set some constraints on how to perform the drills to control the experiment, and in a later stage, being able to process and analyse the data of the different measurement methods. The protocol trial has been of great help on optimising this. The participant should perform the drills in a normal and clear manner, without playing with the ball and limit lots of movement in between the situations. Therefore, after each drill with a ball, the researcher will collect them. The drill consists of the following three elements. First, a jog and a sprint, which are around 60% and 100% of the maximum speed, respectively. Second, turn with one leg at the location of the cone not around the cone -, it does not matter which leg. Third, if the situations involve a ball, the ball will replace the last cone, and the researcher places a new ball for all 10 or 5 repetitions - drill A and drill B, respectively. To be consistent, set a target to aim for when passing or shooting to create a similar movement. However, the shooting leg between participants does not matter. Last, pass or shoot the ball directly with the inside of the foot, without any small touch before hitting the ball. The protocol summarises the drill instructions – Appendix C –, explain these clearly to the participant.



D

Figure 2.2 – A-B: Schematic representation of drill A and B, including the situation descriptions; C-D: Picture of drill A and B during the experiment.

Drills versus hypothesis. Link the hypothesis to the drills. (A) Intensity increase of jogging - hypothesis A.I - and sprinting hypothesis A.II - back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration. (B) Intensity increase of jogging - hypothesis B.I - and sprinting - hypothesis B.II - a zigzag by a shot will increase the local load similarly as the experienced load, but not global, based on acceleration. Figure 2.3 shows an overview of the expected muscle load with intensity increase - low, medium, and high - when measuring with a subjective - left -, objective global - middle -, and objective local - right - method. It is expected that global and local methods can differentiate between the situations when the intensity increases from a jog to a sprint. However, the LPM system is not able to differentiate the load within the situations, i.e. increasing the intensity by a pass/shot. However, from practice, the local muscle load is higher. The new local acceleration method is expected to include a pass/shot, due to the consideration of all leg movements.



Figure 2.3 – Link drills to the hypothesis: the expected muscle load with intensity increase – low, medium, and high – when measuring with a subjective – left –, objective global – middle –, and objective local – right – method.

#### 2.1.4 Experiment protocol

Perform all experiments in a similar way by clearly describing and standardising the experiment protocol. The standardisation of the set-up will not limit the participant in performing the drills in a natural football way. The description of each step is with a high level of detail, see Appendix C. The explanation of all relevant information considering the participants, measurement methods, and drills have been discussed in the previous paragraphs. The protocol consists of 4 steps: pre-preparation, preparation, experiment, and completion.

Step 0: Pre-preparation. The pre-preparation step includes the set-up of the experiment. First, test and get familiar with all measurement methods and design the drill, legging, and protocol. Next, develop all documents: ethics checklist, informed consent, information letter participants, and information participant form and drill questionnaire, see Appendix D, E, A, and B, respectively. The experiment deals with human participants and approval by the ethical committee of the Delft University of Technology has been permitted, see Appendix D. Last, collection or knowing where to find all equipment, reservation of the pitch, and inviting participants.

Use three trials to evaluate, improve, and optimise the experiment: (i) Shimmer3 IMU and *ConsensysBasic* trial, (ii) LPM system and *Inmotio* trial, and (iii) a protocol trial. The first two trials are to test and familiarise with the measurement methods and figure out their limitations. Use the observations to make the protocol draft. Next, conduct a trial to test the protocol and drills on the pitch with one participant, including all three measurement methods. See Appendix F and G for the trial protocol and questionnaire document, respectively. Use all knowledge and improvements to optimise the final experiment protocol, not for further processing and analysing.

Step 1: Preparation. First, preparations before the participant arrives: collection of all equipment and measurement methods, drill preparations on the pitch, and the preparations of the IMUs for data logging. To perform the experiment, 10 footballs and a minimum of 11 cones for the drills are needed. Use a large tape measure to set-up the drills with the correct dimensions. Second, preparations when the participant arrives: conduct all participant formalities – explain the experiment and sign the informed consent –, start the IMUs, attach all sensors to clothing after the participant has changed, measure sensor distance, and start the LPM system to capture data.

Step 2: Experiment. Instruct the participant on how to perform the experiment at the pitch. Between the situations is a resting time of 3 minutes and between drill A and B there is a pause of 5 minutes.

Step 3: Completion. First, completion before the participant leaves: stop the LPM system, detach all sensors from clothing, and stop the IMUs. Second, when the participant leaves: import data from all individual IMUs. Last, possible at a later stage, export the LPM data from *Inmotio* and Shimmer3 IMU data from *ConsensysBasic* for data processing and analysing.

### 2.2 Data processing and analysing

Develop a data processing and analysing tool to test different measures to predict local muscle load based on local leg acceleration data obtained by the experiments. The processing of lots of data can be easily done by an algorithm in MATLAB (Namal et al., 2016 and Channells et al., 2005). Base the algorithm on drill A and use drill B to test if the methods also work for a slightly more advanced exercise. A main file runs different functions. Every function performs specific actions and contributes to the data processing and translation of the local acceleration data into a single value to indicate local muscle load per situation. Conduct a peak and cumulative data analysis. Analyse different local measures by varying the input of data process method and measure design to compare the measurement methods.

#### 2.2.1 Data processing

This paragraph will explain the data processing functions: preprocess data, data process methods, and situation segmentation.

**Pre-process data.** First, load and select the objective raw global and local data. Second, resample the local data from 199.8Hz to 200Hz and include the sensor correction sampling frequency percentages – Equation A1-2. Third, synchronise timelines of local data – 6 IMUs, see Appendix H.3. Followed by the synchronisation of the local and global timelines by using the reference IMU – 6 IMUs and LPM, see Appendix H.4. For both synchronisations use cross-correlation and process the leg differences into the local and global data, see Equation A3-5. Last, filter the local acceleration data by a moving-average 1D filter, see Equation A6.

**Data process methods.** This processing step includes the different methods to process the local data, see Equation A7-13 for an overview of the options and their calculations, in the order of testing. Furthermore, normalise the local acceleration data -0-100 - to the maximum of the experiment - Equation A14 - to select zones and peaks according to these zones in the measure design - Appendix H.5. Find the maximum within the participant and not of all 5.

The following reasoning results in the data process methods. First, only methods that use absolute values are important, meaning not differentiating between accelerations and decelerations. Second, the synchronisation of the internal timelines will not be exact on the timestamp. Therefore, do not combine the local sensors, because 100% accuracy cannot be guaranteed. However, it is possible to use the individual signals or to combine the x-, y-, and z-components per sensor. Calculations between sensors a few timesteps off could make a big influence due to the fast leg movements. Third, IMUs have an internal coordinate system. The orientation of the sensor is needed to separate the inertial and gravitational acceleration components during movement. A gyroscope can calculate the orientation but exceeds the range, see Appendix H.1. Therefore, do not consider gravity. However, if the participant stands still, the effect of gravity is visible in the y-component - Appendix H.6 -, but during movement, this effect influences all components. So, it would be best to use the individual signals or a method which combines the x-, y-, and z-components.

Situation segmentation. Conduct the segmentation selection of the drills manually into situations. Base this on the changes in global speed and acceleration data and check if the selected segments – including a safe margin – are correct for the local data – Appendix H.7. A method or algorithm to select the drills and situations automatically which would work for all experiments and situations has not been found, as some of the participants perform more movement in between the situations. The situations of drill A have a specific

segment selection method and are carefully selected manually. Keep this method constant for all experiments and situations. However, roughly select the situations of drill B to check if the measure will also work for entire exercises by loosely selecting the start and end times - i.e. to check if this approach works if a coach or trainer selects a certain part of the training. Include the walking part of drill B, eliminate the time this part takes by conducting calculations in the measure design per travelled distance, which is kept constant. First, select drill A very precisely with a specific method: (i) count the peaks in the global speed - 10 back/forth repetitions, so 20 times -, (ii) select the start and end times in the global absolute acceleration and speed. Start time: if acceleration is zero before the first large acceleration of the situation and the speed increases from zero. End time: if acceleration is zero after the last large acceleration of the situation and the speed decreases towards zero. Due to some movements before and after the situations, the acceleration is not always exactly zero. However, it is quite clear to see, and the design of the experiment eliminates this as much as possible. Second, select drill B roughly: (i) count the zigzags in global data - 5 repetitions -, (ii) select roughly the start and end times in timeframes. At some of the experiments too many repetitions of the situations are performed, to make a fair comparison, the surplus will be manually removed. Next, load and select the start and end times of the situations per drill and per experiment from an excel sheet - see Appendix I. Furthermore, add a safe margin of three seconds before and after each situation, see Equation A15. Use a safe margin to include all data, because: (i) leg movement starts earlier and ends later than the global whole body movement, (ii) synchronisation of the timelines is not exact, compensate for any small mis-synchronisation, and (iii) some participants conduct small movements before and after the situations, compensate for any mis-selection in the global data. Last, use the start and end times to select the situations in the local acceleration signal, see equation A16, but also to cut the global data.

> Resample local x-, y-, and z-acceleration data of all sensors		
$[p,q] = rat \left( \frac{SampRate_{reference}}{SampRate_{local} \cdot SampRate_{ercentage_{local}}}, 0.000 \right)$	01)	1
$ACC_{resample} = resample(ACC_{raw}, p, q)$	)	2
neceresample resumpte (neceraw, p, q)		~
> Synchronise timelines		
1: synchronise timelines of local acceleration data by cross correlation of local z-angular rate data and process		
the lag differences into the local acceleration data		
2: synchronise timelines of local and global acceleration data by cross correlation of global acceleration and		
local x-acceleration data of local reference sensor X and process the lag differences into the global and local		
acceleration data		
[C, lag] = xcorr(DataSignal1, DataSignal2)	Find cross correlation	3
$[\sim, I] = \max(abs(C))$	Find the index of the highest peak	4
LagDiff = lag(I)	Sample difference between the signals	5
((1))	\ \	
> Filter local acceleration data $filter\left(\left(\frac{1}{WS}\right) \cdot or\right)$	nes(1,WS), 1, ACC) WS = WindowSize = 2	6
> Data process methods		
1: absolute values of all individual x,y,z acc		
	$1_z  R2_x  R2_y  R2_z  L1_x  L1_y  L1_z  L2_x  L2_y  L2_z]$	7
2: absolute values of sum of local x,y,z acc	0.14.10	8
$abs (ACC_x + ACC_y + ACC_z)  for ACC = [P  R1  R]$ 3: sum of absolute values of local x,y,z acc	2 L1 L2]	0
abs $(ACC_x) + abs (ACC_y) + abs (ACC_z)$ for $ACC =$	[c	9
4: magnitude of combined local x,v,z acc	[F R1 RZ L1 LZ]	9
sqrt( $ACC_r^2 + ACC_r^2 + ACC_r^2$ ) for $ACC = [P R1 P]$	22 11 12	10
5: absolute values of gradient of magnitude of combine		10
· · · · · · · · · · · · · · · · · · ·		11
$abs\left(gradient\left(sqrt\left(ACC_{x}^{2}+ACC_{y}^{2}+ACC_{x}^{2}\right)\right)\right)$ for		11
6: absolute values of difference of magnitude of combin		
$abs\left(diff\left(sqrt\left(ACC_{x}^{2} + ACC_{y}^{2} + ACC_{x}^{2}\right)\right)\right)$ for ACC	C = [P  R1  R2  L1  L2]	12
7: envelope of magnitude of combined local x,y,z acc		
$envelope(sqrt(ACC_x^2 + ACC_y^2 + ACC_x^2), peak)$ for	ACC = [P  R1  R2  L1  L2]	13
> Normalise signal to 0–100 (ACCmasser/max	$(ACC_{process})) \cdot 100$	14
process?	(	
> Add safe margin per situation [StartT - SafeM	[argin · SampRate EndT – SafeMargin · SampRate]	15
> Segmentation of situations ACC(StartTimeN	lew:EndTimeNew)	16

Equations A - Calculation overview of data processing.

#### 2.2.2 Local acceleration measure design

This paragraph will focus on calculating the global measure and the local acceleration measure design, which is a combination of measure calculations and the combined measure methods.

*Measure calculations per travelled distance.* First, calculate the acceleration index and travelled distance from the global data per situation – Equation B1 –, the *Inmotio* software calculates this automatically per experiment. Second, apply different operations to

the local acceleration data: (i) allocate the accelerations in zones – Equation B2-4 –, (ii) find the peaks in the local acceleration data – Equation B5 –, (iii) allocate the peaks in zones – Equation B6-8 –, (iv) conduct measure calculations, see Equation B9-23 for an overview of the options and their calculations, in the order of testing, and (v) divide the measures by the travelled distance, see Equation B24.

Determine three intensity zones – low, medium, and high – at the data process method function by reviewing the intensity increase of the situations in the normalised local acceleration data – Appendix H.5. Use the lower boundary to exclude very small peaks, which could be due to the noise of the wide-range accelerometer or small sensor movements. Furthermore, introduce a weighting factor for each of the three intensity zones in a way that they represent that higher intensity increases the muscle load more. Use the value of the low boundary of each zone as the weight factor. Vary the zones and weight factors to obtain a decent distribution.

Develop measures to differentiate high- and low- intensity movements – maximum and minimum peaks, respectively – and the overall – cumulative – situation load. The measures identified based on the local acceleration data are number of, average, sum, and area under the curve and are divided into 4 categories, measures with: all data points – 1-3 –, peak data points – 4-9 –, normal data points weighted per zone – 10-12 –, and peak data points weighted per zone – 13-15, all per travelled distance.

Choose measures per travelled distance, instead of per second. First, because it allows the introduction of a safe margin in the data segment function, and therefore, includes the entire situation – global movements start later than the local leg movements. Furthermore, the participants are standing still before and after the situations or move very slowly, so the travelled distance has a smaller influence than time. Third, the drill scheme is based on a fixed distance scheme. Last, include walking back in drill B. Taking the distance – which is constant for all situations and participants –, will eliminate the time it takes of walking or slowly jogging back, which varies between participants. Calculations of the travelled distance per situation are from the global data.

tion index per experiment and per situation	
and the state of t	1
res for all local acceleration data and per situation	
$ZT1 = ACC(Zone(1) < ACC \& ACC \leq Zone(2))$	2
$ZT2 = ACC(Zone(2) < ACC \& ACC \leq Zone(3))$	3
$ZT3 = ACC(Zone(3) < ACC  \&  ACC \leq Zone(4))$	4
$[PKS, \sim, W] = findpeaks(ACC)$	5
$2D1 = DVC(7_{max}(1) < DVC = 0  DVC < 7_{max}(2))$	6
	7
	8
$ZP3 = PKS(Zone(3) \le PKS \& PKS \le Zone(4))$	8
mean(ACC)	9
sum (ACC)	10
trapz(ACC)	11
length (PKS)	12
mean(PKS)	13
sum (PKS)	14
trapz (PKS)	15
sum(W)/length(W)	16
sum(W)	17
$length(ZT1) \cdot WF(1) + length(ZT2) \cdot WF(2) + length(ZT3) \cdot WF(3)$	18
$mean(ZT1) \cdot WF(1) + mean(ZT2) \cdot WF(2) + mean(ZT3) \cdot WF(3)$	19
$sum(ZT1) \cdot WF(1) + sum(ZT2) \cdot WF(2) + sum(ZT3) \cdot WF(3)$	20
$length(ZP1) \cdot WF(1) + length(ZP2) \cdot WF(2) + length(ZP3) \cdot WF(3)$	21
$mean(ZP1) \cdot WF(1) + mean(ZP2) \cdot WF(2) + mean(ZP3) \cdot WF(3)$	22
$sum(ZP1) \cdot WF(1) + sum(ZP2) \cdot WF(2) + sum(ZP3) \cdot WF(3)$	23
measure/travelled distance (obtain this by global data)	24
and z-components per sensor	
	25
neasures of individual local sensors in order to obtain one value	
	26
	27
	28
	29
	30
	res for all local acceleration data and per situation $ZT1 = ACC(Zone(1) < ACC & ACC \le Zone(2))$ $ZT2 = ACC(Zone(2) < ACC & ACC \le Zone(3))$ $ZT3 = ACC(Zone(3) < ACC & ACC \le Zone(4))$ $[PKS, \sim, W] = findpeaks(ACC)$ $ZP1 = PKS(Zone(1) < PKS & PKS \le Zone(2))$ $ZP2 = PKS(Zone(2) < PKS & PKS \le Zone(3))$ $ZP3 = PKS(Zone(3) < PKS & PKS \le Zone(4))$ mean(ACC) sum (ACC) trape_ACC) length (PKS) trape (PKS) trape (PKS) sum (W)/length(W) sum(W)/length(W) sum(W)/length(W) sum(2T1) · WF(1) + length (ZT2) · WF(2) + length (ZT3) · WF(3) mean(ZT1) · WF(1) + sum(ZT2) · WF(2) + mean(ZT3) · WF(3) sum (ZT1) · WF(1) + sum(ZT2) · WF(2) + mean(ZT3) · WF(3) length (ZP1) · WF(1) + sum(ZP2) · WF(2) + mean(ZP3) · WF(3) sum (ZP1) · WF(1) + sum(ZP2) · WF(2) + sum(ZP3) · WF(3) sum (ZP1) · WF(1) + sum(ZP2) · WF(2) + sum(ZP3) · WF(3) sum (ZP1) · WF(1) + sum(ZP2) · WF(2) + sum(ZP3) · WF(3)

Equations B - Calculation overview of measure design.

Combined measure methods. Sum the measures of the individual local sensors in different ways into one value and obtain the combined measure to indicate local muscle load, see Equation B2630 for an overview of the options and their calculations, in the order of testing. If necessary, first combine x-, y-, and z-components per sensor, see Equation B25. The standard combined measure method is the original experimental set-up of all five sensors (1). However, it would be interesting to investigate if different sensor combinations will be sufficient, thus consider the following combined measure methods as well: (2) only upper and lower legs, (3) only pelvis and upper legs, (4) only upper legs, and (5) only lower legs. The combination of the measure calculations and combined measure methods result in new local measures.

#### 2.2.3 Data analysing

The goal is to design local acceleration measures to represent the players' experienced load. The steps to analyse and evaluate the measures – obtained by the experiments and the processing of the local leg acceleration data – will be explained in this paragraph.

Result selection. First, load and select the experienced load subjective - data of the situations per drill and per experiment from an excel sheet - see Appendix I. Second, select and re-organise the objective results per measure and situation of all 5 experiments. Next, calculate the mean - Equation C1 - and standard deviation -Equation C2 - of all experiments per measure and situation subjective, objective global, and objective local measures. Note that the standard deviation can be above the normalised maximum of 10. which is allowed. Fourth, normalise the average - Equation C3 - and standard deviation - Equation C4 - to the maximum value - 0-10 per measure and drill. Fifth, calculate trend percentages per situation - i.e. per hypothesis. An indicative percentage per measure of the jog/sprint without shoot to the jog/sprint with shoot - i.e. select the first and last per situation -, see Equation C5. It has been chosen to use the without/with shoot situations, so the method used to analyse and evaluate drill A and B are consistent. Last, allocate all the trend lines of the objective global and local measures into three groups according to their trend percentages to compare different measures and test the hypotheses: (1) larger, (2) similar, and (3) smaller, see Equation C6-8. Base the group boundaries on the trend percentages of the subjective measure. Plot different line sorts per group in the next analysing step.

>	Mean of experiments per m	neasure and situation	mean(measure results per situation)	
>	Standard deviation per me	asure and situation	std(measure results per situation)	
>	Normalise measures to 0-1	10 per drill	$(measure_{mean}/max(measure_{mean})) \cdot 10$	
			$(measure_{std}/max(measure_{mean})) \cdot 10$	
>		<del></del>	neasure and per situation – i.e. per hypothesis	
	Trend = round (((measure	SitShoot – measure <sub>SitNoBe</sub>	$_{all})/measure_{SltNoBall}) \cdot 100)$	
	Trend = round (((measure	sitshoot – measure <sub>sitNoBe</sub> groups per situation – I	<sub>all</sub> )/measure <sub>sitNoBall</sub> ) · 100) base groups on subjective trend	
	Trend = round (((measure	SitShoot – measure <sub>SitNoBe</sub> groups per situation – I end <sub>Local</sub> && Group(2	<sub>all</sub> )/measure <sub>SitNeBall</sub> ) · 100) base groups on subjective trend c) = Trend <sub>Local</sub>	

Visualisation of the results. Develop a standard figure - to test all possibilities in the same format - to find, analyse, and evaluate different measures. The standard figure contains: (i) line plot of the results and (ii) an experiment, processing, and measure design summary. First, the visualisation of the results to test the hypotheses. Plot the mean and standard deviation of all experiments and per measure - subjective, current objective global, and new objective local. Separate the drills into jogging and sprinting situations, i.e. per hypothesis. Second, display the experiment, data processing, and measure design summary: the drill and the situations, a picture of the drill, measurement methods - including trend percentage and group allocation -, a picture of the sensor locations, and process methods and measure design used to obtain new local measures - including trend percentage and group allocation. The output is a line plot of the results per situation, including an experiment, processing, and measure design summary.

The units are not relevant because of the normalisation of the data. Normalisation occurs in two functions: (i) the data process methods function – normalisation of the acceleration data to select

zones – and (ii) the results function – normalisation of the measures to calculate the trend of the situation intensity increase per measure. Furthermore, it is not necessary to translate the time from timeframes to seconds – the depended factor is chosen to be distance.

The trend is important - it is a qualitative study -, and not the comparison of the values with each other - i.e. quantitative research and visualisation of the data should be done carefully. First, use a line plot to simplify the comparison of the different measures when the intensity of the situations increases - within the measure -, instead of comparing the different methods per situation - between the measures. The latter cannot be compared with each other because the values of the measures are qualitative. The lines of the local measures are divided and visualised into the groups because it is about comparing to the experienced load and find consistency throughout the measures, and not to find the best measure therefore, a summary of the used data process methods and measure design are added to the figure. Furthermore, visualise all measures on the same y-axis as a result of the normalisation of the results. However, the location of the different measure lines relative to each other does not mean anything. It has been chosen not to let all the measures start at the same position to clearly show the difference between jogging and sprinting per drill. Next, the intensity steps on the x-axis between low-medium-high do not represent the same intensity increase amount. Therefore, it is not possible to state that the increase is - for example - linear. Furthermore, the ability to plot subjective results, current global measure, and multiple new accelerometer measures - different combinations of data process method, measure calculations, and combined measure methods -, in the same figure simplifies analysing and interpreting the results. Moreover, it reduces the running time. However, only one of the three inputs can have multiple options to compare and visualise these relative to each other in one graph. Note that the subjective and current objective results remain the same per situation. So, the focus is not on evaluating the results of different measurement methods per situation, but on the trend of one measure when the intensity increases of the situation.

Analysing and evaluating the results. This part will elaborate on a systematic method to analyse and evaluate the newly designed local measures and the current global measure in comparison to the players' experienced load. It is expected that multiple new local measure designs could be successful to predict the local muscle load. (1) Define three intensity zones and weight factors for each zone. The experiment is designed on increasing the drill intensity. Therefore, roughly select the zones and weight factors by observation of the normalised processed data and evaluating the intensity increase of the situations. (2) Calculate the trend percentages of the subjective load measure and formulate groups. Obtain the trend percentages from the situations without a ball to the ones with a shot for the jogging and sprinting situations and for drill A and B. Next, based on these results formulate three groups per situation, i.e. per hypothesis: larger, similar, and smaller, include a  $\pm 10\%$  margin to create the groups. (3) Calculate the trend percentages of the current objective global and new objective local measures and allocate to the groups. Conduct these calculations with fixed zones and weight factors. Then, based on these trend percentages, allocate the global and local objective measures into the three groups. (4) Conduct a rough analysis by making one big overview of all possible combinations of data process methods and measure designs with fixed zones and weight factors according to their allocated groups. Select all potentially successful process method and measure design variations

for further analysis. (5) Conduct a more in-depth analysis. (i) Vary data process methods: plot all potential measure calculations in one figure per potential data process method for drill A and with the standard combined measure method. This standard considers adding all sensors, which is the original experiment set-up. Evaluate the figure and select successful process methods. (ii) Vary measure calculations: plot all potential data process methods in one figure per potential measure calculation for drill A and with the standard combined measure method. Evaluate the figure and select successful measures. (iii) Vary combined measure methods: plot all combined measure methods in one figure per selected data process method and selected measure calculation for drill A. Evaluate the figure and select successful combined measure methods. (iv) Varying drills: plot successful combinations with drill B. Note that 'successful' refers to this pilot study, and therefore, is interesting to consider in further research. By carefully conducting this analysis, successful new local measures to represent the experienced load can be obtained.

#### 2.2.4 Data processing and analysing flow chart

Figure 2.4 shows the data process and analyse flow chart and see Appendix I for the MATLAB code of the main script and functions, including input tables. This is a summary of previous sections.

- (I) Input: (1) drill, data process method, measure calculations, combined measure method, three intensity zones, weight factors for the three zones, and group allocation, these variables can be variated, (2-3) objective raw global and local data, (4) start and end times situations of drill A or B, and (5) subjective experienced load data of drill A or B.
- (A) Data processing: (1) pre-process data load the data, synchronise the global and local sensors, and filter the local acceleration data, (2) process methods – test different data process methods and normalise the local acceleration data, and (3) segmentation – cut the data into the situations.
- (B) Local acceleration measure design: (1) measure calculations – test different operations applied to the local acceleration data, and (2) combined measure – test different methods to add measures of the individual sensors together.
- (C) Data analysing: (1) results re-organise the results and calculate the normalised mean and standard deviation, trend percentages, and group allocation, to compare the measures, and (2) visualisation – plot the results.
- (O) Output: plot of subjective, objective global, and objective local muscle load measures to test the hypotheses.



Figure 2.4 – Data processing and analysing flow chart.

# Results 3

This chapter shows the results after processing the experimental data. The previous section explained a systematic approach to analyse and evaluate these results. The results of executing these steps will be central in this chapter. The global acceleration index and the new local acceleration measure designs – which are systematically combined by different data process methods, measure calculations, and combined measure methods – are compared to the experienced load.

First, the intensity zones are defined as 10%-40% - low - 40%-70% - medium -, and 70%-100% - high -, with weight factors 1, 4 and 7, respectively for the three intensity zones.

Second, the experienced load trend percentages from low to high intensity per hypothesis are A.I = 96%, A.II = 24%, B.I = 39%, B.II = 7% – drill A and situation 1, drill A and situation 2, drill B and situation 3, and drill B and situation 4, respectively. Based on these results, three groups – (1) larger, (2) similar, and (3) smaller – are formulated per situation including  $\pm 10\%$  margin. A.I: (1) 106 to infinity, (2) 86 to 106, and (3) -infinity to 86; A.II: (1) 34 to infinity, (2) 14 to 34, and (3) -infinity to 14; B.I: (1) 49 to infinity, (2) 29 to 49, and (3) - infinity to 29; B.II: (1) 17 to infinity, (2) -3 to 17, and (3) -infinity to -3.

Third, the trend percentages of the objective global and local measures with fixed zones and weight factors are calculated. Allocate these global and local trend percentage into the three groups, which are based on the subjective experience. The results for the global acceleration index are A.I = 8%, A.II = -5%, B.I = 5%, B.II = -6%, thus all allocated in group 3. See Appendix J for all possible local measure designs and their group allocation.

Fourth, the results of a rough analysis on all possible combinations of data process methods (P) and measure designs - i.e. measure calculations (M) and combined measure methods (S) - with fixed zones and weight factors according to their allocated groups can be found in Figure 3.1A and B, and the extended version in Appendix J. Figure 3.1A shows the results of all data process methods per situation - i.e. per hypothesis - and per measure calculation, with the standard combined measure method (S1). A grey dot is group 3, meaning smaller, and therefore, not representing the experienced load. A green dot is either group 1 or group 2, indicating a similar or larger trend percentage than the experienced load. Figure 3.1B includes all five combined measure methods. In this figure, the same dot system is applied. However, only a green dot is permitted if the data process method and measure design is group 1 or 2 for all hypotheses - i.e. A.I, A.II, B.I, and B.II. The grey shadow in Figure 3.1B is the overall result of Figure 3.1A: if all situations per data process method and measure calculation variation have a green dot in Figure 3.1A, a green dot is permitted in Figure 3.1B. The green shadow is explained in the in-depth analysis, see next paragraph. The seventh data process method does work, however, will not be further considered due to the long running time. All potentially successful data process method and measure design variations for further analysis are selected based on Figure 3.1A and B and are highlighted with green text. Figure 3.1C summarises the potential successful options. The green text in this overview is for the in-depth analysis. Only use the potential successful combinations for further analysis.

Fifth, an in-depth analysis is conducted on the potential data process methods and measure designs. (i) Vary data process methods: all potential measure calculations are plotted in one figure per potential data process method for drill A and with the standard combined measure method, see Appendix K. Evaluating the figures of the appendix results in successful data process method 1, 4, 5, and 6. (ii) Vary measure calculations: all potential data process methods are





plotted in one figure per potential measure calculation for drill A and with the standard combined measure method, see Appendix L. Evaluating the figures of the appendix results in successful measure 12 and 15. (iii) Vary combined measure methods: all combined measure methods are plotted in one figure per successful data process method and successful measure calculation for drill A, see Appendix M. Evaluating the figures of the appendix results in all combined measure methods if using a combination of data process method 1, 4, 5, or 6 with measure calculation 12 or 15. (iv) Varying drills: the successful combinations are plotted with drill B. See Figure 3.1A for an overview of successful combinations highlighted in green shadow – after evaluating the figures in Appendix K and L – considering potential data process methods and measure calculations

with the standard combined measure method obtained from the rough analysis. Furthermore, see Figure 3.1B for an overview of successful combinations highlighted in green shadow – after evaluating the figures in Appendix M – considering green highlighted data process method and measure calculation combinations of Figure 3.1A with all combined measure methods. The final results are highlighted in green

shadow in Figure 3.1B and summarised in green text in Figure 3.1C. The following three figures show the results with combinations of data process methods (P), measure calculations (M), and combined measure methods (S): P1,4,5,6, M12, and S1 for drill A and B in Figure 3.2, P1,4,5,6, M15, and S1 for drill A and B in Figure 3.3, and P4, M15, and S1,2,3,4,5 for drill A and B in Figure 3.4.





Figure 3.3 – Plot of data process method 1, 4, 5, and 6, measure calculation 15, and combined measure method 1 for drill A and B.





# Discussion 4

This pilot study aimed to use a big data analysis approach to translate leg acceleration data into a measure to indicate local muscle load and compare this new local and the current global method to the players' experienced load. It can be concluded that local threedimensional acceleration of the lower extremities, processed with a big data analysis approach, represent the football players' experienced muscular load more accurate than the current global method. The hypothesis: "the intensity increase of a football drill will increase the local load similarly as the experienced load, but not global, based on acceleration" is confirmed for adding a shot. However, both local and global methods identify the intensity increase of a football drill from jogging to sprinting. These conclusions are in line with the expectations that the local data is a more accurate representation of the experienced load than the current global measure, i.e. increasing the drill intensity in football will be visible in the 3D leg acceleration pattern, but not in the global whole body acceleration signal. The concept of measuring a lot of data - including noise and inaccuracies - and processing this with a peak and cumulative big data analysis, instead of focussing on an exact body segment method, is successful in indicating local muscle load during practice in a representative football environment, without restricting the players' movement.

By evaluating trend percentages of the intensity increase, it is clear that a local acceleration measure is comparable to the players' experienced load when it considers the sum of normal or peak data points weighted per zone and per travelled distance. Furthermore, a similar result is obtained when only the upper leg or lower leg accelerations are considered. Multiple new local measure designs are successful. However, the goal is not to find the best, but compare the current global and new local objective measures to the subjective load to indicate muscle load if the drill intensity increases. This is an exploratory study to introduce a new local method, and the hypothesis cannot be proven significant due to the small participant number. The algorithm is made to extend easily to a big group of participants. Further research is needed to define better intensity zones and weight factors, to select the best measure and quantify this, and with larger participant groups to better validate the hypothesis.

#### 4.1 Result interpretation

The conclusions are obtained by processing and analysing the experimental data. Two drills are performed - including specific football movements: jog/sprint, turn, and pass/shoot - on the pitch by five participants: (A) back/forth and (B) zigzag. Different situations of these drills are performed by increasing the intensity from jogging to sprinting and adding a pass/shot. The participants wear a set of sensors to measure the movements. The measurement methods are (I) questionnaire: subjective method to obtain the players' experienced load, (II) 2D LPM: current objective method to obtain the global acceleration index of the whole body, with the sensor location between the shoulder blades, and (III) 3D accelerometers: new objective method to obtain the local acceleration of the lower extremities, with sensor locations at the middle of the pelvis, upper legs, and lower legs. A MATLAB algorithm is used to process the experiment data to find, analyse, and evaluate new measures based on leg acceleration data - to indicate local muscle load. A main file runs different functions to perform specific actions to the data and translate the local acceleration data into a single value to indicate local muscle load per situation by a peak and cumulative data analysis. The input varies between different data process methods and a combination of measure calculations and combined measure methods, i.e. measure design. The hypotheses are tested by calculating the trend percentages – jog/sprint without shoot to the jog/sprint with shoot – and dividing them into groups to compare the global measure and new local measures to the experienced load – which is the benchmark. The interpretation of the obtained results has been done by a systematic rough and in-depth analysis.

Interpretation of the rough analysis. The rough analysis filtered the tested data process methods and measure designs into potential combinations. The rough analysis is based on the experienced load group formulation without plotting the figures. Therefore, these do not include the pass situation of drill A. It became clear that measures in categories considering normal and peak data points per travelled distance are not in line with the subjective load, i.e. measures which are not weighted per zone. This can be explained by the very high and narrow - i.e. short - shot peaks. This results in negligible effects, due to the long measuring times per situation, which include many low and medium movements. Therefore, intensity zones and weight factors are introduced - to indicate if a higher muscle load would increase the chance of overuse or muscle damage - which is expected to differentiate the movement intensities. The results confirm that measures regarding normal and peak data points weighted per zone per travelled distance show potential.

Within the weighted per zone categories, the number of points – normal and peak – show no success. This is due to the constant travelled distance, and the fact that measures are calculated per travelled distance. Some variability in the constant distance occurs due to the differences in turning and adding a ball at the end of the drill – the passing/shooting movement will result in a few extra meters. This is eliminated by calculating the measures per meter. When repeating this study, it would be best to place the ball one meter before the end of the drill to compensate for the extra movement.

The results of the different measure calculations are very consistent throughout all data process methods. Data process method 7 – involving envelope to process the acceleration signals – has a very long computational time. It is preferable to obtain a fast running data process method to make this a practical measurement method. Therefore, no further analysis has been conducted with this method. The potential data process methods and measure designs are plotted and evaluated by an in-depth analysis.

Interpretation of the in-depth analysis: experienced load. The players' experienced load has been chosen to be the standard. In the in-depth analysis, figures are plotted to conduct a visual evaluation of the trend. The pass situation of drill A is included, which is of added value to check the consistency of the measures. The obtained result supports the expectation of increased experienced load when drill intensity increases. A football-like environment was correctly simulated by including the football-specific movements into drills with short distances in an out-of-lab setting. The short distances represent the many accelerative and decelerative changes occurring in football, which are known to have a high muscle load.

Appearing from the response of the participants, it was an exhausting and intense experiment. Specifically, the fatigue starts to play a role during drill B – because this was performed after drill A –, which will influence the performance of the drill. However, exhaustion is a common phenomenon in normal training. The role of conducting drill B is to test the measures in a slightly more advanced exercise. This results in a better simulation of the real football environment. Some thoughts on eliminating this factor are to decrease the amount of drills, situations per drill, repetitions per situation, or add more time in between the situations.

The participant reported the experienced load during the experiment at the end of each situation. However, the experiments were experienced very heavy – especially the sprint situation of drill B – and sometimes the scale of 1-10 was not sufficient when the participant started with a relatively high mark. Therefore, also group 1 – larger trend than the experienced load trend – is considered.

Interpretation of the in-depth analysis: global measure. The global acceleration index does not differentiate within the situations. However, as expected, there is a load increase if the intensity increases to sprinting. Compared to the players' experienced load, the group allocation is 3, which is smaller. The acceleration index is a cumulative measure defined as the acceleration count which meet the condition of at least 0.5s above 1.6 m/s<sup>2</sup> and lead to ≥10 km/h<sup>2</sup>. The accelerations below 1.6 m/s<sup>2</sup> are considered to be noise and do not count. These boundaries and thresholds are not based on scientific research but on experience. This index could exclude short highintensive and low-speed movements, however these contribute to muscle load increase. Furthermore, the movement of the whole body does not represent the many leg acceleration movements. Therefore, it did not register any passes or shots. The results obtained by this experiment were expected, and the global measure does not represent the experienced load accurately

Interpretation of the in-depth analysis: local measure. The in-depth analysis is first conducted with the standard combined measure method, which is the original local measurement set-up of all sensors. The trend percentage is chosen to be from low to high intensity, to be consistent between both drills. However, during this indepth analysis, a visual comparison easily observes if unexpected and inconsistent trends occur, as the pass situation is included. Therefore, all the potential data process method and measure calculation combinations are plotted and evaluated. It is observed that using the same measure calculation, normal and peak data points weighted per zone have a very similar outcome. Furthermore, different observations per data process method when adding a pass: pass had a slightly higher or similar load as the shot, the jog and pass situation has a similar load as sprinting, or when sprinting is higher than sprinting with a pass. All these observations occurred in the same measure calculation. Therefore, eliminate the average of all normal and peak data weighted per zone measures, because it does not represent the experienced load. The in-depth analysis is conducted on drill B with the successful measure calculation - the sum of all normal and peak data weighted per zone and per travelled distance - and successful data process methods, a comparable result to the experienced load is achieved.

Combined measure methods are included to test the relevance of the sensor locations. Testing different sensor combinations will evaluate the potential of using short tight leggings – i.e. upper legs – or adding accelerometers in the shin guards – i.e. lower legs –, which would be very convenient. The results show a very consistent outcome of all the five methods tested, and a similar result is obtained when using the accelerations of the upper or lower legs.

#### 4.2 Implications for practice

The ultimate goal is to gain more insight into how to prevent muscle injuries and optimise performance. This can be achieved by differentiating the local muscle load between activities or drills, to categorise exercise intensity in muscle load zones, and measure data for a long period of time - i.e. multiple practices and matches. In the future, this should be a standard, easy to use, and intuitive measure for players and staff to continuously monitor local muscle load. An example is how total travelled distance and high-speed travelled meters as an indication of physical load and performance is currently used. A second example is the concept of the metabolic equivalent of a task - MET -, which can be used to categorise the intensity level of a specific activity (Jetté et al., 1990). The designed measures should provide insight into the following questions: (i) how many practices and what type of drills should be performed, (ii) how many matches should be performed and when should a player be substituted, and (iii) monitoring the intensity - frequency, load, and duration - of the drills, practices, and matches. The newly proposed method in this study shows excellent potential to monitor local muscle load during practice and matches continuously, to reduce the amount of thigh muscle injuries, and to adjust and optimise the training load.

The new local measurement method could be embedded in short training leggings or in shin pats to improve usability. This is comfortable to wear during activity without restricting the player and gain data instantly on the pitch. Using accelerometers to obtain kinematic data is made possible as a result of the many technological improvements of the last decade. It is a sourceless, small, light, low-cost, onboard data-logging, optional wireless, and easy to use sensor. This can be used in any area without restricting the football player and in any environment – outside laboratories – to provide valuable objective kinematic information to evaluate the musculoskeletal system during movement. Local acceleration of the lower extremities is promising to continuously monitor local muscle load in a real football setting on the pitch, in dynamic situations, and during entire drills, practices and matches.

Furthermore, local data should be tracked real-time during practices and matches to find the peak and cumulative values. To continuously monitor the muscle load of the legs, real-time feedback can be a major support for football staff (Halson, 2014 and Sato et al., 2009). This can be achieved because a big data analysis approach is used. The algorithm to translate the acceleration is a simple and low computational load algorithm, leading to short processing times. Real-time measuring and monitoring allows direct observing and intervening when the muscular load becomes too high, and therefore, preventing muscle injuries.

In football, a dominant and non-dominant leg exists, which could lead to different muscle injury risks. A study by Svensson et al. (2016) on the difference of muscle injuries in the dominant and non-dominant leg showed no significant difference in the adductors and quadriceps, while structural hamstring injuries were found to have a higher injury rate in the dominant leg. According to Ekstrand et al. (2011), muscle tears in the shooting leg – i.e. dominant leg – occurred more often in the quadriceps – 60% –, while it was found to be about the same in the hamstrings – 50% – and adductors – 54%. During this study, the average of all participants is used and both left- and right-footed players were identified. Therefore, no combined measure method is tested on the separate left or right leg. After developing and further testing of the activity monitoring system, it could be used for individual athletes. The different loading of the left and right leg could be differentiated.

During this exploratory study, the application within football has been central, but also other sports can benefit from this method and it can be useful in clinical applications. First, the motion activities of elite football players are comparable with elite field-hockey, rugby and Australian football players (Spencer et al., 2004). So, besides using this method in football, similar type of intermitted sports can be targeted, for example, field hockey, rugby, volleyball, handball, basketball, and baseball. Measuring local acceleration profiles would even apply to sports like athletics and speed skating. Similarly, Paralympic sports could benefit from monitoring local muscular load. Furthermore, the use of a big data analysis approach can be an affordable easy to use measurement method for recreational use. A whole team can be tracked for long periods of time. This shows the broad usability of this method in sports. Second, this method can be potentially used as a measurement tool in clinical applications. To monitor the local muscular load of patients while performing certain activities and during revalidation of muscle injuries in sports. For example, patients with muscle disorders. Last, the focus in this study is on the muscles around the thigh, but expanding this to monitor around other joints, like the knee, shoulder, elbow, wrist, is possible. This could be an advantage in sports like basketball, handball, baseball, tennis, and volleyball. This overview shows the wide applicability of using local acceleration to obtain local muscle load. Before the method can be deployed for all these applications, further research is needed.

### 4.3 Recommendations and further research

This study has been done to elaborate on the whole new concept of integrating commercially available IMUs in a sports legging and perform football drills with increased intensity on the pitch to obtain the leg acceleration pattern. It can be concluded that measuring local acceleration shows great potential to use and translate into a measure by a big data analysis approach to predict muscle load and meet the set requirements. However, further research is needed to develop an activity monitor based on measuring a lot of data to support medical and technical football staff. (i) Define accurate intensity zones, (ii) define weight factors and investigate if there exists a connection between heavier movements and higher muscle load, (iii) differentiate acceleration and deceleration, (iv) differentiate left and right leg, (v) investigate to what extent muscle fatigue influences this method, (vi) select the best measure and quantify this by conducting maximal tests of individual athletes, (vii) use the obtained local acceleration data to perform pattern identification, in case of this data: jog/sprint, turn, pass/shot, and intensity classification of these elements related to muscle load, (viii) use larger participant groups and (ix) validate to obtain how accurate and reliable this method is, and (x) reduce the size of the accelerometers – i.e. IMUs used in this study are relatively large – if the research progressed to a later stage. Many topics should be addressed before the concept of leg acceleration measurements can be commercially available.

A validation method can show if the obtained local acceleration data is representative and accurate to predict local hip and thigh muscle load. Methods to validate and evaluate the new local method currently exist because this could be performed in lab settings. VICON is a 3D movement analysis method which can measure a variety of variables. The VICON system can be relevant for observation and validation purposes, more precisely: (i) to validate measured accelerations and decelerations by IMUs, (ii) to find the optimal amount and location of sensors needed to give an accurate acceleration profile of the lower extremities, and (iii) the combination with the force plate could support on finding an accurate prediction to muscular loads. The force plate is about one square meter, and therefore, one activity/movement at the time can be measured, like one walking, running, or sprinting step, one shot, one jump, etc. VICON could have a positive contribution in later research phases.

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# Appendix 16

- Appendix A Information letter participant
- Appendix B Information participant and drill questionnaire
- Appendix C Experiment protocol
- Appendix D Filled-in and signed ethics checklist: approved TU Delft
- Appendix E Informed consent
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- Appendix H Plots to check the functions
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- Appendix L Results in-depth analysis: figures of different data process methods
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## Appendix A – Information letter participant



Graduation project – Measure local muscle load in football Experiment phase – Information letter participant Rozemarijn Schotel



## Scientific research to measure local muscle load in football

Football is an intermittent sport including high-intensity activities. High physical demands occur during the many explosive leg movements, resulting in high musculoskeletal loads around the thigh, which can cause thigh muscle injuries – 25% of all injuries affect hamstrings, adductors and quadriceps in football. To prevent muscle injuries and optimise performance it is necessary to identify when and how frequent high local muscle loads develop in the thigh muscles in real live football situation in order to adjust the training load accordingly. The KNVB in collaboration with Delft University of Technology will conduct scientific research to gather local translational acceleration and rotational velocity information of the legs and a global motion profile during specific football movements. This data will be used to predict local muscle load.

You are invited to participate in this research and in this letter you can find information about the project.

Why is this research being conducted? • In this project we gain insight in the local acceleration profile of the lower extremities during specific football movements, search for the link to local muscle load, and look for the difference between a local and global measurement method. The proposed method will be able to differentiate between high and low intensity activities, obtain overall muscle load of a drill, and identify different muscle load zones related to exercise intensity – on a local muscle level. The eventual goal is to support medical and technical football staff by continuously monitoring the musculoskeletal load of the most injury-sensitive muscle groups during matches and practices, in order to reduce the amount of thigh muscle injuries and optimise performance.

What does it mean in practice? • As a participant, you will perform two specific football drills with different levels of intensity to gather data – this will take approximately 30 minutes. In total the experiment will take about an hour. The drills consist of normal football activities, like jogging, sprinting, passing, shooting, and turning. During the drills the participant will wear multiple sensors to collect data: heart rate belt around the chest, local positioning measurement – LPM – system with a sensor in between the shoulder blades attached to a t-shirt, and 5 sensors attached to a legging. The measurement equipment will not hamper performance or restrict the participant during the drills. No risk is involved in joining this research.

What happens with my data? • The collected data will be used for further scientific research regarding the use of leg acceleration to predict local muscle load. All published data will be made fully anonymous and there will not be a possibility to track this data back to the participant it belongs to. The trackable personal data will only be made available to the participant and researcher. Video recordings will be made during the experiment by the LPM system, these will only be used as helping tool during the data processing/analysing phase by the researcher. Furthermore, you will receive an individual summary of your personal results after the data is processed (this is expected to be in April/May) and full data is available upon request.

How can I participate? • At the start of the experiment you have to sign a form, in order to legally agree to the conducted research. Your participation is entirely voluntary and you can decide to refuse or stop participation at any time.

Further information? • After you read the information you can ask questions about anything you do not understand before deciding whether or not to participate. You can contact the researcher at any time. A short explanation will be given to inform you about the research before the experiment starts. If there are any questions left you can ask them anytime, even after the study has started.

Researcher: Supervisors: Rozemarijn Schotel
Daan Bregman
Compared
Data Bregman
Delft University of Technology
Edwin Goedhart
Compared
Co

## Appendix B – Information participant and drill questionnaire



Graduation project - Measure local muscle load in football Experiment phase - Information participant form and drill questionnaire Rozemarijn Schotel





2 > Situation 2a: sprint + turn + no ball 4 > Situation 4a: sprint + turn + no ball S > Situation 2b: sprint + turn + pass S > Situation 4b: sprint + turn+ shoot > Situation 2c: sprint + turn + shoot

Notes:

S

configuration to the selected Shimmer

Click on Configure

Check configuration

· Click on Done when configuration is completed

> Check configuration for each Shimmer - repeat 6x

· Click on Back and OK if the configuration is correct

0

**PRE-PREPARATION** 

1

**PREPARATION** 

## Experiment protocol (1/2)



## Start LPM system to capture data

- > Click on *imoServer* at desktop
- Select Revalidatie Campus at Prepare in Measurement Selection field and click on Activate
- Check box of Cam 1 and Cam 2 of number 054
- > Open Inmotio Client at desktop
- > Click on Live/Record Start and click on OK to start

Sources:

http://www.shimmersensing.com/images/uploads/docs/Consensys\_User\_Guide\_rev1.4a.pdf https://www.pinterest.co.uk/pin/43136108902151520/ (seen on 14.03.2018)

## Experiment protocol (2/2)



## 3 A COMPLETION Stop LPM system with capturing data > Click on Yes to save > Save as ExpReal#\_date in

2

EXPERIMENT

## ExperimentsRozemarijn folder at desktop Detach all sensors from

clothing > Detach LPM sensor off shirt and Shimmer X off LPM sensor

Click in Inmotio Client on

Live/Record Stop to stop

**Completion before** 

participant leaves

- Take Shimmer P, R1, R2, L1, and L2 out legging
- > Participant takes off legging, heart rate belt, and shirt

### Stop Shimmer sensors to capture data

- > Create a mark in Shimmer data by turning 15x around z-axis
- Dock Shimmers into Base to stop data capturing

## B Completion after participant leaves

#### Import data from each Shimmer repeat 6x

- > Scanning SD Cards one chance: Select 1 Shimmer in graphic
  - · Click on Import and click on Next when scanning is completed
- Configuring import sessions:
  - Select ExpReal#
  - Click on >> to add data as new session to the list
  - · Click on Next to continue to the next stage and click on Yes to proceed
- > Importing session
  - · Data selected for import is now being imported into the Consensys database
  - · Click on Done when import is completed
  - · Go to Manage Data and check if import is successful - check configuration and time

#### Put all the equipment away – if done

- > Undock Shimmers out Base and switch off power
- Bring LPM sensor and heart rate belt back, place LPM sensor in charger, and close all programs at computer
- Take off the cones and balls from the pitch and put away

## Manage and export data

This stage can be done at another/later moment

#### Export data LPM – .csv file

(C

Export and safe LPM data at a sampling rate of 200 Hz and safe video recordings - ask Rosanne

#### Export data per Shimmer – .mat file – repeat 6x

- > Click on Manage Data
- > Select data: ExpReal# repeat 6x
- > Select format:
- File Format: mat
  - Timestamp Format: unix
  - Data Format: calibrated
- > Click on Export to export the selected data to a file in the requested format
- Select ExpReal# date folder in Data Processing and Analysing folder, and click on Save
- > Click on Open Path when export is completed to navigate to the file(s)
- > Click on Done in Consensys

#### Process and analyse data in MATLAB

Sources

http://www.shimmersensing.com/images/uploads/docs/Consensys User Guide rev1.4a.pdf https://www.pinterest.co.uk/pin/43136108902151520/ (seen on 14.03.2018)

## Appendix D – Filled-in and signed ethics checklist: approved TU Delft

## Delft University of Technology ETHICS REVIEW CHECKLIST FOR HUMAN RESEARCH (Version 10.10.2017)

This checklist should be completed for every research study that involves human participants and should be submitted before potential participants are approached to take part in your research study.

In this checklist we will ask for additional information if need be. Please attach this as an Annex to the application.

Please upload the documents (go to this page for instructions).

Thank you and please check our <u>website</u> for guidelines, forms, best practices, meeting dates of the HREC, etc.

### I. Basic Data

Project title:	Measure local muscle load in football
Name(s) of researcher(s):	Rozemarijn Schotel
Research period (planning)	February – March 2018
E-mail contact person	
Faculty/Dept.	3mE BioMechE
Position researcher(s):1	Student
Name of supervisor (if applicable):	
Role of supervisor (if applicable):	Assistant professor

### II. A) Summary Research

What indicators based on local leg acceleration data can be used to predict local thigh muscular load in football players to prevent muscle injuries and optimise performance?

Local translational acceleration and rotational velocity will be used as objective indirect measurements to predict muscle load of the most-sensitive muscle groups (hamstrings, adductors and quadriceps). A sensor legging prototype will be developed with 5 Shimmer IMU sensors to measure 3D local movements of the pelvis, upper and lower leg of football players during specific football drills. This will be combined with a local positioning measurement system to obtain 2D global positional data and a heart rate belt. The gathered data will be processed and analysed by a MATLAB model to find a measure to indicate and predict the muscle load. The participants (max. 20 participants) will be amateur football players, which play all around the Netherlands, and will be approached via the sport arts of the KNVB medical centre.

The eventual goal is to support medical and technical football staff by continuously monitor the musculoskeletal load of the most injury-sensitive muscle groups during matches and practices, in order to reduce the amount of thigh muscle injuries and improve performance.

#### **B)** Risk assessment

No risk is involved in joining this research. The participant will perform a few football drills during the experiment. These consist of normal football activities, which the football players are used to do on a daily basis.

A heart rate belt around the chest, local positioning measurement (LPM) system with a sensor in between the shoulder blades attached to a t-shirt and 5 Shimmer IMU sensors attached to a legging will be used to collect the data. All devices are commercial products. To indicate the low risk of wearing these systems, the heart rate belt and LPM system are used by all football players at every training conducted at the KNVB campus, without risk or any restrictions. Furthermore, football players are used to wearing sport leggings, so this won't restrict them in any way. Apart from wearing the sensors, no other differences than normal. So, the participant won't be restricted during the experiment and it does not hamper the performance. Therefore, I expect a very low risk for the participants.

<sup>1</sup> For example: student, PhD, post-doc

#### III. Checklist

QL	restion	Yes	No
1.	Does the study involve participants who are particularly vulnerable or unable to give informed consent? (e.g., children, people with learning difficulties, patients, people receiving counselling, people living in care or nursing homes, people recruited through self-help groups).		×
2.	Are the participants, outside the context of the research, in a dependent or subordinate position to the investigator (such as own children or own students)? <sup>2</sup>		X
3.	Will it be necessary for participants to take part in the study without their knowledge and consent at the time? (e.g., covert observation of people in non-public places).		Х
4.	Will the study involve actively deceiving the participants? (e.g., will participants be deliberately falsely informed, will information be withheld from them or will they be misled in such a way that they are likely to object or show unease when debriefed about the study).		x
5.	Will the study involve discussion or collection of information on sensitive topics? (e.g., sexual activity, drug use, mental health).		X
6.	Will drugs, placebos, or other substances (e.g., drinks, foods, food or drink constituents, dietary supplements) be administered to the study participants?		X
7.	Will blood or tissue samples be obtained from participants?		X
8.	Is pain or more than mild discomfort likely to result from the study?		X
9.	Does the study risk causing psychological stress or anxiety or other harm or negative consequences beyond that normally encountered by the participants in their life outside research?		x
10.	Will financial inducement (other than reasonable expenses and compensation for time) be offered to participants?		Х
	Important: if you answered 'yes' to any of the questions mentioned above, please submit a full applie (see: website for forms or examples).	cation to	HRE
	Will the experiment collect and store videos, pictures, or other identifiable data of human subjects? <sup>3</sup> If "yes", please fill in Annex 1 and make you sure you follow all requirements of the applicable data protection legislation. In addition, please provide proof by sending us a copy of the informed consent form.	Х	
12.	Will the experiment involve the use of devices that are not 'CE' certified? <i>Only, if 'yes': continue with the following questions:</i> > Was the device built in-house?		Х
	<ul> <li>Was it inspected by a safety expert at TU Delft? (Please provide device report, see: <u>HREC website</u>)</li> </ul>		
	If it was not built in house and not CE-certified, was it inspected by some other, qualified authority in safety and approved?		
	(Please provide records of the inspection).		

#### IV. **Enclosures (tick if applicable)**

- Full proposal (if 'yes' to any of the questions 1 until 10) 0
- Informed consent form (if 'yes' to question 11) 1
- Device report (if 'yes' to question 12) 0
- 0
- Approval other HREC-committee (if 'yes' to question 13) Any other information which might be relevant for decision making by HREC ~

<sup>&</sup>lt;sup>2</sup> Important note concerning questions 1 and 2. Some intended studies involve research subjects who are particularly vulnerable or unable The provide concerning questions 1 and 2, some intended studies adopted is a subject who are participant with the research error research supervisor (e.g., the researcher's or research supervisor's students or staff) may also be regarded as a vulnerable group. If your study involves such participants, it is essential that you safeguard against possible adverse consequences of this situation (e.g., allowing a student's failure to complete their participants, it is essential that you safeguard against possible adverse consequences of this situation (e.g., allowing a student's failure to complete their participants provide the staff) on the second of their coursework). This can be achieved by ensuring that participants remain anonymous to the individuals concerned (e.g., you do not seek names of students taking part in your study). If such safeguards are in place, or the research does not involve other potentially vulnerable groups or individuals unable to give informed consent, it is appropriate to the other that and a place describe description conservation to the second action to a set of students taking part in your study.

place, or the research does not involve other potentially vulnerable groups or individuals unable to give informed consent, it is appropriate to check the NO box for questions 1 and 2. Please describe corresponding safeguards in the summary field. <sup>3</sup> Note: you have to ensure that collected data is safeguarded physically and will not be accessible to anyone outside the study. Furthermore, the data has to be de-identified if possible and has to be destroyed after a scientifically appropriate period of time. Also ask explicitly for consent if anonymised data will be published as open data.

## V. Signature(s)

Signature(s) of researcher(s) Date: 26.01.2018

Bchotel

Signature research supervisor (if applicable) Date: 26.01.2018

## Appendix 1: Privacy and data protection

Please fill this in if you have answered 'yes' to question 11 in the checklist

- Are the research data made anonymous? If no, please explain.
   Yes (the video recordings made during the experiment will only be used as helping tool during the data processing/analysing phase by the researcher, no other purposes)
- b. Will directly identifiable data (such as name, address, telephone number, and so on) be kept longer than 6 months? If yes, will the participants give written permission to store their information for longer than 6 months? No
- c. Who will have access to the data which will be collected? Besides myself, the operator (an employee of the KNVB) of one of the two systems used during the experiment can view the obtained data (movement data and videos of the participants). The videos will only be used as a helping tool while processing/analysing the data. Furthermore, the anonymous data of both systems could be viewed by both my supervisor of the TU Delft (Daan Bregman) and KNVB (sport arts, Edwin Goedhart).
- d. Will the participants have access to their own data? If no, please explain. All participants receive a summary of their results at the end (after the data is processed) and full data is available upon request.
- e. Will covert methods be used? (e.g. participants are filmed without them knowing) No
- f. Will any human tissue and/or biological samples be collected? (e.g. urine) No

## Appendix E – Informed consent



Graduation project – Measure local muscle load in football Experiment phase – Informed consent participant Rozemarijn Schotel



## **INFORMED CONSENT**

Title research:	Measure local muscle load in football
Responsible researcher:	Rozemarijn Schotel
Supervisors:	Daan Bregman – Delft University of Technology
	Edwin Goedhart – KNVB

## Participant

- I have been informed about the objective of the investigation and my role in it and the responsible researcher has answered all my questions.
- I had sufficient time to consider my participation in this investigation and I am aware that it is completely voluntarily.
- The potential risks associated with my participation in this investigation and the anticipated benefits have been discussed with me.
- I realise that I may decide to refuse participation or stop participation at any time.
- I understand and agree that data about me will be collected and processed, either manually or by computer, by the responsible researcher and other researchers in the project.
- I know and agree that video recordings will be made during the experiment, these will only be used as helping tool during the data processing/analysing phase by the responsible researcher.
- I understand and agree that data collected about me will be stored fully de-identified.
- I know that all de-identified data that will be collected in this investigation will be stored for at least 5 years.
- I understand that I am entitled to access the personal information collected about me and to have inaccuracies corrected.
- I agree to participate as a volunteer in this investigation.

Name

Signature

Date

## **Responsible Researcher**

• I have answered all questions about the research project, discussed the meaning and scope of this informed consent, and signed it in the presence of the volunteer.

Name

Signature

Date

## Appendix F – Experiment protocol trail

## Experiment protocol – TRIAL

repare and organise Start	Experiment	Fini	sh
Prepare exp. set-up and protocol       Prepare difference         Approval of ethics committee TU Delft (fill in ethics checklist)       Prepare difference         Make information letter participants       Start LPM         Make information participant form and drill questionnaire       Start Shirm         Make information participant form and drill questionnaire       Start Shirm         Make sensor leggings (size M)       Figure out LPM and Shimmer sensors       Ask 10 participants (Edwin Goedhard)         Reserve pitch (Ton van Klaveren)       Conduct experiment trial       Participan consent         1x LPM system (Rosanne Briggeman)       Fill in inform         5x Shimmer3 IMUS       Participan rate belt         1x legging (M)       Participan rate belt	<ul> <li>Use stopwatch</li> <li>After every situation fill i questionnaire</li> <li>I use stopwatch</li> <li>After every situation fill i questionnaire</li> <li>Perform drill A: <ul> <li>Situation 1a: jog + no ball</li> <li>Situation 2a: sprint + nob</li> <li>Situation 2a: sprint + nob</li> <li>Situation 2a: sprint + shoot</li> <li>Situation 2a: sprint + shoot</li> <li>Situation 3a: jog</li> <li>Situation 4a: sprint series</li> <li>Situation 4a: sprint series</li> <li>Situation 4a: sprint series</li> <li>Situation 4b: sprint series</li> <li>Situation 4b: sprint series</li> </ul> </li> </ul>	(2 min) (2	Synchronise time Shimmers and PM: stand still for 15s in the natomical position So to the lab to finish Participant takes off sensor egging Participant leaves Stop LPM (ask Rosanne) – safe ind export data to excel Stop Shimmer sensors – safe and export data to matlab Process data in MATLAB model Synchronise timelines Vailable data: Heart rate (BPM) Global 2D position-time data > distance [m], velocity [m/s] and acceleration [m/s <sup>2</sup> ] Local 3D translational acceleration [m/s <sup>2</sup> ] and rotational velocity (rad/s) data of pelvis, upper leg and lower leg find suitable indicators per nuscle load, choose relevant: Planes, sensors and parameters

## Appendix G – Information participant and drill questionnaire trial

	Experiment phase – Informat	Neasure local muscle load in football ion participant form and drill questionna zemarijn Schotel	ire	
Part I – Information participant (before experiment)				
Name:			Anonymous number:	
Email address:				
Age: yea	ars			
Length: cm	ſ			
Length legs: cm	ſ			
Weight: kg				
Length between joints and se	ensors (reference: origin o	f coordinate system sensor)		
P to hip_r =	cm	P to hip_I =	cm	
Hip_r to R1 =	cm	Hip_I to L1 = 0	cm	
R1 to knee_r =	cm	L1 to knee_I = 0	cm	
Knee_r to R2 =	cm	Knee_I to L2 = 0	cm	
R2 to ankle_r =	cm	L2 to ankle_I = o	cm	

## Part II – Experienced load per situation (during experiment)

How would you rate the load of the drill? *Rate according to the maximal load experienced during a match* (1: easy – 10: extremely heavy)

Drill A	Variation 1a (jog + no ball):	Variation 2a (sprint + no ball):		
	Variation 1b (jog + pass):	Variation 2b (sprint + pass):		
	Variation 1c (jog + shoot):	Variation 2c (sprint + shoot):		
Drill B	Variation 3a (jog):	Variation 4a (sprint series 1):		
		Variation 4b (sprint series 2):		
Overall experience of drill A:				
Overall experience of drill B:				

## Appendix H – Plots to check the functions

Note, these plots are only plots to check and show examples of functions. Therefore, the plots are very basic, without legends, axis labels, etc.



## Example of x-, y-, and z-gyroscope data of all sensors of one participant

1

Example of processed and segmented global data of one participant




Example of local z-angular rate before and after synchronisation of all sensors of one participant







# Example of normalised local acceleration after data processing including intensity zones of one participant





Example of global speed and acceleration data of one participant

# Appendix I – MATLAB code for main script and functions, including input tables

# Main MATLAB script: DataProcessingAnalysingTool.m

8 Name: Rozemarijn Schotel 8 Course: Graduation project 9 Main file: Data processing and analysing tool 9 Last updated: 12.06.2019 8
<pre>%% SUMMARY PROJECT: % TITLE: Monitoring local muscle load in football % AIM OF STUDY: This pilot study aims to use a big data analysis approach to translate leg acceleration data into a measure to indicate local % muscle load and compare this new local and the current global method to the players' experienced load. % MAIN QUESTION: Could local three-dimensional acceleration of the lower extremities, processed with a big data analysis approach, represent the % football players' experienced muscular load more accurate than the current global method? % HYPOTHESIS: Intensity increase of a football drill will increase the local load similarly as the experienced load, but not global, based on</pre>
acceleration. The current method is an acceleration index based on two-dimensional position data of the whole body obtained by the local positioning measurement system - LFM for short - and the new local method gathers local acceleration data of the lower extremities in three dimensions by using the acceleration module of Shimmer3 IMUs. The expectations are that the local data is a more accurate representation of the experienced load than the current global measure, i.e. increasing the drill intensity in football will be visible in the local three-dimensional acceleration pattern of the lower extremities, but not in the current global indication of load. Two drills are performed - including specific football movements: jcg/sprint, turn, and pass/shoot - on the pitch by 5 participants: (A) back/forth and (B) zigzag. Perform different situations of these drills by increasing the intensity from jogging to sprinting and adding a pass/shot. Keep the frequency, and therefore, the travelled distance constant. The participants wear a set of sensors to measure the movements. The measurement methods are (1) questionnaire: subjective method to obtain the experienced load, (2) 2D LFM: current objective method to obtain the global acceleration index of the whole body, with the sensor location between the shoulder blades, and (3) 3D accelerometers: new objective method to obtain the local acceleration of the lower extremities, with sensor locations at the middle of pelvis, upper legs, and lower legs. Use a MATLAB algorithm to process the experiment data to find, analyse, and evaluate new measures - based on local acceleration data and translate the local acceleration data muscle load in football. A main file runs different functions to perform specific actions to the data and translate the local acceleration data winct a single value to indicate local muscle load per situation by a peak and cumulative data analysis. Vary the inputs: different data process the trand percentages - jog/sprint without shoot to the
<pre>% Hypotheses to test HypothesisName = ['A.I: Intensity increase of jogging back/forth by a' 'pass/shot will increase the local load similarly as the' 'experienced load, but not global, based on acceleration'}; {'A.II: Intensity increase of sprinting back/forth by a' 'pass/shot will increase the local load similarly as the' 'experienced load, but not global, based on acceleration'}; {'B.I: Intensity increase of jogging a zigzag by a shot' 'will increase the local load similarly as the experienced' 'load, but not global, based on acceleration'}; {'B.II: Intensity increase of sprinting a zigzag by a shot' 'will increase the local load similarly as the experienced' 'load, but not global, based on acceleration'}; {'B.II: Intensity increase of sprinting a zigzag by a shot' 'will increase the local load similarly as the experienced' 'load, but not global, based on acceleration'}; IntensityName = {{'la: low' 'lb: medium' 'lc: high'},{'2a: low' '2b: medium' '2c: high'};{'3a: low' '3b: high'},{'4a: low' '4b: high'};</pre>
<pre>% Measurement methods used: MeasurementName = {'&gt; Questionnaire (subjective method):' 'experienced load';</pre>
<pre>%% &gt;&gt; ** SELECTION MENU ** &lt;&lt; %% % Make some choices in this selection menu to analyse different processing methods and develop potential measures. It is possible to choose % multiple options in select group 2, 3, and 4 to visualise these in the same figure. However, only one group can have multiple options to % compare and visualise these relative to each other in one graph.</pre>
<pre>% &gt;&gt; ** 1. SELECT DRILL ** &lt;&lt; SelectDrill = 1; % One option = # DrillName = {'A - 10x back and forth per situation (6x)';</pre>
<pre>'B - 5x zigzag per situation and walk back (4x)'}; SitName = {{'&gt; Situation 1a: jog + turn + no ball'; '&gt; Situation 1b: jog + turn + pass'; '&gt; Situation 1c: jog + turn + shoot'}; {'&gt; Situation 2a: sprint + turn + no ball'; '&gt; Situation 2b: sprint + turn + pass'; '&gt; Situation 2c: sprint + turn + shoot'}; {'&gt; Situation 3a: jog + turn + no ball'; '&gt; Situation 3b: jog + turn + shoot'}; {'&gt; Situation 4a: sprint + turn + no ball'; '&gt; Situation 4b: sprint + turn + shoot'};</pre>
<pre>% &gt;&gt; ** 2. SELECT DATA PROCESS METHOD ** &lt;&lt; SelectProcess = 4; % One option = #; multiple option = [#, #, #, etc] ProcessName = {'1: absolute values of all individual x,y,z acc'; '2: absolute values of sum of local x,y,z acc'; '3: sum of absolute values of local x,y,z acc'; '4: magnitude of combined local x,y,z acc'; '5: absolute values of gradient of magnitude of combined local x,y,z acc'; '6: absolute values of difference of magnitude of combined local x,y,z acc'; '7: envelope of magnitude of combined local x,y,z acc';</pre>
<pre>% &gt;&gt; ** 3: SELECT MEASURE CALCULATION ** &lt;&lt; SelectMeasure = 15; % One option = #; multiple option = [#, #, #, etc] MeasureName = {'1: average'; % Measures with all data points (per travelled distance) '2: sum'; % "</pre>
'3: area under curve';       % "         '4: peak amount';       % Measures with peak data points (per travelled distance)         '5: peak average';       % "         '6: peak sum';       % "         '7: area under peak curve';       % "
<pre>'8: peak width average'; % " '9: peak width sum'; % " '10: time spend weighted per zone'; % Measures with normal data points weighted per zone (per travelled distance) '11: average weighted per zone'; % " '12: sum weighted per zone'; % "</pre>
<pre>12. Sum weighted per 2016 ; % Measures with peak data points weighted per zone (per travelled distance) '13: peak average weighted per zone'; % " '14: peak average weighted per zone'; % "</pre>
<pre>% &gt;&gt; ** 4: SELECT COMBINED MEASURE METHOD ** &lt;&lt; SelectCombine = 1; % One option = #; multiple option = [#,#,#,etc] CombineName = {'1: P + R1 + L2 + L1 + L2'; % P = pelvis '2: R1 + R2 + L1 + L2'; % P = pelvis '3: P + R1 + L1'; '4: R1 + L1'; '5: R2 + L2'};</pre>

% >> \*\* 5: DEFINE OTHER OPTIONS \*\* << Zone = [10 40 70 100]; % Define three intensity zones (low, medium, and high) to categorise the peaks WeightFactor = [1 4 7]; Group = {[inf 96+10 96-10 -inf; inf 24+10 24-10 -inf]; ... [inf 39+10 39-10 -inf; inf 7+10 7-10 -inf]}; % Define weighting factors for the three zones % Define group allocation, based on experienced load trend percentages: A.I=96%, A.II=24%, B.I=39%, B.II=7% (inclusive +/- 10) PLOT AND/OR SAFE VISUALISATION: OFF=0 / ON=1 \*\* << % Visualisation of the results after data processing to analyse the results % Save the generated figure in the allocated folder for later use FinalPlotC2 = 1;SaveFigureC2 = 1; %% PLOTS TO CHECK FUNCTIONS % OFF=0 / ON=1. Only use when one option is selected per select group. Furthermore, these are only plots to check functions, therefore, the plots % are very basic, without legends, axis labels, etc. CheckPlotA1 = 0; % Plot 1: Check synchronisation timeline of local GYR-Z data % Plot 2: Check synchronisation timeline of global ACC and local X ACC-X data % Plot 3: Check normalised local acceleration data after data process methods CheckPlotA2 = 0; % Flot 5: Check momanised focal acceleration data arter data process methods % Flot 4: Check start and end times of situations in global speed and acceleration data % Flot 5: Synchronised and segmented global data % Flot 6: Synchronised and segmented local acceleration data % Flot 7: Check zone and peak selection in local acceleration data (plot is executed in A2\_DataProcess) CheckPlotA3 = 0; CheckPlotB1 = 0; **%% PARAMETERS** ExpNr = 5; SampRate = 200; SrLocal = 199.8; % 5 participants performed the experiment % Global (= LPM, reference) and local (= IMUs) sampling rate [Hz] % A safe margin of 3 seconds at the start/end of the situations SafeMargin = 3; % A sale margin of 3 seconds at the statistic of the situations % 7 sensors: 1x LPM + 6x (incl. 1 reference) IMUs, with 3 accelerometers (x,y,z) % Load indication of (1) global and (2) local method, 1 = # and 2 = # per travelled distance % Colours used for plotting: experienced load, current global method, and new local method ); HypCat = [1 2]; end % Number of situations of drill A (6x10 back/forth) HypCat = [3 4]; end % Number of situations of drill B (4x5 zigzags and walk back) TotSen = 7; SenLocal = 6; AccLocal = 3; LoadMeasure = [1 2]; Colour = [107 134 137; 0 166 214; 0 102 109]/255; if SelectDrill==1; SitNr = 6; SitCat = [1 2 3; 4 5 6]; HypCat = [1 2]; end if SelectDrill==2; SitNr = 4; SitCat = [1 2; 3 4]; HypCat = [3 4]; end % The units are not relevant because of the normalisation of the acceleration data to select zones (see data process method section) and % Inclusive not relevant because of the normalisation of the acceleration data to select zones (see data process method section) and % measures to calculate the trend of the situation intensity increase per measure and compare the measures within and not between the measures % (see results section). Normalise the measures per drill (so not per hypothesis) in order to compare them on the same y-axis. It is a % qualitative study (i.e. about the trend), not a quantitative research (i.e. it is not to compare the values with each other). Furthermore, it % is not necessary to translate the time from timeframes to seconds (the depended factor is chosen to be distance, not time). **%% FUNCTION A1: PRE-PROCESS DATA** <sup>6</sup> Load and select the correct raw objective global and local data, resample the local data, synchronise internal timelines of all global and % local sensors, and filter the local acceleration data. Data PreProcess = cell(ExpNr,1); Exp = 1:ExpNr for Data PreProcess {Exp, 1} = A1 DataPreProcess (Exp, CheckPlotA1, SampRate, SrLocal, SenLocal, AccLocal, Colour); end %% FUNCTION A2: DATA PROCESS METHODS % Different methods to process the data and normalise the local acceleration data (0-100) to the maximum. Data\_Process = cell(ExpNr,1); for Exp = 1:ExpNr
 for Process = 1:length(SelectProcess) ProcessMethod = SelectProcess(Process); PreProcessData = Data\_PreProcess(Exp,1); Data\_Process[Exp,1]{Process,1} = A2\_DataProcess(Exp,ProcessMethod,PreProcessData,Zone,CheckPlotA2,CheckPlotB1,TotSen,SenLocal,Colour); end end %% FUNCTION A3: SEGMENTATION OF THE DRILLS AND SITUATIONS
Data\_Segment = cell(ExpNr,1);
for Exp = 1:ExpNr
 for Process = 1:length (SelectProcess)
 for Sit = 1:SitNr
 ProcessData = Data\_Process(Exp,1){Process,1};
 Data\_Segment{Exp,1}{Process,Sit} = A3\_DataSegment(Exp,Sit,ProcessData,SelectDrill,CheckPlotA3,SampRate,SafeMargin,SenLocal,Colour);
 end end end end %% FUNCTION B1: GLOBAL AND POTENTIAL LOCAL MEASURE CALCULATIONS % Conduct measure calculations, i.e. apply different operations to the local acceleration data. Measure\_Calculations = cell(ExpNr,1); for Exp = 1:ExpNr
for Process = 1:length(SelectProcess)
 for Sit = 1:SitNr Sit = 1.Sitwi
SegmentData = Data\_Segment{Exp,1}{Process,Sit};
Measure\_Calculations{Exp,1}{Process,Sit} = B1 MeasureCalculations (SegmentData, SelectMeasure, MeasureName, Zone, WeightFactor, LoadMeasure); end end end **%% FUNCTION B2: COMBINED MEASURE** Sum the measures of the individual local sensors in different ways into one value and obtain the combined measure to indicate local muscle load. Measure\_Combined = cell(ExpNr,1); for Exp = 1:ExpNrfor Process = 1:length(SelectProcess)
 for Sit = 1:SitNr CalculationsMeasure = Measure Calculations{Exp,1}{Process,Sit}; Measure\_Combined(Exp,1){Process,Sit} = B2\_MeasureCombined(CalculationsMeasure,SelectMeasure,SelectCombine,CombineName,SenLocal); end end end %% FUNCTION C1: RESULTS % First, load and select the subjective data, and select and re-organise the results. Furthermore, calculate and normalise (0-10) the mean and % standard deviation of all experiments per measure and per drill to the maximum. Last, calculate the trend percentage from the first to last of % the situation (per hypothesis) and allocate into three groups to compare different combined measures and test the hypotheses: larger, similar, % and smaller, base this on experienced load trend percentage. Data\_Results = C1\_Results (Measure\_Combined,SelectDrill,SelectProcess,SelectMeasure,SelectCombine,Group,ExpNr,SitNr,SitCat);

#### %% FUNCTION C2: VISUALISATION OF THE RESULTS TO TEST THE HYPOTHESES

% Develop a standard figure (in order to test all possibilities in the same format) to find, analyse, and evaluate different measures for local % muscle load in football, and compare these to the current global measure and subjective measure. Furthermore, the figure shows a summary of the % experiment, processing, and measure design. Data\_Visualisation = C2\_Visualisation(Data\_Results,HypothesisName,IntensityName,MeasurementName,SelectDrill,DrillName,SitName,SelectProcess, ...

Data\_visualisation = C2\_visualisation Data\_Results, HypothesisName, IntensityName, MeasurementName, Selectrin, DiliName, Selectrocess, ... ProcessName, SelectMeasure, MeasureName, SelectCombine, CombineName, Zone, WeightFactor, Group, FinalPlotC2, SaveFigureC2, ExpNr, SampRate, LoadMeasure, ... Colour, SitCat, HypCat);

# MATLAB function A1\_DataPreProcess.m

%
<pre>function Data_PreProcess = A1_DataPreProcess(Exp,CheckPlotA1,SampRate,SrLocal,SenLocal,AccLocal,Colour)</pre>
<pre>% (1) Anonymous experiment number; (2) Approximate experiment length based on the video (duration in timeframes [Hz]): ExpStart (from % start of 15x jumping) and EndTime (after last shot + 10 seconds = 2000 timeframes), this will exclude any warming-up, cooling-down, and % weird peaks because LPM sensor is inside building; (3) Sampling frequency percentages per experiment [P Rl R2 L1 L2 X]. if Exp==1; ExpCd='Expl'; ExpStart=44600; ExpEnd=632600; Sr_Exp=[0.997 0.997 0.997 0.997 0.999 0.997]*SrLocal; end if Exp==2; ExpCd='Exp2'; ExpStart=35400; ExpEnd=680400; Sr_Exp=[0.997 0.997 0.997 0.997 0.999 0.620]*SrLocal; end if Exp==3; ExpCd='Exp3'; ExpStart=39400; ExpEnd=689400; Sr_Exp=[0.997 0.997 0.997 0.997 0.999 0.997]*SrLocal; end if Exp==4; ExpCd='Exp4'; ExpStart=39400; ExpEnd=534600; Sr_Exp=[0.997 0.997 0.997 0.999 0.997]*SrLocal; end if Exp==5; ExpCd='Exp5'; ExpStart=106800; ExpEnd=734800; Sr_Exp=[0.997 0.997 0.997 0.999 0.997]*SrLocal; end</pre>
<pre>%% LOAD AND SELECT CORRECT RAW OBJECTIVE DATA % Define location of stored data. RootPath = 'C:\Users\Rozemarijn Schotel\Google Drive\TU Delft\Graduation project\5. Data Processing and Analysing'; DataFolder = strcat(RootPath,'\',ExpCd);</pre>
<pre>% Read global data from exported .csv file. Select relevant rough global data: 2D position and motion data, heartbeat, and acc count/index. % Correct for weird peaks in global signal at start and end if the LPM sensor is outside the measuring area. Global_Load = csvread(strcat(DataFolder,'\',ExpCd,'_LPM_200Hz.csv'),1,0); % 1:t, 2:X, 3:Y, 4:Spd, 5:Acc, 6:Dist, 7:HB, 8:AccCnt, 9:AccIdx Global_Rough = Global_Load(ExpStart:ExpEnd,[2,3,6,4,5,7,8,9]); % 1:X, 2:Y, 3:Dist, 4:Spd, 5:Acc, 6:HB, 7:AccCnt, 8:AccIdx</pre>
<pre>% Load local (calibrated) data from exported .mat file. Select relevant rough local data: wide range accelerometer (+/- 16g), because the % fast movements performed during the experiment exceed the low-noise accelerometer of +/- 2g. The calibrated data is exported from the % ConsensysBasic program, which imports the measured data from the Shimmer3 IMUs, so no further calibration is needed. Furthermore, resample % local data (= 199.8 Hz, including the correction percentages) to sampling rate reference (= 200 Hz; to meet sampling rate of LPM). Local_NameSen= {'P' 'R1' 'R2' 'L1' 'L2' 'X'}; % Data of pelvis, right upper and lower leg, left upper and lower leg, and extra upper back Local_NameAccVar = ('Accel_WR_X_CAL' 'Accel_WR_Y_CAL' 'Accel_WR_Z_CAL'); Local_Load = cell(1,SenLocal); Local_RoughAcc(1,SenLocal) = struct; Local_AccLength = zeros(1,SenLocal);</pre>
<pre>for i = 1:SenLocal Local_Load(i) = load(strcat(DataFolder,'\',ExpCd,'_',Local_NameSen(i),'_','Calibrated.mat'));</pre>
<pre>for j = 1:AccLocal SelectSen = strcat(Local_NameSen{i},Local_NameAccVar{j}); [p,q] = rat(SampRate/Sr_Exp(i),0.0001); Local_RoughAcc(i).data(:,j) = resample(Local_Load{1,i}.(SelectSen),p,q); Local_AccLength(i) = length(Local_RoughAcc(i).data(:,j));</pre>
end end
<pre>%% SYNCHRONISE TIMELINES OF LOCAL DATA (6 IMUS) % The Shimmer3 IMUs are simultaneously rotated around the same axis, to create a mark in the signal. The mark is created before the sensors % are attached to the participant. Based on local angular rate of z-axis (GYR-Z), therefore, select relevant rough local data: GYR-Z. % Resample local data (= 199.8 Hz), including the correction percentages) to sampling rate reference (= 200 Hz) Local_NameGyrVar = {'_Gyro_Z_CAL'}; t_rot = 5*60*SampRate; % End time (5 min) of timeframe to find the rotation </pre>
Local_SelectGyr(1,SenLocal) = struct; Local_RoughGyr = zeros(t_rot,SenLocal); for i = 1:SenLocal
<pre>SelectSen = strcat(Local_NameSen(i),Local_NameGyrVar{1});   [p,q] = rat(SampRate/Sr_Exp(i),0.0001);   Local_SelectGyr(i).data(:,1) = resample(Local_Load{1,i}.(SelectSen),p,q);   Local_RoughGyr(:,i) = Local_SelectGyr(i).data(1:t_rot,1); end</pre>
% Find cross correlation in local GYR-Z data. lag diff1 = zeros(1,SenLocal);
<pre>iag_unit = 2eros(r)senfocal for i = 1:Senfocal [C1,lag1] = xcorr(Local_RoughGyr(:,i),Local_RoughGyr(:,1)); % Find cross correlation in rotation local GYR-Z data [~,I1] = max(abs(C1)); % Find the index of the highest peak lag_diff1(i) = lag1(I1); % Sample difference between the signals end</pre>
<pre>% Manually compensate for wrong calibration R2 and X in experiment 2. if Exp==2; lag_diff1 = [lag_diff1(1) lag_diff1(2) lag_diff1(3)-2113 lag_diff1(4) lag_diff1(5) lag_diff1(6)-2289]; end</pre>
<pre>% Process the lag differences found in local GYR-Z data. Local_StartValue = lag_diff1+abs(min(lag_diff1))+1;</pre>
% Plot 1: Check synchronisation timeline of local GYR-Z data
<pre>% Use the lag differences found in local GYR-Z data and process into the local acceleration data to synchronise the timelines. Crop to % shortest vector and place these local acceleration data in one matrix. Local_AccLength = min(Local_AccLength)-max(Local_StartValue)+Local_StartValue; % Compensation for new length Local_SynlAcc = zeros(min(Local_AccLength), SenLocal*AccLocal); for i = 1:SenLocal for j = 1:AccLocal</pre>
<pre>Local_SynlAcc(:,j+3*(i-1)) = Local_RoughAcc(i).data(Local_StartValue(1,i):Local_AccLength(1,i),j); end</pre>
end
<pre>%% SYNCHRONISE TIMELINES OF LOCAL AND GLOBAL DATA (6 SHIMMERS AND LPM) % Based on local X ACC-X and global ACC data: find cross correlation of local X ACC-X and global ACC [C2,lag2] = xcorr(Local_Syn1Acc(:,16),Global_Rough(:,5)); % Find cross correlation in local X ACC-X and global ACC data [~,I2] = max(abs(C2)); % Find the index of the highest peak lag_diff2 = lag2(I2); % Sample difference between the signals</pre>
<pre>% Use the lag differences found and process into the global and local ACC data to synchronise the timelines A = length(Global_Rough); B = length(Local_SynlAcc)-lag_diff2; % Crop to length of global data if B&gt;A; Local_Syn2Acc = Local_Syn1Acc(lag_diff2:A+lag_diff2-1,:); Global_Syn2 = Global_Rough; end if A&gt;B; Local_Syn2Acc = Local_Syn1Acc(lag_diff2:B+lag_diff2-1,:); Global_Syn2 = Global_Rough(1:B,:); end</pre>
% Plot 2: Check synchronisation timeline of global ACC and local X ACC-X data
<pre>%% FILTER ACCELERATION SIGNALS % Consider the filtering of the local acceleration signal as a pre-processing step to smoothening the data. Inmotio (i.e. LPM program) % filters the global acceleration signal. The chosen filtering method is a moving-average 1D filter. 'A moving-average filter is a common % method used for smoothing noisy data. The filter function is used to compute averages along a vector of data. A moving-average filter % slides a window of length WindowSize along the data, computing averages of the data contained in each window' (source: mathworks.com). The % filtered data will return in the same length vector, and combined to a matrix. Filter functions tested (only one dimensional): smooth, % filter, medfilt1, hampel, filtfilt, sgolayfilt &gt;&gt; chosen filter. WindowSize = 2; b = (1/WindowSize)*ones(1,WindowSize); a = 1; Local_Syn2FiltAcc = zeros(size(Local_Syn2Acc)); for i = 1:size(Local_Syn2Acc,2); Local_Syn2FiltAcc(:,i) = filter(b,ā,Local_Syn2Acc(:,i)); end</pre>
84 DESITE FINCTION A1

### MATLAB function A2\_DataProcess.m

```
Function A2: data process methods. Different methods to process the data and normalise the local acceleration data (0-100) to the maximum.
function Data Process = A2 DataProcess(Exp, ProcessMethod, PreProcessData, Zone, CheckPlotA2, CheckPlotB1, TotSen, SenLocal, Colour)
       PreProcess_Gen = PreProcessData(:,[1:4,6:8]);
                                                                                             % Select global general data
      PreProcess Acc = PreProcessData(:,[5,9:end]);
                                                                                             % Select global and local ACC data
%% DATA PROCESSING METHODS
      DATA PROCESSING METHODS

% First, only test methods with absolute or positive values, meaning not differentiating between accelerations and decelerations. Second, the

% synchronisation of the internal timelines will not be exactly on the timestamp. Therefore, do not combine the local sensors, because 100%

% accuracy cannot be promised. However, it is possible to use the individual signals or to combine the x,y,z-components per sensor.

% Calculations between sensors a few timesteps off could make a big influence due to the fast leg movements. Third, all local sensors have

% their own internal coordinate system. Therefore, do not consider gravity, because the inertial and gravitational acceleration components

% cannot be separated during movement. The position of the sensor is needed to do so. A gyroscope is able to support on calculating the

% position, but exceeds the range of the IMUs. However, if the participant stands still, the effect of gravity is clearly visible in the

% y-component, but during movement this effect influences all x,y,z-components. So, in general without being able to obtain the position of

% the sensor, the individual x,y,z-component do not mean anything. Therefore, it would be best to use a method which combines the

% x,y,z-components. Multiple manners to combine the x,y,z-components have been considered.
      acc = PreProcess Acc;
      if ProcessMethod==1 % 1 = absolute values of all individual x,y,z acc
Data_ProcessAcc = zeros(length(acc),size(acc,2));
    for 1 = 1:size(acc,2)
                    Data_ProcessAcc(:,i) = abs(acc(:,i));
             end
      end
       if ProcessMethod==2
                                              % 2 = absolute values of sum of local x,y,z acc
              Data ProcessAcc = zeros(length(acc), TotSen);
              Data_ProcessAcc = zeros, ...
for i = 1:TotSen
    if i==1; Data_ProcessAcc(:,i) = abs(acc(:,i));
    else; Data_ProcessAcc(:,i) = abs(acc(:,(i-1)*3-1)+acc(:,(i-1)*3)+acc(:,(i-1)*3+1));
       end
       if ProcessMethod==3
                                              % 3 = sum of absolute values of local x,y,z acc
              Data ProcessAcc = zeros(length(acc), TotSen);
              for \overline{i} = 1:TotSen
                     if i==1; Data_ProcessAcc(:,i) = abs(acc(:,i));
                                    Data_ProcessAcc(:,i) = abs(acc(:,(i-1)*3-1))+abs(acc(:,(i-1)*3))+abs(acc(:,(i-1)*3+1));
                    else;
                     end
             end
      end
                                              % 4 = magnitude of combined local x,y,z acc
       if ProcessMethod==4
              Data_ProcessAcc = zeros(length(acc),TotSen);
              for i = 1:TotSen
                     if i==1; Data_ProcessAcc(:,i) = sqrt(acc(:,i).^2);
else; Data_ProcessAcc(:,i) = sqrt(acc(:,(i-1)*3-1).^2+acc(:,(i-1)*3).^2+acc(:,(i-1)*3+1).^2);
                     end
             end
       end
       if ProcessMethod==5
                                              % 5 = absolute values of gradient of magnitude of combined local x,y,z acc
             % 'Numerical gradient of a function is a way to estimate the values of the partial derivatives' (mathworks.com).
Data_ProcessAcc = zeros(length(acc),TotSen);
             Data_ProcessAcc = 2clostic_c, in the form i = 1:TotSen
    if i==1; Data_ProcessAcc(:,i) = abs(gradient(sqrt(acc(:,i).^2)));
    else; Data_ProcessAcc(:,i) = abs(gradient(sqrt(acc(:,(i-1)*3-1).^2+acc(:,(i-1)*3).^2+acc(:,(i-1)*3+1).^2)));
             end
       end
             ProcessMethod==6 % 6 = absolute values of difference of magnitude of combined local x,y,z acc
% Calculate the differences, therefore, the vector length will decrease by 1.
PreProcess_Gen = PreProcess_Gen(1:end-1,:); Data_ProcessAcc = zeros(length(acc)-1,TotSen);
       if ProcessMethod==6
              PreProcess_gen = firstsen
for i = 1:TotSen
if i==1; Data_ProcessAcc(:,i) = abs(diff(sqrt(acc(:,i).^2)));
else; Data_ProcessAcc(:,i) = abs(diff(sqrt(acc(:,(i-1)*3-1).^2+acc(:,(i-1)*3).^2+acc(:,(i-1)*3+1).^2)));
             end
       end
       if ProcessMethod==7
                                               \% 7 = envelope of magnitude of combined local x, y, z acc
              Data_ProcessAcc = zeros(length(acc),TotSen);
              for \overline{i} = 1 \cdot TotSen
                     if i==1; [Data_ProcessAcc(:,i),~] = envelope((sqrt(acc(:,i).^2)),1,'peak');
                     else;
                                     [Data_ProcessAcc(:,i),~] = envelope((sqrt(acc(:,(i-1)*3-1).^2+acc(:,(i-1)*3).^2+acc(:,(i-1)*3+1).^2)),1,'peak');
                     end
              end
```

end
% NORMALISE SIGNAL TO 0-100
% Normalise the data (0-100) to the maximum of the experiment to select zones and peaks according to these zones in the measure function. % Percentage of maximal (distinguish global and local): select absolute maximal value in global and local acceleration data and normalise. % Find the maximum within the participant and not the overall maximum of all 5 participants.
<pre>MaxGlobal = max(Data_ProcessAcc(:,1)); GlobalAcc_Norm = (Data_ProcessAcc(:,1)./MaxGlobal)*100; MaxLocal = max(max(Data_ProcessAcc(:,2:end))); LocalAcc_Norm = (Data_ProcessAcc(:,2:end)./MaxLocal)*100;</pre>
% Plot 3: Check normalised local acceleration data after process methods
% RESULT FUNCTION A2
<pre>b Data_Process = [1:X, 2:Y, 3:Dist, 4:Spd, 5:HB, 6:AccCount, 7:AccIndex, 8:AccGlobal, 9-end:AccLocal] per experiment and per data process metho Data_Process = [PreProcess_Gen GlobalAcc_Norm LocalAcc_Norm];</pre>
8 PLOTS TO CHECK FUNCTION
if CheckPlotA2==1    CheckPlotB1==1
% Plot 3: Check normalised local acceleration data after process methods
<pre>figure('Name','3: CHECK NORMALISED LOCAL ACCELERATION DATA AFTER HANDLING','NumberTitle','off','Visible','on');</pre>
<pre>set(gcf,'Position',get(0,'Screensize'));</pre>
<pre>for k = 1:size(LocalAcc_Norm,2)</pre>
<pre>subplot(SenLocal,size(LocalAcc_Norm,2)/SenLocal,k); hold on; plot(LocalAcc_Norm(:,k),'Color',Colour(3,:));</pre>
xlim([0 length(LocalAcc_Norm)]); ylim([-10 110])
if CheckPlotB1==1
% Plot 7: Check zone and peak selection in local acceleration data. Execute this plot in A2_DataProcess, because it is easier 1
% check the zone and peak selection before the data is segmented into multiple parts.
for i = 1:length (Zone); yline (Zone (i), ''); end % Zone selection
<pre>%[pks,loc] = findpeaks(LocalAcc_Norm(:,k),'MinPeakHeight',Zone(1)); plot(loc,pks,'r.'); % Peak selection</pre>
end end
end satile(['NORMALISED LOCAL ACCELERATION DATA OF EXPERIMENT ' num2str(Exp)])
end
end de la constant de

input 4a: stan	and end	times of a	riii A			input 40: Star	t and end	times or a				
Exp. code	Sit 1a	Sit 1b	Sit 1c	Sit 2a	Sit 2b	Sit 2c		Exp. code	Sit 3a	Sit 3b	Sit 4a	Sit 4b
Exp1_Start	13271	62666	110276	159469	229068	278160		Exp1_Start	366600	427000	500400	561600
Exp1_End	23332	73556	121313	167439	238352	287553	ļ	Exp1_End	390000	449300	524000	586500
Exp2_Start	9752	59946	114298	166311	210607	264587		Exp2_Start	336500	407000	475600	540000
Exp2_End	23745	76217	130755	174362	220405	275085	ļ	Exp2_End	368300	441300	502500	569100
Exp3_Start	17189	63643	111916	159789	204523	252412		Exp3_Start	335200	401100	464600	548500
Exp3_End	26923	73803	121837	166703	212527	260968	ļ	Exp3_End	364300	428000	505500	588200
Exp4_Start	3057	47910	94602	141293	184389	234245		Exp4_Start	302700	360400	416100	473200
Exp4_End	11626	57222	104668	147781	191707	242032	ļ	Exp4_End	325100	382500	437000	493500
Exp5_Start	24965	75489	121659	176872	229618	284035		Exp5_Start	389400	461900	532200	604600
Exp5_End	33097	83730	129164	182840	236316	291184		Exp5_End	414200	484600	556100	626400

#### MATLAB function A3\_DataSegment.m

Input to, start and and times of drill A

Function A3: Segmentation of the drills and situations.

function Data\_Segment = A3\_DataSegment(Exp,Sit,ProcessData,SelectDrill,CheckPlotA3,SampRate,SafeMargin,SenLocal,Colour)

% Segment selection. Conduct manually the segmentation selection of the drills into situations. Base this on the changes in global speed and % acceleration data (plot 4) and check if the selected segments (including +/- a safe margin) are correct for the local data (plot 6). A % method or algorithm to select the drills and situations automatically which would work for all experiments and drills/situations has not % been found, as some of the participants perform more movement in between the situations. Select drill A very precisely with a specific method: (i) count the peaks in the global speed (10 back/forth repetitions, so 20 times), (ii) select the start and end times in the global absolute acceleration and speed. Start time: if acceleration is zero before the first large acceleration of the situation and the speed increases from zero. End time: if acceleration is zero after the last large acceleration of the situation and the speed decreases towards zero. Due to some movements before and after the situations it is not always exact zero. However, it is quite clear to see and the design of the experiment eliminates this as much as possible. Select drill B more roughly: (i) count the zigzags in global data (all 5 8 repetitions, except for situation 3b of experiment 1 and situation 3a of experiment 5, which have 6 repetitions), (ii) select roughly the 8 start and end times in timeframes (only select 5 repetitions). Use drill B to see if the measure will also work for entire exercises by 8 roughly selecting the start and end times. This is also the reason to include the walking part, eliminate the time this part takes by % roughry selecting the start and end times. This is also the feasible to include the writing pair % conducting calculations in the measure design per travelled distance, which is kept constant. if SelectDrill==1; StartEndTimes\_Load = xlsread('Input4a\_StartEndTimes\_DrillA.xlsx'); end % if SelectDrill==2; StartEndTimes\_Load = xlsread('Input4b\_StartEndTimes\_DrillB.xlsx'); end % if SelectDrill==2; StartEndTimes\_DrillB.xlsx'); end % if SelectDrill==2; StartEndTimes\_Load = xlsread('Input4b\_StartEndTimes\_DrillB.xlsx'); end % if SelectDrill==2; StartEndTimes\_DrillB.xlsx'); end % if SelectDrill==2; StartEndTimes\_DrillB.xlsx'); end % if SelectDrill==2; StartEndTimes\_DrillB.xlsx'; if SelectDrill==2; % Start and end time of drill

t\_StartEndLoad = StartEndTimes\_Load(Exp\*2-1:Exp\*2,:)';

% Start and end time of drill B % Selection of correct experiment

Input the start and and times of drill P

% Add a safe margin of three seconds before and after each situation. It turned out that this safe margin was not enough for experiment 2, % therefore, add an extra of 3 seconds (600 timeframes) to the start time in the excel file. Use a safe margin to include all data according % to the situation because of three reasons. First, the local acceleration of the legs start earlier and end later than the global whole body % acceleration. Second, the synchronisation of the sensor timelines is not exact, so this safe margin compensates for any small mis % synchronisations. Third, some participants conduct small movements before and after the situations, include a safe margin to compensate for % any mis selections in the global data for movements which do not belong to the situation. time = [t StartEndLoad(:,1)-SafeMargin\*SampRate t StartEndLoad(:,2)+SafeMargin\*SampRate];

% Plot 4: Check start and end times of situations in global speed and acceleration data

% Plot 5: Synchronised and segmented global data % Plot 6: Synchronised and segmented local acceleration data

#### %% RESULT FUNCTION A3

Data\_Segment(if drill A) = [1: Sitla, 2: Sitlb, 3: Sitlc, 4: Sit2a, 5: Sit2b, 6: Sit2c] per experiment and per data process method and [1:X, 2:Y, 3:Dist, 4:Spd, 5:HB, 6:AccCount, 7:AccIndex, 8:AccGlobal, 9-end:AccLocal] per situation. Data\_Segment(if drill B) = [1: Sit3a, 2: Sit3b, 3: Sit4a, 4: Sit4b] per experiment and per data process method and [1:X, 2:Y, 3:Dist, 4:Spd, 5:HB, 6:AccCount, 7:AccIndex, 8:AccGlobal, 9-end:AccLocal] per situation. Data\_Segment = ProcessData(time(Sit,1):time(Sit,2),:);

#### %% PLOTS TO CHECK FUNCTION

if CheckPlotA3==1 && Sit==1

- heverothors a ster-1
  t = [time(:,1);time(:,2)];
  % Plot 4: Check start and end times of situations in global speed and acceleration data
  figure('Name','4: CHECK START/END TIMES OF SITUATIONS IN GLOBAL SPEED AND ACCELERATION DATA','NumberTitle','off','Visible','on');
- set(gcf, 'Position', get(0, 'Screensize'));
- plot(ProcessData(:,8), 'Color',Colour(2,:)); hold on; plot(ProcessData(:,4), 'c'); for i = 1:length(t); xline(t(i), 'r'); end title(['GLOBAL SPEED AND ACCELERATION DATA OF EXPERIMENT ' num2str(Exp)])

<pre>% Plot 5: Synchronised and segmented global data figure('Name','5: SYNCHRONISED AND SEGMENTED GLOBAL DATA','NumberTitle','off'); set(gcf,'Position',get(0,'Screensize')); subplot(4,2,[1,3]); plot(ProcessData(:,1),ProcessData(:,2),'Color',Colour(2,:)); xlim([-45 -25]); ylim([-6 2]); title('Position') subplot(4,2,2); plot(ProcessData(:,5),'Color',Colour(2,:)); title('Heartbeat'); hold on; for i = 1:length(t); xline(t(i),'r'); end subplot(4,2,4); plot(ProcessData(:,3),'Color',Colour(2,:)); title('Distance'); hold on; for i = 1:length(t); xline(t(i),'r'); end subplot(4,2,[5,6]); plot(ProcessData(:,4),'Color',Colour(2,:)); title('Speed'); hold on; for i = 1:length(t); xline(t(i),'r'); end subplot(4,2,[7,8]); plot(ProcessData(:,4),'Color',Colour(2,:)); title('Acceleration'); hold on; for i = 1:length(t); xline(t(i),'r'); end subplot(['SYNCHRONISED AND SEGMENTED GLOBAL DATA OF EXPERIMENT ' num2str(Exp])</pre>	
<pre>% Plot 6: Synchronised and segmented local acceleration data figure('Name', '6: SYNCHRONISED AND SEGMENTED LOCAL ACCELERATION DATA', 'NumberTitle', 'off'); set(gcf, 'Position',get(0, 'Screensize')); Data ExpHanLocal = ProcessData(:,9:end); for k = 1:size(Data ExpHanLocal,2) subplot(SenLocal,size(Data ExpHanLocal,2)/SenLocal,k); xlim([0 length(Data ExpHanLocal)]); ylim([-10 110]) plot(Data_ExpHanLocal(:,k), 'Color',Colour(3,:)); hold on; for i = 1:length(t); xline(t(i),'r'); end</pre>	
end sgtitle(['SYNCHRONISED AND SEGMENTED LOCAL ACCELERATION DATA OF EXPERIMENT ' num2str(Exp)])	
end	
end	

### MATLAB function B1\_MeasureCalcualtions.m

```
Function B1: Global and potential local measure calculations. Conduct measure calculations, i.e. apply different operations to the local
     acceleration data.
function Measure Calculations = B1 MeasureCalculations (SegmentData, SelectMeasure, MeasureName, Zone, WeightFactor, LoadMeasure)
                                                                        % Select global general data = [1:X, 2:Y, 3:Dist, 4:Spd, 5:HB, 6:AccCount, 7:AccIndex]
% Select global and local acceleration data = [1:AccGlobal, 2-end:AccLocal]
      SegmentData Gen = SegmentData(:,1:7);
      SegmentData_Acc = SegmentData(:,8:end);
%% OBJECTIVE DATA: GLOBAL MEASURE CALCULATIONS
      Dist = SegmentData_Gen(end, 3)-SegmentData_Gen(1,3); % Trat
AccIndex = SegmentData_Gen(end, 7)-SegmentData_Gen(1,7); % Acc
if LoadMeasure(1)==1; CurrentMeasure_Global = AccIndex; end
if LoadMeasure(1)==2; CurrentMeasure_Global = AccIndex/Dist; end
                                                                                                  % Travelled distance [m] per experiment and per situations
                                                                                                    % Acceleration index per experiment and per situations
%% OBJECTIVE DATA: LOCAL MEASURE CALCULATIONS
      SigNr = size(SegmentData_Acc,2); % Number of global and local acceleration signals (based on process method used)
CalMeasure_Local = zeros(length(MeasureName),SigNr); % Number of total amount of measures tested
      for i = 1:\overline{S}igNr
             acc = SegmentData_Acc(:,i);
            % Note, determine the zones and weight factors on the results at the data process method stage by reviewing (plot 3) the normalised local
% acceleration data, as the intensity increases of the situations. Test some variation, which will result in a decent distribution of the
             % zones and weight factors.
             % Allocate the accelerations in zones (it is not needed to divide by the sampling rate and obtain per second).
ZT1 = acc(Zone(1)<acc & acc<=Zone(2)); ZT2 = acc(Zone(2)<acc & acc<=Zone(3)); ZT3 = acc(Zone(3)<acc & acc<=Zone(4));
if isempty(ZT1); ZT1 = 0.001; end; if isempty(ZT2); ZT2 = 0.001; end; if isempty(ZT3); ZT3 = 0.001; end
             % Find the peaks in the global and local acceleration data and allocate the peaks in zones
               Plot 7: Check zone and peak selection in local acceleration data (execute plot in A2 DataProcess)
             [pks,~,w] = findpeaks(SegmentData_Acc(:,i));
             ZPI = pks(Zone(1)<pks & pks<=Zone(2)); ZP2 = pks(Zone(2)<pks & pks<=Zone(3)); ZP3 = pks(Zone(3)<pks & pks<=Zone(4));
if isempty(ZP1); ZP1 = 0.001; end; if isempty(ZP2); ZP2 = 0.001; end; if isempty(ZP3); ZP3 = 0.001; end
             % Potential measures to test per signal (in the order of trying) in four categories: measures with all data points, measures with peak
             % data points, measures with normal data points weighted per zone, and measures with peak data points weighted per zone, all per
             % travelled distance.
                 = WeightFactor;
             CalMeasure Local(:,i) = ...
                   [mean(acc) ...
                                                                                                                        8 1
                                                                                                                              = average
                                                                                                                              = sum
                     sum(acc)
                     trapz (acc)
                                                                                                                       % 3 = area under curve
                                                                                                                               = peak amount
                     length(pks) ...
                    mean(pks) ..
                                                                                                                       8 5
                                                                                                                              = peak average
                     sum (pks)
                                                                                                                             = peak sum
= area under peak curve
                     sum(w)/length(w) ...
                                                                                                                        % 8 = peak width average
                                                                                                                               = peak width sum
                     sum(w)
                     length(ZT1)*WF(1)+length(ZT2)*WF(2)+length(ZT3)*WF(3) ...
                                                                                                                       % 10 = time spend weighted per zone
                     mean(ZT1)*WF(1)+mean(ZT2)*WF(2)+mean(ZT3)*WF(3) ...
                                                                                                                                               weighted per
                                                                                                                          11 = average
                     sum (ZT1) *WF (1) +sum (ZT2) *WF (2) +sum (ZT3) *WF (3)
                                                                                                                       % 12 = sum weighted per zone
                    sum(ZT1) *WF(1) +sum(ZT2) *WF(2) +sum(Z13) *WF(3) ...
length(ZP1) *WF(1) +length(ZP2) *WF(2) +length(ZP3) *WF(3) ...
mean(ZP1) *WF(1) +mean(ZP2) *WF(2) +mean(ZP3) *WF(3) ...
                                                                                                                       % 13 = peak amount weighted per zone
% 14 = peak average weighted per zone
                                                                                                                       % 15 = peak sum weighted per zone
                     sum(ZP1)*WF(1)+sum(ZP2)*WF(2)+sum(ZP3)*WF(3)]';
      end
      % Measures per travelled distance [#/m] per experiment, per data process method, and per situation. Choose measures per travelled distance,
% instead of per second. First, because it allows the introduction of a safe margin in the data segment function, and therefore, include the
% entire situation (global movements start later than the local movements of the legs). Furthermore, the participants are standing still
% before and after the situations or move very slowly, so the travelled distance has a smaller influence than time. Third, include walking
% back in drill B. Taking the distance (which is constant for all situations and participants), will eliminate the time it takes of walking
% or slowly jogging back, which varies between participants. Last, the drill scheme is based on a fixed distance scheme. Calculations of the
% travelled distance per situation are from the global data.
if LoadMeasure(2)==1; NewMeasure_Local = CalMeasure_Local; end
if LoadMeasure(2)==2; NewMeasure_Local = CalMeasure_Local/Dist; end
%% RESULT FUNCTION B1
% Measure Calculations = {1,1} current global measure and {1,2} new local measures per acceleration signal per experiment, per data process
% method, and per situation.
Measure Calculations = {CurrentMeasure Global NewMeasure Local (SelectMeasure,:)};
%% PLOTS TO CHECK FUNCTION
% Execute this plot in A2_DataProcess, because it is easier to check the peak and zone selection before the data is segmented into multiple
% parts.
end
```

#### MATLAB function B2\_MeasureCombined.m

% Function B3: Combined measure. Sum the measures of the individual local sensors in different ways into one value and obtain the combined % measure to indicate local muscle load.

\$-----



## MATLAB function: C1 Results.m

Input 5a: experienced load of drill A										
Exp. code	Sit 1a	Sit 1b	Sit 1c	Sit 2a	Sit 2b	Sit 2c				
Exp1	1,0	2,0	3,5	6,0	7,5	9,0				
Exp2	1,0	2,0	3,5	5,5	5,0	7,5				
Exp3	3,0	3,5	4,5	7,5	8,0	7,5				
Exp4	3,0	3,5	4,0	5,5	8,0	7,5				
Exp5	3,5	5,5	7,0	8,5	8,5	9,5				

Input 5b: experienced load of drill B									
Exp. code	Sit 3a	Sit 3b	Sit 4a	Sit 4b					
Exp1	7,0	10,0	10,0	10,0					
Exp2	2,5	4,0	7,5	8,0					
Exp3	4,0	4,5	7,0	8,0					
Exp4	3,0	5,0	7,0	8,0					
Exp5	4,0	5,0	9,0	9,5					

Function C1: results. First, load and select the subjective data, and select and re-organise the results. Furthermore, calculate and normalise (0-10) the mean and standard deviation of all experiments per measure and per drill to the maximum. Last, calculate the trend percentace the first to last of the situation (per hypothesis) and allocate into three groups to compare different combined measures and test the hypotheses: larger, similar, and smaller, base this on experienced load trend percentage. trend percentage from function Data\_Results = C1\_Results (Measure\_Combined, SelectDrill, SelectProcess, SelectMeasure, SelectCombine, Group, ExpNr, SitNr, SitCat) %% LOAD AND SELECT SUBJECTIVE DATA % Read experienced load (subjective) data of the situations per drill and per experiment - from an excel sheet. if SelectDrill==1; ExperiencedLoad\_Load = xlsread('Input5a\_ExperiencedLoad\_Drill8.xlsx'); end % Experienced load of drill A if SelectDrill==2; ExperiencedLoad\_Load = xlsread('Input5b\_ExperiencedLoad\_Drill8.xlsx'); end % Experienced load of drill B Select SubLoad = ExperiencedLoad Load; %% SELECT AND RE-ORGANISE THE OBJECTIVE RESULTS (CURRENT AND NEW MEASURES) Select AND No Converte in a construction in the convertex is a convertex in the measure and per situation of all 5 experiments. P = length(SelectProcess); M = length(SelectMeasure); C = length(SelectCombine); Select\_CurGlobal = cell(1,1); % Currently used method to indicate load, based on global ACC data (acceleration index [#]) Select\_NewLocal = cell(max([P,M,C]),1); % Processed data, resulted in measures for local muscle load, based on local ACC data for Exp = 1:ExpNr Exp = 1:ExpNr
for Process = 1:P
 for Sit = 1:SitNr for Measure = 1:M for Combined = 1:C Select\_NewLocal{i,1}(Exp,Sit) = Measure\_Combined{Exp,1}{Process,Sit}{1,1}(1,1); % Vary pe Select\_NewLocal{i,1}(Exp,Sit) = Measure\_Combined{Exp,1}{Process,Sit}{1,3}(Measure,Combined); % Vary per experiment and situation end end end end end %% MEAN AND STANDARD DEVIATION OF ALL EXPERIMENTS PER MEASURE AND SITUATION Results of subjective and objective data: mean of all experiments, standard deviation of all experiments, and minimum/maximum value of the experiments (calculate the maximum in order to use this in normalising the signal). elect\_Results = [Select\_SubLoad;Select\_CurGlobal;Select\_NewLocal]; % All selected data: subjective, current global and new local Select\_Results = [Select\_SubLoad;Select\_CurGlobal;Select\_NewLocal]; MeanStd\_Results = cell(length(Select\_Results),1); for i = 1:length(Select\_Results) MeanStd\_Results(i,1) = [mean(Select\_Results(i,1));std(Select\_Results(i,1));min(Select\_Results(i,1));max(Select\_Results(i,1)); end %% NORMALISE SIGNAL TO 0-10 % Normalise the average and standard deviation to the maximum value (0-10) per measure and per drill (so not per hypothesis). Normalise the % measure per drill in order to compare them on the same y-axis, it is about the trend: qualitative measure, not a quantitative, i.e. it is % not to compare the values with each other. Select maximal value per measure and normalise: (1) subjective, (2) current objective global, % and (3) new objective local. Norm\_Results = cell(length(MeanStd\_Results),1); Max\_Results = cell(length(MeanStd\_Results),1); Norm\_Results(i,1) = max(MeanStd\_Results(i,1)(4,:)); Norm\_Results(i,1) = (MeanStd\_Results(i,1)./Max\_Results(i,1))\*10; %% TREND PERCENTAGES PER SITUATION (I.E. PER HYPOTHESIS) \* An indicative percentage per measure of the jog/sprint without shoot to the jog/sprint with shoot (i.e. select the first and last per \* situation): (1) subjective, (2) current objective global, and (3) new objective local. It has been chosen to use the without/with shoot \* situations, so the method used to analyse and evaluate drill A and B are consistent. Trend Results = zeros(length(Norm\_Results),1); SC = SitCat; for i= llogath(Norm\_Results). for i = 1:length(Norm\_Results)
 for j = 1:2 Trend Results(i,j) = round(((Norm\_Results{i,1}(1,SC(j,end))-Norm\_Results{i,1}(1,SC(j,1)))/Norm\_Results{i,1}(1,SC(j,1)))\*100);

end	
end	
<pre>%% GROUP ALLOCATION % Allocate all the trend lines of the objective global and local measures into three groups av</pre>	ccording to their trend percentages to compare
<pre>% different measures and test the hypotheses: (1) larger, (2) similar, and (3) smaller. Base % of the subjective measure. So, in the next analysing step (C2_Visualisation), plot different</pre>	the group boundaries on the trend percentages
<pre>Group Results = zeros(size(Trend_Results)); SD = SelectDrill; for i = 1:length(Trend_Results)</pre>	
<pre>if Group(SD,1)(j,1)&gt;Trend_Results(i,j) &amp;&amp; Group(SD,1)(j,2)&lt;=Trend_Results(i,j); Group if Group(SD,1)(j,2)&gt;Trend_Results(i,j) &amp;&amp; Group(SD,1)(j,3)&lt;=Trend_Results(i,j); Group if Group(SD,1)(j,3)&gt;Trend_Results(i,j) &amp;&amp; Group(SD,1)(j,4)&lt;=Trend_Results(i,j); Group end</pre>	Results(i,j) = 2; end % Similar
end	
%% RESULT STEP C1	
<pre>% Data Results = {1: selected results normalised to the maximum ([1: average of all participants; % 4: maximum value] per situation; 2: trend percentages; 3: group allocation} and per category: [ % global measure; 3-end: new objective local measure].</pre>	
<pre>Data_Results = {Norm_Results;Trend_Results;Group_Results};</pre>	
end	

### MATLAB function: C2\_Visualisation.m

```
Function C2: visualisation of the results to test the hypotheses. Develop a standard figure (in order to test all possibilities in the same format) to find, analyse, and evaluate different measures for local muscle load in football, and compare these to the current global measure and subjective measure. Furthermore, the figure shows a summary of the experiment, processing, and measure design.
function Data_Visualisation = C2_Visualisation(Data_Results, HypothesisName, IntensityName, MeasurementName, SelectDrill, DrillName, SitName,
                      SelectProcess, ProcessName, SelectMeasure, MeasureName, SelectCombine, CombineName, Zone, WeightFactor, Group, FinalPlotC2, SaveFigureC2, ...
                      ExpNr, SampRate, LoadMeasure, Colour, SitCat, HypCat)
          % Abbreviations to keep the code short and clear
         % Abbreviations to keep the code shift and clear
R = Data_Results{1};
TP = Data_Results{2}; TPI = num2str(TP(:,1)); TPII = num2str(TP(:,2));
GR = Data_Results{3}; GRI = num2str(GR(:,1)); GRII = num2str(GR(:,2));
                                                                                                                                                                                                     \ensuremath{\$} Results per measure (subjective, objective global and local)
                                                                                                                                                                                                    % Trend percentages, incl. the separation per hypothesis
% Group formulation, incl. the separation per hypothesis
         % Abbreviations and general calculations (L: length; N: numbers of used processing options to text; S: select names of used processing
% options; C: translate these names to text) to keep the code short and clear for drill (A), process (P), measure (M), and combined (C
PL = length(SelectProcess); PN = num2str(SelectProcess); PS = ProcessName(SelectProcess); PC = char(PS); % Data process methods
ML = length(SelectMeasure); MN = num2str(SelectDeasure); MS = MeasureName(SelectMeasure); MC = char(MS); % Measure calculations
CL = length(SelectCombine); CN = num2str(SelectCombine); CS = CombineName(SelectCombine); CC = char(CS); % Combined measure
                                                                                                                                                                                                                                                                          (P), measure (M), and combined (C).
          SD = SelectDrill:
          LMG = LoadMeasure(1); LML = LoadMeasure(2);
%% FIGURE GENERAL
        FIGURE GENERAL
% Visualisation of the results after data processing and obtaining new measures to analyse and evaluate the obtained results, in order to
% test the hypotheses. Plot the mean and standard deviation of all experiments and per measure, according to the selected hypothesis.
figure('Name','VISUALISATION OF THE RESULTS AFTER DATA PROCESSING TO ANALYSE AND EVALUATE THE OBTAINED RESULTS','NumberTitle','off');
set(gcf,'Position',get(0,'Screensize'),'Color','w');
row = 7; column = 6;
% Subplot dimensions: a=rows and b=columns
F1 = 12; F2 = 10; F3 = 9;
% Font size of title, plot, and summary, respectively
annotation('line',[.660 .660],[0.05 0.94],'Color',[0.7 0.7 0.7]); annotation('line',[.661 .661],[0.05 0.94],'Color',[0.7 0.7 0.7]);
if PL>1; TitleAdd = ' - test different data process methods';
ID_Number = [num2str(SD),'.', FN,'.', MN,'.', CN];
elseif ML>1; TitleAdd = ' - test different combined measure methods'; ID_Number = [num2str(SD),'.', FN,'.', MN,'.', CN];
else;
TitleAdd = '';
end
          end
         S_G = subplot(row,column,[1,2,3,4]); text(0,1,['\bfRESULTS PER HYPOTHESIS' TitleAdd],'FontSize',F1,'VerticalAlignment','middle'); axis off
OldPosG = get(S_G,'Position'); NewPosG=OldPosG; NewPosG(1)=NewPosG(1)-.028; set(S_G,'Position',NewPosG)
%% PLOT RESULTS
          Plot results: (1) subjective measure, (2) current objective global measure, and (3) new objective local measures. Use a line plot to
         % simplify the comparison of the different measures if the intensity of the situations increases (within the measures), instead of
% comparing the different methods per situation (between the measures). The latter cannot be compared with each other, because the values
         % of the measures are qualitative, not quantitative. The trend is important.
Coll = [Colour;Colour(end,:);Colour(end,:)]; % Plot colours [1:QNR, 2:LPM, 3:AccGR1, 4:AccGR2, 5:AccGR3]
Col2 = {['\color[rgb] {' num2str(Colour(1,:)) '}';['\color[rgb] {' num2str(Colour(2,:)) '}'];['\color[rgb] {' num2str(Colour(2,:)) '}'];['\
                                                                                                                                                                                                                                                                                          num2str(Colour(3,:)) '}'];
                   for i = 1:2
                             i = 1:length(R)
                    for
                              if i==1; k=1; elseif i==2; k=2; else; if GR(i,j)==1; k=3; elseif GR(i,j)==2; k=4; elseif GR(i,j)==3; k=5; end; end
                             title({HypothesisName{Hyp(j),1};HypothesisName{Hyp(j),2};HypothesisName{Hyp(j),3}},'FontWeight','normal','FontAngle','italic');
                    ylim((-1.9 10.5)); if j==1; ylabel('Normalised load'); end; if j==2; set(gca, 'ycolor', [1 1 1]); end
xlim([Sit(1,1)-0.2 Sit(1,end)+0.2]); xticks(Sit(1,:)); xticklabels(IntensityName(SD,j)); xlabel('Intensity');
                    set(gca, 'FontSize', F2);
                        Legend design
                    L = zeros(size(Coll,1),1); for l = 1:size(Coll,1); L(l) = plot(NaN,NaN,Symbol{l},'Color',Coll(l,:),'LineWidth',Line2(l)); end
                   L = 2eros(sre(col,(),1); for 1 = 1:size(col1,); L(1) = pict(max,Max,Symbol(1), 'col1','col1(1;); Linewidth',Linez(1)
legend(L,[Col2(1) 'Questionnaire'],[Col2(2) 'LPM'], ...
[Col2(3) 'Accelerometer (1 - larger: ' num2str(Group{SD,1}(j,2)) ' tot ' '\infty' ')'], ...
[Col2(3) 'Accelerometer (2 - similar: ' num2str(Group{SD,1}(j,3)) ' tot ' num2str(Group{SD,1}(j,2)) ')'], ...
[Col2(3) 'Accelerometer (3 - smaller: ' '-\infty' ' tot ' num2str(Group{SD,1}(j,3)) ')'], ...
[Col2(3) 'Accelerometer (3 - smaller: ' '-\infty' ' tot ' num2str(Group{SD,1}(j,3)) ')'], ...
          end
%% PROCESSING SUMMARY
        AddNew = '\newline '; AddBlt = ' - ';
if IMG==1; AddLMG = ''; elseif IMG==2; AddLMG = '\rm (per distance)'; end
if IML==1; AddLML = ''; elseif LML==2; AddLML = '\rm (per travelled distance)'; end
                                                                '; AddBlt = '
         ' num2str(ExpNr) ' participants)'];['ID number: ' ID_Number];''; ...
                                                                                                                       ' char(DrillName{SD})]; char(SitName{SD*2-1}));
         SummaryPlb = {'';'';'';'';char(SitName{SD*2})};
subplot(row,column,5); text(0.0,1.1,SummaryPla,'FontSize',F3,'VerticalAlignment','top'); axis off
subplot(row,column,6); text(0.2,1.1,SummaryPlb,'FontSize',F3,'VerticalAlignment','top'); axis off
```

% Part 2: Display a picture of the drill if SD==1; Load PictureD = 'Picture DrillA.png'; elseif SD==2; Load PictureD = 'Picture DrillB.png'; end subplot(row,column,[11,12]); [PictureD,~,alphaD] = imread(Load\_PictureD); showD = imshow(PictureD); showD.AlphaData = alphaD; % Part 3: Display experiment and data processing summary > measurement methods, incl. trend percentage and group formulation SummaryP3 = {['\rm\bfMeasurement methods (SR = ' num2str(SampRate) 'Hz):\rm'];'\it(trend L-H and group allocation)\rm'; ...  $SummaryP3 = \{ [$ '\rm\bf' Col2{1} MeasurementName{1,1} AddNew MeasurementName{1,2}]; ... '\rm\it (I = ' TPI(1,:) '% and II = ' TPII(1,:) '%)']; ...
'\rm\it (I = ' TPI(2,:) '% = G' GRI(2,:) ' and II = ' TPII(2,:) '% = G' GRI(2,:) ')']; ... ['\rm\it [ '\rm\bi Col2(c) MeasurementName(), ' MedsurementName(), ' MedsurementName(), '' MeasurementName(), '' M % Part 4: Display a picture of the sensor locations S\_P4 = subplot(row,column,[18,24]); [PictureS,~,alphaS] = imread('Picture\_Sensors.png'); showS = imshow(PictureS); showS.AlphaData = alphaS; OldPosP4 = get(S\_P4,'Position'); NewPosP4=OldPosP4; NewPosP4(1)=NewPosP4(1)+.05; set(S\_P4,'Position',NewPosP4) % Part 5: Display data processing and measure design summary > selected options, incl. trend percentage and group formulation if PL>1||ML>1||CL>1; TPI = TPI(3:end,:); TPII = TPII(3:end,:); GRI = GRI(3:end,:); GRII = GRI(3:end,:); TPGR = cell(max([PL,ML,CL]),1); for i = 1:max((PL,ML,CL)); TPGR(i) = ['\it (I = 'TPII(i,:) '% = G' GRI(i,:) ' and II = 'TPII(i,:) '% = G' GRI(i,:) ')rm1; end if PL>1; AddP = cell(PL,1); for j = 1:PL; AddP(j) = [AddBlt char(PS(j)) AddNew TPGR[j]; end; AddM = [AddBlt MC]; AddC = [AddBlt CC]; elseif ML>1; AddP = [AddBlt PC]; AddM = cell(ML,1); for j = 1:ML; AddM(j) = [AddBlt char(MS(j)) TPGR[j]; end; AddC = [AddBlt CC]; elseif CL>1; AddP = [AddBlt PC]; AddM = [AddBlt MC]; AddC = cell(CL,1); for j = 1:CL; AddC(j) = [AddBlt char(CS(j)) TPGR[j]; end end else; AddP = [AddBlt PC]; AddM = [AddBlt MC]; AddC = [AddBlt CC]; end end Z1 = num2str(Zone(1)); Z2 = num2str(Zone(2)); Z3 = num2str(Zone(3)); Z4 = num2str(Zone(4)); WF1 = num2str(WeightFactor(1)); WF2 = num2str(WeightFactor(2)); WF3 = num2str(WeightFactor(3)); AddZWF = [' (Zones and weight factors: I=' Z1 '-' Z2 '&=' WF1 ', II=' Z2 '-' Z3 '&=' WF2 ', III=' Z3 '-' Z4 '&=' WF3 ')']; SummaryP5 = [' ('I'm\bfLocal data processing and measure design:\rm\it (trend L-H and group allocation)\rm' Col2{3}]; ... '\bf> Data process methods:\rm '; char(AddP); ... ['\bf> Measure calculations:\rm' AddLML]; AddZWF; char(AddM); ... '\bf> Dota process methods:\rm ': char(AddV); ... WF; char(AddM); ... Save the figure with the ID\_Number name in the folder: Visualisation Results - Figures if SaveFigureC2==1 annotation('rectangle',[0.1 0.05 0.868 0.89],'Color',[0.7 0.7 0.7]); % A rectangle box around the figure, to cut around for the report saveas(gcf,['Visualisation Results - Figures\' 'ID\_Number\_' ID\_Number '.jpg']); end % Close the figure if FinalPlotC2==0; close all; end %% RESULTS OF STEP C2 % Data Visualisation = visualisation of the results after data processing (subjective, objective global, and objective local measures, including % an experiment, data processing, and measure design summary) to analyse and evaluate the obtained results (based on trend percentages and group % allocation) in order to test the hypothesis. Data Visualisation = ID Number;

end

# Appendix J – Results rough analysis: overview of all measures divided into groups

P = data process method; M = measure calculations; S = measure combined method.

			<b>S</b> : A		в			<u>S</u> :		3			A S:	= 3	3			S :	= 4 E	3			S =	В	2
Measures			<u> </u>	1	Î II		<i>`</i>	ÌII	1	́ II	_	, i	Ì II		_ II		Т	` II		́ II		1	Î II	I	, II
Experienc		2	2	2	2	Y	2	2	2	2	Y N	2	2	2	2	Y	2	2	2	2	Y N	2	2	2	2
Acceleration P = 1	M = 1	3	3	3	2	N N	3	3	3	2	N	3	3	3	3	N N	3	3	3	3	N	3	3	3	3
	M = 2	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 3 M = 4	3 3	3 3	3 3	2	N N	3 3	3 3	3 3	2	N N	3 3	3 3	3 3	2	N N	3 3	3 3	3 3	2	N N	3	3 3	3	2
	M = 5	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 6	3	3	3	2	Ν	3	3	3	2	Ν	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 7 M = 8	3	3 3	3 3	2 2	N N	3	3 3	3 3	2 2	N N	3	3	3	2 2	N N	3	3 3	3 3	2 2	N N	3	3 3	3	2 2
	M = 9	3	3	3	3	N	3	3	3	3	N	3	3	3	3	N	3	3	3	3	N	3	3	3	2
	M = 10	3	3	3	2	N	2	3	3	2	N	3	3	3	2	N	3	3	3	2	N	1	3	2	2
	M = 11	1	2	1	1	Y	1	2	1	1	Y	1	2	1	2	Y	1	2	1	1	Y	1	1	1	1
	M = 12 M = 13	1	2	2	2	Y	1	2	1	2	YN	1	2	2	2	Y	1	2	2	2 2	Y	1	2	1	2 2
	M = 14	1	2	1	1	Y	1	2	1	1	Y	1	2	1	2	Y	1	2	1	1	Y	1	1	1	1
	M = 15	1	2	1	2	Y	1	2	1	2	Y	1	2	2	2	Y	1	2	2	2	Y	1	2	1	1
P = 2	M = 1 M = 2	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3	2 2
	M = 3	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 4	3	3	3	3	N	3	3	3	3	Ν	3	3	3	3	N	3	3	3	3	N	3	3	3	3
	M = 5 M = 6	3	3 3	3 3	2 2	N	3	3 3	3 3	2 2	N N	3	3 3	3	2 2	N	3	3 3	3 3	2 2	N	3	3 3	3	2 2
	M = 0 M = 7	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 8	3	3	3	2	N	3	3	3	2	Ν	3	3	3	2	N	3	3	3	2	Ν	3	3	3	2
	M = 9 M = 10	3	3	3	3	N	3	3	3	3	N	3	3	3	3	N	3	3	3	2 2	N	3	3	3	3
	M = 10 M = 11	1	3	2	2	Y	1	3	2	2	N Y	1	3	3	2	Y	2	3	3	2	Y	1	3 3	2	2
	M = 12	1	3	1	2	N	1	3	1	2	N	1	3	2	2	N	1	3	2	2	N	1	3	1	2
	M = 13	2	3	3	2	N	2	3	3	2	N	3	3	3	2	N	3	3	3	2	N	1	3	2	2
	M = 14 M = 15	1	2 2	1	1	Y Y	1	2 2	1	1	Y Y	1	1	1 2	1	Y	1	1	1 2	1	Y Y	1	3	1	2
P = 3	M = 1	3	3	3	2	N	3	3	3	2	Ν	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 2 M = 3	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 3 M = 4	3 3	3 3	3	2	N N	3	3 3	3 3	2	N N	3 3	3 3	3 3	2	N N	3 3	3 3	3 3	2	N N	3	3 3	3	2
	M = 5	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 6 M = 7	3 3	3 3	3	2 2	N	3 3	3	3 3	2 2	N	3 3	3	3	2 2	N	3 3	3 3	3 3	2 2	N	3	3	3 3	2 2
	M = 7 M = 8	3	3	3 3	2	N N	3	3 3	3	2	N N	3	3 3	3 3	2	N N	3	3	3	2	N N	3	3 3	3	2
	M = 9	3	3	3	3	Ν	3	3	3	3	Ν	3	3	3	3	Ν	3	3	3	3	N	3	3	3	3
	M = 10 M = 11	1	3	2	2	N	1	3	2	2	Y	2	3	3	2	Y	2	3	3	2	N Y	1	3	2	2
	M = 11 M = 12	1	1	1	1	Y	1	1	1	1	Y	1	1	1	1	Y N	1	1	1	1	Y N	1	2	1	1
	M = 13	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	1	3	2	2
	M = 14 M = 15	1	1	1	1	Y Y	1	1	1	1	Y Y	1	1	1 2	1	Y	1	1	1	1	Y N	1	2	1	1
P = 4	M = 15	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 2	3	3	3	2	Ν	3	3	3	2	Ν	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 3 M = 4	3 3	3 3	3 3	2	N	3	3 3	3 3	2	N N	3	3 3	3	2	N N	3 3	3 3	3 3	2	N N	3	3 3	3	2
	M = 4 M = 5	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 6	3	3	3	2	N	3	3	3	2	Ν	3	3	3	2	N	3	3	3	2	Ν	3	3	3	2
	M = 7 M = 8	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2
	M = 9	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 10	2	3	2	2	N	2	3	2	2	Ν	3	3	3	2	N	3	3	3	2	N	1	3	2	2
	M = 11 M = 12	1	1	1	1	Y Y	1	1	1	1	Y Y	1	1	1	1	Y	1	1	1 2	1	Y Y	1	2 2	1	1
	M = 13	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	1	3	2	2
	M = 14	1	1	1	1	Y	1	1	1	1	Y	1	1	1	1	Y	1	1	1	1	Y	1	2	1	1
P = 5	M = 15 M = 1	1	2	1	2	Y N	1	2	1	2	Y N	1	2	2	2	Y N	1	2	2	2	Y N	1	2	1	2
-= 0	M = 1 M = 2	3	3 3	3	2	N	3	3 3	3	2	N	3	3 3	3	2	N	3	3 3	3 3	2	N	3	3	3	2
	M = 3	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 4 M = 5	3	3 3	3 3	3	N N	3	3 3	3 3	3	N N	3	3 3	3 3	3	N N	3	3 3	3 3	3	N N	3	3 3	3	3
	M = 6	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 7	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 8 M = 9	3	3 3	3	2 2	N	3	3 3	3	2 2	N N	3	3	3	2 2	N	3	3	3	2 2	N	3	3 3	3 3	2
	M = 10	1	3	2	2	N	1	3	2	2	N	3	3	2	2	N	3	3	2	2	N	1	3	2	2
	M = 11 M = 12	1	2 2	1	1	Y	1	2	1	1	Y	1	2	1	1	Y Y	1	2	1	1	Y	1	2	1	1
	<b>M = 12</b> M = 13	1	3	1	1	Y N	1	2	1	1	Y N	1	1	1	2 2	Y N	1	1	1	1	Y N	1	2	1 2	1
	M = 14	1	2	1	1	Y	1	2	1	1	Y	1	2	1	1	Y	1	2	1	1	Y	1	2	1	1
	M = 15	1	2	1	1	Y	1	1	1	1	Y	1	1	1	2	Y	1	1	1	1	Y	1	2	1	1
9 = 6	M = 1 M = 2	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2
	M = 3	3	3	3	2	N	3	3	3	2	Ν	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 4	3	3	3	3	N	3	3	3	3	N	3	3	3	3	N	3	3	3	3	N	3	3	3	3
	M = 5 M = 6	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2
	M = 0 M = 7	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 8	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 9 M = 10	3	3 3	3	2	N N	3	3 3	3	2 2	N N	3 3	3 3	3	2 2	N N	3 3	3 3	3	2 2	N N	3	3 3	3	2
	M = 11	1	1	1	2	Y	1	1	1	2	Y	1	2	1	2	Y	1	2	1	2	Y	1	1	1	2
	M = 12	1	2	1	1	Y	1	2	1	1	Y	1	2	1	2	Y	1	2	1	1	Y	1	2	1	1
	M = 13 M = 14	3	3 1	2	2 2	Y	3	3	2	2 2	N Y	3	3	2	2 2	Y	3	3	3	2 2	N Y	1	3	2	2 2
	M = 15	1	2	1	1	Ý	1	2	1	1	Y	1	2	1	2	Y	1	2	1	2	Ý	1	1	1	1
° = 7	M = 1	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 2 M = 3	3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N N	3	3 3	3 3	2 2	N N	3	3 3	3 3	2 2	N N	3	3 3	3 3	2 2
	M = 3 M = 4	3	3	3	3	N	3	3	3	3	N	3	3	3	3	N	3	3	3	3	N	3	3	3	3
	M = 5	3	3	3	2	N	3	3	3	2	Ν	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 6 M = 7	3 3	3 3	3 3	2 2	N	3 3	3 3	3 3	2 2	N N	3 3	3 3	3 3	2 2	N	3 3	3 3	3 3	2 2	N N	3	3 3	3 3	2 2
	M = 8	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2	N	3	3	3	2
	M = 9	3	3	3	3	N	3	3	3	3	N	3	3	3	2	N	3	3	3	3	N	3	3	3	3
	M = 10 M = 11	3	3	3	2	N Y	3	3	3	2	N Y	3	3	3	2 2	Y	3	3	3	2 2	N Y	1	3	2 1	2
	M = 12	1	2	2	2	Y	1	2	1	2	Y	2	2	2	2	Y	1	2	2	2	Y	1	2	1	1
	M = 13	3	3	3	2	N Y	3	3	3	2	N	3	3	3	2 2	N Y	3	3	3	2 2	N	2	3	3	2
	M = 14	1	1	1			1	1	1	1	Y	1	1	1			1	1	1		Y	1	2	1	1

# Appendix K – Results in-depth analysis: figures of different measure calculations

#### **RESULTS PER HYPOTHESIS - test different measure calculations**



#### DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.1.M.1



#### **RESULTS PER HYPOTHESIS - test different measure calculations**

A.I: Intensity increase of jogging back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration

A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



- Questionnaire AIPM - Accelerometer (1 - larger: 34 tot ∞)

#### DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.2.M.1

Situations of drill: A - 10x back and forth per situation (6x)

- > Situation 1a: jog + turn + no ball
   > Situation 1b: jog + turn + pass > Situation (ox)
   > Situation 2a: sprint + turn + no ball
   > Situation 2b: sprint + turn + pass
  - > Situation 2c: sprint + turn + shoot
- > Situation 1c: jog + turn + shoot

target shoot jog / sprint turn

#### Measurement methods (SR = 200Hz):

- (trend L-H and group allocation) Questionnaire (subjective method):
- experienced load
   (*l* = 96% and *l* = 24%)
   1x 2D LPM (current objective method):
- global acceleration index (I = 8% = G3 and II = -5% = G3) > 5x 3D Accelerometer (new objective

method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation) > Data process methods:

- 2: absolute values of sum of local x,y,z acc

- 2: absolute values of sum of local x,y,z acc
   > Measure calculations: (per travelled distance).
   > (Zones and weight factors: l=10.40%=1, ll=40.70%=4, lll=70.100%=7)
   11: average weighted per zone (l = 702% = G1 and ll = 25% = G2)
   12: sum weighted per zone (l = 269% = G1 and ll = 11% = G3)
   14: peak average weighted per zone (l = 702% = G1 and ll = 27% = G2)
   15: peak sum weighted per zone (l = 217% = G1 and ll = 20% = G2)
- > Combined measure methods: 1: P + R1 + R2 + L1 + L2



Intensity

2a: low

2c: high

#### **RESULTS PER HYPOTHESIS - test different measure calculations**



#### DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.3.M.1



# Measurement methods (SR = 200Hz): (trend L-H and group allocation)

- Questionnaire (subjective method) experienced load
- (*I* = 96% and *II* = 24%) 1x 2D LPM (current objective method): > global acceleration index
- (l = 8% = G3 and ll = -5% = G3)> 5x 3D Accelerometer (new objective method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation) > Data process methods:

- 3: sum of absolute values of local x,y,z acc
- 3: sum of absolute values of local x.y.z acc
  > Measure calculations: (per travelled distance) (Zones and weight factors: I=10.40%=1, II=40-70%=4, III=70-100%=7)
   11: average weighted per zone (*I* = 533% = G1 and *II* = 38% = G1)
   12: sum weighted per zone (*I* = 245% = G1 and *II* = 18% = G2)
   14: peak average weighted per zone (*I* = 529% = G1 and *II* = 39% = G1)
   15: peak sum weighted per zone (*I* = 200% = G1 and *II* = 22% = G2)
  > Combined measure methods:
   1: P + R1 + R2 + L1 + L2

2c: high

#### **RESULTS PER HYPOTHESIS - test different measure calculations**



A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.4.M.1

Situations of drill: A - 10x back and t	
> Situation 1a: jog + turn + no ball	> Situation 2a: sprint + turn + no ball
> Situation 1b: jog + turn + pass	> Situation 2b: sprint + turn + pass
> Situation 1c: jog + turn + shoot	> Situation 2c: sprint + turn + shoot
target shoot jog / sp	€inttum

#### asurement methods (SR = 200Hz)

- (trend L-H and group allocation) Questionnaire (subjective method)
- experienced load (I = 96% and II = 24%) > 1x 2D LPM (current objective
- global acceleration index
- (I = 8% = G3 and II = -5% = G3) > 5x 3D Accelerometer (new objective
- method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation) > Data process methods:

- agnitude of combined local x.v.z acc 4: m

- 4: magnitude of combined local x,y,z acc
   > Measure calculations: (per travelled distance)
   > Measure calculations: (per travelled distance)
   11: average weighted per zone (l = 445% = G1 and ll = 45% = G1)
   12: sum weighted per zone (l = 200% = G1 and ll = 45% = G2)
   14: peak average weighted per zone (l = 142% = G1 and ll = 45% = G1)
   5: peak sum weighted per zone (l = 175% = G1 and ll = 24% = G2)
   Combined measure methods:
- Combined measure methods: 1: P + R1 + R2 + L1 + L2

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#### **RESULTS PER HYPOTHESIS - test different measure calculations**



#### DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.5.M.1



- global acceleration index (*I* = 8% = G3 and *II* = -5% = G3) > 5x 3D Accelerometer (new objective
- method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation) > Data process methods:

- > Data process methods:
  5: absolute values of gradient of magnitude of combined local x,y,z acc
  Measure calculations: (per travelled distance)
  (Zones and weight factors: l=10-40%=1, ll=40-70%=4, ll=70-100%=7)
   11: average weighted per zone (l = 605% = G1 and ll = 28% = G2)
   12: sum weighted per zone (l = 246% = G1 and ll = 32% = G2)
   13: peak sum weighted per zone (l = 241% = G1 and ll = 28% = G2)
   15: peak sum weighted per zone (l = 241% = G1 and ll = 33% = G2)
  Combined meanum embed actions

- > Combined measure methods: 1: P + R1 + R2 + L1 + L2

#### **RESULTS PER HYPOTHESIS - test different measure calculations**



A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.6.M.1



#### Measurement methods (SR = 200Hz): (trend L-H and group allocation)

- Questionnaire (subjective met (bor experienced load
   (*l* = 96% and *ll* = 24%)
   1x 2D LPM (current objective model)
- global acceleration index 8% = G3 and II = -5% = G3)
- 5x 3D Accelerometer (new objective method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation) > Data process methods:

- Data process methods: 6: absolute values of difference of magnitude of combined local x,y,z acc Measure calculations: (per travelled distance) (Zones and weight factors: |=10-40%=1, ||=40-70%=4, |||=70-100%=7) 11: average weighted per zone (l = 413% = G1 and l = 35% = G1) 12: sum weighted per zone (l = 232% = G1 and l = 35% = G2) 14: peak average weighted per zone (l = 413% = G1 and l = 35% = G1) 15: peak sum weighted per zone (l = 215% = G1 and l = 29% = G2) Combined measure methods:
- > Combined measure methods: 1: P + R1 + R2 + L1 + L2

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# Appendix L – Results in-depth analysis: figures of different data process methods

#### **RESULTS PER HYPOTHESIS - test different data process methods**



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.P.11.1



- 4: magnitude of combined local x,y,z acc (*I* = 445% = G1 and *II* = 45% = G1)
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- (I = 413% = G1 and II = 35% = G1)
- Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7)
- 11: average weighted per zone
- Combined measure methods: 1: P + R1 + R2 + L1 + L2

#### **RESULTS PER HYPOTHESIS - test different data process methods**



A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.P.12.1

Situations of drill: A - 10x back and forth per situation (6x) > Situation 1a: jog + turn + no ball

 Situation (a)
 Situation 2a: sprint + turn + no ball
 Situation 2b: sprint + turn + pass > Situation 1b: iog + turn + pass > Situation 1c: jog + turn + shoot > Situation 2c: sprint + turn + shoot

#### surement methods (SR = 200Hz):

- (trend L-H and group allocation) Questionnaire (subjective method) experienced load
- 96% and II = 24% > 1x 2D LPM (current objective method)
- global acceleration index (I = 8% = G3 and II = -5% = G3)
- > 5x 3D Accelerometer (new objective method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation)

Data process methods:
 1: absolute values of all individual x,y,z acc

#### (I = 173% = G1 and II = 19% = G2)

- (1 175% 07 and 1 15% 05% -

- (I = 245% = G1 and II = 18% = G2) 4: magnitude of combined local x,y,z acc (I = 200% = G1 and II = 19% = G2)
- b) a construction of the second (I = 232% = G1 and II = 31% = G2)
- (1-2027/0-01 and 1-01/0-02) Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7)
- 12: sum weighted per zone
   > Combined measure methods:
   1: P + R1 + R2 + L1 + L2

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#### **RESULTS PER HYPOTHESIS - test different data process methods**



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.P.14.1

- Situations of drill: A 10x back and forth per situation (6x) > Situation (x)
   > Situation 2a: sprint + turn + no ball
   > Situation 2b: sprint + turn + pass
   > Situation 2c: sprint + turn + shoot Situation 1a: jog + turn + no ball
   Situation 1b: jog + turn + pass
   Situation 1c: jog + turn + shoot target shoot jog / sprint turn Measurement methods (SR = 200Hz): (trend L-H and group allocation) > Questionnaire (subjective method): experienced load 96% and II = 24%) 1x 2D LPM (current objective method): global acceleration index (I = 8% = G3 and II = -5% = G3)
- > 5x 3D Accelerometer (new objective method): local acceleration measure

# Local data processing and measure design: (trend L-H and group allocation) > Data process methods: - 1: absolute values of all individual x,y,z acc

- (I = 563% = G1 and II = 29% = G2)
- 2: absolute values of sum of local x,y,z acc (*I* = 702% = G1 and *II* = 27% = G2)
- 3: sum of absolute values of local x,v,z acc
- (*I* = 529% = G1 and *II* = 39% = G1) 4: magnitude of combined local x,y,z acc (*I* = 442% = G1 and *II* = 45% = G1)

- (*l* = 442% ∈ 01 kin(*l*) = +63% − 61) 5: absolute values of gradient of magnitude of combined local x,y,z acc (*l* = 601% ∈ 61 and *l* = 29% = 62) 6: absolute values of difference of magnitude of combined local x,y,z acc
- $\begin{array}{l} \textbf{(i=413\%=61 \text{ and } ll=35\%=61)}\\ \textbf{Measure calculations: (per travelled distance)}\\ \textbf{(Zones and weight factors: l=10-40\%=1, ll=40-70\%=4, lll=70-100\%=7)} \end{array}$
- 14: peak average weighted per zone
   Combined measure methods:
   1: P + R1 + R2 + L1 + L2

#### **RESULTS PER HYPOTHESIS - test different data process methods**

A.I: Intensity increase of jogging back/forth by a

pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration 10 8 6 Normalised load 4 2 - Questionnaire 0 -LPM - Accelerometer (1 - larger: 106 tot ∞) - -\* - Accelerometer (2 - similar: 86 tot 106) .....\* Accelerometer (3 - smaller: -∞ tot 86) 1b: medium 1a: low 1c: high Intensity

A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.P.15.1

Situations of drill: A - 10x back and forth per situation (6x) > Situation (ax)
 > Situation 2a: sprint + turn + no ball
 > Situation 2b: sprint + turn + pass
 > Situation 2c: sprint + turn + shoot > Situation 1a: jog + turn + no ball
> Situation 1b: jog + turn + pass > Situation 1c: jog + turn + shoot target shoot jog / sprint turn Measurement methods (SR = 200Hz): (trend L-H and group allocation) Questionnaire (subjective method):

- experienced load (I = 96% and II = 24%) 1x 2D LPM (current objective method)
- global acceleration index (I = 8% = G3 and II = -5% = G3)
- > 5x 3D Accelerometer (new objective method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation)

- > Data process methods:
  - 1: absolute values of all individual x,y,z acc (*l* = 182% = G1 and *ll* = 22% = G2)
    2: absolute values of sum of local x,y,z acc
  - (I = 217% = G1 and II = 20% = G2)

  - 3: sum of absolute values of local x,y,z acc (*I* = 200% = G1 and *II* = 22% = G2)
  - 4: magnitude of combined local x,y,z acc
  - $\begin{array}{l} \text{(I)} = 175\% = \text{G1} \text{ and } \text{II} = 24\% = \text{G2} \\ \text{5: absolute values of gradient of magnitude of combined local x,y,z acc } \end{array}$
- (I = 241% = G1 and II = 33% = G2)
- 6: absolute values of difference of magnitude of combined local x,y,z acc (I = 215% = G1 and II = 29% = G2)
- > Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7) - 15: peak sum weighted per zone
- > Combined measure methods:
- 1: P + R1 + R2 + L1 + L2

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# Appendix M – Results in-depth analysis: figures of different combined measure methods

#### **RESULTS PER HYPOTHESIS - test different combined measure methods**

A.I: Intensity increase of jogging back/forth by a

pass/shot will increase the local load similarly as the

A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration





#### **RESULTS PER HYPOTHESIS - test different combined measure methods**

A.I: Intensity increase of jogging back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration

A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.1.15.C

Situations of drill: A - 10x back and forth per situation (6x)

- Situation 1a: jog + turn + no ball
   Situation 1b: jog + turn + pass > Situation (ox)
   > Situation 2a: sprint + turn + no ball
   > Situation 2b: sprint + turn + pass
   > Situation 2c: sprint + turn + shoot > Situation 1c: jog + turn + shoot
  - target shoot jog / sprint tur

#### Measurement methods (SR = 200Hz): (trend L-H and group allocation)

- Questionnaire (subjective method)
- experienced load (I = 96% and II = 24%)
   1x 2D LPM (current objective method):
- global acceleration index (l = 8% = G3 and ll = -5% = G3)
- > 5x 3D Accelerometer (new objective method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation)

- Data process methods:

   1: absolute values of all individual x.y.z acc
   Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7)

   15: peak sum weighted per zone

2c: high

- 15: peak sum weighted per zone
  2 Combined measure methods:
  1: P + R1 + R2 + L1 + L2 (*l* = 182% = G1 and *ll* = 22% = G2)
  2: R1 + R2 + L1 + L2 (*l* = 191% = G1 and *ll* = 21% = G2)
  3: P + R1 + L1 (*l* = 120% = G1 and *ll* = 19% = G2)
  4: R1 + L1 (*l* = 124% = G1 and *ll* = 18% = G2)
  5: R2 + L2 (*l* = 299% = G1 and *ll* = 24% = G2)



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.2.12.C

Situations of drill: A - 10x back and forth per situation (6x)

 > Situation (x)
 > Situation 2a: sprint + turn + no ball
 > Situation 2b: sprint + turn + pass
 > Situation 2c: sprint + turn + shoot Situation 1a: jog + turn + no ball
Situation 1b: jog + turn + pass
Situation 1c: jog + turn + shoot

terget shoot jog / sprint turn

# Measurement methods (SR = 200Hz):

- (trend L-H and group allocation) > Questionnaire (subjective method): experienced load (I = 96% and II = 24%)
- > 5x 3D Accelerometer (new objective method): local acceleration measure



Local data processing and measure design: (trend L-H and group allocation)
> Data process methods:
- 2: absolute values of sum of local x,y,z acc

- > Measure calculations: (per travelled distance)
- (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7) 12: sum weighted per zone > Combined measure methods:
- $\label{eq:constrained measure methods:} \begin{array}{l} \mbox{Constrained measure methods:} \\ -1:P+R1+R2+L1+L2 \quad (l=269\%=G1 \mbox{ and } ll=11\%=G3) \\ -2:R1+R2+L1+L2 \quad (l=276\%=G1 \mbox{ and } ll=11\%=G3) \\ -3:P+R1+L1 \quad (l=187\%=G1 \mbox{ and } ll=12\%=G3) \\ -4:R1+L1 \quad (l=189\%=G1 \mbox{ and } ll=12\%=G3) \\ -5:R2+L2 \quad (l=432\%=G1 \mbox{ and } ll=10\%=G3) \end{array}$

#### **RESULTS PER HYPOTHESIS - test different combined measure methods**



A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.2.15.C

- Situations of drill: A 10x back and forth per situation (6x)

   > Situation 1a: jog + turn + no ball
   > Situation 2a: sprint + turn + no ball

   > Situation 1b: jog + turn + pass
   > Situation 2b: sprint + turn + pass

   > Situation 1c: jog + turn + shoot
   > Situation 2c: sprint + turn + shoot

target \_\_\_\_\_\_\_ jog / sprint \_\_\_\_\_\_ turn

#### Measurement methods (SR = 200Hz):

- (trend L-H and group allocation)
- Questionnaire (subjective method): experienced load 96% and II = 24%)
- > 1x 2D LPM (current objective method)
- global acceleration index (I = 8% = G3 and II = -5% = G3)
- > 5x 3D Accelerometer (new objective method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation) > Data process methods:
 - 2: absolute values of sum of local x,y,z acc
 > Measure calculations: (per travelled distance) (Zones and weight factors: 1=10-40%=1, II=40-70%=4, III=70-100%=7)

- $\begin{array}{l} \text{(Zones and weight factors: } I=10-40\%=1, II=40-70\%=4, III=70-100; \\ -15: peak sum weighted per zone \\ \textbf{Scombined measure methods:} \\ -1: P+R1+R2+L1+L2 \quad (I=217\%=G1 and II=21\%=G2); \\ -2: R1+R2+L1+L2 \quad (I=226\%=G1 and II=21\%=G2); \\ -3: P+R1+L1 \quad (I=151\%=G1 and II=21\%=G2); \\ -4: R1+L1 \quad (I=157\%=G1 and II=22\%=G2); \\ -5: R2+L2 \quad (I=349\%=G1 and II=20\%=G2) \end{array}$

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DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.3.12.C



 > Situation (ox)
 > Situation 2a: sprint + turn + no ball
 > Situation 2b: sprint + turn + pass
 > Situation 2c: sprint + turn + shoot > Situation 1a: jog + turn + no ball
> Situation 1b: jog + turn + pass
> Situation 1c: jog + turn + shoot target shoot jog / sprint turn

# Measurement methods (SR = 200Hz):

- (trend L-H and group allocation) > Questionnaire (subjective method): experienced load 96% and II = 24%) > 1x 2D LPM (current objective method) global acceleration index (I = 8% = G3 and II = -5% = G3)
- > 5x 3D Accelerometer (new objective method): local acceleration measure



- Local data processing and measure design: (trend L-H and group allocation)
  Data process methods:
  3: sum of absolute values of local x,y,z acc
- Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7)
   12: sum weighted per zone
- > Combined measure methods:
- Consumed measure methods:

   - 1: P+ R1 + R2 + L1 + L2 (l = 245% = G1 and ll = 18% = G2)

   - 2: R1 + R2 + L1 + L2 (l = 259% = G1 and ll = 17% = G2)

   - 3: P + R1 + L1 (l = 161% = G1 and ll = 11% = G3)

   - 4: R1 + L1 (l = 170% = G1 and ll = 11% = G3)

   - 5: R2 + L2 (l = 384% = G1 and ll = 23% = G2)

#### **RESULTS PER HYPOTHESIS - test different combined measure methods**



A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.3.15.C

Situations of drill: A - 10x back and f	forth per situation (6x)
> Situation 1a: jog + turn + no ball	> Situation 2a: sprint + turn + no ball
> Situation 1b: jog + turn + pass	> Situation 2b: sprint + turn + pass
> Situation 1c: jog + turn + shoot	> Situation 2c: sprint + turn + shoot
target shoot	rint. Lum

#### Measurement methods (SR = 200Hz):

- (trend L-H and group allocation) > Questionnaire (subjective method):
- experienced load (I = 96% and II = 24%) 1x 2D LPM (current objective
- global acceleration index
- I = 8% = G3 and II = -5% = G3
  - 5x 3D Accelerometer (new objective method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation)

- Data process methods:
   3: sum of absolute values of local x,y,z acc
- Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7)
   15: peak sum weighted per zone
- > Combined measure methods:
- Combined measure methods: 1: P+ R1+ R2 + L1 + L2 (l = 200% = G1 and ll = 22% = G2) 2: R1 + R2 + L1 + L2 (l = 214% = G1 and ll = 21% = G2) 3: P + R1 + L1 (l = 133% = G1 and ll = 14% = G2) 4: R1 + L1 (ll = 145% = G1 and ll = 13% = G3) 5: R2 + L2 (ll = 313% = G1 and ll = 30% = G2)



#### **RESULTS PER HYPOTHESIS - test different combined measure methods**



A.II: Intensity increase of sprinting back/forth by a pass/shot will increase the local load similarly as the experienced load, but not global, based on acceleration



DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.4.15.C

DATA PROCESSING SUMMARY (total of 5 participants)



#### Measurement methods (SR = 200Hz): (trend L-H and group allocation)

- Questionnaire (subjective method) experienced load (I = 96% and II = 24%) 1x 2D LPM (current objective method) global acceleration index
- = 8% = G3 and II = -5% = G3) > 5x 3D Accelerometer (new objective
- method): local acceleration measure

cal data processing and measure design: (trend L-H and group allocation) Data process methods:
 4: magnitude of combined local x,y,z acc

- Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7)
- 15: peak sum weighted per zone
- > Combined measure methods:
- Combined measure methods: 1: P+ R1+ R2 + L1 + L2 (l = 175% = G1 and ll = 24% = G2) 2: R1 + R2 + L1 + L2 (l = 188% = G1 and ll = 24% = G2) 3: P + R1 + L1 (l = 108% = G1 and ll = 23% = G2) 4: R1 + L1 (l = 115% = G1 and ll = 22% = G2) 5: R2 + L2 (l = 317% = G1 and ll = 25% = G2)

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DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.5.12.C

Situations of drill: A - 10x back and forth per situation (6x) Situation 1a: jog + turn + no ball
 Situation 1b: jog + turn + pass
 Situation 1c: jog + turn + shoot > Situation (ax)
 > Situation 2a: sprint + turn + no ball
 > Situation 2b: sprint + turn + pass
 > Situation 2c: sprint + turn + shoot target shoot jog / sprint

# Measurement methods (SR = 200Hz): (trend L-H and group allocation)

- Questionnaire (subjective method) experienced load
- (*I* = 96% and *II* = 24%) 1x 2D LPM (current objective method): > global acceleration index
- = 8% = G3 and II = -5% = G3) 5x 3D Accelerometer (new objective method): local acceleration measure

cal data processing and measure design: (trend L-H and group allocation) > Data process methods:

- > Data process methods:
   5: absolute values of gradient of magnitude of combined local x,y,z acc
   > Measure calculations: (per travelled distance) (Zones and weight factors: l=10-40%=1, II=40-70%=4, III=70-100%=7) 12: sum weighted per zone
- 12: sum weighted per Zone
   2 Combined measure methods:
   1: P + R1 + R2 + L1 + L2 (l = 246% = G1 and ll = 32% = G2)
   2: R1 + R2 + L1 + L2 (l = 256% = G1 and ll = 33% = G2)
   3: P + R1 + L1 (l = 177% = G1 and ll = 34% = G1)
   4: R1 + L1 (l = 180% = G1 and ll = 36% = G1)
   5: R2 + L2 (l = 429% = G1 and ll = 30% = G2)

#### **RESULTS PER HYPOTHESIS - test different combined measure methods**



- Questionnaire A IPM → Accelerometer (1 - larger: 34 tot ∞)
- → Accelerometer (2 - similar: 14 tot 34) Accelerometer (3 - smaller: -∞ tot 14) 2a: low 2b: medium 2c: high Intensity

A.II: Intensity increase of sprinting back/forth by a

pass/shot will increase the local load similarly as the

DATA PROCESSING SUMMARY (total of 5 participants) ID number: 1.5.15.C

Situations of drill: A - 10x back and forth per situation (6x)

Situation 1a: jog + turn + no ball Situation 1b: jog + turn + pass > Situation (ox)
 > Situation 2a: sprint + turn + no ball
 > Situation 2b: sprint + turn + pass
 > Situation 2c: sprint + turn + shoot > Situation 1c: jog + turn + shoot

## target shoot jog / sprint turn

#### Measurement methods (SR = 200Hz): (trend L-H and group allocation)

- Questionnaire (subjective method) experienced load (*I* = 96% and *II* = 24%) > 1x 2D LPM (current objective method):
- global acceleration index (I = 8% = G3 and II = -5% = G3) > 5x 3D Accelerometer (new objective
- method): local acceleration measure

Local data processing and measure design: (trend L-H and group allocation) > Data process methods:

- Data process methods: 5: absolute values of gradient of magnitude of combined local x,y,z acc Measure calculations: (per travelled distance) (Zones and weight factors: I=10-40%=1, II=40-70%=4, III=70-100%=7)
- 15: peak sum weighted per zone

- 15: peak sum weighted per zone
   Combined measure methods:

   1: P + R1 + R2 + L1 + L2 (l = 241% = G1 and ll = 33% = G2)
   2: R1 + R2 + L1 + L2 (l = 254% = G1 and ll = 34% = G1)
   3: P + R1 + L1 (l = 164% = G1 and ll = 34% = G1)
   4: R1 + L1 (l = 170% = G1 and ll = 36% = G1)
   5: R2 + L2 (l = 449% = G1 and ll = 32% = G2)

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#### **RESULTS PER HYPOTHESIS - test different combined measure methods**







Situations of drill: A - 10x back and forth per situation (6x) > Situation 1a: jog + turn + no ball
 > Situation 1b: jog + turn + pass Situation 2a: sprint + turn + no ball
 Situation 2b: sprint + turn + pass > Situation 1c: jog + turn + shoot > Situation 2c: sprint + turn + shoot target shoot Measurement methods (SR = 200Hz): (trend L-H and group allocation) Questionnaire (subjective method): experienced load (I = 96% and II = 24%) > 1x 2D LPM (current objective method): global acceleration index (I = 8% = G3 and II = -5% = G3) > 5x 3D Accelerometer (new objective method): local acceleration measure Local data processing and measure design: (trend L-H and group allocation) Local data processing and measure design: (trend L-H and group allocation > Data process methods: • Catsbolute values of difference of magnitude of combined local x,y,z acc > Measure calculations: (per travelled distance) (Zones and weight factors: |=10.40%=1, ||=40-70%=4, ||=70-100%=7) • 15: peak sum weighted per zone > Combined measure methods: • 1: P + R1 + R2 + L1 + L2 (|=215%=61 and ||=29%=62) • 2: R1 + R2 + L1 + L2 (|=223%=61 and ||=25%=62) • 3: P + R1 + L1 (|=130%=61 and ||=25%=62) • 4: R1 + L1 (|=129%=61 and ||=25%=62) • 5: R2 + L2 (|=460%=61 and ||=25%=61)

DATA PROCESSING SUMMARY (total of 5 participants)

ID number: 1.6.15.C

DATA PROCESSING SUMMARY (total of 5 participants)