Lower limb musculoskeletal modeling during normal walking, one-legged forward hopping, side jumping and knee flexion

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A validation study of the AnyBody Modeling System for optimizing Anterior Cruciate Ligament reconstruction

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The Front cover:
The background shows steps of one legged forward hopping during simulation

The back cover shows one example of a musculoskeletal model during one-legged forward hopping

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To my greatest love:

Sista, Arzade and Belva, thanks for all your patience and love till this thesis is doneperfectly

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Chapter 1: General Introduction

1.1 Introduction

The knee is one of the most complex joints in the human body considering its anatomical structure and its biomechanical functioning. It is very important because of its contribution to human locomotion. To restrict the motion of the knee, several ligaments surround and are present in the joint. The Anterior Cruciate Ligament (ACL) is one of them and also the most vulnerable one. Rupture of it is reported in many cases, especially the incidence among athletes is high and the treatment is costly [Janssen et al., 2011;Woo et al., 2006; Lattermann et al., 2005]. The annual incidence in the USA is about 150.000 cases per year [www.sportsmed.org;Moses et al., 2012;Csintalan et al., 2008]. A damaged ACL can introduce damage on other structures in the knee such as Posterior Cruciate Ligament (PCL) and medial and lateral collateral ligament (MCL and LCL) and thus lead to knee instability. This again could result in degenerative joint disease. Therefore, to avoid all these effects and to restore normal activities, patients must undergo an ACL reconstruction [Lavoie et al., 2000]. Various ACL reconstruction strategies have been developed up to now, but results are still disappointing. We hypothesize that this is caused by inter-individual differences that are not taken into account in the surgical reconstruction procedure. Our grand project is to introduce an individual numerical model of the knee, with which the surgeon can plan his surgery for the individual patient.

1.2 Anatomy of the human knee

The knee system is composed of 3 bones (femur, tibia and patella), 3 compartments (medial, lateral, patella femoral) and 4 ligaments, Medial Collateral Ligament (MCL), Lateral Collateral Ligament (LCL), Anterior Cruciate Ligament (ACL) and Posterior Cruciate Ligament (PCL) [Prentice., 2011]. The ACL consists of two main bundles, an antero-medial (AM) bundle and a postero-lateral bundle (PL) [Petersen et al., 2007;Lattermann et al., 2005; Strocchi et al., 1992]. Articular cartilage covers the femoral and tibial joint surfaces [Prentice.,2011].To protect the vulnerable cartilage layer from becoming damaged, the kneecontains a meniscus. It absorbs peak loadsand so protects [Messner et al., 1998].The meniscus consists of two parts, a medial part, C-shaped, and a lateral part, circular shaped.Muscles around the knee will stabilize it during standing and initiate rotation during walking and running.

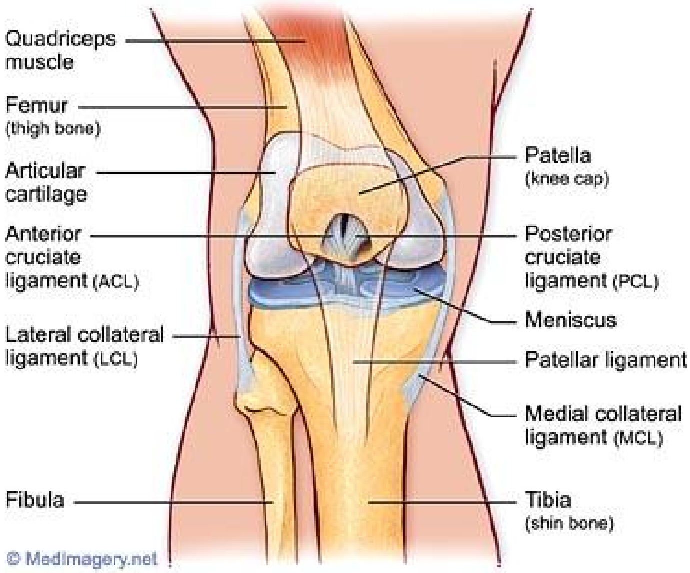

Fig1. A right knee, front view (www.sportsmedicineuk.co.uk/knee.html)

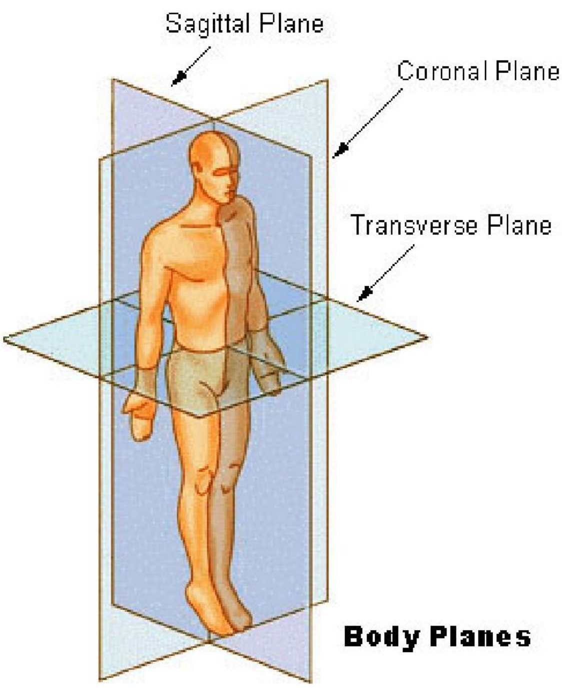

Fig2. Planes of Motion (www.warriorfitnessworld.com)

1.3 Physiology of the human knee

The basic function of the knee is to allowrotation of the femur, relative to the tibia [McGinty et al., 2000]. The primary rotation of the knee is in the sagittal plane (flexion and extension); during walking there is some rotation present in the coronal plane (varus-valgus motion) and internal and external rotation.In combination with these rotations, small translations are present as well, especially during knee flexion, when the femoral condyles slidealong the tibial condyles [Li et al., 2004].

Because the knee joint is such a complex structure, the kinematics and kinetics of the knee have been studied for many years in order to improve surgery so that patients can go back to their normal activities. However, its complex mechanism during motion and its capability in absorbing and distributing forces over the joint are still difficult to understand and to explain from a kinematical and kinetical point of view. Many researchers are exploring knee functions by observing what ishappening inside the knee during various activity tests. With a better insight in the functioning of the knee, injury of it due to an abnormal or extreme motion especially during sport could be avoided.

Cadaveric studies have also been done by many scientists in the past, not only to measure the mechanical properties of the knee [Horsman et al., 2007] but also to look into detail to the composition of ligaments, muscles and tendons between femur and tibia bone and to determine muscle origin and insertion points in the knee.This information supports the development of a biomechanical model of the knee. With such a model, the axis of rotation of the knee and the position of it during flexion and extension can be determined.

During those studies, researchers have revealed significant knowledge of the role of the ligaments in the knee including the ACL [Gollehon et al., 1987; Markolf et al., 1993]. The ACL has a significant role in the knee in the full range from standing until the knee is flexed at its maximum [Petersen et al., 2007]. The ACLis located between the anterior-medial sideof the tibial bone to the posterior-lateral side of the femoral bone. However, up to now there is only limited knowledge of the kinematics and kinetics of the knee during motion and no knowledge on modeling of an individual detailed knee in such a way that the real knee can be imitated very closely [Leyvraz et al., 2000].

1.4 Anterior Cruciate Ligament reconstruction

ACL reconstruction is the only way for patients with ACL injury or ACL tear to return to their daily activities. Nowadays, most of ACL reconstructions are done by using intra-articular tissue grafts [Woo et al., 1998]. In this reconstruction, several material options are used by the surgeons, they are: autograft, allograft and synthetic graft. Autograft material is taken from the patient’s own body, allograft material is taken from a donor and synthetic graft is made from synthetic material such as carbon fiber [www.kneeguru.co.uk]

Several techniques for ACL reconstruction have been developed by many scientists and surgeons [Marcacci et al., 2003; Bellier et al., 2004; Takeuchi et al., 2002; Hara et al., 2000]. Some surgeons use single bundle reconstructions, others prefer a double bundle, because it resembles the original anatomy more closely [Petersen et al., 2007]. Currently the most applied method that is used by many surgeons in performing ACL reconstruction is the semitandinosus-gracilis single bundle auto-graft ACL reconstruction [Rue et al., 2008; Brown et al., 2012]. For this technique, [Brown et al., 2012] explained that the tunnel between Tibia and Femur bone must be drilled separately. The hole drilled from Tibia did not have to compromise with the one from Femur, so that the surgeons then can approximate the best position on the Tibial side. During this drilling process the knee must be positioned at 120^{o} of flexion or higher for avoidingthe femoral guide pin goes too posteriorly.

In addition to that advance technique, there are some important aspects that need to be considered during performing ACL reconstruction by surgeons as explained by [Arnold et al., 2004]. The first aspect is: defining the tunnel position of both bones femur and tibial [Arnold et al., 2004].This is a very crucial phase. Mis-determining of these two locations could potentially create a graft failure[Garofalo et al., 2007]. [Giron et al., 1999] explained that whenthe ACL graft is positioned too far anteriorly some impingement may happen on the graft. A standard in determining the position of the new ACL ligament is known as a Blumensaat’s line [Giron et al.,1999].

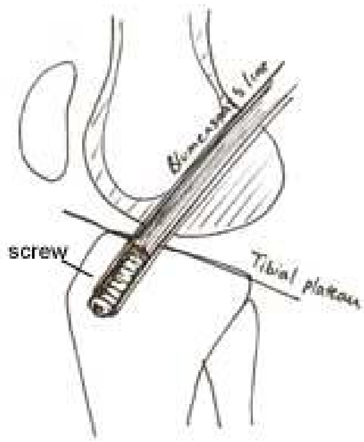

Fig 3. Blumensaat’s line relative to the tibia plateau [www.kneeguru.co.uk]

The next aspect is determining the geometrical properties of the ACL-reconstruction: length, and cross sectional area.This decision has to be donepatient-specific, since all those properties vary among subjects as it was studied by [Chandrashekar et al., 2006], by an in-vivo measurement using MRI

[Anderson et al., 2001; Chaudhari et al., 2009] and in a cadaveric study [Muneta et al., 1997]. There is definitely a gender influence on geometrical properties of ACL as it was reported that females have smaller ACL-dimensions. In addition to that, [Chandrashekar et al., 2006] also reported some differences in mechanical properties between male and female. Female ACL was found to have lower mechanical properties than male. The final aspect is determining the mechanical properties of the ACL resonstuction: its tensile and viscoelastic properties.

All these aspects mentioned above will determine the result of the ACL reconstruction.There are no clear procedures for optimal and patient-specific choices. So surgeons perform the surgery based on their own experience and approximation. And the ACL reconstruction strategy is often based on a general approach for every patient.

Although several surgeonsclaim that their method give the best results [Zantop et al., 2006; Adachi et al., 2004; Giron et al., 1999; Beasley et al., 2005], as a result of the lack of clear guidelines, there are many variations in the patient's recovery condition after operation and these conditions are certainly not optimized [Beasleyet al., 2005; Giron, et al., 1999]. A study done by [Brandssonet al., 2002] showed that often after ACL reconstruction the knee laxity was reduced.

1.5 Main goal of the overall study (grand project)

As we have seen in literature, the geometrical and biomechanical properties of the knee differ among persons. So building the best strategy for doing ACL reconstruction should not be done based on a general patient, but, based on the patient's specific circumstances. Due to these reasons, our grand project is to realize a patient-specific 3D model of the knee, with which the surgeons can plan their ACL reconstruction and optimize their surgery outcomes. This 3D knee model will contain the most important structures that will influence the success of ACL reconstruction. Part of this grand project will be studying the properties of the most important structures in the knee, the two bones (femur and tibia), the ligaments (ACL, PCL, MCL, LCL), the menisci and articular cartilage and their role during ACL reconstruction both geometrically and biomechanically using finite element model, while in this study, we will analyze the knee in more dynamic condition through its important aspects such as knee internal moments, knee muscle activity and knee joint forces using a numerical model.

1.6 Modeling system

A very suitable modeling system to simulate ACL reconstruction is the AnyBody Modeling System (AMS). AMS is software for simulating and analyzing human biomechanics during motion. It uses motion data and ground reaction forces to predict the muscle forces and muscle activity including the joint reaction forces. AMS applied inverse dynamics analysis in its prediction. By calculating the impact of a body segment that moves at a certain velocity, the amount of force to generate that segment's motion can be calculated. When these muscle forces are known, the joint reaction forces can be calculated as well.

All these predictions of AMSare only possible because several assumptions and simplifications are included. An example of such an assumption in the modeling process is the muscle recruitment criterion. The basic reason for the necessity of a muscle recruitment criterion is that in every segment of the human body there are more muscles than what it is needed to make a certain motion. So from a mechanical point of view the force of each muscle cannot be determined, since the system is mechanically over-determined. On this point, we cannot really mimic the human central nervous system behavior in activating muscles to exert the force. To solve this problem, several muscle recruitment theories have been constructed. An example is the theory of an equal load sharing system to all muscles, this then will lead to an equal sharing load on a group of small muscle fibers or on bigger muscle fibers. From an efficiency point of view, this cannot be applicable in the human body because then we must be exhausted easily because the small muscles fibers take similar loads as the bigger muscles do. If one should choose only the bigger muscles to be activated, this choice is also not realistic because then those small muscles fiber would be useless. A better muscle recruitment theory is used by AMS.It is based on an objective function with polynomial criteria to mimic the physiology of human muscles. Referring to the analysis of human movement based on Newton-Euler equation:

$$F = \begin{bmatrix} Fx \\ Fy - m.g \\ -r\ \sin\emptyset\, Fy - \ r\ \cos\emptyset\, Fx \end{bmatrix} = \text{m .r''} = \begin{bmatrix} m & 0 & 0 \\ 0 & m & 0 \\ 0 & 0 & J \end{bmatrix} \begin{bmatrix} x'' \\ y'' \\ \emptyset'' \end{bmatrix} \qquad (1)$$

The objective function is defined as follow:

$$G\left(f^{(M)}\right) = \sum_{i=0}^{n^{(M)}} \left(\frac{f_i^{(M)}}{N_i}\right)^p \qquad (2)$$

So equation (2), [Fluitet al.,2010] is the objective function of AMS in solving the muscle recruitment criterion, $G\left(f^{(M)}\right)$ is the force prediction function which can only be active to pull with value 0<$f_i^{(M)} < N_i$. $N_i$is the maximum muscle force for a certain muscle. If p=1 then the muscle recruitment criterion behaves linearly. Linear muscle recruitment means it will choose the minimal number of muscles that will be activated. If p=2, the muscle recruitment criterionbehaves quadratic and an additional constraint is needed in order to avoid muscles being overloaded. Generally speaking the higher the value of p, the more muscles are being recruited, and in the end, this would lead also to an abrupt system. Due to this analysis, AMS applied an algorithm called min/max criteria [Rasmussen et al., 2001].

$$G\left(f^{(M)}\right) = min/max \sum_{i=0}^{n^{(M)}} \left(\frac{f_i^{(M)}}{N_i}\right)^p \quad (3)$$

Formula (3) [Fluit et al., 2010] explains the process of minimization of the maximal muscle activity. This objective function provides several advantages.The first is that the criterion tends to distribute the relative muscle load evenly.So assuming that muscle fatigue and activity are proportional, the min/max criterion postpones fatigue as much as possible. The second is that the criterion is numerically efficient and robust, while it is not very different from the polynomial criterion (for large p, the polynomial criterion in fact converges to the min/max criterion). The third is that the load and muscle recruitment are proportional. This implies no need for additional constraints to avoid overloaded muscles. The disadvantage of the min/max criterion is that it can rapidly recruit muscles as soon as their moment arm is big enough to balance the system. The same holds for a polynomial muscle recruitment with large p. Since there is no criterion that is proven to be superior, the only solution of validating the muscle recruitment model is comparing and verifying it with EMG measurements [Zee et al., 2007].

AMS applied a mechanical model to represent the complex system of human body motion. In that model, every segment of the human body is represented by a rigid segment. AMS adopts inverse dynamics analysis (IDA) in its calculation to predict muscle force and muscle activity. Analysis of movements of the human body using inverse dynamics follows the Newton-Euler equation.

$$F = m \cdot \mathrm{r}'' \quad (4)$$

Equation 4 [Fluitet al.,2010] is applied to every segment of body for a full multi-body analysis. If the Newton-Euler equation for example is applied to a segment, it would yield:

$$F = \begin{bmatrix} Fx \\ Fy - m.g \\ -r\ \sin\emptyset\, Fy - r\ \cos\emptyset\, Fx \end{bmatrix} = \mathrm{m}\ .\mathrm{r}'' = \begin{bmatrix} m & 0 & 0 \\ 0 & m & 0 \\ 0 & 0 & J \end{bmatrix} \begin{bmatrix} x'' \\ y'' \\ \emptyset'' \end{bmatrix} \quad (1)$$

AMS uses a generalized concept of this highly simplified example. In reality, every segment has an inertia tensor which refers to the centroidal body-frame. All segments have 6 degrees of freedom (DOFs), making F a vector with 3 forces and 3 moments. The vector F can be subdivided into forces and moments of the muscles, denoted by $g_i^{(M)}$, reactions, $g_i^{(R)}$ and known applied forces, $g_i^{(app)}$. Taking everything into account, the generalized Newton-Euler equation for each segment yields:

$$g_i^{(M)} + g_i^{(R)} = g_i^{(app)} - \begin{bmatrix} m_i I & 0 \\ 0 & J_i' \end{bmatrix} \ddot{\mathrm{r}} - (\tilde{\omega}_i' J_i' \omega_i') \quad (5)$$

In this equation all of unknown parameters have been shifted to the left-hand side and all of known parameters to the right hand side [Fluitet al.,2010].

1.6.1 Generalized model

To define the structure of a body, AMS uses a generalized model (GLEM) based on a cadaveric study [Horsman et al., 2007]. To adapt the model for a specific person, scaling rules based on ISB standard [Andersen et al., 2010] are applied to the model. Material properties like fat percentage, viscoelastic properties of ligaments, tendons and joints are scaled as well. Individual body mass, thigh length, shank length, pelvis width and foot length are implemented in the model.

Like every model, AMS is a simplification from reality. Not only the material properties and dimensions are not fully subject-specific, other simplifications are also present. The knee is modeled as a single hinge, the foot as one segment. Besides providing some advantages such as lowering the computation cost and simplifying the model for a better understanding, these assumptions and simplifications potentially will result in non-accurate predictions. Therefore, validation study needs to be performed in order to scientifically judge the quality and the potential of this modeling application before being applied for a clinical use.

We think that the best way to perform such a validation study is to compare muscle activity predicted by AMS with in vivo measured muscle activity by EMG [Hermenset al., 2000; Merletti et al., 2009]. Limitations of this comparison are the fact that they are not in the same unit. EMG is defined as the electrical activity of a muscle. Muscle activity in AMS is calculatedfrom the predicted muscle force as the cause of motion of a specific segment divided by the maximal muscle force for that specific muscle at that specific time [Zee et al., 2007].

Another important output from AMS is knee joint forces and joint moment prediction. Since there were many studies in the past that explored knee joint forces and moments during active motion and its effect in patients rehabilitation program [Meyer et al., 2008; Hashemi et al., 2011; Lundberg et al., 2012; D'Lima et al., 2006; Komistek et al., 2005; Meakin et al., 2003], validation on that output is feasible as well.

1.6.2 Electromyography

Electromyography is the most advanced tool in studying muscle activity generated for human motion [Konrad., 2005; Cram et al., 1998]. Many scientists investigated electrical muscle activity [Basmajian., 1985; Cram et al., 1998; Reaz et al., 2006]. The first one, as reported by Reaz et al., [Reaz et al., 2006] was a scientist named Walsh in 1773, who was able to demonstrate the electrical spark out of an Eel fish. Applying EMG for clinical use was reported for the first timeby Weddel in 1942 [Katirji., 2002] who performed a study using needle electrodes. Hardyck analisedmuscle disorders in 1960 [Reaz et al., 2006]. In the early 1980s, EMG was applied to scan a variety of muscles [Cram JR et al., 1998].

Nowadays many studies have been performed to develop better EMG devicesfor implementing EMG in many clinics[Howard Jr et al., 2013; Katirji., 2002;Clarys et al., 2000;Stegeman et al., 2000;Kleissen et al., 1998; Nikias et al., 1987]. EMG is now routinely used to observe and diagnose neurological [Howard Jr et al., 2013] and neuromuscular problems [Katirji., 2002]. There are two ways EMG is applied, a non-invasive and an invasive way. For non invasive EMG, electrodes are attached to the skin on top of a muscle. For invasive EMG, needle electrodes are placed in the muscle to record the electrical activity of the muscles [Daube Jr et al., 1991]. For studies on human motion, non-invasive EMG is used in most cases rather than invasive due to the fact that the invasive EMG will interfere with the motion tests.

1.7 Purpose of this study

Due to several inevitable simplifications and assumpions, the accuracy of the predictions, given by AMS, will not be 100%. Up to now it is unknown to which extent AMS is a good predictor of muscle activity and knee joint forces during active motion. In this study we present a research on validating the accuracy of the GaitLowerExtremity model (GLEM), a musculoskeletal model from the AMS repository folder (www.AnyBodytech.com) in predicting muscle activity and knee joint forces during four dynamic movements, normal walking, one-legged forward hopping, side jumping and knee flexion. The accuracy is determined by the rate of comparison between predicted and measured muscle activity during those activities in healthy subjects. For measured muscle activity, a non-invasive surface EMG will be used as a golden standard. For knee joint forces, results from literature studies will be used as a comparison standard. Normal walking is included as a basic performance of human and a basic form of biomechanics that has been explored by many biomechanical scientists [Lovejoy., 2007; Winter., 1991; Chang et al., 2009].One-legged forward hopping and side jumping are included, because both are commonly used for patient activity tests pre and post ACL-reconstruction surgery [Sekiya et al., 1998; Tveter et al., 2010; Hobara et al., 2010]. Knee flexion motion will be used to complete the analysis as an example of a more static type of movement and because it is a common test for patients that underwent a total knee arthroplasty (TKA) or patients suffering from osteoarthritis (OA) [Meyer et al., 2008; Hashemi et al., 2011].

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Chapter 2

Musculoskeletal model of human lower limb during normal walking:

Comparison of measured EMG and predicted muscle activity patterns during normal walking

Abstract

This study focused on validating muscle activities predicted by the AnyBody Modeling System (AMS) against EMG measurements from ten healthy subjects who performed a normal walking task. The GaitLowerExtremity Model (GLEM) from AMS was used in this study. Eight EMG electrodes measured the activity of eight muscles of the right leg: Vastus Medialis (VM), Vastus Lateralis (VL), Rectus Femoris (RF), Semitendinosus (ST), Biceps Femoris (BF), Gastrocnemius Medialis (GM) and Lateralis (GL) and Tibialis Anterior (TA). Specific thresholds per muscle were applied in the EMG data before being compared. These threshold levels were determined by equalizing the duration of EMG to AMS muscle activity. Three graph variables, number of onsets, offsets, and hills were used to quantify the level of agreement between predicted muscle activitywith measured EMG by using Cohen's kappa analysis. The Pearson correlation coefficient of the data of both graphs was also calculated to give a comparative result.

Overall, visual inspection showed similar activity patterns for several muscles. However, some differences did exist. For the variable number of onsets, there were 4 muscles that showed a slight positive agreement, while the other 4 muscles showed a negative agreement. For the variable number of offsets, there were only three muscles that showed a slight positive agreement, while the other five showed a negative agreement. For the variable number of hills, a better result was obtained; there were five muscles that showed a slight positive agreement, while the other 3 muscles showed negative agreement. Pearson correlation coefficient between the two showed that GM and GL muscle had a quite high correlation (0.76 and 0.80, respectively), while the rest of the muscles showed a lower correlation.

This explorative study shows that there are distinct differences between the muscle activity levels as predicted by AMS and the measured EMG patterns. These differences can be attributed to the comparative method that we used, the modeling errors within the AMS framework, EMG measurement errors, and the fact that AMS muscle activity is not exactly the same quantity as measured EMG. Despite these uncertainties, this study can serve as a baseline measurement allowing to progress scientific work in order to reduce these uncertainties with the

aim to generate more reliable and robust musculoskeletal models that simulate human walking in a valid manner.

Keyword: Muscle activity, EMG, Musculoskeletal Model, AnyBody Modeling System, Inverse dynamics analysis

2.1. Introduction

Musculoskeletal modeling is a commonly used method to study and understand biomechanical aspects of complex systems like the human body. These models enable simulation of the human body in dynamic conditions, and can provide many practical insights for surgeons and practitioners in the development of new surgical techniques and rehabilitation procedures [Delp et al., 2006; Komistek et al., 2005; Damsgaard et al., 2006]. One such model is the AnyBody Modeling System (AMS). This modeling system is commercially available and enables prediction of muscular forces and activity during movement [Damsgaard et al., 2006]. This modeling tool, especially the GaitLowerExtremity Model (GLEM), has already been used by many scientists to study human locomotion (http://forum.anyscript.org/). However, up to date, there are no quantitative studies that have validated muscle activities predicted by AMS.

Measuring EMG with electrodes is still the best tool to determine muscle activity nowadays [Angkoon et al., 2012; Hof et al., 2005; Hermens et al., 2000; Kasai et al., 1994], as EMG is one of the few methods that directly measures the electrical activity of muscles during motion [Drost et al., 2006; Anders et al., 2006]. For AMS validation, it is important to point out that the predicted muscle activity by AMS is not the same entity as the measured muscle activity (EMG). This is because the predicted muscle activity is determined from calculating the predicted muscle force divided by the maximal muscle force for that specific muscle at that specific time frame [Zee et al., 2007]. Since predicted muscle force and maximal muscle force are largely dependent on the subject's anatomical position, condition, and exertion [Andersenet al., 2010; Rasmussen et al., 2001], the variable that can be validated with the AMS model is the timing of muscle activity.

Quantifying muscle activity is difficult. Traditionally, three variables of quantification are used: number of onsets, number of offsets [Lee et al., 2007; Konrad., 2005] and the duration of muscle activity [Brunner et al., 2008]. In this study, a fourth parameterwas added, the number of hills. An onset is defined as the start of a muscle activity, so when the baseline threshold is exceeded, while an offset is defined as the end of an activity, so when the baseline threshold is passed. A hill is defined as the part of the activity graph that starts just above the predefined baseline and ends below the predefined baseline (see Figure 1). Each pair of consecutive onset and offset will form a hill. Since it is almost impossible to compare the peak value of EMG with the predicted muscle activity (since the EMG data depends largely on subject's anatomical position), we felt that number of hills could represent the data more objectively for quantifying muscle activity.

The baseline threshold value of EMG has a major impact on the duration of EMG signals. A low threshold value leads to long durations; a high threshold value will result in short EMG durations. Thus in this paper, we defined the EMG baseline threshold as the value where the duration of EMG was equal to the AMS duration. As a consequence, each muscle from every model would have a different baseline threshold. All variables for this quantification study, number of onsets, offsets, and hills were then calculated and compared to each respective EMG baseline threshold.

The main goal of this study was to quantitatively compare muscle activity predicted by AMS with EMG measurements during normal walking after having normalized the EMG signal for duration to AMS activity level. As previously mentioned, a new variable (hills), was introduced to help objectively quantify muscle activity, among the other two (onsets and offsets).

The second goal was to explore which underlying mechanisms are responsible for differences between AMS activity level and surface EMG measurements as quantified in this study.

2.2. Materials and Methods

This study involved ten healthy subjects. The inclusion criteria for participation in the experiment were: being able to walk without any help or support and age above 18 years. The exclusion criteria were defined as follows: subjects should have: no pain in the knee or other lower limb parts that could cause abnormal walking, no lower limb trauma that cause an imbalance in walking, no neurological and metabolic disorders that have an effect on lower limb functioning (diagnosed by a sports physician) and noinflammatory arthritis of the foot, ankle, knee, hip or back (diagnosed by a sports physician).

The characteristics of all subjects (6 males and 4 females) were: mean age of 29.8 ± 6.6 years, mean body weight 67.7 ± 8.18 kg, mean body height 168 ± 4.6 cm, and mean right leg length of 87.0 ± 4.9 cm. The study was approved by the Medical Ethical Committee of the University Medical Center Groningen (UMCG). Every subject signed an inform consent before performing the trials in the gait lab.

2.2.1Test set-up

The study was performed in a Gait Laboratory (Centre for Rehabilitation, UMCG, The Netherlands) which was equipped with an 9.0 m long walkway. Two force plates (BP400600-1000, AMTI, Watertown, MA, USA) were embedded halfway on the floor of the walkway. The force plates measured the ground reaction force (GRF) with a sampling frequency of the 1000 Hz. Two cameras (Basler A602 FC, Basler AG, Ahrensburg, DE) in fixed positions were used to record the gait of the subjects to check for abnormal walking with sampling frequency was 50 Hz. Recording, synchronising and analysis were performed with a motion system (Vicon Motion System, 14 Minus Park, West Way, Oxford, OX-2OJB, UK).

Sixteen reflective markers were attached to bony landmarks on both lower limbs of the subjects so that the eight infrared cameras could record the trajectories of the movement of the markers during motion. The location of placing all the markers on lower limb was based on Helen Hayes and Roy Davis study [Davis et al., 1991].

For subject comfort, we used non-invasive EMG Zerowire electrodes (ConMedCleartrode ref. 1720-003, Aurion SRL, Milan, Italy) to record the muscle activity of the right lower limb. The skin was shaved and cleaned carefully with alcohol before the EMG electrodes were attached on eight muscles: Rectus Femoris (RF), VastusMedialis (VM), VastusLateralis (VL), Semitendinosus (ST), Bicep Femoris (BF), Gastrocnemius Medialis (GM), Gastrocnemius Lateralis (GL) and Tibialis Anterior (TA) of the right leg.The EMG electrodes placement was based on the SENIAM standard [Hermens et al., 2000].

2.2.2Protocol and Data Verification

The subjects were asked to walk at a self-selected walking speed on the walking path in the gait lab. For every subject, three trials with "clean" hits (i.e. full foot support of the right leg/foot on one of the force plates) were recorded.

The data were taken from a full gait cycle (from the first right leg initial contact until the second right leg initial contact). The first signal from the force plate due to the foot initial contact was used to define the first initial contact timing. The measured data were then verified using visual inspection (video) to remove abnormal walking patterns (compared to normal walking as described by [Winter., 1991]).

2.2.3. Lower Limb Musculoskeletal Modeling

AMS version 5.0 with the GLEM (AnyBody Managed Model Repository - AMMR v.1.3.1) was used to model the lower limb. Anthropometric data such as body weight, body height, pelvis width, thigh, shanks and foot length were imported in the model. The default scaling algorithm in AMS, based on mass-fat scaling algorithm was applied [Andersen et al., 2010]. In the inverse dynamic analysis computations, a 3rd order polynomial muscle recruitment criterion was applied [Damsgaard et al., 2006] in this modeling.

Additional script files were added in AnyBody to automatically compute the envelope of the raw EMG. The raw EMG data was filtered using a fourth-order, zero-phase Butterworth band pass filter [Luca et al., 2010] with a frequency range of 30-200 Hz, rectified and finally low pass filtered at 6 Hz using a fourth-order, zero-phase Butterworth filter.

2.2.4Comparison strategy

2.2.4.1Defining the EMG graph

As the starting point of EMG varies significantly from person to person and depends largely on the subject's anatomy, it is important to process the EMG graph into a more reproducible way. In this study, we found that some EMG data started their activity level far above the zero level, and some other started at about the zero level. To make all data better comparable, we crop the EMG data according to [Konrad., 2005] from the lowest value to the highest value, see figure 3. Subsequently, we compared the duration of the cropped EMG signal and AMS muscle activity. It turned out that the cropped EMG signal was always longer than that of the AMS activity level. We therefore normalized the EMG signal by choosing a threshold value that would lead to an equal duration of the EMG signal and AMS muscle activity. In essence, the EMG signal was cropped with a minimum threshold value to match the duration of the AMS activity level. This procedure was performed for each individual muscle. As a consequence, each muscle from every model would have a different baseline threshold. All variables for this quantification study such as number of onsets, offsets, and hills were then calculated and compared to each respective EMG baseline threshold. An illustration for this method is given in figure 1.

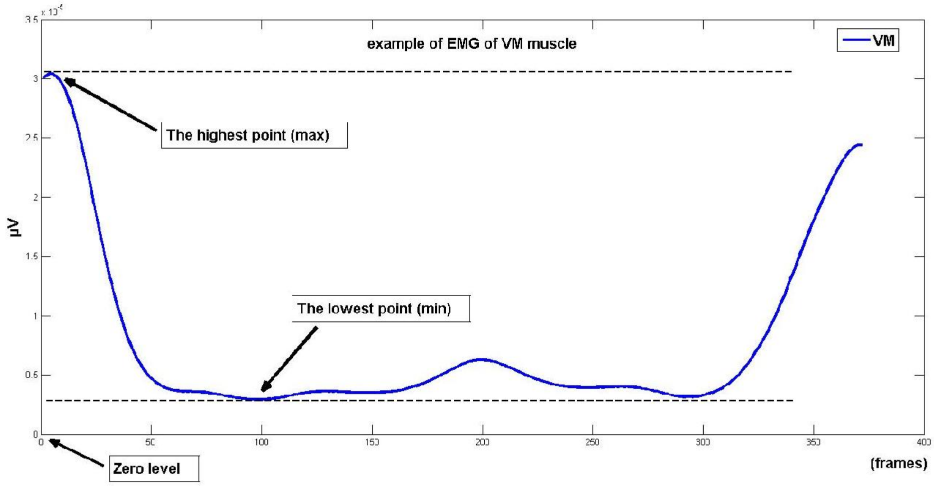

Fig1. Method of cropping an EMG-graph

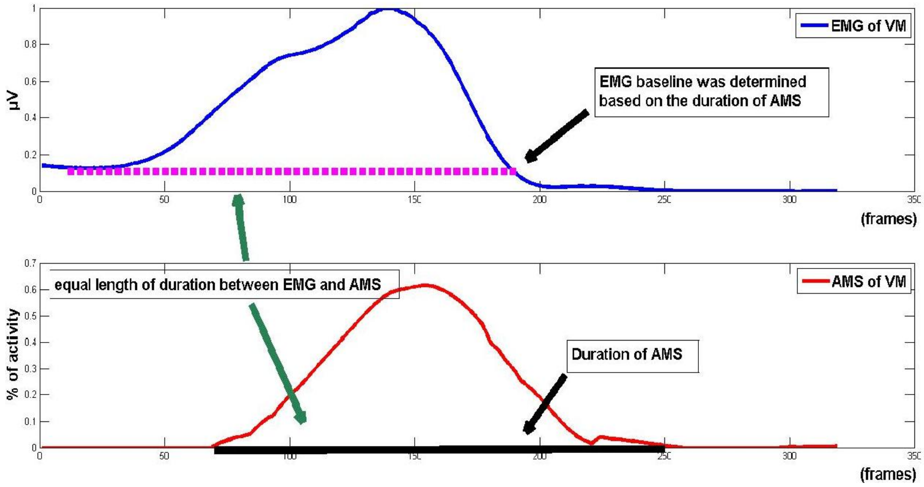

Fig2. Illustration of determining the EMG baseline threshold based on the duration of the predicted AMS activity

2.2.4.2Defining the AMS muscle activity pattern

For predicted muscle activity (AMS) processing, there was only one threshold that was applied on the graph, the baseline threshold (BT). This BT was determined by value 10^{-7} meaning that all values below 10^{-7} will be zeroed. This is necessary, because data of predicted muscle activity from AMS never reached a zero level. This processing was done using Mathlab version 2009a (www.mathworks.com).

The unit of predicted muscle activity is a percentage. However, some muscles consist of several fiber bundles, such as VM, VL, RF, BF and TA, the activity is calculated from the sum of all fiber bundles. So, the unit of VM, VL, RF, BF and TA is the sum of percentage of activity (total percentage of activity).

2.2.4.3Comparing EMG andAMS data

To find the level of agreement between EMG and predicted muscle activity two statistical methods were applied. The first uses Cohen's kappa value which ranks from 0 to 1. Kappa values<0.20 are qualified as poor agreement, between 0.21 - 0.40 as fair, between 0.41 - 0.60 as a moderate, and between 0.61 - 0.80 as good [Altman., 1991; Cohen., 1960]. MedCalc version 12.0 was used to calculate this Cohen's kappa value by gathering all data of number of onset, for example, from all models (EMG) and put them in one column from model 1 to the last model. The same method was applied on AMS data with the same order of models as in EMG. After that then Cohen's kappa value was calculated. This process was done per muscle.

The second statistical analysis uses the Pearson correlation coefficient. For calculating the Pearson correlation coefficient Mathlab version 2009a was used. The Pearson correlation coefficient was calculated per muscle. In this statistical analysis we categorized the correlation value into 3 levels, from 0.0 – 0.40 as a poor correlation, 0.41-0.60 as a moderate correlation, and 0.61-1 as a good correlation.

2.3 Results

From our ten healthy subjects, three subjects were excluded from the analysis due to the non-standard walking pattern compared to the normal walking pattern [Winter., 1991]. Since every subject performed three walking trials, in total 21 models were analyzed. Fig 3 and 4 show the typical data of muscle activity from both EMG and predicted muscle activity by AMS with knee flexion data presented during one full gait cycle. Visual inspections of the results showed a good matched between measured and simulated data.

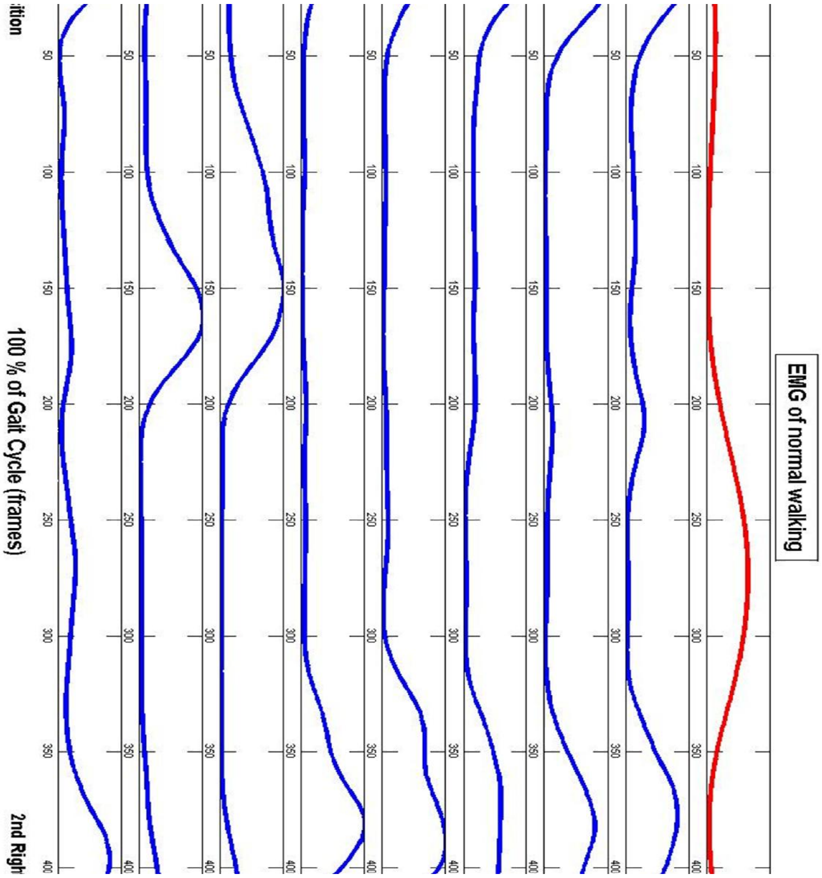

Fig3.Typical cropped EMG data during normal walking of eight muscles. Knee flexion is depicted in the upper graph (red line).

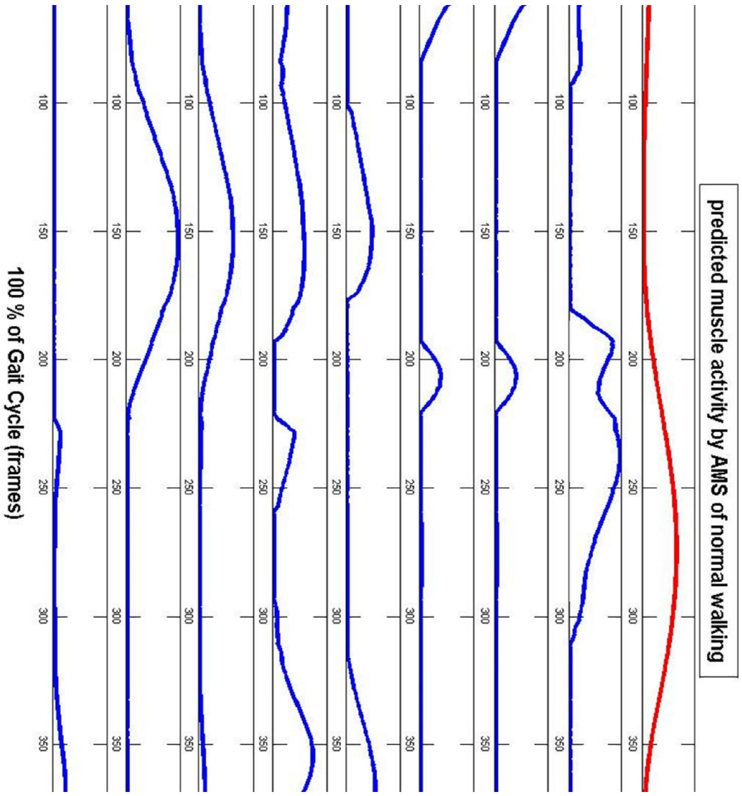

Fig4. Typical predicted muscle activity by AMS during normal walking of eight muscles. Knee flexion is depicted in the upper graph (red line).

2.3.1Level of agreement in Cohen's kappa value

The level of agreement between EMG and the predicted muscle activity in all three variables is shown in Fig 5. For the variable number of onsets, there were 4 muscles (VM, BF, GM and TA) that showed a slight positive agreement, while the other 4 showed a negative agreement. For the variable number of offsets, there were again 4 muscles that showed a positive slight agreement (VM, VL, BF and TA), while the other 4 muscles showed a negative agreement. For the variable number of hill, there were 5 muscles that showed a positive agreement, the other 3 muscles showed a negative agreement.

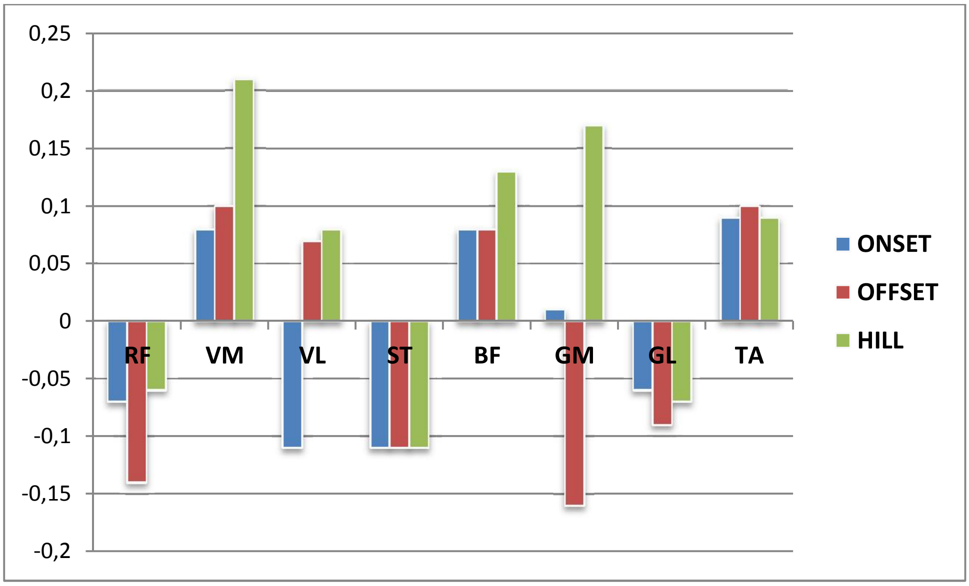

Fig5. Cohen's Kappa value (level of agreement) of eight muscles for the comparison of EMG and predicted muscle activity (AMS) during normal walking (from 21 models)

2.3.2Pearson correlation coefficient

In Fig 6 the results of the Pearson correlation coefficient calculation between EMG and AMS is depicted. There were only two muscles (GM and GL) that showed a good correlation, while the other 6 muscles showed a poor correlation.

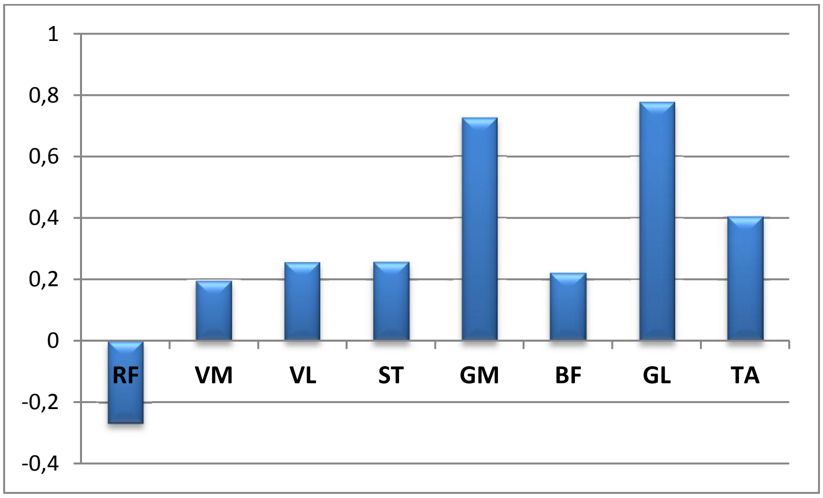

Fig6. Mean of Pearson correlation coefficient per muscle as a result of EMG and predicted muscle activity data set comparison during normal walking (from 21 models)

2.4. Discussion and Conclusion

Numerical models like the GLEM from AMS can be of great help in determining muscle activity patterns. However, these patterns must be validated to allow them to be applied. The most obvious way is to use EMG-patterns, although these measurements also have their deficiencies. Visual inspection showed that the predicted muscle activity by AMS seems to match rather well with the EMG results (see Fig. 3). However, clear differences became apparent after analyzing the data using Cohen's kappa value and Pearson correlation coefficient (see figure 5 and 6). In general, the level of agreement of the three parameters was not so satisfying (see kappa value fig 5). Pearson correlation coefficient also showed only two muscles (GM and GL) with high correlation value. The other 6 muscles showed a lower correlation coefficient value. Figure 3 and 4 is representing mostly the condition of EMG and AMS in all of our data. Even though some small differences happened among those data certainly, but generally, their patterns are similar.

If we look at figure 3 and 4, some differences can be seen that could explain the low level of agreement. For example, in EMG data (fig 3), at about 25%-60% of the gait cycle (frame 100-250), during stance-phase, some muscles showed a decreased activity. This can be explained by the absence of knee or ankle flexion activity, so the knee flexor muscles like BF and ST were less active, so did VM and VL, because the leg was already standing. Compared to predicted muscle activity (AMS) at about the same time frame (frame 100-250), VM and VL showed similar behavior by decreasing the activity, while BF and ST muscles showed contrary to EMG by increasing the activity.

Moreover, TA that was active during dorsiflexion or plantar flexion (from heel strike until toe-off) was less active too due to the small amount of dorsiflexion or plantar flexion during the stance-phase. At about 60% of the gait cycle (frame 250th), when toe-off of the right foot starts, some muscles were about to become active (RF, VM, VL, ST, BF and TA) according to the EMG data. However, according to AMS only BF, ST and TA muscles showed some activation.

Some differences were also present in the last part of the gait cycle. From figure 3, we see that before the 2nd right heel strike, several muscles active (RF, VM, VL, ST, BF and TA) according to EMG, while according to AMS, all muscles are inactive.

We speculated that all of these differences were caused by several aspects. The first is that we have to acknowledge that EMG and predicted muscle activity by AMS are a different entity. EMG is an electrical activity of muscle fibers [Konrad., 2005; Bilodeau et al., 1992] and is measured via the human skin using electrodes that are influenced by the fat, muscle belly and the age of the subjects [Merletti et al., 2009]. The predicted muscle activity from AMS is defined as the muscle force divided by the maximal muscle force for that particular muscle at that particular instant in time, so indeed a different entity.

The second explanation is marker trajectories data and knee net moment. AMS predicts muscle activity based on data of marker trajectories and ground reaction force (GRF). False interpretation of marker data could generate a systematic error.

For example, if we look at figure 3, during the initial stance phase until toe-off, at about 25%-60%, as the leg was in standing position, knee flexor muscles (BF and ST) should be less active.

Compared to AMS (see figure 4), knee flexor muscles (ST and BF) were active during the stance phase. We opinioned that during this stance phase, the whole right leg segment was moving forward due to the swinging of left leg subsequently this condition would be interpreted by AMS as a marker's movement, so that muscle activity was predicted.

Vice versa condition regarding marker's movement interpretation was present at about 70%-80% of gait cycle, when the foot was preparing a toe-off, some muscles in EMG were starting to become active (RF, VM, VL, BF, ST and TA) as the foot was preparing toe-off, while in AMS, this position was read as inactive condition because the markers movement was very small (see figure 4).

These differences could also be attributed to the knee net moment calculation in the model. AMS calculates muscle activity around the joint based on the knee net moment in that joint. Since the knee net moment is not zero, all muscles around that knee joint would be activated to encounter that knee net moment. During this standing position, AMS may be still calculate some knee net moment so that it still needs to activate some muscles to encounter this moment.

Co-contraction phenomenon is also an important issue that has not yet implemented in AMS in its prediction since some muscles in the knee joint such as BF and ST are functioning at the same time for a reason of stability [McGinty et al., 2000]. This condition provides also some differences in muscle activation.

Ignorance of individual differences such as muscle geometry, joint stiffness properties, ligaments properties, fat percentage and other important body structures was also an important aspect that could cause these differences. All of these individual differences ideally should be made subject-specific, but this study uses a general model.

Various assumptions in the model have also a big impact on the validation results. One example for this is muscle recruitment algorithm. AMS applied 3rd order polynomial muscle recruitment criterion as the default of muscle recruitment criteria in its system. This criterion is ideal in term of mathematics analysis since it minimizes the maximum load of each muscle fiber involved so that the fatigue can be avoided to happen easily and the load was shared equally to all muscles. This recruitment system seems mimic the human body system perfectly. However, since this process is controlled by our central nervous system and up to now this mechanism is unclear [Damsgaard et al., 2006; Deliagina et al., 2007] this certainly would cause differences. Besides that each individual or each gender may have different way in muscle recruitment algorithm or fatigue control [Tirosh et al., 2005].

Furthermore, simplification is also difficult to avoid in a modeling process. Simplification in modeling reduces computation time. However, it also decreases the accuracy on predicting muscle activity. An example of this was modeling the foot as one rigid segment that was connected to the tibia bone through the talus and subtalar joint. In the model, the foot does not have phalangeal bones, so phalangeal dorsiflexion during toe-off, which can trigger more activity of the TA and Gastrocnemius muscle through the extensor digitorum longus tendon or extensor hallucis longus tendon [Aronow et al., 2006; Macklin et al., 2012] was not possible.

A last important explanation for these differences is the parameter choice used to compare the AMS muscle activity patterns with those of the EMG signals, and especially the statistical method applied to these results. The statistical method has a potential of misleading conclusion. For example, in the number of onsets variable, even though statistically the number of onsets between the two patterns was exactly the same, but in the data, if the time shift happened greatly between EMG and AMS, thus statistically it will be interpreted as a good correlation or agreement, whereas in scientific point of view, this condition should be interpreted as a low agreement condition.

In general, we conclude that AMS is a complex and powerful musculoskeletal modeling tool, capable of describing human biomechanics during walking. However, using statistical validation some improvement is necessary. One idea could be to extend the model and EMG processing such that the comparison can be done based on a physical quantity that both the model and EMG estimate. There are two possible ways to obtaining this, the first is by extending the model to estimate EMG or, the second is processing the EMG to give an estimate of the muscle activity. Even though that is not easy to develop and needs a huge effort.

In statistical method issue, some ideas for getting a more objective result such as calculating the correlation level in partial condition or applying a linear regression method may yield a better result, because then we could compare objectively the same part of the graphs. However, this method may also need large efforts and intensive visual observation in order to make sure that we are comparing the same part of the graphs since there is a time shift between EMG and AMS.

The type of activity could also define the level of agreement, we speculated that a more prescribed movement with a more prescribed moments, compared to normal walking, would result in a better agreement.

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Chapter 3

Lower limb musculoskeletal model validation during one-legged forward hopping and side jumping in healthy subjects using EMG

Abstract

Musculoskeletal modeling is a powerful tool for analyzing human biomechanics, especially during active movement. It has the ability to determine important kinetic and kinematic data during motion such as muscle force, muscle activity and knee joint force. However, validation of these models need further study to determine the quality of their predictions. In the past, we validated the GaitLowerExtremity model (GLEM) of the AnyBody Modeling System (AMS) by a series of experiments, where subjects walked normally, while their movements and EMG were measured. The movements were used by AMS to predict muscle activity, and these predictions were then compared by EMG activities. Although visual inspection showed a good comparison, quantitative comparison results were rather disappointing.

We think that a more prescribed movement could result in a better comparison. In this study muscle activity during one-legged forward hopping and side jumping were measured by EMG and compared to the muscle activity, predicted by AMS. Three variables were used to quantify muscle activity, number of onsets, offsets and hills. The Cohen's Kappa value was calculated to determine the level of agreement. The Pearson correlation coefficient between the EMG and AMS data set was calculated as a second measure of agreement.

During one-legged forward hopping (FH), for variables number of onsets and hills, there were 7 muscles showed poor agreement (a slight positive value) and only one muscle showed a negative agreement (TA). For variable number of offsets, there were 6 muscles showed a poor agreement, one muscle showed a moderate agreement (GM) and one muscle showed a negative agreement (TA). During side jumping (SJ), for all three variables, there were 7 muscles showed poor agreement (a slight positive value) and one muscle showed a fair agreement (ST). Pearson correlation coefficient showed that 4 muscles showed a good agreement, 3 muscles showed a moderate agreement and one other muscle showed a poor agreement. This result demonstrates that during more prescribed movements, AMS predicts muscle activity much better than compared to our previous validation study during normal walking.

Keywords: one-legged forwardhopping, side jumping, EMG, AnyBody Musculoskeletal System, Inverse dynamics analysis

3.1 Introduction

Modeling of the human movement is an alternative way in studying human biomechanics during motion, while measuring in vivo of human biomechanics is still challenging especially during motion [Delp et al., 2007; Komistek et al., 2005]. Numerical modeling such as AnyBody Modeling System (AMS) (from Aalborg University, Denmark) can be a breakthrough for these complexities [Damsgaard et al., 2006; Koopman et al., 1995; Zee et al., 2007].

TheGaitLowerExtremity model (GLEM), lower leg model from AMS repository folder, has been used widely to study human locomotion. Like all models, GLEM is capable to calculate muscle forces and muscle activity by a series of assumptions. The influence of these assumptions is never determined, so the accuracy of these models is not known. We did a first attempt in determining the accuracy of GLEM by performing an experiment, in which volunteers were asked to walk with their self comfortable speed, while their gait was recorded by a camera system and muscle activity was measured with EMG-electrodes. In this way we were able to compare the temporal parameters of muscle activity, predicted by GLEM with the measured activity by EMG. Visual inspection in general pattern of muscle activity showed a reasonable match for most muscles, but after quantifying the results were disappointing. The main reasons for this were the assumptions and simplifications of the modeling process,besides the type of movement[see chapter 2].Walking is a complex movement. During walking leg has more degree of freedom, especially during landing, as the knee was able to rotate internaly or externaly, besides that leg was also less stiff.

To our opinion, a better way to compare predicted and measured muscle activity would be to use a more prescribed movement like one-leggedforward hopping (FH) and side jumping (SJ). These movements have more defined moments in which muscles are active. In addition, muscle activity peaksduring FH and SJ are also more prescribed due to the shorter moments of activation so that they are less ambiguous during muscle activity comparison. So a better comparison between predicted and measured muscle activity could be possible. Moreover, one legged hopping was also important motion test for ACL deficient knee pateints [Hobara et al., 2010; Tveter et al., 2010; Sekiya et al., 1998].

The main goal of this study was to validate quantitatively muscle activity predicted by AMSwith EMG measurements during FH and SJ in eight lower limb muscles: Rectus Femoris (RF), VastusMedialis (VM) and Lateralis (VL), Semitendinosus (ST), Bicep Femoris (BF), Gastrocnemius Medialis (GM) and Lateralis (GL), and Tibialis Anterior (TA). In validating predicted muscle activities, it is important to point out that muscle activity predicted by AMS has a different dimension from the measured muscle activity (EMG), because the predicted muscle activity is calculated from predicted muscle force divided by the maximal muscle force for that specific muscle at that specific time frame[Zee et al., 2007]. What can be validated is the timing of muscle activity. The comparison was quantified by three variables; number of onsets, offsets and hills. An onset is defined as the start of a muscle activity, so when the baseline threshold is exceeded, while an offset is defined as the end of an activity, so when the baseline threshold is passed. A hill is a muscle activity starting at an onset point and ending at the next offset point. The unique and novelty of this study is proving our hypotheses that during more prescribed movement like FH and SJ, GLEM predicts much better muscle activity when compared to EMG.

3.2 Material and Methods

Ten healthy subjects were participating in this experiment. The inclusion criteria for participation in the experiment were: being able to do walking, one-legged forward hopping and side jumping without any help or support and their age should above 18 years. The exclusion criteria were defined as follows: the healthy subjects should not have pain in the knee or other lower limb parts that could cause abnormal NW, FH or SJ, should not have lower limb trauma that caused an imbalance in NW, FH and SJ, should not have neurological and metabolic disorders that have an effect on lower limb functioning (diagnosed by a sports physician) and should not have inflammatory arthritis of the foot, ankle, knee, hip or back (diagnosed by a sports physician).The characteristics of all subjects (6 males and 4 females) were: mean age of 29.8 ± 6.6 years, mean body weight 67.7 ± 8.18 kg, mean body height 168 ± 4.6 cm, and mean right leg length of 87.0 ± 4.9 cm. This study was approved by the Medical Ethical Committee of the University Medical Center Groningen (UMCG). Every subject signed an inform consent before performing the trials in the gait lab.

3.2.1 Test set-up

Thisexperiment was performedat theUMCG Gait Laboratory (Centre for Rehabilitation Medicine, University Medical Centre Groningen, the Netherlands) which was equipped with an 9.0 m long walkway for performing FH and SJ. Two force plates (BP400600-1000, AMTI, Watertown,MA, USA) were embedded in the floor. The force plates measured the ground reaction force (GRF) with a sampling frequency of 1000 Hz. Two cameras (Basler A602 FC, Basler AG, Ahrensburg, DE) in fixed positions were used to record the FH and SJ performance with sampling frequency of 50 Hz. Recording, synchronising and analysis were performed with a motion system (Vicon Motion System, 14 Minus Park, West Way, Oxford, OX-2OJB, UK).

Sixteen reflective markers were attached to bony landmarks on both lower limbs of the subjects so that the eight infrared cameras could record the trajectories of the movement of the markers during motion. The location of placing all the markers on lower limb was based on the study of Hayes and Davis [Davis et al., 1991].

Non-invasive EMG Zerowire electrodes (ConMedCleartrode ref. 1720-003, Aurion SRL, Milan, Italy) were used for subjects comfort to record the muscle activity of the right lower limb. The skin was shaved and cleaned carefully with alcohol before the EMG electrodes were attached on the muscles: RF, VM, VL, ST, BF, GM, GL and TA. The EMG electrodes placement was based on the SENIAM standard placement [Hermens et al., 2000].

3.2.2 Protocol

3.2.2.1 Forward Hopping

The subjects were asked to perform one-legged forward hopping (FH) on two force plates on the floor of the gait lab. The starting point of the 1st jump was set 80 cm long before the first force plate. The second jump was from the 1st force plate to the 2nd force plate, being continued with the 3rd jump, from the 2nd force plate to the ground at about 80 cm outside the 2nd force plate (landing area). A small step of the right foot prior the 1st jumping was usually done by subjects in order to prepare their 1stjump.

Data analysis wasstarted at the 1st force peak from the 1st force plate and ended when the foot left the 2nd force plate. Errors during the trials were excluded from further analysis such as the presence of flying markers, unstable/unbalance landing or zigzag hopping. Subjects were asked to repeat the performance until 3 completeand no-errors data sets were obtained from the measurement (see fig. 1).

Fig1.Above : One-legged forward hopping activity (taken from video overlay): (1) starting the jump, (2) right foot landed on the 1st force plate, (3) right foot landed on the 2nd force plate, (4) right foot left force plate – Below: Side Jumping activity

3.2.2.2 Side Jumping

The starting point during SJ was different from FH. In SJ, subjects stood beside the first force plate (see figure 1) and ready to jump with the right leg on the 1st force plate and then jump with the left leg on the 2nd force plate. This performance was done repeatedly during 10 second. Analysis of the data started when the right foot hit the first force plate for the first time until the right foot left the force plate for the 3rd time. This SJ trial was repeated until 3 complete data sets with no-errors of SJ were obtained.

3.2.3 AnyBody Modeling System(AMS)

AnyBody modeling software version 5.0 with the GaitLowerExtremitymodel (AMMR.1.3.1) from the repository folder (www.anybody.aau.dk/repository) was used to model hopping and side jumping activity (GLEM).

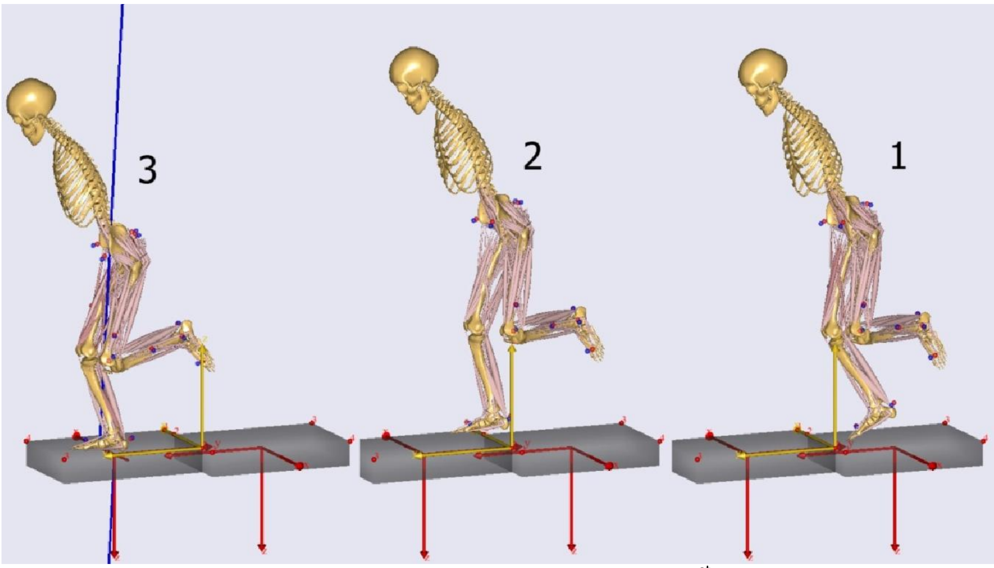

Fig2. FH model from AMS; (1) right foot jumped from the 1st force plate, (2) jumping condition, (3) right foot landed on the 2nd force plate

Anthropometric data such as body mass, body height, pelvis width, thigh, shanks and foot length were input into the model. Bones and muscles geometry were scaled based on the TLEM study [Horsman et al., 2007]. The default scaling algorithm regarding fat percentage was based on mass-fat scaling algorithm [Andersen et al., 2010]. Measured marker trajectories and ground reaction force were imported into the model. In the inverse dynamic analysis computations, a 3rd order polynomial muscle recruitment criterion was applied [Rasmussen et al.,2001]to determine which muscles are active during motion. During simulation, besides performing inverse dynamic calculation, AMS rectifies and filters the raw EMG into smoothed EMG. In this study, AMS filtered the raw EMG using a Butterworth band pass filter with a frequency range of 30-200 Hz and 6 Hz low pass filter [Luca et al., 2010].

3.2.4 Comparison strategy

3.2.4.1Defining the EMG graph

As the starting point of EMG varies significantly from person to person and depends largely on the subject's anatomy, it is important to process the EMG graph into a more reproducible way. In this study, we found that some EMG data started their activity level far above the zero level, and some other started at about the zero level. To make all data better comparable, we cropped the

EMGdata according to [Konrad., 2005] from the lowest value to the highest value, see figure 3. Subsequently, we compared the duration of the cropped EMG signal and AMS muscle activity. It turned out that the cropped EMG signal was always longer than that of the AMS activity level. We therefore normalized the EMG signal by choosing a threshold value that would lead to an equal duration of the EMG signal and AMS muscle activity. In essence, the EMG signal was cropped with a minimum threshold value to match the duration of the AMS activity level. This procedure was performed for each individual muscle. As a consequence, each muscle from every model would have a different baseline threshold. All variables for this quantification study such as number of onsets, offsets, and hills were then calculated and compared to each respective EMG baseline threshold (see figure 3 and 4).

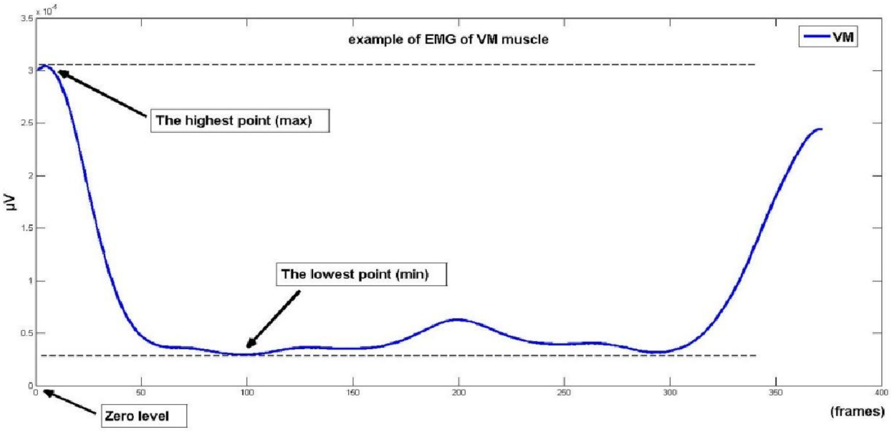

Fig3. Method of defining the graph before defining the baseline

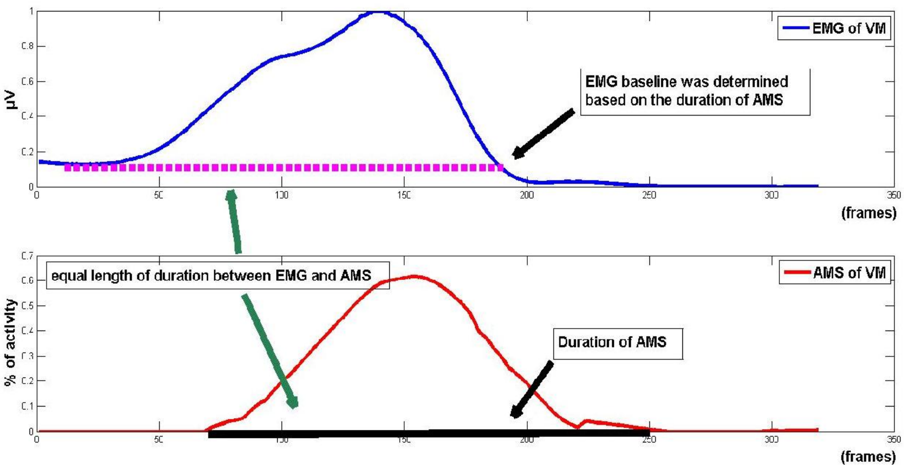

Fig4.Illustration of determining the EMG baseline threshold which was based on the duration of predicted AMS

3.2.4.2Defining the AMS graph

For predicted muscle activity (AMS) processing, there was only one threshold that was applied on the graph, the baseline threshold (BT). This BT was determined by value 10^{-7} meaning that all values below 10^{-7} will be zeroed. This is necessary, because data of predicted muscle activity from AMS never reached a zero level. This processing was done using Mathlab version 2009a (www.mathworks.com).

The unit of predicted muscle activity is a percentage. However, some muscles consist of several fiber bundles, such as VM, VL, RF, BF and TA, the activity is calculated from the sum of all fiber bundles. So, the unit of VM, VL, RF, BF and TA is the sum of percentage of activity (total percentage of activity).

3.2.4.3Comparing EMG andAMS data

To find the level of agreement between EMG and predicted muscle activity two statistical methods were applied. The first was Cohen's kappa value which ranks from 0 to 1. Kappa values<0.20 are qualified as poor agreement, between 0.21 - 0.40 as fair, between 0.41 - 0.60 as a moderate, and between 0.61 - 0.80 as good [Altman., 1991, Cohen., 1960]. MedCalc version 12.0 was used to calculate this Cohen's kappa value by gathering all data of number of onset, for example, from all models (EMG) and put them in one column sequncely from model 1 to the last model. The same method was applied on AMS data with the same order of models as in EMG. After that then Cohen's kappa value was calculated.This process was done per muscle.

The second statistical analysis was the Pearson correlation coefficient. For calculating the Pearson correlation coefficient Mathlab version 2009a was used. Before both data sets (EMG and AMS) were being compared, EMG was cropped using min/max threshold, and AMS was threshold using a certain value to define the zero level (10^{-7}), after that then Pearson correlation coefficient was calculated per muscle. In this statistical analysis we categorized the correlation value into 4 levels, from 0.0 – 0.40 as a poor correlation, 0.41-0.60 as a moderate correlation, and 0.61-0.99 as a good correlation.

3.3 Results

3.3.1 One-legged Forward Hopping (FH)

From the 10 healthy volunteers who were involved in this experiment, 8 subjects were included in the analysis of one-legged forward hopping (FH), two subjects were excluded due to marker trajectory errors during the measurements. Since every volunteer performed 3 good hopping trials, in total we analyzed 24 models of FH activity. Typical muscle activity of both graphs during FH, EMG and predicted muscle activity by AMS, is shown in figure 7 and 8. The peaks of muscle activity from both systems were clearly depicted. A time shifting between peaks and hills between EMG and AMSappears to be present.

The level of agreement in both statistical analysis, Cohen's kappa value for number of onsets/offsets and hills, and Pearson correlation coefficient is shown in figure 5.

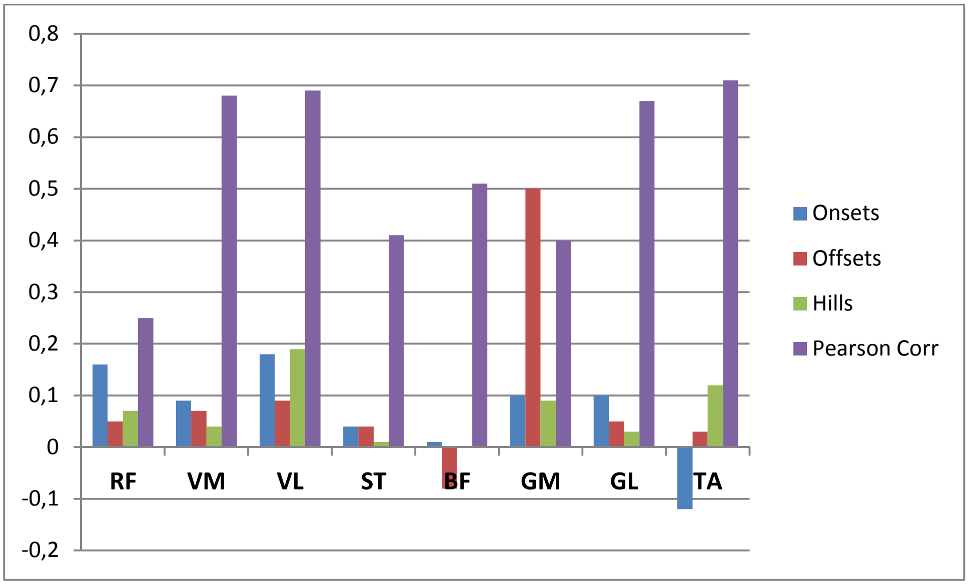

Fig5.Cohen's Kappa value of both sets of data (EMG and predicted muscle activity) from all eight muscles of three variables and Pearson correlation coefficient per muscle during one-legged Forward Hopping (FH)

From figure 5 we can see that for variable number of onsets, there were 7 muscles showed a poor agreement (a slight positive value of agreement) and one muscle showed a negative value of agreement (TA). For the variable number of offsets, 6 muscles showed a poor agreement, one muscle showed a moderate agreement (GM) and one muscles showed a negative value of agreement (BF). For the variable number of hills, all 7 muscles showed a poor agreement (a slight positive value of agreement), except for BF muscles that showed zero agreement.

Concerning the Pearson correlation coefficient, four muscles showed a good correlation (VM, VL, GL and TA), three muscles (ST, BF and GM) showed a moderate correlation and only one muscle (RF) showed a poor correlation.

3.3.2 Side Jumping (SJ)

From all ten healthy volunteers who were involved in this experiment, 9 subjects were included in the analysis. One subject was excluded due to errors in marker data. Since every volunteer performed 3 good side jumping trials, in total we analyzed 27 models of SJ activity. Typical predicted muscle activity and EMG in SJ activity is shown in figure 9 and 10.

The level of agreement (Cohen's kappa value) between EMG and predicted muscle activity from all eight muscles for all three variables and the Pearson correlation coefficient is shown in figure 6.

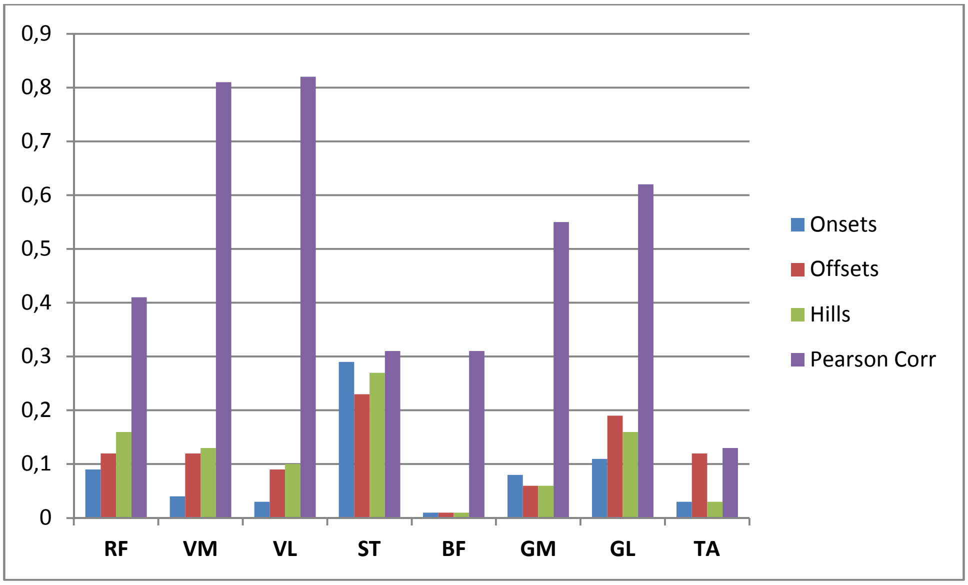

Fig6.Cohen's kappa value of both sets of data (predicted muscle activity and EMG) from all eight muscles of three variables and Pearson correlation coefficient during Side Jumping (SJ)

For all variables, the kappa value is a slight positive, so there is a positive agreement between EMG and predicted muscle activity for all muscles during SJ even though 7 muscles out of it were categorized as a poor agreement, except for ST muscle that showed a fair agreement. Concerning the Pearson correlation coefficient, three muscles show a strong correlation (VM, VL and GL), two muscles (RF, GM) showed a moderate correlation and three other muscles (ST, BF, TA) showed a poor correlation.

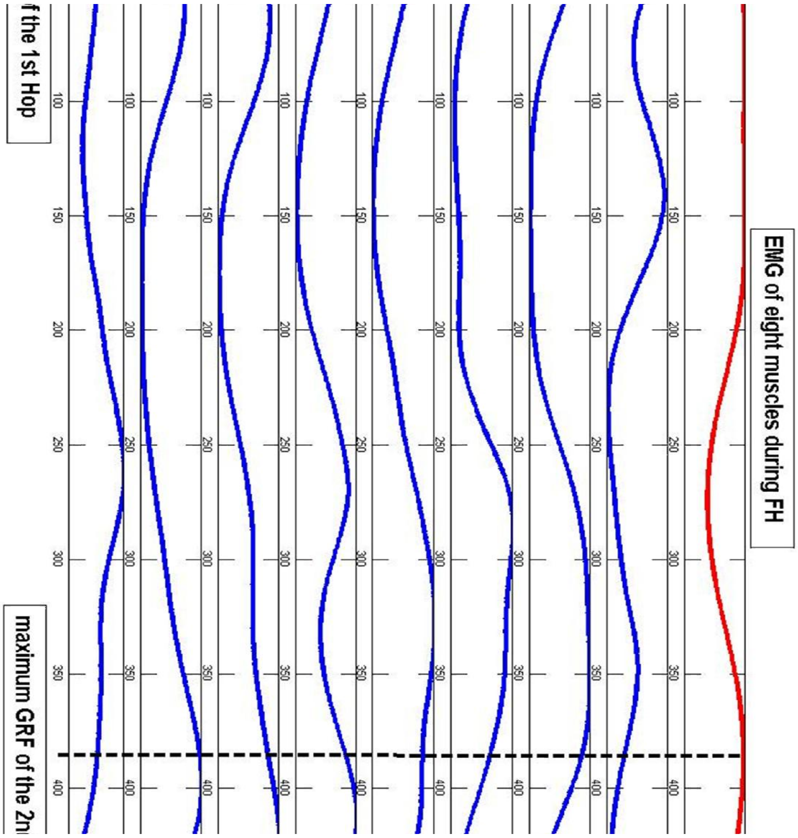

Fig7. Typical EMG of eight muscles (blue line) during one-legged forward hopping (FH) and knee flexion (red line), taken from one of the volunteers (Lydh02)

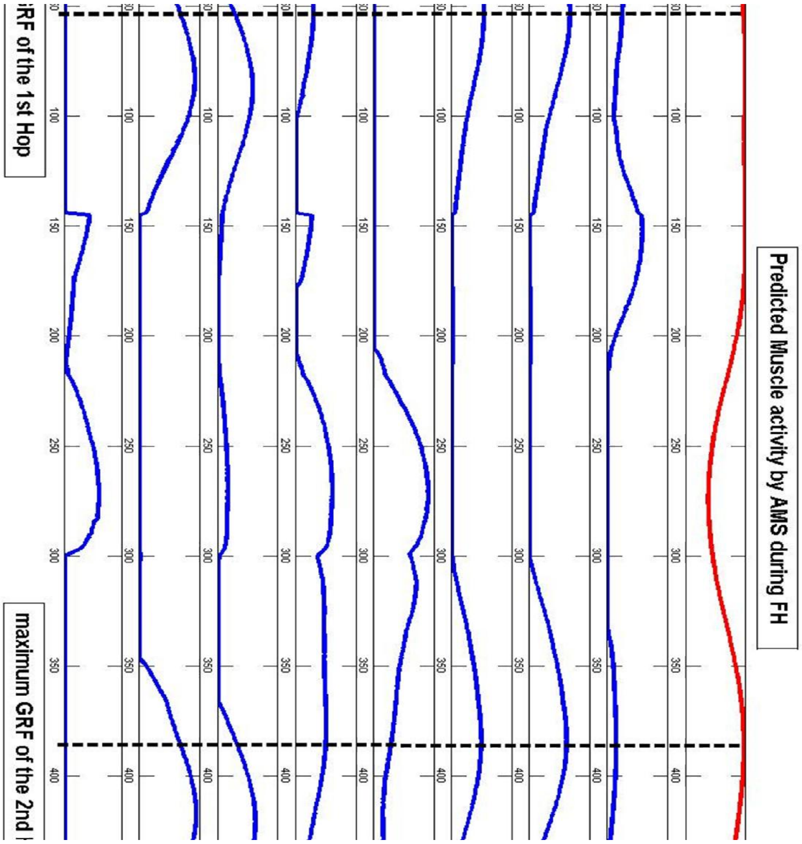

Fig8. Typical predicted muscle activity by AMS of eight muscles (blue line) during one-legged forward hopping (FH) and knee flexion position (red line), taken from one of the models (Lydh02)

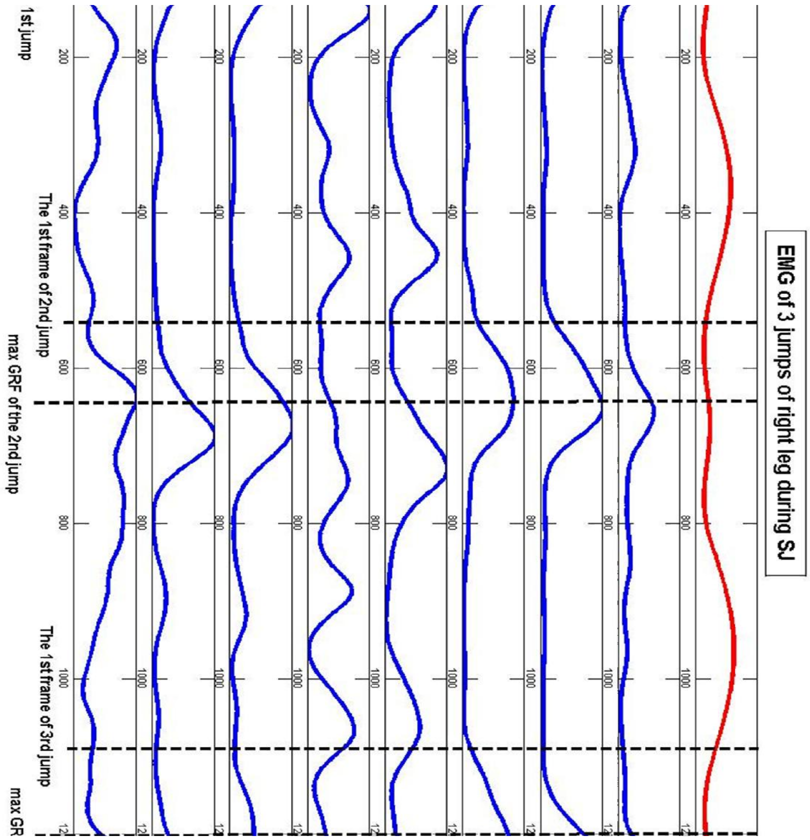

Fig9. Typical EMG of eight muscles (blue line) during 3 times Side Jumping (SJ) and knee flexion position (red line), taken from one of the volunteers (Lydsj01) (Add ‘frames’ as the unit of the numbers of the horizontal axis)

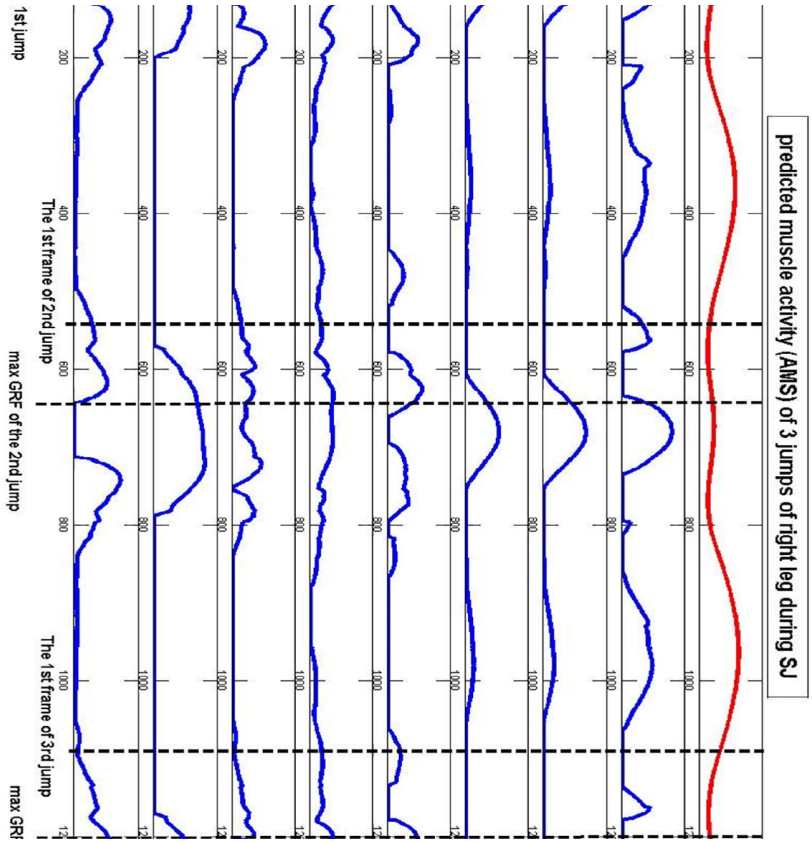

Fig10. Typical predicted muscle activity by AMS of eight muscles (blue line) during 3 times Side jumping (SJ) and knee flexion position (red line), taken from one of the models (Lydh01)

3.4 Discussion and Conclusion

AMS is a very suitable tool for biomechanical studies of the musculoskeletal system, but without information of its accuracy the predictions are of limited use. From a former study [see chapter 2] it was clear that the predictions seemed to match the measured graph rather well, but a quantitative comparison showed a poor match. One of the reasons could have been the type of activity that was chosen, walking. In this study two different activities were chosen, one-leggedforward hopping and side jumping, both of them showed a more distinct type of muscle recruitment. This was confirmed well by more distinct peaks of muscle activity for all muscles. Visual inspection showed a good match between measured and predicted muscle activity during FH and SJ (see fig7-10). However, some differences still occurred between EMG and predicted muscle activity during both activities. Figure 7-10 are representing the typical data in our experiments.

For example during FH, we can see from figure 7 and 8, when the foot was about to land on the 1st force plate, all lower limb muscles were active according to the EMG data. According to AMS, at the same time point, there were only 4 muscles (VM, VL, ST and BF) active, the other two muscles (RF and GL) became active later on and the last two muscles (GM and TA) became active much later. Just before the 1st peak of the ground reaction force, in EMG, GM, GL and TA increased their activity, while RF, VM, VL, ST and BF decreased their activity (see figure 7). According to AMS, at the same time point, GM and GL also increased their activity, but TA was not active at all and ST activity was stopped much earlier. RF, VM, VL and BF showed similar activity as in EMG.

Some delay between EMG and AMS was present in figure 7 and 8. In figure 7, for example, between frame number 200 and 250, the EMG of RF, VM, VL, ST, BF, GL and GL increased. This pattern was predicted well by AMS, but it occurred later.

Also for SJ differences between EMG and AMS were present. If we look at figure 9 and 10, until the 1st peak of GRF, all muscles were active and increasing their activity according to their EMG. According to AMS, some muscles (GM, GL and TA) were not active. Some muscles (RF, VM and VL) became active only some times after the first recorded frame. A delay was also present for some muscles like RF, VM and VL who became active between frame 480th and 500th according to their EMG. But AMS predicted their activity only after frame 600th.

All of these differences, in statistical point of view (whether in Cohen's kappa value or Pearson correlation coefficient) take a great effect on the level of agreement. Predicted muscle activity showed more hills and often rise up and drop to zero level instantaneously [Erdemir et al., 2007] (see figure 9-10).

When compared to the results of our previous study on walking, FH and SJ showed a better validation results. For walking, the Pearson correlation coefficient was good only for GM and GL muscle, while the other 6 muscles showed a poor correlation. Compared to FH, the Pearson correlation coefficient was good for 4 muscles (VM, VL, GL and TA), moderate for ST, BF and GM muscles and poor for RF muscles. For SJ, the Pearson correlation coefficient was good for VM, VL and GL muscle, moderate for RF and GM and poor for ST, BF and TA muscle.

When we consider the Cohen's kappa value, for walking there were 4 muscles showed a poor agreement (a slight positive value of agreement) in onset variable (VM, BF, GM and TA), offset variable (VM, VL, BF and TA), and number of hills variable (VL, BF, GM and TA), while the other 4 muscles showed a negative value of agreement which means lower than poor agreement, except in variable number of hills, there was one muscle showed a fair agreement (VM)[see chapter 2].

For FH, in variable number of onsets and offsets, there were 7 and 6 muscles consecutively that showed a poor agreement (a slight positive value of agreement) except TA muscle that showed a negative agreement in both variables. An exception happened in variable number of offset because there was one muscle (GM) that showed a moderate agreement. In variable number of hills, all 8 muscles showed a poor agreement (a slight positive agreement) see fig 5.

Furthermore, during SJ, in all variables, there were 7 muscles showed a poor agreement (a slight positive value of agreement), and there was one muscle showed a fair agreement (ST). So indeed a more prescribed motion improves the validation results.

Despite the better agreement results, some differences are still present. One of the reasons is the inevitable assumptions and simplifications that in the modeling process. One of them is modeling the foot as just one simple segment, so ignoring the presence phalangeal bones.This will affect TA muscle activation [Aronow et al., 2006; Macklinet al., 2012].

Another aspect that influences the level of agreement was the existence of a delay between EMG and predicted muscle activity. In most cases, EMG activity is ahead of AMS activity. This is because electrical stimulation of muscles by the central nervous system is ahead of mechanical activity [Deliagina et al., 2007] and mechanical activity is ahead of the movement of body segments. A third explanation of the differences between EMG and AMS is the co-contraction phenomenon. During FH and SJ, hamstring muscles (ST and BF) and quadriceps muscles are active at the same time for reasons of stability [Palmitier et al., 1991; McGinty et al., 2000]. This phenomenon is not included in the AMS muscle activity prediction.

But also the used variables show their limitations. For example, for some graphs we found both for EMG and AMS exactly the same number of hills, but the position was shifted in time. This time shift, however, is not depicted in the number of onsets, offsets and hills.

EMG data could also cause errors [Luca et al., 2010] that influence the level of agreement. For example a noise in the EMG signal with higher amplitude than the lowest filtered EMG data will incorrectly be defined as a hill, and thus increase the number of hills, onsets and offsets in EMG.

Every inverse dynamics analysis involves some uncertainfactors [Riemeret al., 2008], such as the need for estimating the segmental parameter like body mass, moment of inertia of every segment mass and the position of center of mass[Kingma et al., 1996; Pearsall et al., 1999; Ganley et al., 2004], inaccuracy in marker's data such as noise in the position of the surface markers [Richards., 1999] or flying markers and error in ground reaction force data [Kuo., 1998]. Since AMS calculates all joint moments based on predefined joint center position, inaccuracy in determining that location isisalso a possible source of differences [Bell et al., 1990; Leardini et al., 1999].

Despite all of these shortcomings, in general the GaitLowerExtremity model from AMS predicts muscle activity during FH and SJ very well. Suggestions for improvement of AMS are inclusion of time delay between predicted muscle activity and EMG, adapting co-contraction and improving the knee joint model from a single hinge one to the one that mimics the anatomical movements.

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Chapter 4

Musculoskeletal model simulation for predicting knee joint forces pattern during normal walking, one-legged forward hopping and side jumping in healthy subjects

Abstract

Determining knee joint forces and knee joint moments is essential for developing total knee replacements, meniscus implants and ACL-replacements. Studying them in vivo is almost impossible; modeling them is an alternative way. AnyBody Modeling System (AMS) is an advance modeling tool, capable of predicting knee joint forces and moments by using inverse dynamic analysis through modeling of human movements from motion capture data. This study investigated knee joint forces and knee joint moments predicted by AMS of 10 healthy volunteers who performed normal walking, forward hopping and side jumping in a gait lab. Knee joint forces and moments prediction pattern among healthy subjects is presented, together with the information of knee flexion position where the knee joint force reached the maximum. Knee joint force and moment data during all three activities were calculated in three planes based on a femoral coordinate system. The results showed that during normal walking (NW), mean of maximum knee compressive force was predicted to be 4.21xBW, during forward hopping (FH) 10.30xBW, and during side jumping (SJ) was 7.88xBW. Mean of maximum knee joint forces prediction in sagittal plane (knee A-P force which are important for ACL-patients) was higher in posterior direction during FH and SJ relative to NW. During FH it was estimated 5.62xBW, SJ was 4.54xBW and NW was 0.52xBW. Knee axial moment was also predicted highest during FH (0.061xBWm), then followed by SJ (0.047xBW), and then NW (0.007xBW). Knee flexion angle, at which knee compressive forces was maximum during motion showed that during NW, the flexion angle was -2,2 (over extension), during FH was 43.9, and SJ was 46.2 degree of angle.

This result demonstrated the potential of AMS to be used in analyzing knee joint force patterns among healthy subjects. Future studies which focus on the comparison with patients pre-post ACL reconstruction during the same type of movement, would generate a clearer view for practitioners or clinicians about the loading condition in the knee during active movements, so that optimized rehabilitation programs for ACL patients can be achieved.

Keywords: musculoskeletal model, AnyBody Modeling System, Knee joint forces and moments

4.1 Introduction

Knowing knee joint forces during gait is very valuable in understanding the biomechanics of normal gait and useful for studying gait abnormalities, rehabilitation procedures of various injuries, and essential for designing total knee prostheses (Lundberg et al., 2012; D'Lima et al., 2006) and meniscus implants (Komistek et al., 2005; Meakin et al., 2003) since measuring them in vivo is still a challenging task [Erdemir et al., 2007]. Successful in vivo measurement of human hip joint forces was done by a few scientists in the past [Rydell., 1966; Davy et al., 1988, Bergmann et al., 1993]. Also knee joint forces were measured [Kutzner et al., 2010; D'Lima et al., 2006; Burny et al., 2000; Morris et al., 2001].

In the past, some studies have been done to predict the knee joint forces or knee compressive force during normal walking [Lundberg et al., 2012]. A study done by [Paul., 1965 and 1976] predicted knee compressive force during level walking (2.7 BW during slow walking and 4.3 BW during fast walking), another study by [Taylor et al., 1998] who applied a telemetric distal femoral replacement device to measure maximum knee joint force during level walking showed that 2.2 to 2.5 BW was the result. A more up to date study using instrumented knee implant by [Kutzner et al., 2010] showed knee compressive force at 2.61 BW during level walking. Different activities have also been tested by [Taylor and Walker., 2001; Kutzner et al,. 2010], Bergmann reported knee joint forces during stair ascending (3.16 BW), stair descending (3.46 BW), one-legged stance (2.59 BW) and knee bending (2.53 BW). During jogging, the maximum knee compressive force was increased to 3.6 BW, reported by [Taylor and Walker., 2001].

These studies mostly tested normal walking activity through prostheses. Disadvantage of those measurements is that they used instrumented joint prostheses, which is not really representing a real physiological situation and does not provide insights into joint loading related to (ACL) ligament injuries. An alternative way to assess internal joint forces and moment prediction is to use numerical models or simulation models [Komistek et al., 2005;Erdemir et al., 2007].

Modeling studies for predicting knee compressive force have also been done by some researchers in the past, such as [Rosenthal and Sherman., 1986; Fregly and Zajac., 1996]. They developed a model with fluoroscopic data input and predicted that the maximum knee compressive forces during walking with female subjects depends on the walking speed and was in the range of 1.7 – 2.3 BW. Moreover, other modeling studies which have used the AMS for prediction purposes have been done by [Damsgaard et al., 2006; Zee et al., 2007; Rasmussen et al., 2001; Andersen et al., 2011]. Even though some different activities such as stair climbing or jogging were also tested and modeled previously, we could find no publications about the force predictions with activities that are highly relevant to ACL-deficient patients such as one-legged forward hopping and side jumping [Sekiya et al., 1998].

The AnyBody Modeling System (AMS) is a modeling tool for simulating human dynamics, capable of predicting knee joint forces and moments by using motion capture data and force plate information from a gait lab. The AMS repository folder includes many musculoskeletal models. The most common model that is used to analyze lower extremity motion is the GaitLowerExtremity model (www.anyscript.org). It is a musculoskeletal model of the human lower extremity, and it consists of the limbs including pelvis, but without upper body. This model is equipped with all muscles in the lower limb. When a movement is defined using markers and ground reaction forces (GRF), muscle forces and knee joint forces can be estimated by inverse dynamic calculations.

The main goal of this modeling study is to determine the knee joint forces in all three planes among healthy volunteers who performed normal walking (NW), one-legged forward hopping (FH) and side jumping (SJ), and to record individual and inter-individual differences. These results can be used to optimize ACL reconstruction. The second goal was to provide data for detailed knee modeling.

4.2 Materials and Methods

This study involved ten healthy subjects. The inclusion criteria for participation in the experiment were: being able to walk, do one-legged forward hopping and side jumping without any help or support and age above 18 years.

The exclusion criteria were defined as follows: the healthy subjects should not have pain in the knee or other lower limb parts that could cause abnormal NW, FH or SJ, should not have lower limb trauma that caused an imbalance in NW, FH and SJ, should not have neurological and metabolic disorders that have an effect on lower limb functioning (*diagnosed by a sports physician*) and should not have inflammatory arthritis of the foot, ankle, knee, hip and back (*diagnosed by a sports physician*).

The characteristics of all subjects (6 males and 4 females) were: mean age of 29.8 ± 6.6 years, mean body weight 67.7 ± 8.18 kg, mean body height 168 ± 4.6 cm, and mean right leg length of 87.0 ± 4.9 cm. The study was approved by the Medical Ethical Committee of the University Medical Center Groningen (UMCG). Every subject signed an inform consent before performing the trials in the gait lab.

4.2.1.Experiment set-up

This experiment was performed in a Gait Laboratory (Centre for Rehabilitation Medicine, UMCG, Groningen, The Netherlands) which was equipped with an 9.0 m long walkway for performing NW, FH and SJ. Two force plates (BP400600-1000, AMTI, Watertown, MA, USA) were embedded on the floor. The force plates measured the ground reaction force (GRF) with a sampling frequency of 1000 Hz. Two cameras (Basler A602 FC, Basler AG, Ahrensburg, DE) in fixed positions were used to record the performances with sampling frequency of 50 Hz. Recording, synchronising and analysing were performed with a motion system (Vicon Motion System, 14 Minus Park, West Way, Oxford, OX-2OJB, UK).

Sixteen reflective markers were attached to bony landmarks on both lower limbs of every subject so that the eight infrared cameras could record the trajectories of the markers during motion. The location of placing the markers was based on the study of Hayes and Davis [Davis et al., 1991]. Non-invasive EMG Zerowire electrodes (ConMedCleartrode ref. 1720-003, Aurion SRL, Milan, Italy) were used for subjects comfort to record the muscle activity of the right lower limb. The skin was shaved and cleaned carefully with alcohol before the EMG electrodes were attached on the muscles: Rectus Femoris, VastusMedialis, VastusLateralis, Semitendinosus, Bicepfemoris, Gastrocnemius Medialis, Gastrocnemius Lateralis and Tibialis Anterior. SENIAM standard placement was used as guidance for EMG electrodes placement [Hermens et al., 2000].

4.2.2Protocol for Normal Walking, Forward Hopping and Side Jumping

4.2.2.1 Normal Walking (NW)

The subjects were asked to walk at a self-selected walking speed on the walking path in the gait lab. For every subject, three trials with “clean” hits (i.e. full foot support of the right leg/foot on one of the force plates) were recorded. The data were taken from 100% of gait cycle (from the first right leg initial contact until the second right leg initial contact). The first signal from the force plate due to the foot initial contact was used to define the first initial contact timing. The measured data were then verified using visual inspection (video) and measured EMG were also being compared to normal walking as described by [Winter., 1991] in order to remove trials with abnormal walking patterns.

4.2.2.2 Forward Hopping (FH)

The healthy volunteers were asked to perform one-legged FH on the two force plates on the floor of the gait lab. Only the right leg was used. The starting point of the 1st jump was set 80 cm before the first force plate. The second jump was from the 1st force plate to the 2nd force plate, being continued with the 3rd jump, from the 2nd force plate to the ground at a about 80 cm after the 2nd force plate (landing area). A small step of the right foot prior the 1st jumping was usually done by every subject in order to prepare their 1st jump. Analysis of the data started at the 1st force peak from the 1st force plate and ended when the foot left the 2nd force plate. Errors during the trials were excluded from further analysis such as the presence of flying markers, unstable/unbalance landing or zigzag hopping. Subjects were asked to repeat the performance until 3 complete FH data sets were obtained from the measurement (see figure 1).

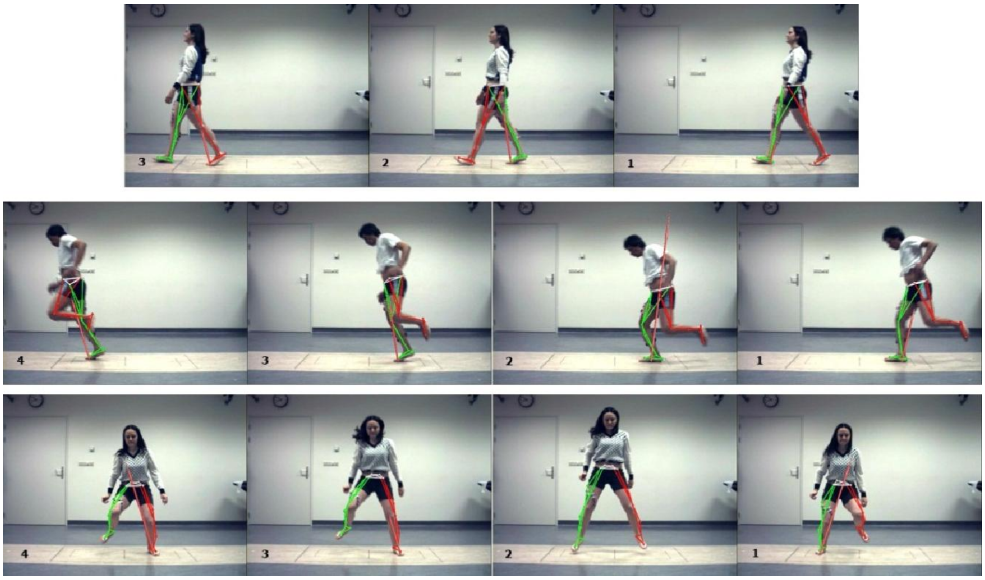

Fig1. Video view of all three activities, first row: normal walking ; second row: one-legged forward hopping; third row: side jumping (the performance was described in sequence number)

4.2.2.3 Side Jumping (SJ)

The starting point during SJ was different from FH. In SJ, thesubject stood beside the first force plate (see figure 1), ready to jump with the right leg on the 1st force plate and then to jump with the left leg on the 2nd force plate. This performance was done repeatedly during 10 seconds. Analysis of the data started when the right foot hit the first force plate for the first time until the right foot left the force plate for the 3rd time. This SJ trial was repeated until 3 complete data sets with no-errors of SJ were obtained.

4.2.3 AnyBody Modeling System(AMS)

AnyBody modeling software version 5.0 with the GaitLowerExtremity model (AMMR.1.3.1) from the repository folder (www.anybody.aau.dk/repository) was used to model NW, FH and SJ activity. Anthropometric data such as body weight, body height, pelvis, thigh, shanks and foot length were imported from measurements. The default scaling algorithm in AMS, which was based on mass-fat scalingalgorithm, was applied [Andersen et al., 2010]. In this model, the knee is represented by a hinge. This type of the knee enables only rotation in the sagittal plane. With inverse dynamic algorithms applied in AMS, all knee joint forces in 3 planes (anterior-posterior: AP, medial-lateral: ML, proximal-distal: compressive force) and 2 knee joint moments (axial moment and varus valgus moment) were predicted. The orientation of the 3 knee joint forces and 2 knee joint moments is defined relative to the femur coordinate system as depicted in fig 2.

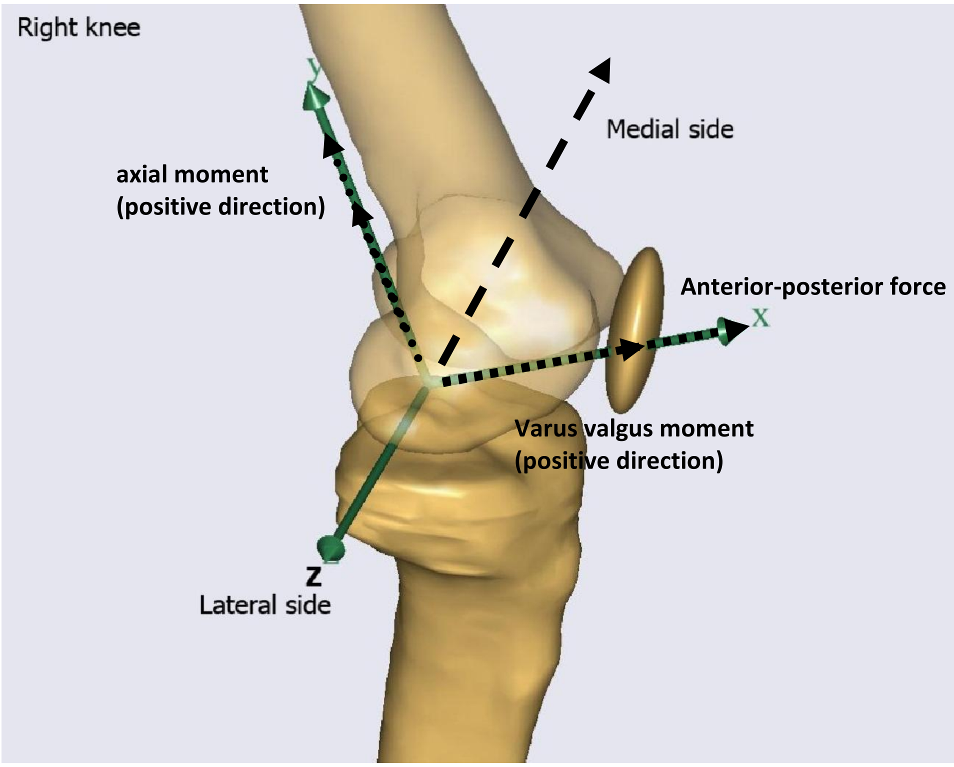

Fig2. Femur coordinate system of a right knee for determining the positive knee joint force directions, X-direction = Anterior-Posterior force, Y-direction = Proximal-Distal force (compressive), Z-direction= Medial-Lateral force. Positive moment is following the right hand rule (the figure was grabbed from the simulation).

4.2.4 Data analysis

From the 10 healthy subjects who performed waking (NW), forward hopping (FH) and side jumping (SJ), we determined 30 models for each activity because every activity was performed three times. Due to some marker errors during the measurements, for NW we included 24 models (from 8 subjects), for FH 30 models (from 10 subjects) and for SJ 27 models (from 9 subjects). From each model, we took the maximum knee joint force and in all 3 directions, compressive (C), medial-lateral (M-L) and anterior-posterior (A-P) and the maximum knee joint moment, axial moment (AX) and varus-valgus moment (VV), divided by the individual body weight to make it independent from the individuals weight (in BW and BMm). The individual knee joint forces variation (in BW) and intra-individual knee joint forces variation were calculated.

4.3 Results

Typical knee joint force and moment graphs with knee flexion information from the same subject during 3 different activities are shown in figure 2-4. Table 1 shows the individual variation during all three activities (from the 7 subjects who completed three good trials for three activities). We can see that during FH, the mean of knee compressive force (Cf) (in BW) was the biggest (ranging from 7.14-12.94 BW), followed by SJ (ranging from 5.49-9.82 BW) then NW (ranging from 3.08-6.06 BW). T-test showed a significance difference between mean of maximum knee Cf in FH and NW, and in SJ and NW. Between FH and SJ, the difference was also significance ($p<0.05$).

Table 2 shows the prediction of knee joint forces and moments relative to BW. In that table we see that FH contributed the biggest mean of knee compressive force (Cf) (10.3BW), followed by SJ (7.9BW) and then NW (4.2BW). Similar condition happened also in knee anterior-posterior force (A-P), FH showed the biggest mean of A-P force (5.62 BW), followed by SJ (4.54 BW), then NW (0.52 BW). This A-P force directed posteriorly, since this force is a reaction force in the knee in A-P plane, it shows that during FH and SJ, the ACL ligament is much more stretched and riscier to injury compared NW.

Table 3 shows the relative relationship betweenother knee joint forces and moments with knee compressive force (CF). From this table we can see that knee A-P forces from FH and SJ that directing posteriorly were more than 50% of knee Cf. Since the knee contact area was modeled by GLEM as a knee contact point, it is important to understand the relation of knee A-P force and knee M-L force with the knee Cf, since those all 3 forces are the projection of the real knee reaction force in 3 direction.

Table 4 shows the mean of the flexion angle where the knee joint forces and moments were maximum. It is shown that during NW, the maximum knee Cf was achieved when the knee flexion was at about zero or standing position (-2.2 degree), compared to FH and SJ, the knee Cf was maximum when the knee was at 43.9 and 46.2 degree of flexion respectively (in average 45 degree). If we look at the knee A-P force, during NW, the maximum knee A-P force was achieved when the knee was at 4.86 degree of flexion (almost standing), while in FH, the knee was at about 17.5 degree of flexion, and during SJ was 43.2 degree of flexion.

If we look at table 1 and table 2, AMS described well that the leg produced bigger knee joint forces and moment during FH and SJ, compared to NW. This described also the potential of knee injury during those two activities compared to NW.

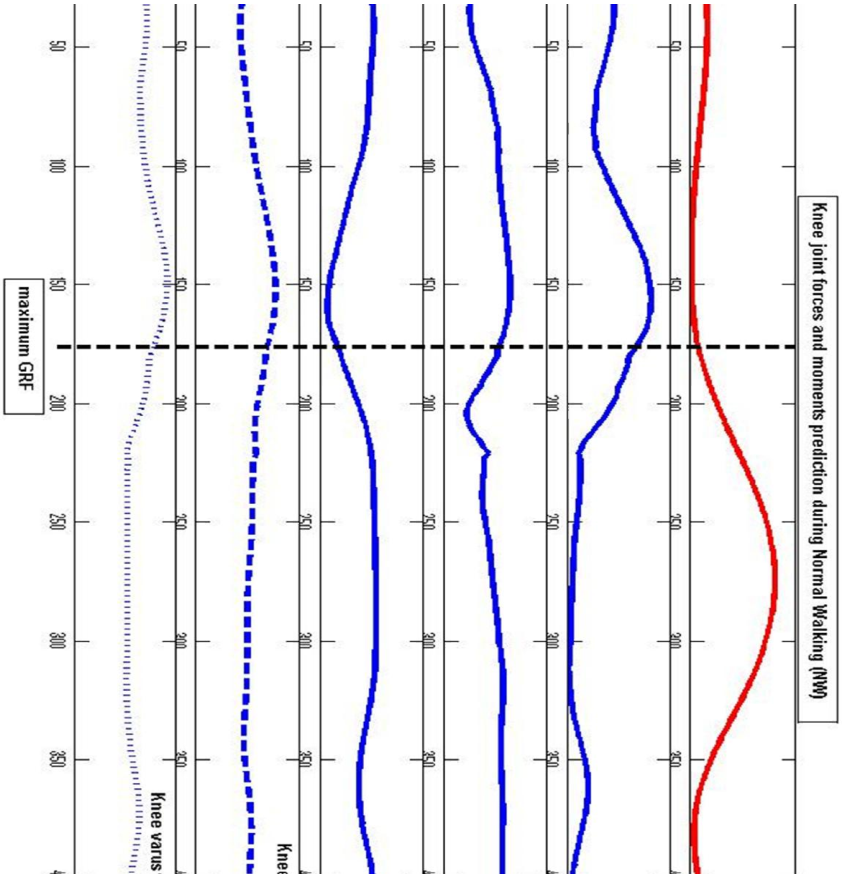

Fig3. Typical knee joint forces and moments prediction during NW (from model lydw02), red line is knee flexion angle , blue line is the 3D knee joint force prediction, dash line and dot line are the knee joint moment prediction

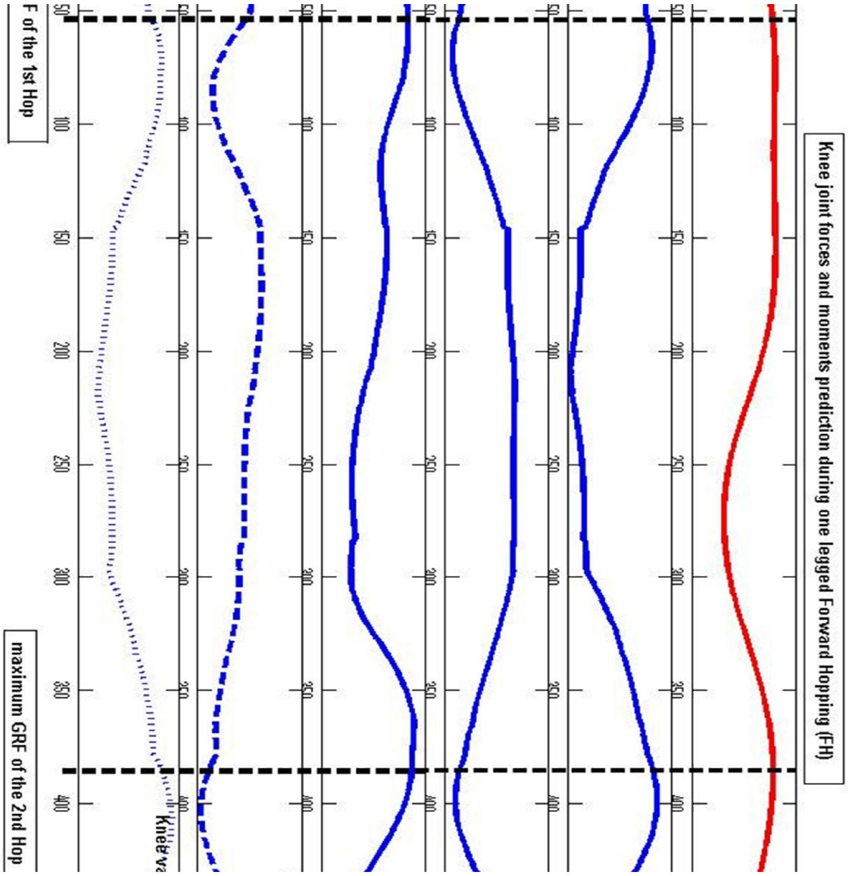

Fig4. Typical knee joint forces and moments prediction during one-legged Forward Hopping (FH) (from model lydh02), red line is knee flexion angle , blue line is the 3D knee joint force prediction, dash line and dot line are the knee joint moment prediction

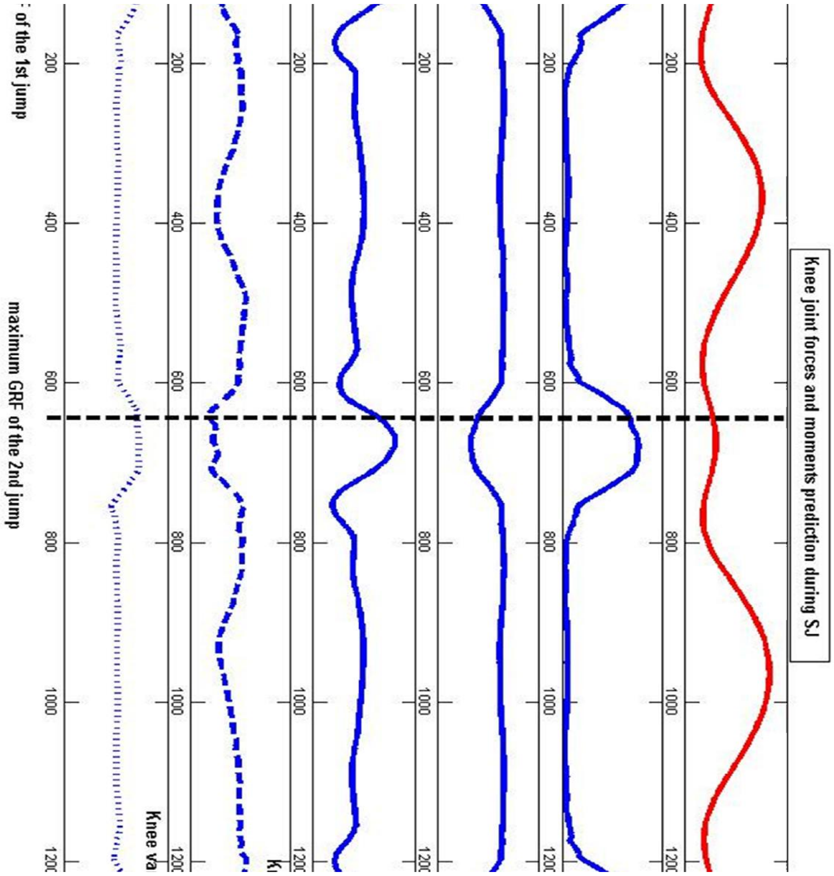

Fig5. Typical knee joint forces and moments prediction during Side Jumping (SJ) (from model lydsj01), red line is knee flexion angle , blue line is the 3D knee joint force prediction, dash line and dot line are the knee joint moment prediction

Table 1. Individual knee compressive force relative to individual BW during NW, FH and SJ

Knee Compressive force relative to BW

Normal Walking (NW)		**Forward Hopping (FH)**		**Side jumping (SJ)**	
	(BW)		(BW)		(BW)
Subject1	6.06	Subject1	11.36	Subject1	7.23
Subject2	3.08	Subject2	10.82	Subject2	7.04
Subject3	4.02	Subject3	10.46	Subject3	7.84
Subject4	3.89	Subject4	9.82	Subject4	8.71
Subject5	4.63	Subject5	12.94	Subject5	9.82
Subject6	6.00	Subject6	9.65	Subject6	6.78
Subject7	3.76	Subject7	9.93	Subject7	7.97

Min – Max (BW)	**3.08 – 6.06**	**Min – max (BW)**	**7.14 – 12.94**	**Min – max (BW)**	**5.49 – 9.82**

Table 2. Knee joint forces and moments during NW, FH and SJ averaged over all models;

Mean of maximum Knee compressive (N)				**Mean of maximum Knee anterior – posterior force (N)**					
	Compressive force	SD	BW	Anterior	SD	BW	Posterior	SD	BW
NW	2865	771	4.2	210	250	0.31	357	191	0.52
FH	7015	728	10.3	23	47	0.03	3825	773	5.62
SJ	5365	947	7.9	34	17	0.05	3095	481	4.54

Mean of maximum Knee medial – lateral force (N)					
Medial	SD	BW	Lateral	SD	BW
16	8	0.02	231	76	0.34

178	105	0.26	239	165	0.35
179	70	0.26	238	77	0.35

	Mean of maximum Knee axial moment(Nm)						**Mean of maximum Knee varus-valgus moment(Nm)**					
	Medial	SD	BWm	Lateral	SD	BWm	Valgus	SD	BWm	Varus	SD	BWm
NW	12	5	0.1	5	2	0.01	2	1	0.003	56	16	0.08
FH	6	3	0.01	42	14	0.06	2	4	0.003	90	20	0.13
SJ	4	3	0.01	32	12	0.05	9	4	0.013	72	21	0.11

*BW is calculated by dividing the mean of predicted knee joint forces or moments by mean of the body weight

Table 3.Knee joint forces relative to knee compressive force (CF), averaged from all over the models

	Normal Walking (NW)	**Forward Hopping (FH)**	**Side jumping (SJ)**
Direction of force	**(in Cf)**	**(in Cf)**	**(in Cf)**
Anterior	0.073	0.003	0.006
Posterior	**0.12**	**0.55**	**0.57**
Medial	0.005	0.025	0.03
Lateral	0.08	0.034	0.04

*This data was taken from the mean of maximum forces from all models during NW, FH and SJ

Table 4. Mean (and ± SD) of knee flexion angle where the knee joint forces and moments were maximal during NW, FH and SJ

	Mean of knee flexion angle (Degree)	SD
Normal Walking		
Compressive force	**-2.2**	6.4
A-P force	**4.86**	23.3
M-L force	**37.2**	20.6
Axial moment	**-2.7**	6.6
Varus Valgus moment	**-2.4**	6.5
One-legged Forward Hopping		
Compressive force	**43.9**	7.3
A-P force	**17.5**	11.9
M-L force	**41.8**	10.9
Axial moment	**25.2**	7.9
Varus Valgus moment	**41.2**	6.0
Side Jumping		
Compressive force	**46.2**	7.0
A-P force	**43.2**	15.8
M-L force	**61.6**	25.6
Axial moment	**51.2**	19.3
Varus Valgus moment	**46.7**	7.2

*this mean value was taken from 7 subjects who performed equally 3 trials in each activity (refers to table 3)

4.4 Discussion and Conclusion

This result has shown the kinetic differences during three different activities (NW, FH and SJ), which is certainly has shown too the capabilities of AMS in describing different motions. These knee joint force and moment data is essential in describing the motion condition of healthy subjects performing those three activities, especially in this pilot study. A good example can be seen using Knee A-P force prediction. In this prediction we can see clearly that knee A-P force (relative to knee compressive force – see table 2) during NW was not significant compared to FH and SJ, scientifically this express the more important role of the ACL during those two activities rather than in NW.

In general (see table 1), knee compressive force (Cf) was the biggest reaction force in the knee. Significant difference was recorded when comparing knee Cf during NW, FH and SJ. As we expected, during FH and SJ, knee Cf reached much higher peaks compared to NW. The mean knee Cf during NW, FH and SJ from all models consecutively was 2865N, 7015N and 5365N.

When comparing with other studies, the results of mean maximal knee compressive force (CF) predictions during normal walking (4,2 x BW) was comparable to former studies done by Paul (1965, 1976) during fast walking and Morrison (1970) during normal walking (4.2 BW). A modeling study on normal gait done by [Winby et al., 2009] gave a range of results between 3.2 – 4.9 BW with average 3.9 BW, so again confirming our results. Studies done by [Komistek et al., 2005]and [Wimmer et al., 1997] found lower CF, 1.7 – 3.3 BW during normal walking, but they tested (patients with) knee endoprostheses(TKA) for their prediction. Some aspects in modeling process may cause this difference such as inaccuracy in defining muscle attachment points or muscle-tendon parameter values which can alter the muscle moment arm that determines knee joint forces, especilly knee Cf [Fregly et al., 2011].

During FH and SJ, AMS predicted higher level of knee CF, as well as knee A-P and M-L forces compared to the same forces during NW. This was caused by higher knee muscle forces during FH and SJ, compared to NW, which again was caused by the more abrupt movements and thus higher muscle effort to control these movements. If we compare FH and SJ, during FH there is a higher knee CF than during SJ (see table 2) again due to higher muscle activity and more abrupt movements. When considering the role of the Anterior Cruciate Ligament (ACL) during FH, SJ with NW, if we look at the absolute (table 2) and relative (table 3) knee A-P force, during FH and SJ the mean of maximum knee reaction force pointing out in theposterior direction was dominant compared to that during NW. This shows the potential loads that must be taken by ACL during those movements.

Another factor that influences the tension of the ACL during active motion is the knee axial moment. In certain circumstances, this knee axial moment will twist the ACL, and could possibly lead to the ACL injury [Georgouliset al., 2010;

Woodford-Rogers et al., 1994; Uhorchak et al., 2003]. Table 2 shows that the highest knee axial moment was predicted during FH rather than during SJ and NW. The peak of knee axial moment during FH and SJ in general was negative, except during NW. This can be explained by the fact that during one-legged FH, when only the right leg was making contact with the floor, the upper-body mass tends to move laterally to avoid falling, this condition would cause the knee to rotate laterally, and create a bigger lateral moment, which, in turn, will create knee axial moment medially (negative) as a reaction of this knee moment.

When comparing to the knee lateral moment (varus-valgus moment), at the same scenario above, when there is a big knee lateral moment due to the movement of most of the upper-body to the lateral side, subsequently varus rotation (varus moment) is achieved positively (pointing out to the frontal plane) (see fig 6). This condition works also during side jumping. Even SJ creates more prescribed impact on the lateral side during motion.

This result again showed that FH and SJ activity exposed higher ACL loads compared to NW, and the potential of these activities in rupturing ACL.

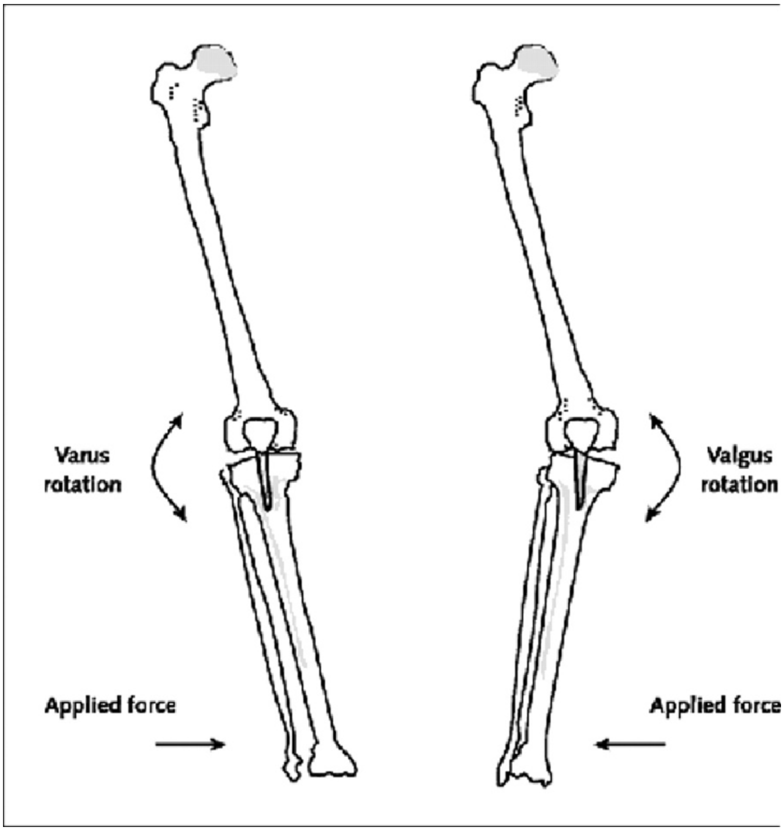

Fig 6.Varus-valgus moment of the right knee (http://annals.org)

Overall, we conclude that AMS predicted the knee joint forces and joint moments during NW, FH and SJ well, considering the agreement of our results with the previous studies described above [Winby et al., 2009]. The differences that are present can be caused by the different methods that were performed by those previous studies [Komistek et al., 1998; Wimmer et al., 1997]. Even so, referring to our result, there is still also a possibility of error in AMS's prediction, since inaccuracy in determining many important parameters such as muscle attachment point and muscle-tendon parameter values can alter the result of knee joint forces prediction [Fregly et al., 2011]. In addition to that, in inverse dynamics analysis, there are also some uncertainties in its calculation in which can cause a misleading result in modeling prediction [Riemer et al., 2008].

Despite all of those differences, the role of the ACL during active movement [McGinty et al., 2000; Meyer et al., 2008] such as NW, FH and SJ was describd very well by this musculoskeletal model, considering the prediction on knee compressive force and knee A-P force during NW, FH and SJ. In the future, this healthy knee joint force and moment pattern can be used as a comparison tool for patient pre or post ACLreconstruction.

This result has demonstrated obviously a high potential of AMS to be used for developing clinical interventions for patients, like pre or post ACL reconstruction, by studying their 3D knee joint forces and moments prediction patterns during rehabilitation program.Further studies on full body part modeling should predict more accurately and objectively knee joint forces during the same movement since according to [McGinty et al., 2000] these activities (NW, FH and SJ) are categorized as Closed Kinetic Chain (CKC) motions which means that the distal segment of the knee joint was influenced by the moment of the upper body part [Mesfar et al., 2005], which is not yet done in this study.

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Chapter 5

Muscle activity and knee joint forces prediction during kneeflexion motion

Abstract

Validating a musculoskeletal model is still a citical issue, since adequate validation is important from a scientific as well as a clinical perspective. Validating a musculoskeletal model of AnyBody modeling system (AMS) especially during a knee flexion motionusing EMG is not yet done. Knee flexion motion is defined as a motion of the subject's lower limbs from standing position into knee flexed at 90 degrees, and keep that 90 degrees position for several seconds. Knee flexion motion is an important aspect in human locomotion and its analysis can be used to quantify the functional recovery of patients after total knee arthroplasty (TKA) surgery or patients suffering from osteoarthritis. This study modeled knee flexion motion by using the GaitLowerExtremity model (GLEM)from AMS (AMMR.1.3.1). The model used marker's motion data and ground reaction force which were obtained during in vivo experiments in a gait lab. Inverse dynamics analysis, which was adopted in AMS, was then performed by AMS to predict muscle activity and knee joint forces and moments during motion. During the experiments, EMG was measured to determine the activity of 8 lower limb muscles and used to validate the predicted muscle activity by calculating the Pearson correlation coefficient. In addition, knee compressive force during knee flexion, as one of the prediction outputs, was compared with reported studies.

According to the Pearson correlation coefficient, three muscles showed a strong correlation, four muscles showed a moderate correlation and one muscle showed a weak correlation. Time delay between AMS and EMG was recorded for muscles Vastus Medialis (18.38ms) and Vastus Lateralis (22.8ms) with EMG was prior to AMS. The mean of the maximum knee compressive force prediction was 2.29xBW. The differences between AMS and EMG can be explained by the reduced co-contraction phenomenon in GLEM (AMMR.1.3.1), besides time delay in activating muscles by AMS.

Keywords: Knee flexion motion, AnyBody Musculoskeletal System, Inverse dynamics analysis, EMG

5.1 Introduction

Studying human biomechanics especially during active movements is still challenging nowadays. Muscle activation during active motion is controlled and triggered by the central nervous system (CNS). The exact mechanism of muscle activation by the CNS and all aspects that may influence the resulting movement are not clear [Deliagina et al., 2007]. In addition, forces and moments in joints such as the knee are difficult to obtain and thus remain causes of knee ligament injuries during movement unclear [Meyer et al., 2008; Hashemi et al., 2011]. An alternative way in accessing knee joint forces and joint moments is by developing a prediction tools like a musculoskeletal model [Damsgaard et al., 2006]. We intend to use such a model for optimizing anterior cruciate ligament (ACL) reconstruction. In that project, the role of ACL and its position in the knee will be simulated during active movement so that ACL reconstruction can be done in a subject-specific manner, which will optimize the functional outcome. To allow the use of such a model, its predictive quality needs to be validated first. From a previous study, we have analyzed three movements (normal walking, one-legged forward hopping and side jumping) using a musculoskeletal modeling tool called GaitLowerExtremity model (GLEM) of AnyBody Modeling System (AMS). During those studies, muscle activity predicted by AMS model was compared to EMG using three variables: number of onset, offset and hills of the activation and EMG patterns, respectively. The match between AMS and EMG during normal walking was low. However, during more prescribed movements like one-leggedforward hopping (FH) and side jumping (SJ), the validation results were much better [see chapter 3]. In another study, we also analyzed knee joint forces and moments during the same activities, and the overall result was quite satisfying as the knee compressive force predictions from AMS during normal walking (NW) were close compared to previous studies [Winby et al., 2009; Paul., 1965 and 1976]. Essential information for future modeling studies such as knee flexion angle prediction in which the knee compressive force reaches its maximum and individual variation in knee compressive force during those three activities are the topic of this study.

From our previous studies, we found that the type of movement was playing a significant role in determining the level of agreement between GLEM of AMS and EMG. The more prescribed the motion is, the better the agreement. If we continue this line of thought, the simplest motion like knee flexion motion may show an even better agreement between modeling and in vivo measurement. Since knee flexion motion is such a basic human motion many studies have been published that explored the biomechanical aspects of this motion [Dennis et al., 2013;Erdemiret al., 2007; Kaufman et al., 1991]. Another potential of this motion is its use in describing the quality of Total Knee Arthroplasty (TKA) surgery [Dennis et al., 2013] or quantifying the limitations of patients suffering from Osteoarthritis (OA) or rheumatoid arthritis [Harato et al., 2008]. Some modeling studies in approximating knee joint forces or muscle forces during knee flexion were done by several researchers in the past [Dul et al., 1984; Li et al., 1999; Forster et al., 2004], a robotic simulation study by using cadavers in approximating knee kinematics and kinetics was also done previously by [Li et al., 2004]. However, analyzing and comparing the predicted muscle activity by the GaitLowerExtremity model from AMS with EMG information from an in vivo experiment and predict knee joint forces through AMS modeling during knee flexion motion has not been done yet.

The first goal of this study is exploring the level of agreement between muscle activity which is predicted by GLEM and muscle activity derived from EMG measurement during knee flexion motion. Knee flexion motion is a motion starting from standing, then flexing the knee into about 90 degrees, and then keep that position for several seconds.The reason we chose this motion is because it is a very simple and reproducible motion which is rather slow and even static at 90 degrees of flexion allowing for an optimal comparison of the model predictions with EMG measurements.

The musculoskeletal model output depends quite heavily on the optimization criterion chosen to calculate the muscle activation levels. If activation energy or maximal muscle forces is minimized it is logical that the model will not predict a great deal of co-contraction. We therefore hypothese that since AMS has not adopted yet a co-contraction term in the optimization criterion, some muscles (like knee flexors or extensors) will show a significant different activity compared to EMG.

The second goal is analyzing knee joint forces and moments which are predicted by the model, and compare the result with previous studies. Furthermore, it will be analyzed under which circumstance AMS predicts better or less in terms of muscle activity compared to our previous studies.

5.2 Material and method

This study involved five healthy subjects performing knee flexion motion. The characteristics of the subjects (2 males and 3 females) are: mean age of 27.8 ± 5 years, mean body weight 63.9 ± 4.9 kg.The exclusion criteria were defined as follows: the healthy subjects should not have pain in the knee or other lower limb parts that could cause abnormal knee flexion, should not have lower limb trauma that caused an imbalance during knee flexion, should not have neurological and metabolic disorders that have an effect on lower limb functioning and should not have inflammatory arthritis of the foot, ankle, knee, hip and back. The study was approved by the Medical Ethical Committee of the University Medical Center Groningen (UMCG). Every subject signed an inform consent before performing the trials in the gait lab.

5.2.1.Experimental set-up

This experiment was performed in a Gait Laboratory (Centre for Rehabilitation Medicine, UMCG, Groningen, The Netherlands) which was equipped with an 9.0 m long walkway. Two force plates (BP400600-1000, AMTI, Watertown, MA, USA) were placed in the floor. The force plates measured the ground reaction force (GRF) with a sampling frequency of 1000 Hz. Two cameras (Basler A602 FC, Basler AG, Ahrensburg, DE) in fixed positions were used to record the performances with sampling frequency of 50 Hz. Recording, synchronising and analysing were performed with a motion system (Vicon Motion System, 14 Minus Park, West Way, Oxford, OX-2OJB, UK). Sixteen reflective markers were attached to bony landmarks on both lower limbs of every subject so that the eight infrared cameras could record the trajectories of the markers during motion. The location of placing the markers was based on the study of Hayes and Davis [Davis et al., 1991].

Non-invasive EMG Zerowire electrodes (ConMedCleartrode ref. 1720-003, Aurion SRL, Milan, Italy) were used for subjects comfort to record the muscle activity of the right lower limb. The skin was shaved and cleaned carefully with alcohol before the EMG electrodes were attached on the muscles: Rectus Femoris (RF), Vastus Medialis (VM), Vastus Lateralis (VM),Semitendinosus (ST), Bicep Femoris (BF), Gastrocnemius Medialis (GM), Gastrocnemius Lateralis (GL) and Tibialis Anterior (TA). SENIAM standard placement was used as guidance for EMG electrodes placement [Hermens et al., 2000].

5.2.2 Protocol and modeling of knee flexion

The subjects were asked to stand on the force plate in an upright position (the position in fig. 1a), and wait for a sign before performing a flexion. When a sign was given, subjects performed knee flexion to approximately 90^0 (the position in fig. 1b) and maintain that position for about 3-5 seconds, then rise up again, back to the starting upright position. This performance was done three times in each trial (meaning that subjects performed three times a knee flexion). For data modeling and analysis, we limited the number of frames only until subjects maintain a position of knee flexed for a computation time reason. Hence, we did not analyse and model the motion from knee in flexed position into standing up again. All data, including EMG data, were implemented in a so-called C3D file. The marker trajectories and ground reaction force data were then used to model the motion.

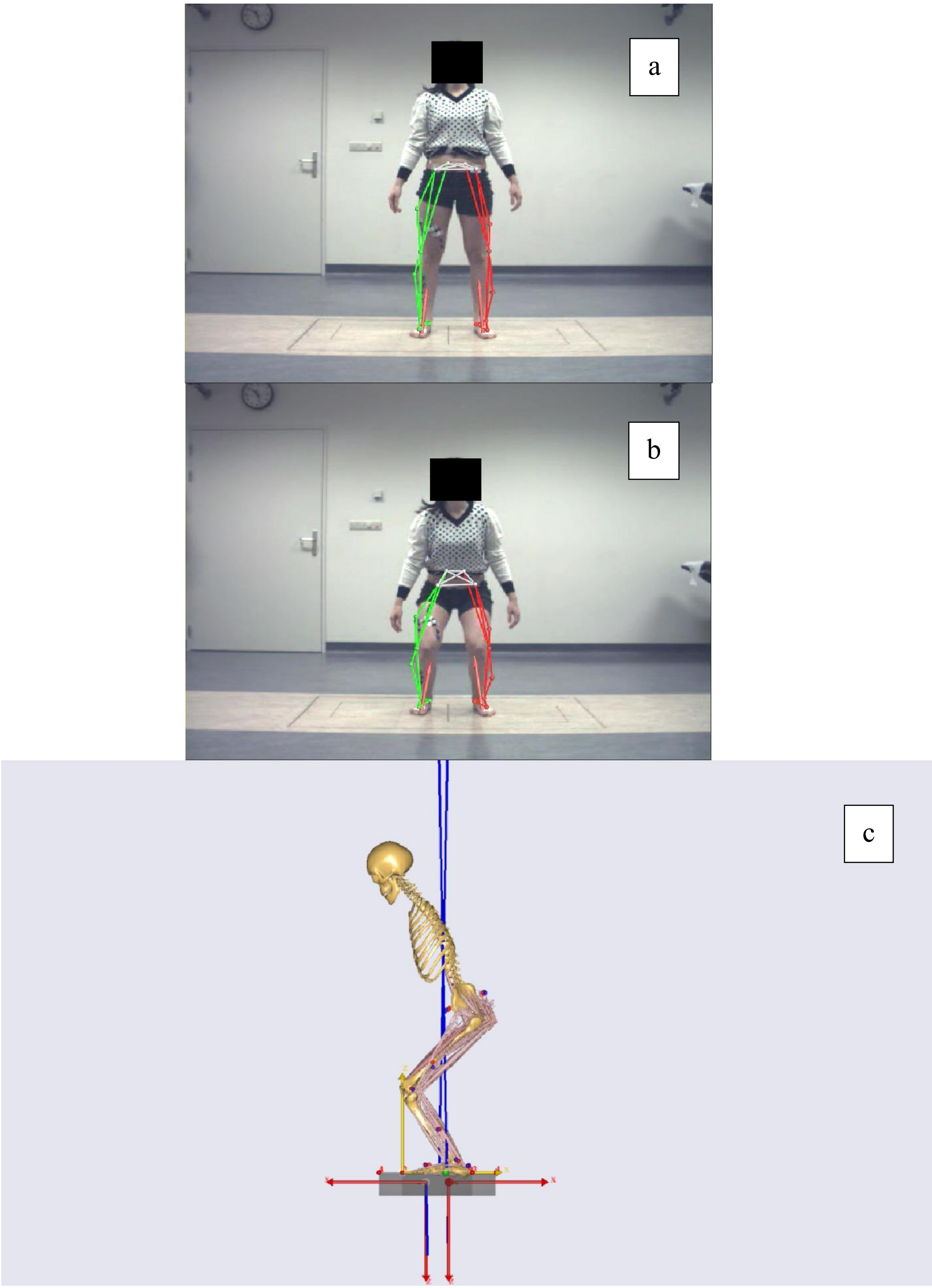


Fig1.Standing position before knee flexion (a); Knee flexion position (b); Resulting model of knee flexion (c)

We used AMS software version 5.0 with the GaitLowerExtremity model (AMMR.1.3.1) from the repository folder (www.AMS.aau.dk/repository). GaitLowerExtremity model (GLEM) is a common model that is used to study human locomotion. It consists of two lower limbs and the pelvis, with all muscles and tendons attached, but without upper body. Anthropometric data such as body weight, body height, pelvis, thigh, shanks and foot length were imported. The default scaling algorithm in AMS, which is based on a mass-fat scaling algorithm, was applied[Andersen et al., 2010]. In the model, the knee is represented by a hinge, connecting femur and tibia. This type of knee enables only movement in the sagittal plane. With inverse dynamic algorithms applied in AMS, muscle activity and all knee joint forces in 3 directions (anterior-posterior: AP, medial-lateral: ML, proximal-distal: compressive force) and 2 knee joint moments (axial moment and varus valgus moment) were predicted. The orientation of the 3 knee joint forces and 2 knee joint moments is defined by the femur coordinate system as described in fig 2.

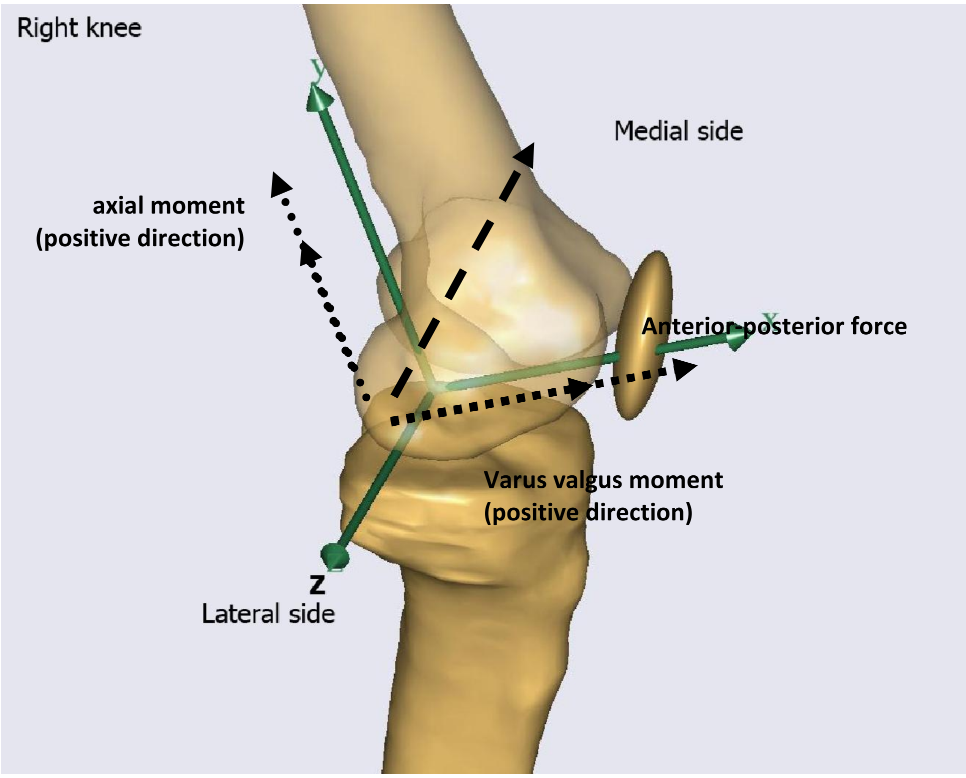


Fig2. Femur coordinate system for determining the knee joint forces direction
(the figure was grabbed from the simulation)

During the simulation, besides performing inverse dynamic calculations, AMS also was used for rectifying and filtering the raw EMG data into smoothed EMG data. In this study, AMS filtered the raw EMG using Butterworth band pass filter [Luca et al., 2010] with a frequency range of 30-200 Hz and 6 Hz low pass filter [Konrad., 2005].

5.2.3 Data analysis

5.2.3.1 Knee joint forces and moments prediction

The 5 subjects performed 3 trials of knee flexion motion, resulting in 15 knee flexion models for analysis, but due to some marker errors during experiment, there were only 13 valid knee flexion models. For knee joint forces and moments prediction analysis, the maximum value of knee joint forces and moments in all 3 direction, proximal-distal (compressive), medial-lateral (M-L) and anterior-posterior (A-P), were calculated. Subsequently the mean value of each force over allmodels was obtained.

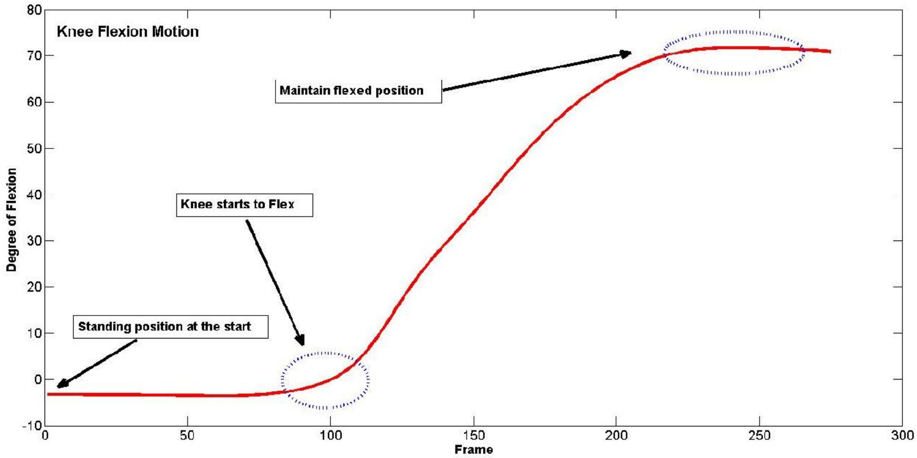
5.2.3.2 EMG comparison

Activation level of EMG is specific for each subject. This level depends greatly on subject’s anatomical condition [Luca et al., 2010; Konrad., 2005], therefore it is important to process the EMG graph, especially its baseline threshold, into a more reproducible way. In this study, before the EMG was being compared with AMS, the data were cropped from the minimum value (the lowest point of the graph) until the maximum value of the graph. So the baseline was determined by the lowest EMG data for each muscle.

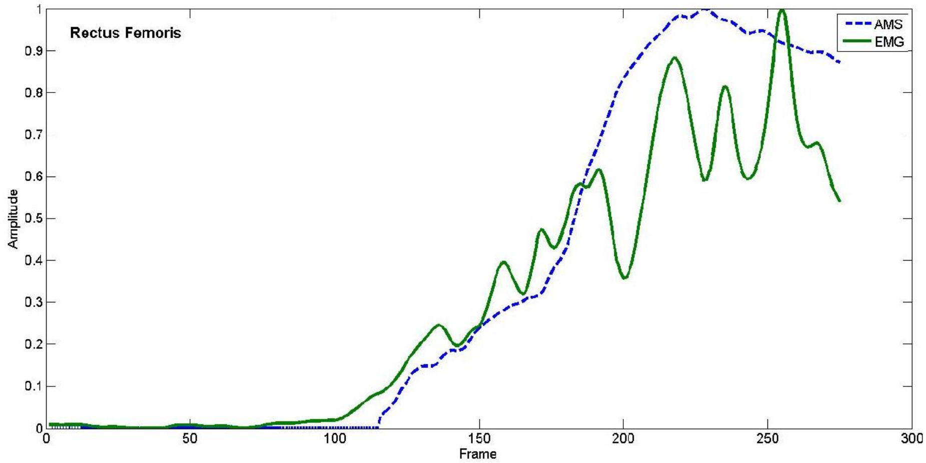
For the predicted muscle activity from AMS, baseline threshold was set at 10^{-7} meaning that all values below 10^{-7} will be zeroed. This was done because the data of predicted muscle activity from AMS never reach a zero level, so we need this threshold to define the zero level. All data processing was done using Mathlab version 2009a (www.mathworks.com). When both data (EMG and predicted muscle activity) were collected the Pearson correlation coefficient was determined as a measure for the level of agreement by comparing the graph of both dataset.Difference in number of onset and offset between EMG and AMS in this comparison is not taken into account.

5.3. Results

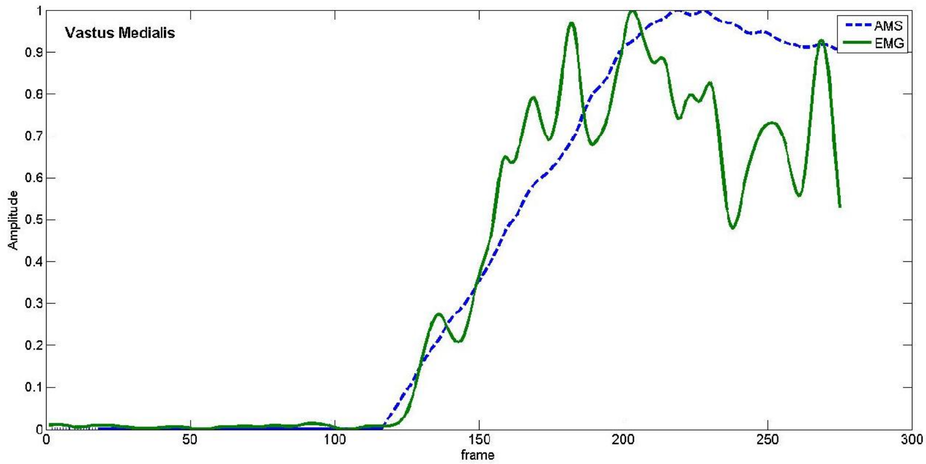
Typical EMG and predicted muscle activity by AMS per muscle during knee flexion is depicted in figure3.Other volunteers showed similar patterns. Fig. 3 shows the AMS activation and EMG signals of the leg in three stages, starting from standing position, flexing and maintaining flexing position. In general during the entire stage of motion, similar muscle activity patterns wererealized by only three muscles, RF, VM and VL. The other muscles (ST, BF, GM, GL, TA) show an opposite pattern.



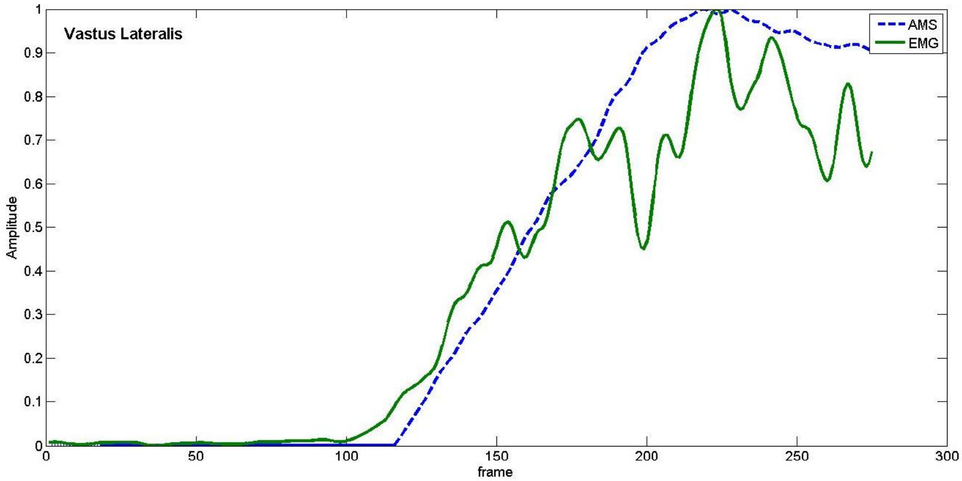
Knee Flexion Motion
Maintain flexed position
Knee starts to Flex
Standing position at the start
Degree of Flexion
Frame

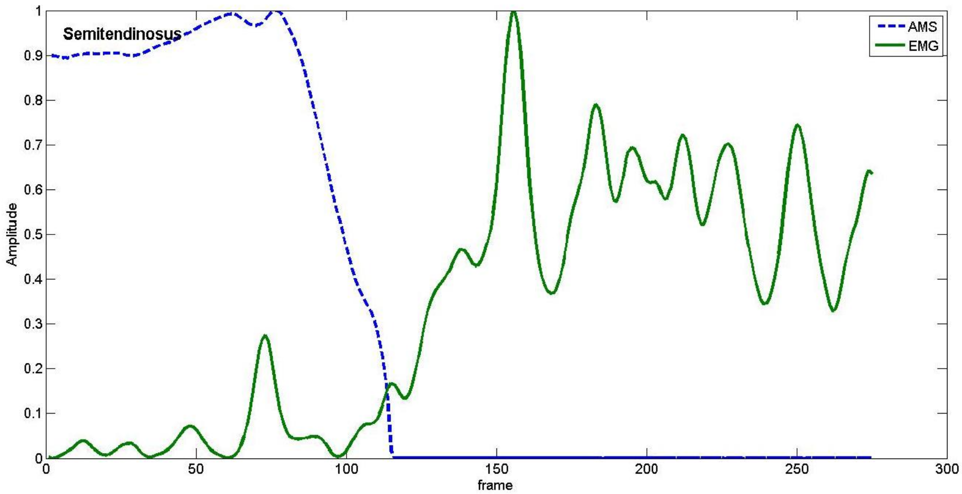


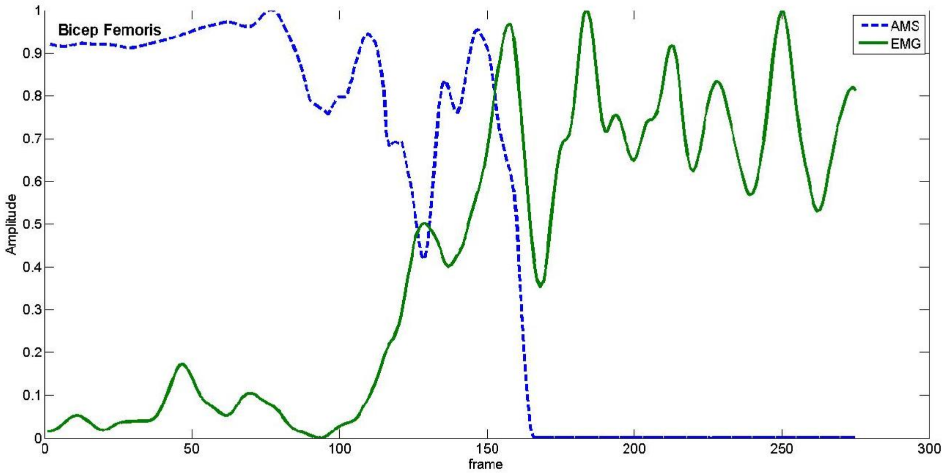
Rectus Femoris
AMS
EMG
Amplitude
Frame

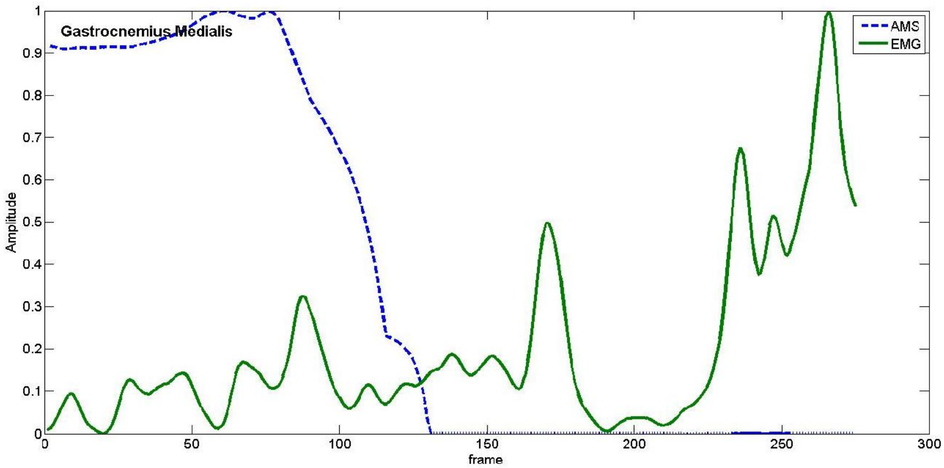


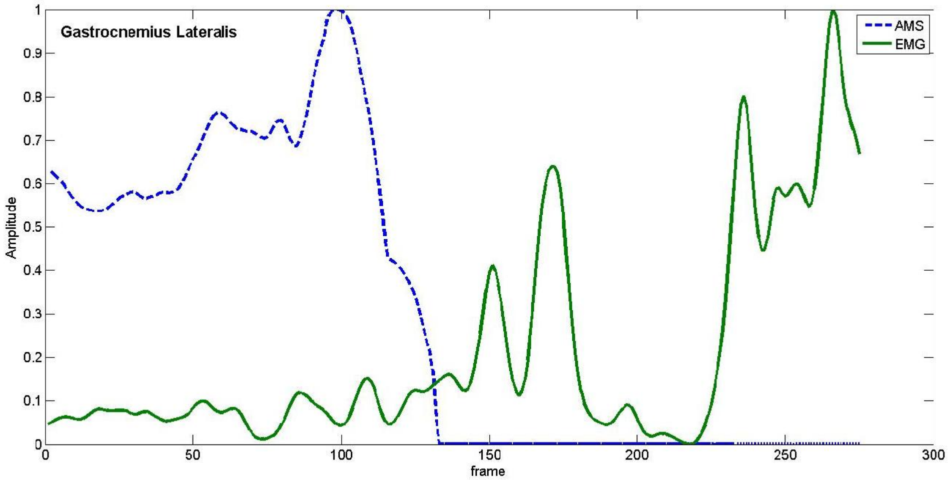
Vastus Medialis
AMS
EMG
Amplitude
frame


Vastus Lateralis
AMS
EMG
Amplitude
frame


Semitendinosus
AMS
EMG
Amplitude
frame


Bicep Femoris
AMS
EMG
Amplitude
frame


Gastrocnemius Medialis
AMS
EMG
Amplitude
frame



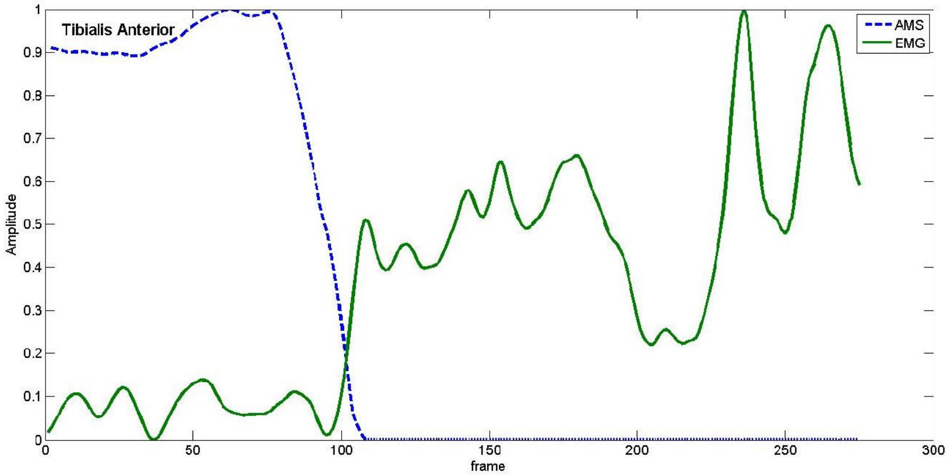


Fig 3. Group of figures of EMG and AMS comparison per muscle during knee flexion motion

When we compare EMG and predicted muscle activity by GLEM-AMS per stage, from standing position (stage 1), flexing (stage 2) and keeping the knee flexed position (stage 3), we can see that in stage 1some differences are present (see figure 3). EMG-activity of muscles ST, BF, GM, GL and TA is limited, while according to AMS those muscles show significant activity.

In stage 2, during flexing, according to the EMG first ST, BF and TA become active, followed by RF, VM and VL (see about frame 100th till 200th in figure 3). A similar pattern is present for muscle activity predicted by AMS, especially for RF, VM and VL. However, for ST, BF, GM, GL and TA the activity was even contrary to EMG.In stage 3, when the knee was maintaning the flexed position, basically all 8 muscles measured showed activity. In contrast, AMS predicted different patterns, because ST, BF, GL, GM and TA were inactive. There were only three muscles that showed a pattern similar to EMG, namely RF, VM and VL in this stage.

Typical knee joint force and moment predictions during knee flexion that also represents data of the other volunteers is shown in figure 4. The direction of forces and moments are based on femur coordinate system as described in figure 2. In fig 4 we see from frame 100 an increase of knee joint forces and moments due to flexion activity. At frame 125, the knee joint forces and moments became constant due to maintaining the flexed position.

In figure 5and 6 the mean of the maximum knee joint forces and moments over all 13 models is depicted, consecutively. The mean of maximum knee compressive force (Cf) reached 1478 N (2.3xBW), while for the knee anterior-posterior force (A-P force) was 1372 N (2.15xBW) directing posteriorly in all data (negative). The knee medial-lateral force (M-L force) reached 120 N (1.9xBW) directing laterally. The mean of the maximum knee axial moment was relative small, 7.7 Nm (0.12xBWm) directing negatively, the knee varus-valgus moment was a bit higher, 20.3 Nm (0.3xBWm) directing positively (see fig. 4). Knee compressive force per model in relation with body weight (BW) is presented in figure 7.It is shown that the variation within an individual was small, but that inter-individual variations were larger.

The Pearson correlation coefficient between muscle activity predicted by AMS and measured with EMG for all eight muscles during knee flexion motion is shown in figure 9. Only 3 muscles show a strong correlation (RF, VM and VL), one muscle (GM) shows a moderate correlation and the other 4 (ST, BF, GL and TA) show a poor correlation.

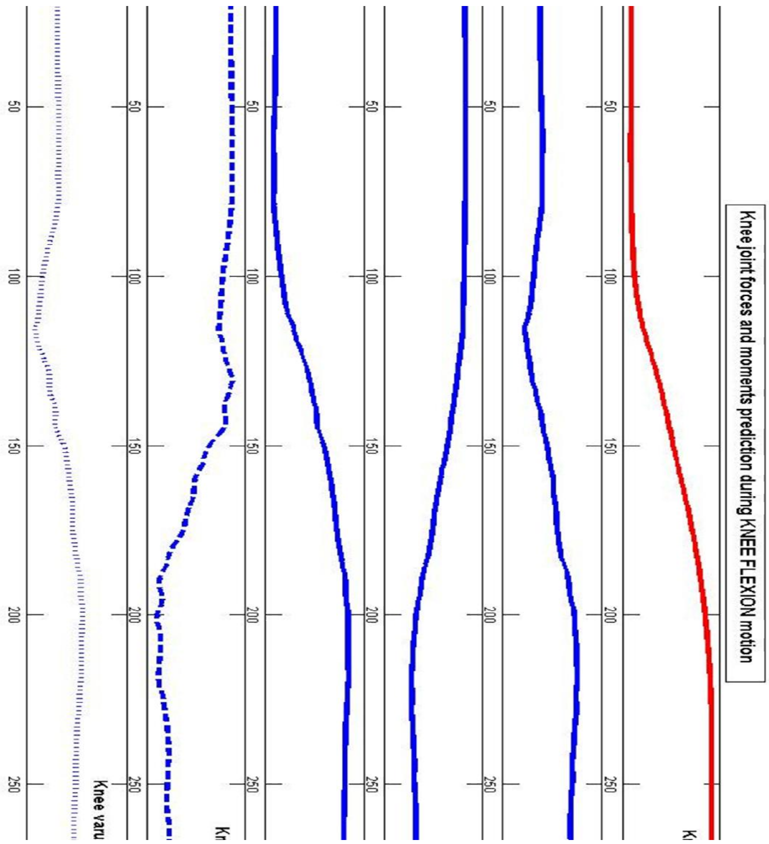


Fig4. Typical knee joint forces and moments prediction by AMS (red line is knee flexion angle, blue continues line consecutively is knee compressive force, knee anterior-posterior force and knee medial-lateral force, blue dash line and dot line consecutively are knee axial moment and knee varus valgus moments). Direction of every force and moment is refering to the description on figure 2

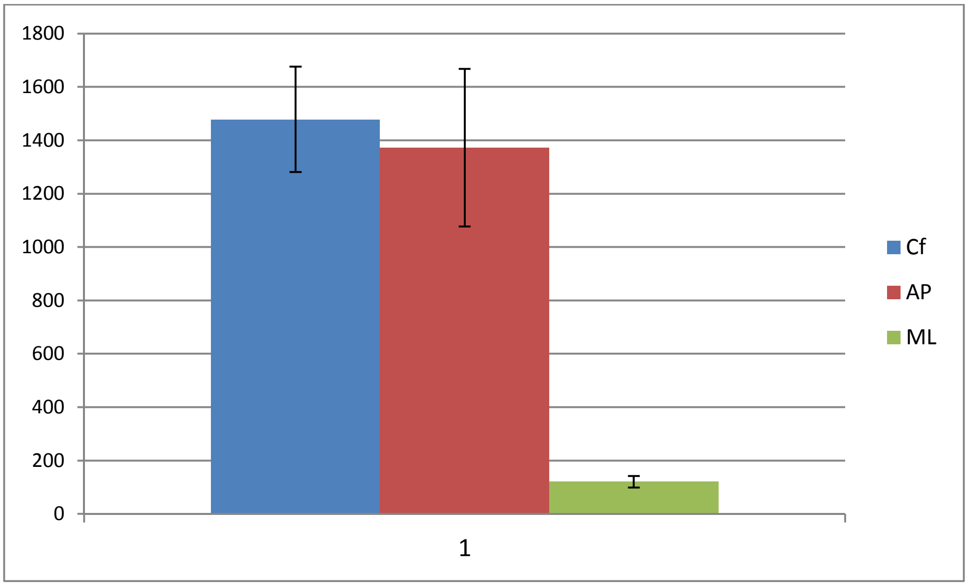


Fig5. Mean of the maximum knee joint force (N) predictions during knee flexion motion over all 13 models. (Cf : knee compressive force; AP: knee anterior-posterior force; ML: knee medial-lateral force)

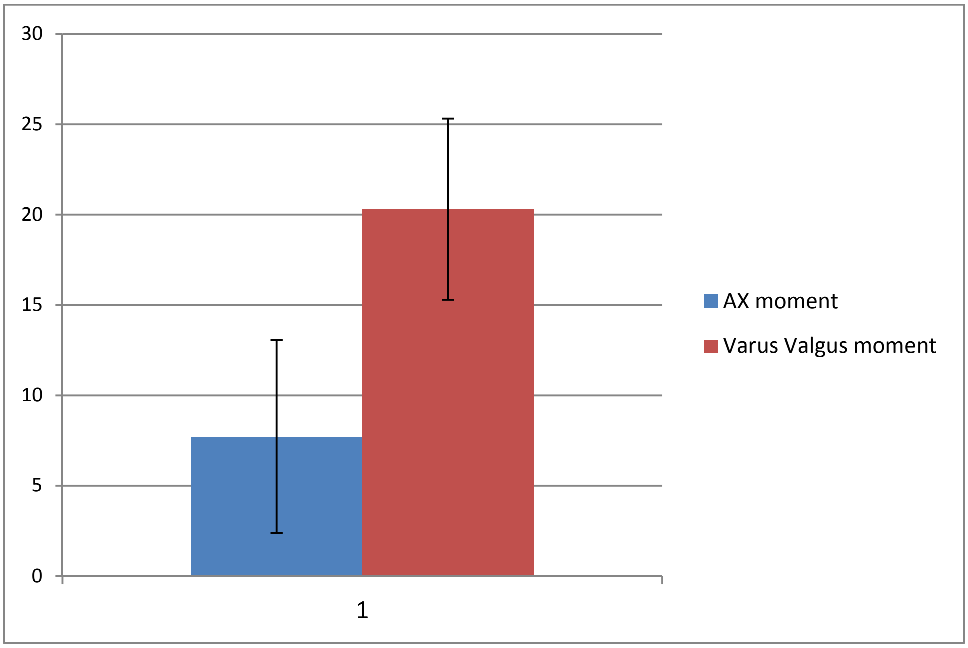


Fig6. Mean of the maximum knee joint moments (Nm) predictions during knee flexion motion over all 13 models (AX moment: knee axial moment)

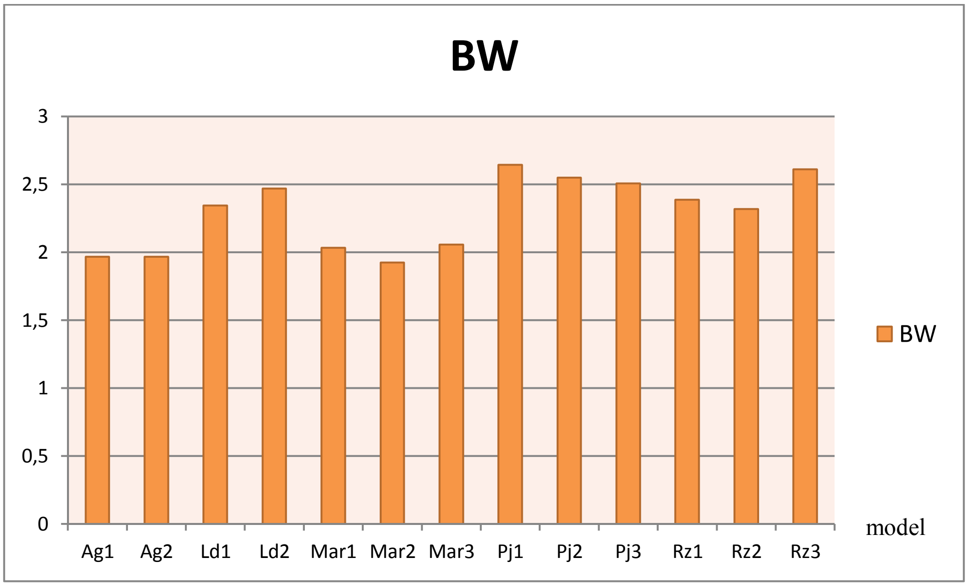


Fig7. Knee compressive force during knee flexion motion per model (two subjects (Ag and Ld) contributed 2 models, and three subjects (Mar, Pj and Rz) contributed 3 models

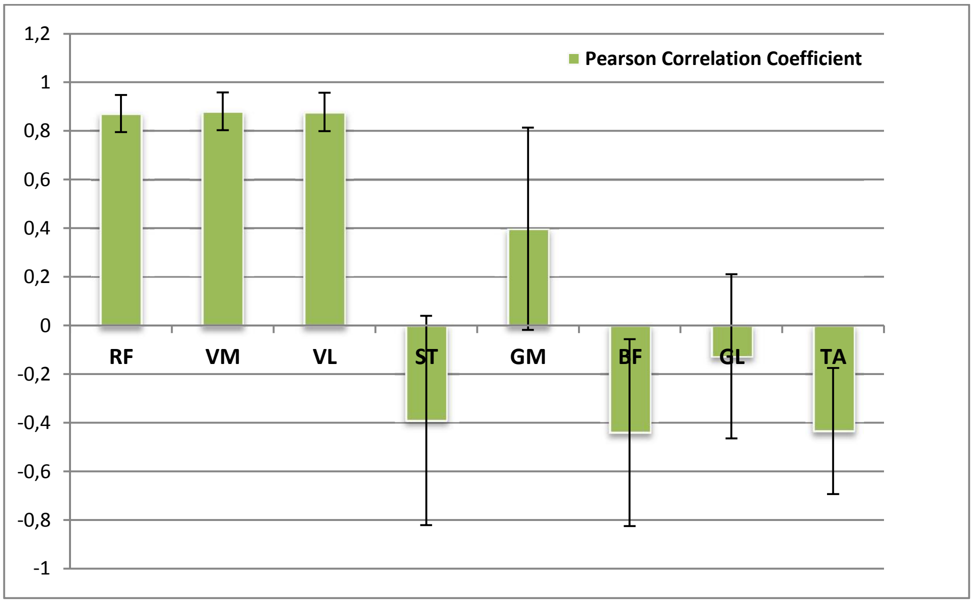


Fig8. Pearson correlation coefficient between muscle activity predicted by AMS and measured by EMG for all eight muscles during knee flexion motion

From our previous study, we found that there is a time delay between EMG and AMS. In this knee flexion modeling that delay was shown clearly especially on muscles VM and VL. VM and VL showed clear onset timing from standing position, until subject was in flexing position (see fig 3-4). Therefore, we used these two muscles to calculated the time delay of muscle activation between EMG and AMS.

The mean of time delay happened for all models in VM and VL muscle was 18.38ms, and 22.8ms.

5.4 Discussion and conclusion

In our previous simulation studies, we found that for normal walking (NW) there were two muscles showing a strong Pearson correlation (GM and GL), while the other 6 muscles showed poor correlation. For one-leggedforward hopping (FH) we found that 4 muscles showed a strong correlation (VM, VL, GL, TA), 3 muscles (ST, BF, GM) showed a moderate correlation and only one (RF) a poor correlation. For side jumping (SJ) we found that two muscles showed a strong correlation (VM and VL), five muscles (RF, ST, BF, GM and GL) showed a moderate correlation and only one (TA) a poor correlation. In this study, three muscles showed a strong correlation (RF, VM and VL), one muscle (GM) showed a moderate correlation and the other 4 (ST, BF, GL and TA) showed a poor correlation.

It is clear that AMS shows some shortcomings in its muscle activity prediction during all stages. Knee flexion motion is generated when hip joint, knee joint and ankle joint are flexing together. Rectus Femoris (RF) muscles are mainly activated for hip joint flexion, biceps femoris (BF), semitendinosus (ST) and gastrocnemius (GM, GL) muscles are mainly activated for knee joint flexion, and the tibialis anterior (TA) muscle is mainly activated for ankle joint dorsiflexion [He et al., 2007].

When we look at stage 1, for muscles RF, VM and VL, AMS and EMG show a similar pattern, namely limited activity.For muscles ST, BF, GM, GL and TA, AMS's prediction was different compared to EMG. We speculate that this is caused bya miscalculation of the knee net moment by AMS during standing position, which can be caused by the way a subject stands, such as standing with some degree of hip abduction so that AMS calculates a knee net moment and then activates some muscles to compensate that knee net moment. Similar analysis may work on the ankle net moment calculation, in which during standing position, TA muscle should be inactive (or less active) as shown by EMG, but by the model, TA was activated during standing. Compared to EMG, whatever the position of the leg when the subject is standing, as long as that standing position is in their relax standing position, the EMG activity is less or even inactive (see figure 3 for muscles: ST, BF, GM, GL and TA). Some small EMG activity is also shown by BF during stage 1, this is because BF has a double function, not only as a knee flexor, but also as a hip extensor.

During stage 2 and 3, when the knee is flexed and then being continued by keeping the knee in flexed position, the knee flexor muscles ST and BF (Biceps muscles) and quadriceps muscles (RF, VM and VL) should be more active compared to their previous position on stage 1 in order to stabilize the knee during flexing process and aferwards. In addition, since the ankle is flexing due to the knee is flexing, the moment arm in the ankle is increasing causing GM and GL to be active to compensate the increased moment arm. TA as a co-contraction muscle of GM and GL is then being activated to stabilize the ankle joint. However, when comparing to the model, model's prediction during stage 2 and 3 showed an opposite pattern. We opinioned that fixed knee joint center position in the model has a great potential in causing these differences. There are two effects of the fixed knee joint center position that may have affected the results. The first is, calculating the knee net moment with the knee joint center is fixed in a certain position (scaled by the model in a fixed position) ignores the fact that the knee joint center is changing due to the gliding process in the knee during flexing motion. That gliding process would potentially shift the position of the knee joint center, which in turn would also change the calculation of the knee net moment in reality. The second effect is the fact that the optimization criterion does not consider joint (knee) instability, whereas in reality this is an issue that the muscles (as active joint stabilizers) will respond to. This phenomenon is missing in musculoskeletal models and further studies need to be performed to assess the impact of this speculation.

At stage 2 and 3, three muscles, RF, VM and VL, showed some agreement between AMS and EMG. We think that the reason for this good agreement is because during stage 2, the moment in the knee is increasing by the changed position of the knee center relative to the ground reaction force (GRF). This higher knee moment must be compensated for by activating the knee extensors (RF, VM and VL).

In stage 3, when the knee was keeping a flexed position,there is a significant difference between EMG and AMS, most probably caused by not simulating the co-contraction to ensure joint stability. Both knee flexors (ST and BF)and extensor muscles(RF, VM and VL) must be active to keep the knee stable in flexed position and hold the upper body weight from falling as is shown clearly by the EMG-patterns. Similar co-contraction is present between TA and Gastrocnemius muscles. TA, GM and GL must be activated to keep the knee joint and ankle joint stable in flexed position. From a mechanical point of view, without modeling joint stability, co-contraction is not required and thus not modeled in AMS, which explains the differences in muscle activity in this stage 3. However, since we have not applied the maximum voluntary contraction (MVC) in defining muscle activity by EMG, we realize that the maximal EMG values may be rather low (although they are scaled to 1). Similarly, we scaled the AMS activity to 1. Consequently, the patterns discussed may be subject to errorsas the signals may in fact be rather low and subject to considerable noise.

Other factors that could also potentially cause these differencesare inaccuracy in segmental parameter (including mass, moment of inertia and center of mass), inaccuracy in marker trajectory data or in ground reaction force or inaccuracy in determining the location of the knee joint and ankle joint center [chapter 2 and 3 of this thesis].

Furthermore, a time delay was found between EMG and AMS. In this study, we used only two muscles (VM and VL) to calculate time delay between EMG and AMS because only for these two muscles the activation time point was clearly shown (see figure 3). The calculated time delay is approximately 20ms, where AMS activity is delayed. This can be understood as the EMG activation is always initiated from our central nervous system [Deliagina et al., 2007], before the motion itself. Compared to AMS, the activition of a muscle is based on the marker's trajectories and GRF that are running behind the EMG-patterns.

Regarding knee joint loads, figure 3 showed clearly that the knee compressive force is the highest knee joint force during knee flexion. In comparison to our previous study during one-legged forward hopping and side jumping, knee A-P forces were about 50% of the predicted knee compressive force. However in this modeling, knee A-P forces was much higher that those two activities. The knee A-P force was almost equal to the knee compressive force (Cf) (see fig. 5). This can be explained by the fact that during flexing and during keeping the knee in flexed position, the quadriceps generates a lot of force to compensate the flexion moment, thereby pushing the femur posteriorly. Therefore, knee A-P force was directing posteriorly. In reality this A-P force is primarily compensated by the ACL.

Regarding knee M-L force, if we compare with our previous study, there was a unique finding in our data since the percentage of knee M-L force relative to the knee Cf in two different activities (FH and SJ) was the same, they were all about 3-4% of knee Cf force. However, during normal walking and knee flexion motion, the knee M-L force was about 8% of the knee Cf. We think that this is because during FH, SJ, the knee rotation whether externally or internally was less causing less knee internal/external moment too, compared to NW and knee flexion motion, the knee was more flexible during movement so that knee rotation internally or externally was more possible. Table 1 shows in detail the comparison of the mean of maximum knee joint force and moment in all four different activities.

Tabel 1. Comparison of mean of maximum knee join forces and moments in 4 different activities

	Cf (N)	A-P force (N)	M-L force (N)	AX (Nm)	VV (Nm)
NW	2865	357 (P)	231 (L)	12 (In)	56 (Varus)
FH	7015	3825 (P)	239 (L)	42 (Ex)	90 (Varus)
SJ	5365	3095 (P)	238 (L)	32 (Ex)	72 (Varus)
KF	1478	1372 (P)	120 (L)	7.7 (Ex)	30 (Varus)

KF is knee flexion motion, AX is knee axial moment, VV is knee varus valgus moment
P: posteriorly; L: Laterally; M: Medially; Ex: the moment rotating externally; In : the moment rotating internally

When comparing our result to other study, this study showed mean of maximum knee compressive force (Cf) was 2.29 times BW, while other studies showed higher forces, up to 4xBW but they were using different motion test [Taylor et al., 2001], knee isokinetic exercise [Kaufman et al., 1991] andsquatting and rising up from a deep squatting [Dahlkvist et al., 1982]. The main difference between knee flexion motion and normal walking is that during knee flexion motion, there is no significant impact on the knee that can cause higher knee Cf force.

In conclusion, AMS muscle activity predictions of knee flexion motion are less accurate in more dynamic circumstances than during more prescribed movements like one-leggedforward hopping and side jumping. The main cause of these differences are mostly from the modeling process such as inaccurate simulation of muscle co-contraction to stabilize the joints and inaccuracy in determining the muscle moment arm due to inaccurate muscle attachment point or joint axis location or muscle-tendon parameter values [Fregly et al., 2011]. The level of agreement between activation level and EMG measurements also depend on the type of motion. In addition to that, EMG as our standard of validation is also not free of errors. Improving AMS is possible by implementing joint instability and co-contraction of muscles to stabilize these joints (knee and ankle) especially during no movement activity such as maintaining the knee in flexed position. Subsequently these new optimization criteria can be tested with other motions that may explain the accurcy of the model's prediction in more detail. When comparing GLEM of AMS with EMG, time delay has to be taken into account.

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Chapter 6

General Discussion and Conclusion

Biomechanics is a very good example of a relatively new research area that became available when two fully different disciplines started to work together. Progress in biomechanics became only possible after mechanical engineers and experts from the medical field started working together. Mechanical laws applied to anatomical structures with physiological behavior created insight in human movement, movement disorders and effective treatment methods. Numerical modeling of the musculoskeletal systemenabled a detailed look in the activation of muscles, in the resulting joint movements and the internal and external loading of the skeleton. It became possible to analyze human locomotion with much more detail and certainty than with in-vivo measurements only. One such a numerical modeling tool is the AnyBody Modeling System (AMS) (from Aalborg University, Denmark). The GaitLowerExtremity model (GLEM), a lower leg model from the AMS repository, has been used widely to study human locomotion. Like several other models, GLEM is capable to calculate muscle forces and activity and joint loading .

One possible application of such a model is to optimize ACL-replacement. Optimization is necessary, since many patients have complaints after ACL-replacement. It is our hypothesis that this is caused by considering all patients as equal in terms of geometry and tissue properties and by ignoring the fact that patients have individual differences in geometry and material properties.

To improve ACL-replacement, we aim to create patient-specific numerical models of the leg with which the orthopedic surgeon can perform virtual surgery, judge the outcome in terms of range of motion and loading of the knee joint structures and modify the surgical procedure when the outcome is disappointing. This patient-specific model is based upon the GLEM of AMS. It uses input from external measurements such as ground reaction forces and motion capture data.

A requirement for good predictions is a good model and good input. Since every model is a simplification of reality, the quality of its predictions is not always guaranteed. In this thesis we have investigated the quality of the model. We have decided to do the validation tests from very well defined movementslike side jumping to complex motions like walking and knee flexionto study the quality of AMS during different situations and to determine its capability in predicting muscle activity and knee joint forces and moments under these circumstances.

6.1 Modeling simplifications and assumptions

Inverse dynamics analysis (IDA) is the basic concept of AMS in predicting musculoskeletal biomechanics [Damsgaard et al., 2006]. One of the advantages of using AMS is its low cost of computation. By using a standard personal computer, all simulations and analyses can be done in minutes. As everymodeling tool, AMS needs to apply several assumptions and simplification to be able to realize the predictions. The limitations of inverse dynamics calculations have been discussed by [Riemer et al., 2008] and others. Aspects are the influence of inaccuracy in segmental parameter like mass, moment of inertia and center of mass [Kingma et al., 1996; Pearsall et al., 1999; Ganley et al., 2004], or noise in data of the ground reaction force [Kuo., 1998]. However, in this study our focus was not determining the effect of those aspects with AMS modeling.

Since simplifications and assumptionsare inevitable in any modeling aplication, we assessed the effects of these aspects by comparing predicted muscle activation levels by AMS with EMG measurements. We speculate that simplification and assumption have significanly influenced the prediction result. We start the discussion on the simplification of the knee model. In AMS, the knee is modeled as a hinge joint that connects two segment bones, tibia and femur. The first problem with that is that this may lead to differences in muscle activation due to inaccuracies of the definition of the location of the joint center [Bell et al., 1990]. For example, a study done by [Leardini et al., 1999] who inverstigated intra-individual difference of a hip joint center (HJC) location resulted a ranged from 5 to 11 mm difference of HJC location among the subjects. We think that in mechanical point of view this range will certainly generate different muscle moment arm in AMS modeling which in turn will affect also muscle activity prediction. More over, AMS assumes the position of a knee joint center is fixed, this assumption is good in term of stability of the joint, however, in real muscles as a joint stabilizer work around the knee joint, ignoring this stabilization aspect around the knee joint would lead to a different result.

The second simplification is the use of scaling algorithms. To scale all body parts in the modelto an individual, AMS uses the general rule of linear scaling [Andersenet al., 2010]. That scaling rule was based on the data set which was obtained from the study of [Horsman et al., 2007] (TLEM dataset) who measured the geometry of all body segments and ligament properties of a human cadaver. The idea behind the TLEM project is actually projected to make a personalized model so that all of the individual difference can be adapted into the model. However, that seems still to be our future work. In AMS, all the subject's segments and ligament properties were scaled using that standard (TLEM dataset) linearly, even though in reality the geometrical properties from ligaments, bonesand muscles vary not always linearly from person to person such as for subjects with over body weight etc. So this will cause some errors or differences between EMG and AMS predictions. Further sensitivity studies need to be performed to prove this hypothesis. The TLEM-safe project studies the influence of individual properties in musculoskeletal modeling.Thethird simplification is the modeling of the foot as one rigid segment. This condition makes that the foot is unable to have phalangeal flexion angles, while Phalange bones are important in triggering the activity of Tibialis Anterior and Gastrocnemius muscles especially during an active movement like walking, forward hopping and side jumping since the presure of the foot especially is on the front part of the foot [Luboz et al., 2012; Sasaki et al., 2008; Scott and Winter et al., 1993].

An example of assumption is the muscle recruitment criterion that defines which muscles are active during a movement and which muscles are not [Rasmussen et al., 2001]. The necessity of a muscle recruitment criterion is the presence around every joint in the human body of more muscles than needed to make a certain motion and/or produce a certain moment. So we have to define a strategy that determines which muscles are active at certain stages of a movement. For this, we cannot mimic the human central nervous system behavior in activating muscles to exert the force, because up to now scientists do not know exactly how this process is controlled by the human brain [Deliagina et al., 2007]. One strategy is the principle of equal load sharing of all muscles. In terms of efficiency, this will not be the best criterion, because in that case humans would be exhausted easily due to the small muscles fibers taking similar loads as bigger muscles. If we would select only the bigger muscles to be activated, then the question will be: when are the small muscles being activated? To solve this problem, AMS applied an objective function that mimics the physiology of human muscles in term of fatigue and efficiency. This principle of muscle recruitment will minimize the maximum force of every muscle fiber involved, so that the muscles can efficiently spend energy to perform a motion and/or produce a moment and avoid fatigue as much as possible. This principle is believed to be the best form of mimicking muscle recruitment in a human body [www.anybodytech.com; Damsgaard et al., 2006]. But to our opinion besides those optimal energy consumption and equal sharing load mechanism, there is still other important aspect that needs to be considered especially during side jumping and one-legged forward hopping, which is related to the active stabilization of the joints which is produced by co-contraction of antagonists around the joint. Co-contraction is present in many situations to stabilizea joint against unexpected disturbances or high shearing forces in the joint. In AMS joints are inherently stable and there is no requirement to actively stabilize the joints with muscles that span the joint. Hence, to improve the realism of these models joints should be modeled as sub-stable entities and the active stabilizing effects should be included in the optimization criterion in the muscle activation calculations.Further studies focussing on quantifying this phenomenon should be perfomed.

Moreover, normal walking, one-legged forward hopping, side jumping and knee flexion are categorized as Closed Kinetic Chain (CKC) motions [McGinty et al., 2000]. In CKC motion, muscle forces in the leg are influenced by the position of the torso of the upper body part. In addition to that, the torso of upper body part will trigger also co-contraction activity partly because the length of a muscle will change, partly because the muscles have to balance the torso [Mesfar et al., 2005]. However, unfortunately, in this modeling study that upper body part torso was not modeled in GLEM.

Another aspect that influences also the result of this validation study is the movement of markers relative to the rigid bony skeleton. These artefacts in marker movement are used to define the translations and rotations of the of body segments, which are very important as input of AMS. In this study, we used 16 reflective markers attached tolower leg bony landmarks based on the study of Hayes and Davis [Davis et al., 1991]. The first problem is inaccuracy in marker trajectories data such as the presence of noise in surface marker trajectories [Richards., 1999]. A second problem regarding the marker data is the CKC type motion. Since we did not apply markers for the whole body segments, we did not know yet how big is the difference between this study (which is applying only 16 markers) and applying markers for whole body segments so that the effect of upper body movement can be analyzed in case of trials that are categorized as Close Kinetics Chain (CKC) movement [McGinty et al., 2000].

6.2 EMG- simplifications and assumptions

EMG data played a dominant role in this thesis. Since EMG was our golden standard,especially for muscle activity comparisons [Hermens et al., 2000; Merletti et al., 2009], the way EMG signals are processed would affect significantly the final validation result.One important aspect in EMG processing is the applied threshold method, because it influences all results that were obtained for validation purposes. The role of the EMG threshold and which method is the best for processing EMG data is still subject of discussion [Konrad., 2005].

In this study, we found that some EMG data showed an activity level far above the zero level, and some others started at about the zero level. Due to this finding, we applied a min/max threshold to crop the EMG data. This min/max threshold did crop the EMG data from the lowest value to the highest value [Konrad., 2005].

A second threshold, the baseline threshold was applied to correct for the fact that muscle activity according to EMG was always longer than that predicted by AMS. We defined the EMG baseline threshold as the activation level where the duration of EMG was equal to the AMS duration. In practice this threshold appeared to be different for each muscle and for every model. This method allowed us to study the pattern of EMG signals without interference of the threshold effect.

The explanation for the different activation duration according to EMG and AMS is that EMG is always being activated earlier compared to AMS since EMG's activation is coming from our central nervous system [Deliagina et al., 2007], and it is always active prior the movement itself. If we look at the AMS, the activation level was triggered by the external force in relation to the position of markers on a body segment. Moreover, EMG often ends its activation later compared to AMS, even after the movement in order to control or to stabilize the posture/upper body part, especially during active movement like NW, FH and SJ. Perhaps our natural safety system is more extensive than that of AMS.

Ignoring this fact would have made the comparison between EMG and AMS less realistic (see chapter 2, 3 and 5 on EMG and predicted muscle activity). Based on this condition, we think that validating AMS using EMG should incorporate time delay in EMG processing such as by doing partial EMG data cutting, even though that method would also potentially decrease some of important information in EMG signal.

6.3 Potential bias of parameter choice in statistical analysis

Statistical analysis is not only beneficial in presenting a strong scientifical result but also can create a bias in the outcome parameters. This study has proved that statement. While comparing one of our variables of analysis such as number of onsets/offsets, we have never compared the timing of those variables. For example, for some graphs we found both for EMG and AMS exactly the same number of hills, but the position was shifted in time. This time shift, however, is not depicted in the number of onsets, offsets or hills. In statistical point of view, this matching condition (i.e. having the same number of onset) would be decided as a good validation result, while in scientific point of view, time shift has significant role in judging whether the validation result is good or bad. For future statistical comparison, we suggest an idea to avoid such problem by comparing variables of validation when they have approximately the same position in time. However, this idea would need a huge visual observation since we have to do that per graph per model. In addition, sometimes it was not easy to find which hill in AMS is matched in time with another hill in EMG.

When discussing Pearson correlation coeficient analysis, we found also that comparing both AMS with EMG data graph directly from the start till the end of the garph yielded not very satisfying result. We opinioned that comparing them partially could yield a better validation result. However, that would require a method to quantify visual impression and patterns, which is currently lacking.

6.4 Validation results

From the result of our simulation of normal walking, one-legged forward hopping, side jumping and knee flexion, each subject produceddifferent knee kinetics and muscle activity. This again supports the idea that ACL-reconstruction should be done patient-specific. The main goal of this study was to test the level of agreement of AMS with EMG measurements on healthy persons. Theparameters number of onset, offset and hill were compared using Cohen kappa analysis and thedata-graph pattern correlation between EMG and AMS was compared using Pearson correlation coefficient. Animportant finding in this study is the fact that the type of activity, i.e. normal walking, one-legged forward hopping, side jumping and knee flexion has a considerable effect on the validation result between AMS and EMG. During normal walking, the validation results with both statistical methods were worse compared to the more prescribed motions likeone-legged forward hopping and side jumping (see table 1). This is because during a more prescribed motion, the EMG graph and muscle activity prediction are less ambiguous to determine. In addition, during normal walking the compressive force in the knee is lower (see chapter 4), causing an increase of the knee laxity especially during landing. This condition will allow more variation in terms of muscle activation (such as variation in knee internal or external rotation) thanduring hopping and side jumping, where the knee laxity is lower to realize a more stable situation to prevent falling . So muscle activity patterns from EMG and AMS tend to be more similar.

We also thinkthat during a more prescribed motion the peaks of the graphs were more defined, so that the baseline threshold can clearly separate which one is noise and which one is the actual activation data. As a consequence number of onsets or offsets were less in AMS and closely approached the number of onsets or offsets from EMG. This condition then resulted in a better match between EMG and AMS, even though the overall level of agreement was still only slight. All of these drawbacks, whether from laboratory experimental set up, the nature of modeling or from the potential bias of statistical calculationand EMG processing have had effect on the accuracy and the validity of the prediction result especially on muscle activity parameter.

Tabel 1. Mean of level of agreement using Cohen Kappa analysis in variable: number of onset, offset and hills and mean of Pearson correlation coefficient value from all 8 muscles in all 4 activities.

	Normal Walking	One-leggedForward Hopping	Side Jumping	Knee Flexion Motion
Onset	-0.01	0.07	0.09	-
Offset	-0.02	0.09	0.12	-
Hills	0.05	0.07	0.12	-
Pearson Correlation	0.32	0.54	0.5	0.27

number of onset, offset and hills were not calculated in the knee flexion motion trial, because number of onset is always the same (equal to 1) and there is no offset and hills since at the end of the data, the muscles were still active due to the position of the knee in flexion

Knee joint forces, moments and muscle activity showed to be comparable with results, presented in the literature [see chapter 4]. One example from our study is knee compressive force prediction during normal walking. When comparing with other studies, the results of mean maximal knee compressive force (CF) predictions during normal walking (4.2 x BW) was comparable to former studies done by Paul (1965, 1976) during fast walking and Morrison (1970) during normal walking (4.2BW). A modeling study on normal gait done by [Winby et al., 2009] gave a range of results between 3.2 – 4.9 BW with average 3.9 BW, so this agrees with our results.Some studies showed lower values: a CF of 1.7 – 3.3 BW during normal walking, but they used prostheses (TKA) for their prediction[Komistek et al., 1998, 2005] and [Wimmer et al., 1997]. Most probably this is caused by the way prostheses were modeled. Furthermore, we think that some aspects in modeling process may cause this difference such as in defining muscle attachment points or muscle-tendon parameter values which can alter the muscle moment arm that determines knee joint forces, especilly knee Cf [Fregly et al., 2011].

When discussing knee joint forces, especially on the knee anterior-posterior force (A-P force) we found that AMS described well the role of anterior cruciate ligament (ACL) especially in a more prescribed motion like forward hopping (FH) and side jumping (SJ). In those two movement modeling, statistically the amount of knee A-P force was approximatelly more that 55% of knee compressive force directing posteriorly (see chapter 4). This reaction force direction in the knee (knee A-P force) indicates how much force that must be restrained by the ACL during those two motions, since the ACL will be strecthed in respond to that A-P force, even though in reality it will not only be the ACL which will counter balance the posterior force. However, by using modeling, we can clearly see the different role of ACL during some different activities such as normal walking, forward hopping and side jumping. In the rehabilitation field, especially for patient pre or post ACL reconstruction, this modeling tool can be used as a window to look inside the knee during motion, but still some more workareneeded to validate some others important kinetic data in the knee during a specific task such as the application of the medial or lateral collateral ligaments, the joint capsule etc.

6.5 Suggestions for future work

Regarding our results, it is recommended to find a better variable choice of validation for comparing EMG and AMS muscle activity, especially fora statistical analysis. When considering Cohen's Kappa analysis, we experienced that comparing two graphs (like EMG with AMS) using a variable such as number of onsets, offsets and hills is not an optimal method.

When discussing a more prescribed motion, like FH and SJ, a more objective method could be comparing the peak position of every hill, so that the comparison would be more representative to the data. However, that method would require much preparation, such as defining which one is considered as a peak and which one is not, and which hill is considered as a comparative hill from another graph etc. Visual inspection should also be closely involved to check the position of every related peaks.

When considering the Pearson correlation coefficient method, the partial Pearson correlation coefficient method should be a more objective method, because during the partial comparison process the trend of each graph can be compared objectively. However, this method also involvesa great deal of visual inspection to check whether we compared the same part of the graph, since there is a delay of muscle activation betwen EMG and AMS. From the modeling itself, comparing predicted muscle activity with EMG measurement needs a more detail modeling of body part such as detail knee joint model or foot model so that the kinematics of the lower limb can be analyzed in more realistic way. In addition to that, a time delay adjustment is needed so that the delay between EMG and AMS can be avoided, even though further research is required to determined the way we adjust the time delay between AMS and EMG since AMS is late in activation, and EMG ends its activity later.

From chapter 4, about the knee joint forces prediction, AMS is able to represent the role of Anterior Cruciate Ligament (ACL) during normal walking, one-legged forward hopping (FH) and side jumping (SJ) by showing that the knee reaction force in sagittal plane (anterior-posterior direction) during FH and SJ is bigger in posterior direction, which means that the real force is directing anteriorly. This shows the potential force that has to be handled by ACL. For future work, the surgeon can model the patient of pre/post ACL reconstruction in dynamical situation with a detailed knee model and analyze the knee joint forces in the sagittal plane and then compare them with healthy subjects so that some improvement regarding defining the position of origin and insertion of ACL can be optimized based on a dynamic test. However, for that purpose we would need to model the in great detail with some important ligaments attached to the knee. Subsequently, the knee model should be used in a dynamic situation to get a more detailed result. A sensitivity study is also important in assessing the effects of many important aspects in the modeling such as muscle-tendon parameters, muslce-tendon attachment positions etc. so that a precise model as close as possible to the real human condition can be utilized.

For future modeling work, we suggest that the knee joint should be simulated with the laxity that is present in reality. However, that is not an easy task since we have to formulate knee like laxity in the joint. Muscles with function as the knee stabilizer should be implemented in the model so that the muscle activity respond is human like muscle activity respond.

6.6 Conclusion

In conclusion, despite limitations, GLEM has a good potential for simulating and analyzing human motion biomechanics, with predicting muscle forces and muscle activity. Moreoverit has the capacityto predict 3D knee joint forces and moments during normal walking, one-leggedforward hopping, side jumping and knee flexion motion. AMS has shown its potential to be used in more advanced clinical use and rehabilitation research programs for patients, like pre or post ACL reconstruction. Some improvements are suggested to more realistically simulate the complex biomechanical behavior of human locomotion. Furthermore, improved validation tools should be generated to allow for a more reliable and robust validation of the outcome parameters of these types of musculoskeletal models.

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Summary

Anterior Cruciate Ligament (ACL) surgery is nowadays performed mostly based on the experiences and approximation of the surgeons, especially when determining the origin and insertion of ACL in the knee. The results of these operations, however, are not always satisfying. In several cases, patients must return for a 2nd or 3rd operation. In order to optimize the result of ACL operation, we hypothesized that the origin and insertion of ACL-reconstruction should be determined subject-specific, and the different properties of the ACL-reconstruction structure should be taken into account.

To realise such a patient-specific surgical planning, numerical models can be of great help. Such a model must simulate human movement and should include a detailed knee model. To achieve that goal, in this study we will use the AnyBody Modeling System (AMS). This is used often for musculoskeletal modelling of human movement. By acquiring motion data of a person, the model is able to calculate joint forces, muscle activity and muscle forces. Those data are difficult to obtain in vivo, so this model is a valuable tool.

However, a proper validation of this model has not been done. Goal of this study is to validate this model by comparing the predicted results with real measurements during active motion; normal walking, one-legged forward hopping and side jumping and “static” motion like knee flexion motion. The output variable of AMS prediction that used for the validation in this study is muscle activity. This is because muscle activity is the only output that can be validated using a real measurement with a non-invasive technique, a surface EMG (sEMG). Theoretically, muscle activity defined by AMS is different by definition and in units compared to muscle activity measured by sEMG. Muscle activity defined by AMS is the predicted muscle force divided by the maximal muscle force for that particular muscle at that particular instant in time, while sEMG represents the real electrical activity produced by a muscle during a contraction; the activation is triggered by our central nervous system. To be able to compare the AMS and sEMG-signal, we have defined three parameters: number of onsets, offsets, and hills. To quantify the level of agreement between predicted muscle activity with measured EMG, Cohen’s kappa analysis and the Pearson correlation coefficient were used.

In this study we analysed four activities of human motion, from very well defined movements such as side jumping and forward hopping until a complex motion like walking and knee flexion motionto study the quality of AMS during different situations and to determine its capability in predicting muscle activity and knee joint forces and moments under these circumstances. 10 healthy subjects were involved in this test, 16 reflective markers were attached to their lower limbs based on Helen Hayes marker placement standard. 8 sEMG electrodes were placed on the following muscles in lower limb to capture the activity of these muscles during motion: RF (Rectus Femoris), VM (Vastus Medialis), VL (Vastus Lateralis), ST

(Semitendinosis), BF (Bicep Femoris), GL (Gastrocnemius Lateralis), GM (Gastrocnemius Medialis) and TA (Tibialis Anterior). Specific thresholds per muscle were applied in the EMG data before being compared. These threshold levels were determined by equalizing the duration of EMG to AMS muscle activity.

Overall, visual inspection showed similar activity patterns for several muscles. In detail, a more prescribed movement like one legged forward hopping and side jumping did result in a better match.

When the parameter values were studied, again the validation results with both statistical methods were worse during normal walking compared to the more prescribed motions like one legged forward hopping and side jumping. During a more prescribed motion, the muscle activity predictions are less ambiguous to determine. In addition, during normal walking the compressive force in the knee is lower, causing an increase of the knee laxity especially during landing. This condition will allow more variation in terms of muscle activation (such as variation in knee internal or external rotation) thanduring hopping and side jumping, where the knee laxity is lower to realize a more stable situation to prevent falling. So muscle activity patterns from EMG and AMS tend to be more similar.

In this study we also investigated knee joint forces and knee joint moments predicted by AMS of the same 10 healthy volunteers that performed normal walking, forward hopping, side jumping and knee flexion in a gait lab. Knee joint forces and moments prediction pattern among healthy subjects is presented, together with the information of knee flexion position where the knee joint force reached the maximum. Knee joint forces and moment data during all three activities were calculated in three planes based on a femoral coordinate system.

This explorative study shows that there are distinct differences between the muscle activity levels as predicted by AMS and the measured EMG patterns. Since every model is a simplification of reality, the quality of its predictions is limited. Examples of simplifications include the knee model. In AMS a hinge joint is applied, in reality the location of the center of rotation varies with the knee angle.

A second simplification is the scaling algoritms that are used. To scale all body parts in the modelto an individual, AMS uses the general rule of linear scaling, but in reality the geometrical properties from ligaments, bonesand muscles vary not always linearly from person to person.

A third simplification concerns the foot that is modeled as one rigid segment that is unable to have phalangeal flexion angles, which has distinct influence on the activity of the Tibialis Anterior and Gastrocnemius Muscles.

A fourth simplification is the principle of muscle recruitment. AMS applies a principle that minimizes the maximum force of every muscle fiber involved, so that the muscles can efficiently spend energy to perform a motion and/or produce a moment and avoid fatigue as much as possible. However, in reality the muscle recruitment principle will be much more complex, having a clear influence on the muscle recruitment. Co-contraction of muscles is one such complication that is present in reality, but not yet in AMS.

Despite all differences, several similarities were found, especially when discussing the knee joint force prediction during motion by AMS. During all experiments, AMS has shown its capability in predicting knee joint forces and moments.

In conclusion, despite the inevitable simplifications, AMS is a powerful tool for modeling human motion. More accurate predictions can be obtained when improvements are implemented.

Samenvatting

Voorste kruisbandreconstructie (VKR) wordt veelal gebaseerd op eerdere ervaringen van de chirurg en diens inschatting, met name bij het bepalen van de origo en insertie van de voorste kruisband in de knie. De uitkomst van VKR is niet altijd bevredigend, waardoor patiënten in een aantal gevallen moeten terugkeren voor een 2e of 3e operatie. Om het resultaat van VKR te optimaliseren, veronderstelden wij dat de origo en insertie bij de operatie patiënt-specifiek bepaald zou moeten worden en er ook met andere verschillen van de voorste kruisband rekening gehouden moet worden.

Numerieke modellen kunnen van grote waarde zijn om tot een dergelijke patiënt-specifieke chirurgische aanpak te komen. Een dergelijk model zou zowel een simulatie van de menselijke beweging als een gedetailleerde knie-model moeten bevatten. Om dit te bereiken gebruiken wij in deze studie het AnyBody Modeling System (AMS), hetgeen dikwijls wordt gebruikt voor de musculoskeletale modellering van menselijke bewegingen. Met gegevens van de beweging van een persoon kan het model spieractiviteit, spierkrachten en krachten over het gewricht berekenen. Dit maakt het model tot een waardevol instrument, aangezien die gegevens *in vivo* moeilijk te verkrijgen zijn.

Een degelijke validatie van het model is tot op heden echter niet uitgevoerd. Zodoende is het doel van deze studie om het model te valideren middels een vergelijking tussen de voorspelde resultaten en daadwerkelijke metingen tijdens wandelen, hinkelen, zijwaarts springen en statisch bewegen (zoals bijvoorbeeld knieflexie). Omdat spieractiviteit de enige waarde is die op non-invasieve wijze verkregen kan worden middels oppervlakte EMG, wordt dit gebruikt om de voorspelling door AMS te valideren. Theoretisch verschilt spieractiviteit, bij meting door AMS, zowel qua grootheid als qua eenheid van spieractiviteit gemeten door oppervlakte EMG. Spieractiviteit gedefinieerd door AMS is de voorspelde spierkracht gedeeld door de maximale spierkracht voor die spier op dat moment, terwijl oppervlakte EMG de elektrische activiteit meet van een, door het centrale zenuwstelsel geactiveerde spier tijdens contractie. Om het AMS- en oppervlakte EMG-signaal te vergelijken, hebben we drie parameters bepaald: beginwaarde, eindwaarde en aantal positieve curves. Om de mate van overeenstemming tussen de voorspelde spieractiviteit en EMG te kwantificeren werd de Cohen's kappa analyse uitgevoerd en de Pearson correlatiecoëfficiënt berekend.

In deze studie analyseerden we vier menselijke bewegingen, van zeer specifiek (zijwaarts springen en hinkelen) tot complex (wandelen en knieflexie) om de kwaliteit van de AMS onder verschillende omstandigheden te bepalen en hierbij ook diens voorspellende waarde van spieractiviteit, krachten en momentkrachten over het kniegewricht vast te stellen. Hiertoe zijn 10 gezonde proefpersonen betrokken bij een proef waarin op basis van de Helen Hayes marker-plaatsingstandaard, 16 reflecterende markers op de onderste ledematen werden

aangebracht. Voorts werden 8 oppervlakte EMG elektroden op spieren van de onderste ledematen geplakt om de activiteit van deze spieren tijdens de beweging vast te stellen. Dit betrof de spieren RF (Rectus Femoris), VM (Vastus Medialis), VL (Vastus Lateralis), ST (Semitendinosis), BF (Biceps Femoris), GL (Gastrocnemius Lateralis), GM (Gastrocnemius Medialis) en TA (Tibialis Anterior). Voorafgaand aan data-analyse werden spier-specifieke drempelwaarden in de oppervlakte EMG-gegevens toegepast, welke werden verkregen door de duur van oppervlakte EMG en AMS spieractiviteit gelijk te stellen.

Over het algemeen bleek uit visuele inspectie een soortgelijk patroon van activiteit voor meerdere spieren. Een grotere gelijkenis werd gevonden bij bewegingen die volgens een vast patroon verlopen zoals hinkelen en zijwaarts springen.

Voorts bleek, bij bestudering van de parameters met beide statistische methoden, de validiteit geringer bij lopen dan bij bewegingen volgens een vast patroon zoals hinkelen en zijwaarts springen. Tijdens de beweging volgens een vast patroon zijn de voorspellingen van spieractiviteit eenduidiger. Bovendien is de compressiekracht in de knie bij lopen lager, waardoor er vooral tijdens de landing minder spanning op de knie staat. Onder deze omstandigheid is er meer variatie in spieractiviteit (bijvoorbeeld variatie in endorotaie en exorotatie van de knie) dan tijdens hinkelen en zijwaarts springen, waarbij er meer spanning op de knie staat ten faveure van de stabiliteit en ter voorkoming van vallen. Daardoor is er meer gelijkenis tussen patronen van spieractiviteit gemeten met EMG of AMS.

In deze studie onderzochten wij verder de door AMS voorspelde krachten en momentkrachten over het kniegewricht van de 10 gezonde vrijwilligers die wandelen, hinkelen, zijwaarts springen en statisch bewegen zoals bijvoorbeeld knieflexie hebben uitgevoerd. Bij gezonde individuen wordt het patroon van voorspelde krachten en momentkrachten over het kniegewricht weergegeven, tezamen met gegevens van de positie waarbij bij knieflexie de grootste kracht over het kniegewricht ontstaat. Data van krachten en momentkrachten over het kniegewricht tijdens drie activiteiten (wandelen, hinkelen en zijwaarts springen) werden berekend in drie richtingen op basis van een femoraal assenstelsel.

Deze exploratieve studie toont aan dat er duidelijke verschillen zijn tussen het niveau van spieractiviteit bij voorspellingen door AMS en gemeten EMG-patronen. Omdat ieder model een vereenvoudiging van de werkelijkheid is, is de kwaliteit van de voorspellingen beperkt. Een voorbeeld hiervan is het knie-model. Bij AMS wordt uitgegaan van een simpel scharniergewricht, maar in realiteit verschuift de ligging van het rotatiepunt gedurende de kniebuiging.

Een tweede vereenvoudiging is het schalings-algoritme dat wordt gebruikt. In het model gebruikt AMS gebruikelijke lineaire schalen van het model voor het individu, terwijl de geometrische oriëntatie van ligamenten, beenderen en musculatuur in werkelijkheid niet altijd lineair van persoon tot persoon zullen variëren.

In het model is de voet de derde vereenvoudiging, voorgesteld als een rigide segment zonder phalangeale flexie, hetgeen de activiteit van de Tibialis Anterior en Gastrocnemius spieren beïnvloed.

Een vierde vereenvoudiging is het spierselectie principe. AMS gaat uit van een principe waarin de kracht van elke spiervezel geminimaliseerd wordt, om zo een efficiënte besteding van energie bij bewegingen en/of het creëren van een moment te realiseren en vermoeidheid te vermijden. In werkelijkheid zal het spierselectie principe veel complexer zijn, met een duidelijke invloed op de spierselectie. Een dergelijke kwestie is co-contractie, dat wel aanwezig is in realiteit maar tot op heden niet in AMS.

Ondanks alle verschillen werden meerdere overeenkomsten gevonden, met name bij voorspelling van de kracht over het kniegewricht tijdens beweging met AMS. Tijdens alle experimenten heeft AMS blijk gegeven van haar vermogen krachten en moment over het kniegewricht te kunnen voorspellen.

Concluderend kan worden gesteld dat AMS, ondanks onvermijdelijke vereenvoudigingen, een goed hulpmiddel is voor het modelleren van menselijke beweging. Na het doorvoeren van verbeteringen zullen nauwkeurigere voorspellingen kunnen worden gemaakt.

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Curriculum Vitae

Adhi Dharma Wibawa was born in May 5th 1976, in Surabaya, East Java, Indonesia. He is the 3rd son of 4 children of Darwis Paingan family. He spent his basic education till undergraduate school in Karang pilang, in the south part of Surabaya. He finished his bachelor degree from ITS (Institute of Technology Sepuluh Nopember) in March 2000, majoring in Electrical Engineering. He then worked in PT. Tjiwi Kimia, Mojokerto, East Java Indonesia for about 6 months as a v-team engineer. Big Paper Machine with big sound was less interesting for him in fact, so that in the year 2001, he then quitted the job and moved to work at the Hang Tuah University as a Lecturerat theelectrical engineering department. He worked from August 2001 till December 2008. Teaching in a university seems to be his calling. By the end of 2008, he then joined a bigger university in the east of Indonesia, ITS (Institute of Technology Sepuluh Nopember – www.its.ac.id). He finished his master thesis in March 2004, majoring in Multimedia and Intelligent Network. His thesis in Iridology seemed to be the trigger of his interest in Biomedical Engineering, and has inspired him to pursue a higher level of education by taking a PhD-study. At 6th November 2009, he arrived in the Netherlands for pursuing his dream, working in an international research atmosphere for a PhD-degree, undersupervised by Prof. G.J. Verkerke at theBME department, W.J.kolff Institute, University Medical Center Groningen.Now he finished his PhD-study, he will continue towork as a lecturer at ITS, department of Multimedia and Network Engineering. Hora Finita!!.