Development of a parametric running model in the AnyBody Modeling System based on a pipeline of kinematic running trials

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Submission date

04.01.19

Project group

9217

Semester

4. semester - Master's Thesis, Sports Technology

Supervisor

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Number of Pages: 16

Worksheets: 7

ABSTRACT

The purpose of this study was to create a parametric running model in the AnyBody Modeling System (AMS) based on a large amount of running trials, with the possibility of adding more trials to further develop the model. 149 kinematic running trials were obtained from running customers at the company, Kaiser Sport & Orthopedics (KSO), and was used to drive a full-body musculoskeletal running model, developed in AMS. Mixed terms of Fourier series represented anatomical joint degrees-of-freedom throughout a running cycle. Fourier coefficients were stored in a matrix, from where principal component analysis was performed to interpret variation of the data and correlations between anthropometrics and all anatomical degrees-of-freedom. Eigenvectors acted as measures of the parameters' influence on each principal component (PC). 90 % of the total variance were described by the first 39 PCs and 50 % were described by the first 10 PCs. A parametric running model driven by Fourier coefficients was successfully created. Pseudo-generated models with standard deviation of +/-3 along each PC were compared along with the parameters with the largest eigenvalues to understand the relationship between the top ten PCs and running techniques as interpreted in the clinical practice of KSO.

Introduction

Running is a popular and accessible type of exercise. In Europe, there has been an increase in participation of road running. A survey of the Dutch population (people +6 years old) by van Bottenburg et al. from 2009, revealed an increase from 8 % to 18 % of the total population, regarding people who participated at least once a year in running or jogging. The same survey also found increasing participation throughout the UK, Germany, Belgium and more. A questionnaire from 2009 reported that 62 % of the running events across Europe has had an increase in participants, whereas only 2 % had a decrease in participants (van Bottenburg et al. 2009).

Running is performed as a competitive sport as well as a health-related exercise for recreational runners. Despite of the positive benefits of running (Williams & Thompson 2013) there tends to be a high incidence of running related injuries (RRI) (Van Middelkoop et al. 2008). A systematic review by van Gent et al. (2007) examined 172 relevant articles regarding lower extremity RRI in long distance runners and determined that the overall injury rate ranged from 19.4 % to 79.3 %. Thus, a typical runner has a 19.4-70.3 % risk of sustaining an injury at any given time. Injuries primarily occurred in the knee (7.2 % to 50.0 %), lower leg (9.0 % to 32.2 %), the foot (5.7 % to 39.3 %) and the upper leg (3.4 % to 38.1 %). According to Jin (2014), the most commonly known injuries are Iliotibial band syndrome, patellofemoral pain syndrome, shin splints, Achilles tendonitis and plantar fasciitis.

A study from the 18th Ljubljana Marathon in 2013, revealed that one out of every three participants in the study suffered from an injury every season/year (Vitez et al. 2017). Further, 53 % of the runners had a lifetime prevalence of a running-related injury. Continuous studies support the RRI incidence shown in the study from the Ljubljana Marathon (Linton & Valentin 2018; van Poppel et al. 2018; van Poppel et al. 2016)

Numerous studies acknowledge that biomechanics plays an important role in running injuries (Napier et al. 2018; Almonroeder & Benson 2016; Daoud et al. 2012). Foot inclination angle, pelvic drop, knee flexion during stance, trunk lean, cadence and heel eversion are candidates for factors that may influence injury, according to a summary by Souza et al. (2016). A study by Milner et al. (2010), supports the biomechanical influence on running injuries by comparison of lower limb kinematics between two groups of female runners. One group had a history of tibial stress fracture and the other was a control group. The runners who previously had suffered from tibial stress fracture had significantly greater heel eversion angle and hip adduction angle.

The link between biomechanics and running injuries is acknowledged by most researchers. However, as runners/humans are unique, general recommendations with respect to optimization of biomechanics do not necessarily apply to all (Williams, 2007). Therefore, individual analyses are important to provide the best possible individual feedback, and it should be borne in mind that a wide range of factors may contribute to injury risk. Biomechanical analysis can possibly lead to a deeper understanding of the underlying mechanisms (Williams 2007). Furthermore, Williams stated that biomechanics affects not only injuries but also the performance and economy of a runner.

Different types of gadgets to track and analyze human movement, such as 2D video analysis, accelerometers, gyroscopes, virtual coaching, pulse monitors etc., are coming to the market. These gadgets deliver diverse information regarding human activity. However, none of the mentioned gadgets provide information regarding kinematics and kinetics of a full-body founded on sufficient data. Furthermore, no previous gadgets have been developed to simulate a hypothetic running pattern and thereby alter the movement to analyze the influence of different running kinematics. Computer simulation has previously been used as a tool to simulate circumstances that are impossible to obtain in-vivo or require invasive experiments (Gerritsen 1996 et al.; Diana 2015 et al.).

This study was done in collaboration with the company, Kaiser Sport & Orthopedics (KSO), Denmark. The company is a combination of a physiotherapeutic clinic and shop that specializes in selling running shoes based on biomechanical analysis. Customers entering KSO are often prone to current or previous injuries. Hence, the company strategy is to provide the best possible information to their employees and thereby help the customers improve biomechanics and prevent injuries. However, this information is often based on 2D video recordings of runners from a posterior view. Therefore, in 2017, KSO introduced Kaiser Sports Lab. The lab contains a marker-based 3D motion capture system with a full body marker protocol provided by Qualisys A/S, Sweden. Running is a complicated movement requiring a full body analysis, as it is hypothesized that injuries can occur due to biomechanical factors distant from the injured area. Thus, the purpose is to locate the cause of the injury and thereafter provide a plan for rehabilitation/optimization of biomechanics. However, it is not possible for the coach to simulate the effect of instructions given to analyze the effect of optimizing the running pattern. Moreover, the test in the Kaiser Sports Lab is comprehensive and requires much time for experimental testing and analyzing results. Thus, simulation of running patterns based on simple biomechanical measurements will allow runners to be analyzed more efficiently and with fewer means.

It was proposed that the parametric running model has potential to become an analytic tool for physical therapists, coaches and more. To gain an understanding of the business model of Kaiser Sport & Orthopedics (KSO) and provide a perspective of how the model would fit into this business, and attempt to formulate a value proposition was made based on an interview with the CEO of KSO, Jan Steinicke.
First of all, the reason for the existence of KSO is to help people move freely without sustaining pain, which is believed to make people happier. This is achieved by considering the human body in a three dimensional perspective. Looking at body anatomy, observing the kinematics of the human body and investigating the footwear that the human body moves within. A holistic view comprising these three dimensions is what makes the company unique. The company considers innovation to be important to stay ahead of competitors. Thus, having the newest technologies, providing the best possible equipment, coaching and training is vital to giving the best customer experience. The customer target group has no boundaries, as there are no limits to who would benefit from professional advice and pain-free life. However, company statistics reveals that people between 30-55 years of age are the majority of the customers.
In retail, there has been an increase of online purchasing of equipment in recent years and the Internet also provides information regarding exercises and coaching. Still, there are people who seek the personal feedback and will pay for treatment and personal coaching. Motivation is observed to be at its greatest, when people suffer from pain and want to become pain free. Thus, price becomes a minor issue when professional coaching and treatment has the capability to recover the human body. However, there are competitors in the same field of work, that have the equal analytical tools. Therefore, the prediction of kinetics provides information to coaches that otherwise are unavailable. As running activity is growing and runners still are greatly exposed to injuries, the demand for rehabilitation and injury prevention increases. Subsequently, the simulation of running kinematics and kinetics based on a few parameters, is both unique and efficient in respect to current analytic possibilities. The existing biomechanical feedback is often based on 2D video recordings or in rare cases 3D motion capture systems. Thus, the product is exceptional to the customers, as it is impossible to gain such information and coaching evaluation anywhere else.

For this study, the aim was to create a parametric running model in The Anybody Modeling System (AMS) that could provide information regarding biomechanics to individual runners, based on a continuous pipeline of input-data from running trials. The pipeline was set up to train the AMS model, as more and more kinematic running trials become available. Hence, the model will become more reliable with additional trials. For now, it is possible for individual runners to implement a kinematic running trial into AMS and thereby gain information regarding kinematics and kinetics. However, this process is time-consuming, complicated and error-prone. Therefore, this study strived to create a parametric running model, which would make it more accessible to extract valuable information regarding runners, based on a selection of parameters. To minimize the risk of manual errors and subjective bias in the data processing, a pipeline of data input and automated processing was set up. This allows the model to improve continuously, as running trials are added.

A study by Kloster & Iversen (2017) processed and implemented data from 90 heterogeneous running trials to create a parametric running model. However, their trials came from many different sources and experimental protocols, and some contained incomplete running cycles. Furthermore, 90 trials are likely insufficient to cover all variations of running, for which reason they assumed symmetric running patterns, which is likely not valid in general and specifically not when the model should represent injury conditions. Therefore, the purpose of this study was to create a parametric running model in The AnyBody Modeling System based on a large amount of motion capture data with the possibility of adding more trials to further train a reliable model. The future application is to use the parametric running model as a template to insert data from other gadgets and thereby provide kinematic and kinetic information that otherwise would be difficult to obtain, and to use the model as a robust analysis option for kinetic data for specific runners.

Method

Data Acquisition

Data was obtained from customers running style analysis at KSO. Subjects were male and female adults, and the data were collected and transferred according to the Danish implementation of the EU General Data Protection Regulation. A total number of 149 trials were included in the parametric model in this study from 39 different subjects. As described later in this study, the model was created to allow addition of new trials as they become available to fine-tune the model.

Experimental method

A motion capture system (Qualisys AB, Gothenburg, Sweden) was used to obtain data from running trials at KSO. The subjects ran on a treadmill that was placed in the center of the room. Nine infrared M3 cameras and a real time software, Qualisys Track manager (QTM) version 2.16, obtained data from the trials. The QTM attained the data with a frequency of 300Hz. A total of 35 retroreflective markers were placed on anatomical landmarks at the full body of the subjects, following a marker protocol developed by Qualisys for automated kinematic running analysis as seen in figure 1. Markers were attached directly onto the skin when possible, and otherwise on tight fitting clothes to minimize the soft tissue artefact. None-reflective tape was used to cover up potential reflexes on the subject's shoes and clothes that could disturb the measurement. Prior to every test, the measurement volume was calibrated with a calibration tool provided by Qualisys.

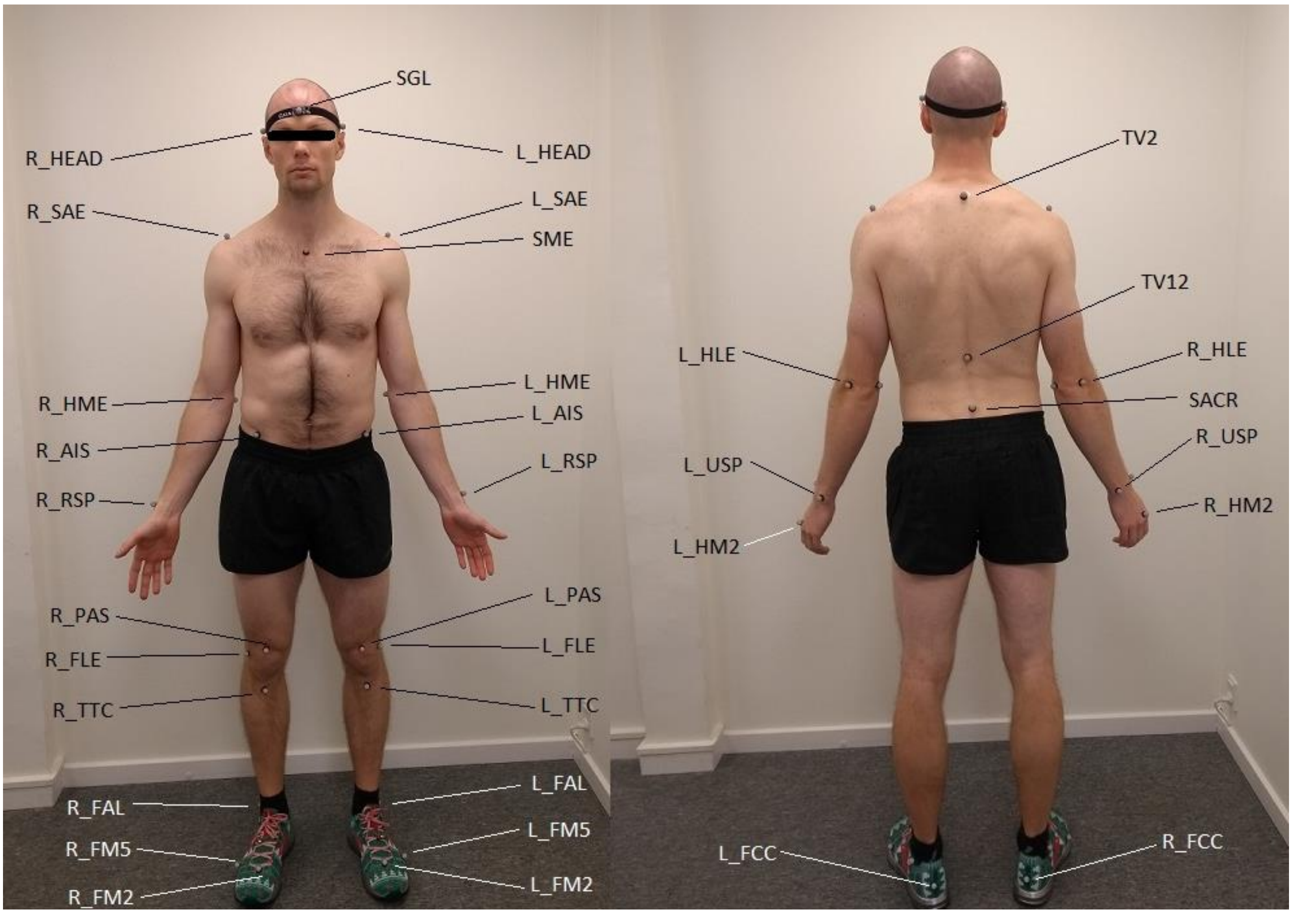

Figure 1 - The Qualisys marker protocol, seen from the front and back.

Movement protocol

The subjects ran at velocities corresponding to different paces during their own running sessions. The subjects performed different numbers of trials, as some were eager to test themselves in several velocities. The velocity of the trials simulated the normality of each subject's training. The capture period for each trial was ten seconds and was considered successful if there were no significant marker dropouts. Otherwise, the trial was repeated. Recordings began when the subject felt accustomed to the velocity of the treadmill and thereby reached a steady state. This procedure was applicable for every trial.

The subjects wore tight-fitting shorts and minimal clothes to the upper body, meaning no shirt or a tight-fitting shirt to minimize fluctuations of markers. All subjects wore their own running shoes, and they all had previous experience with treadmill running. They ran a 1-5 minutes warm up before recordings began, with the purpose of getting familiarized with the environment. Instructions from the coach were to run as naturally as possible.

Computational method

A musculoskeletal running model was developed in The AnyBody Modeling System (AMS) v. 7.1.2 (AnyBody Technology A/S, Aalborg, Denmark). The model was based on a GaitFullBody model from the AnyBody Managed Model Repository version 1.6.3. A subject-specific model was created for every subject. The parameters of the subjects, such as segment lengths, joint rotational axis and marker positions, were scaled by minimizing the least squares difference between the GaitFullBody model and the corresponding marker positions from the kinematic trial, using the a optimization method proposed by Andersen et al. (2010). The local optimization-based method for parameter identification was applied to recover segment lengths from a static posture, and a scaling method proposed by Rasmussen was applied to estimate segment cross-sectional properties (Rasmussen 2005). This method enables subject-specific scaling of the model by establishing coherence between geometry and mass of segments. Furthermore, the paper includes an estimation of strength for the scaled models by implementing fat percentage as a factor. The percentage of body fat is calculated by using the Body Mass Index (BMI) of the subjects.

Figure 2- A musculoskeletal running model in AMS

The models were driven by the marker recordings from C3D files, which were extracted from the kinematic running trials by QTM. The C3D files were smoothed in AMS by adding a low pass zero-lag fourth-order Butterworth filter with a cut-off frequency at 12Hz.

If the AMS model successfully ran the motion optimization process for the trials, .json files were the output for usage in Python. In Python, a script was developed to represent the data as Fourier series. Fourier series are convergent series of sine and cosine waves and can represent any given time signal.

The harmonic nature of sine and cosine functions make Fourier series particularly appropriate for periodic functions, and running kinematics can be represented with good accuracy for most degrees-of-freedom with a few terms in the series. The amplitudes of the Fourier terms are the coefficients of the series, and they become the primal parameters of the parametric running model. A function of a period can be represented as:

$$f(t) = a_0 + \sum_{i}^{n} a_i \cos(i\omega t) + \sum_{i}^{n} b_i \sin(i\omega t)$$

Omega (ω) represents the angular fundamental frequency of each cycle and is denoted as:

$$\omega = \frac{2\pi}{T}$$

where T is the cycle time.

Fourier coefficients $(a_0, a_i, b_i), i = 1..n$ for every trial were derived and stored in a matrix with the derived anthropometric parameters of the subjects, thus establishing a possible connection between anthropometry and running style.

The data processing pipeline was based on a replication of the data storage structure used by KSO and developed by Qualisys. This allows data to flow with as little human interaction as possible from the Kaiser Sport Lab to the data processing facility at Aalborg University, complying with the regulations of the General Data Protection Regulation (GDPR) enforced by the European Community. A batch process automatically discovers all trials and processes the marker trajectories into anatomical joint degrees-of-freedom time series and anthropometric subject data and stores them in .json files for the aforementioned Fourier analysis.

During the running tests, recordings began randomly with respect to the subjects' running cycles, so the recorded signals were not necessarily synchronized in time. For analytical purposes it was important, in order to compare the signals, to correct the displacements in time of the signals. Using cross-correlation adjusted for this time-axis offset, by shifting the signal in time whilst observing the plot as it changed. To ensure obtaining the ideal plot, we analyzed the regression coefficient to get the best correlation between the signals, where the coefficient were greatest.

Data analysis

Principal Component Analysis (PCA) was used as a statistical tool to create a model able to provide information regarding correlation between a large range of parameters with a minimal set of variables. PCA is relevant when dealing with high dimensional data and represents data sets as a number of principal components (PCs). In our case we chose to represent 90 % of the variation and thereby reducing the total dimensionality. PCA is in this study done in a matrix, from which the analysis begins by transforming the data into eigenvectors and finding the PCs that represent the variation of data (Moeslund 2001). This type of analysis is valid in our case, as it is possible to derive correlations between parameters from each of the PCs. An example of how two parameters are correlated are shown in the figure 3.

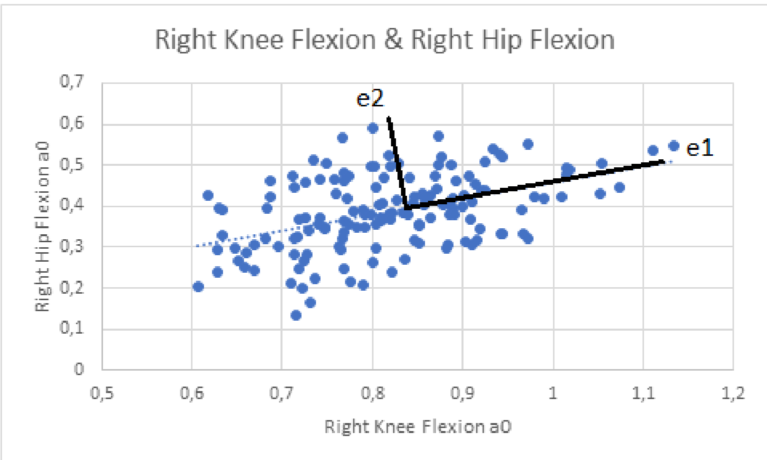

Figure 3 - The figure shows a plot of the correlation of Fourier coefficients between the right knee flexion (a0) and right hip flexion (a0).

The plot of the Fourier coefficients are then sustained to PCA transformation by the following equation.

$$y = A(x - \mu)$$

The transformed dataset is represented as y, A denotes a matrix of eigenvectors, x is the input data and μ is the mean value of the dataset. Moreover, the covariance matrix is termed as $A = [e_1, e_2 \dots e_n]$, where e_n are eigenvectors. An example of how eigenvectors are tabled is shown in figure 3, where e_1 and e_2 are orthogonal and describe variance in different directions. Clearly, e_1 has the largest variance and thereby explains more of the total variance than e_2 in this simplified example. Thus, the majority of the variance can be explained only by the variable e_1.

The PCA process can be explained as: Firstly, primal data in the form of joint angles are parametrized as Fourier series from raw motion capture data. Fourier series are explained by a number of Fourier coefficients that are inserted into a matrix together with anthropometric data identified for each trial. Hereafter, eigenvalue analysis is used to determine the principal directions in the data set and transform the primal data linearly to the principal component space. The number of PCs is depending of the number of data points in the matrix. Parameters with the greatest variation will have the most influence on PCA and data close to the mean value will have very little influence, as their eigenvalues, representing the variance, are small. The direction in the primal data space of each principal component is an eigenvector. Parameters are influential on the PC if their variances are correlated with the PC and entails a great amount of variance in the eigenvector direction.

The parametric running model was tested by variation of the PCs by multiples of the standard deviations and creating AMS models of pseudo runners. The joints and drivers for the pseudo runners were extracted from a script in Python, which created new Fourier coefficients to drive the pseudo running model. The running models were tested by offsetting principal consecutively components by three standard deviations and negative three standard deviations. The resulting motion patterns were evaluated visually to confirm their realism and to interpret the significance of each PC. Further, the pseudo runners were also evaluated based on comparison of anthropometrics and biomechanical parameters. To gain knowledge from experts working with running on a daily basis, two physiotherapists from KSO assisted in the interpretation of the results and provided feedback concerning their own approach when analyzing clients.

PCA was performed on the following primal parameters: Position of pelvis in x,y,z space, Rotation of pelvis about x,y,z axes, Center of Mass (COM) in x,y,z space, Pelvis-thorax extension, Pelvis-thorax lateral bending, Pelvis-thorax rotation, Skull-thorax flexion, Skull-thorax lateral bending, Skull-thorax rotation, Right sternoclavicular protraction, Right sternoclavicular elevation, Right sternoclavicular axial rotation, Right scapula thorax protraction, Right scapula thorax elevation, Right glenohumeral flexion, Right glenohumeral external rotation, Right glenohumeral abduction, Right elbow flexion, Right elbow pronation, Right wrist flexion, Right wrist abduction, Right ankle plantar flexion, Right subtalar eversion, Right knee flexion, Right hip flexion, Right hip abduction, Right hip external rotation, Left sternoclavicular protraction, Left sternoclavicular elevation, Left sternoclavicular axial rotation, Left scapula thorax protraction, Left scapula thorax elevation, Left glenohumeral flexion, Left glenohumeral external rotation, Left glenohumeral abduction, Left elbow flexion, Left elbow pronation, Left wrist flexion, Left wrist abduction, Left ankle plantar flexion, Left subtalar eversion, Left knee flexion, Left hip flexion, Left hip abduction, Left hip external rotation. 11 Fourier coefficients represented each anatomical degree-of-freedom. These were a0 (mean value), a1, b1, a2, b2, a3, b3, a4, b4, a5, b5. Furthermore, we also analyzed anthropometric characteristics: Pelvis width, Trunk height, Thigh length, Shank length, Foot length, Upper arm length, Lower arm length. This resulted in a total of 590 primal parameters to describe each running trial.

Data process

The initial data obtained from running tests, ultimately ending up as a drivers of a parametric running model, went through a series of processes (figure 4). First, data were collected in the KSO Lab as mocap files, with subject data entailing information regarding height, weight, gender, age and marker trajectories. Subsequently, kinematic data were used to drive AMS models and allow the system to optimize the movement pattern and anthropometrics of the subjects to fit the data as well as possible. Outcome from these were .json files, containing a numeric representation of the marker trajectories for every subject and segment dimensions. Further, the joint angle variations were processed in Python, creating Fourier series to simulate the representation of joint movements as functions. Hereafter, Fourier coefficients from every trial for all subjects were stored in a matrix and analyzed using Principal Component Analysis. After plotting coefficients into a PCA matrix, the data were impossible to trace back to any of the subjects. The PCA provided eigenvectors and values to represent the data with a minimal number of parameters. Then, Python was used to create drivers for the parametric running model with user-defined parameters. These Fourier drivers were then inserted into the AMS model, which then allowed for testing the parametric running model in AMS. This also allowed for testing pseudo-generated models from PCs, to evaluate the influence of parameters. Finally, kinematic features of the given running pattern could be extracted from the AMS analysis results.

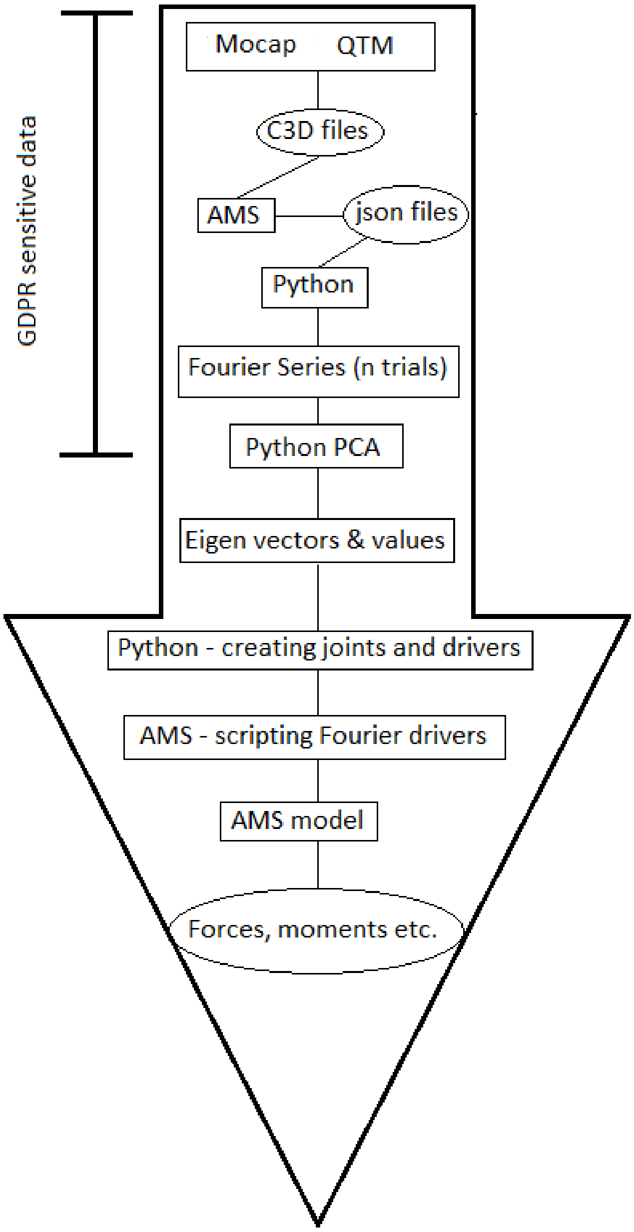

Figure 4 - The figure presents the process from mocap recordings to the finalized AMS parametric running model. The initial steps from mocap to 'Python PCA' are marked as GDPR sensitive data, as the process entail information regarding the subjects until PCA in done. Thereafter, the data is no longer GDPR sensitive and can be used without further considerations towards GDPR. Processes are marked in squares and data is marked in circles.

Data protection

General Data Protection Regulation (GDPR) is a recently introduced regulation that also influences the field of research. Personal data, such as CPR-numbers, name, date-of-birth, etc., are regulated by GDPR. This project only concerns movement and anthropometry of the subjects, but GDPR defines that, if there is a ''key'' to unlock personal information from non-personal information, then the data are still considered personal and comprised by the legislation. After the PCA-step of technical process, it was not possible to track back any kind of information to the subjects and thereby identify them. Thereby data were fully anonymized after this step, as illustrated in figure 4. In the process, where data lacked anonymization, the C3D files and folders regarding subject information was stored at a local server at Aalborg University, with security compliant with GDPR. The C3D files were then used in the process of creating a parametric model. However, after analyzing the outcome of the models, all information was totally anonymized as data then did not contain personal information regarding the subjects, but only mean values and standard deviations of Fourier coefficients and body anthropometry.

Results

The transformed Fourier coefficients for all anatomical degrees-of-freedom and anthropometrics, successfully drove the AMS parametric running model.

Principal components are shown in figure 5, as a plot on how each PC influenced the variance of data in the matrix. PC1 explained for approximately 9 % of the total variance, PC2 8 %, PC3 6.5% etc. In total 90 % of the variance was explained by the accumulation of the first 39 PCs. Furthermore, 50 % of the variance was explained by the first 10 PCs.

The average AMS-modelled runner corresponding to all-zero principal components showed a realistic running pattern, when observed via video animation. There were no irrational movements and the kinematics characterized a typical runner well.

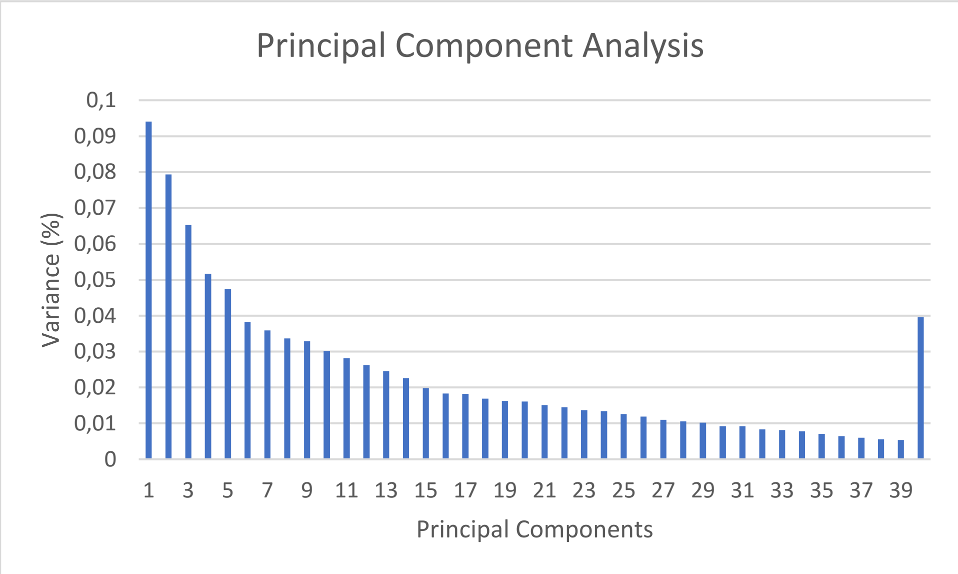

Figure 5 - Principal Component Analysis. Along the x-axis are each PC represented. The y-axis represents the influence of each PC described as the total variance explained. The final PC represents the summation of the PCs from 40-50.

Pseudo-generated running models were successfully driven in order to analyze how the models behaved when deviating from the average runner. Generating pseudo runners was done individually for the first 10 PCs, as the change in running parameters was studied. The pseudo models ran by offsetting principal components by three and negative three standard deviations, which created pseudo models with different running techniques. The pseudo-generated running models also displayed a realistic running pattern, as a result of the PCs representing interpolation within the measured running patterns.

Eigenvalues were denoted for the first 10 PCs and provided an indication of correlations between different biomechanical parameters. A total of 550 primal parameters were included each PC eigenvector, but only the top five most influential PCs were displayed. Nevertheless, the non-displayed parameters were also included during the interpretation of the PCs.

The ten first PCs and the top five most influenced parameters for each PC are listed in table 1. All parameters, except anthropometrics, are referred to as Fourier coefficients from values a0 and b1 to a5 and b5.

PC1	Eigenvector components	PC2*		Eigenvector components
Left Knee Flexion a1	0.1095	Hand Mass	Thorax Mass	0.1193
Right Knee Flexion b3	0.1091	Shank Mass	Pelvis Mass	
Right Knee Flexion a1	0.1039	Lower Arm Mass	Clavicle Mass	
Right Hip Flexion b3	0.1025	Talus Mass	Body Mass	
Right Ankle Plantar Flexion a4	0.0999	Foot Mass	Upper Arm Mass	
		Head Mass	Lumbar Mass	
		Thigh Mass		
PC3	**Eigenvector components**	**PC4**		**Eigenvector components**
Left Hip Abduction a3	0.1328	Right Sternoclavicular Axial Rotation b3		0.1200
Right Hip Abduction a3	0.13067	Right Scapula Thorax Elevation b2		0.1144
Left Hip Flexion a3	0.1287	Right Sternoclavicular Axial Rotation b2		0.1132
Pelvis RotX a3	0.1279	Left Sternoclavicular Axial Rotation b3		0.1120
Right Hip Flexion b2	0.1267	Left Sternoclavicular Axial Rotation a2		0.1106
PC5	**Eigenvector components**	**PC6**		**Eigenvector components**
Left Sternoclavicular Protraction a5	0.1131	Right Elbow Flexion b5		0.1363
Left Scapula Thorax Protraction a5	0.1093	Left Elbow Flexion b5		0.1172
Pelvis RotX b5	0.1047	CoMx b1		0.1171
Left Glenohumeral Flexion b5	0.1029	Pelvis PosX b1		0.1115
CoMx b4	0.1016	Pelvis RotY b1		0.1053
PC7	**Eigenvector components**	**PC8**		**Eigenvector components**
Right Scapula Thorax Protraction a2	0.1409	Pelvis Thorax Rotation b3		0.1443
Right Sternoclavicular Protraction a2	0.1210	CoMx a4		0.1246
Right Sternoclavicular Elevation a0	0.1199	Pelvis RotZ b3		0.1172
Right Scapula Thorax Elevation b5	0.1189	Pelvis PosX a4		0.1146
Left Glenohumeral Abduction b2	0.1187	Right SubTalar Eversion a5		0.1142
PC9	**Eigenvector components**	**PC10**		**Eigenvector components**
Left Elbow Pronation a3	0.1441	CoMy a5		0.1430
Right Hip External Rotation a5	0.1225	Pelvis PosY a5		0.1332
Left Hip External Rotation a5	0.1187	Right Hip Flexion a5		0.1286
Right Glenohumeral Flexion a3	0.1173	Left Hip External Rotation a3		0.1268
Left Wrist Flexion a3	0.1073	Pelvis PosX a0		0.1229

*Table 1 - Overview of the top primal contributors to the first 10 PCs. *PC2 has 13 parameters with the same eigenvector components.*

Eigenvectors is the primary value to assess. The vectors were interpreted as correlations between the parameters for each PC. When offsetting PCs to generate new running patterns, all components in the eigenvector are multiplied by the same number, so smaller entries in the vector change less than larger entries. Variations of principal components PC2, PC4 and PC6 are illustrated in the figures below and seem to lend themselves to obvious physical interpretation.

Figure 6 - PC2 pseudo runners. Obviously there are anthropometric differences between the two AMS models. Standard deviation has been multiplied with negative three for the left AMS model, and multiplied with positive three for the AMS model to the right.

Figure 7 – PC4. There are obvious differences between the two models, for example hip abduction, pelvic rotation and trunk side bend.

Figure 8 - PC6. The major difference is seen at the trunk lean, head and pelvis tilt of the models.

Discussion

This study enabled the investigation of individual running biomechanics. As we covered in the introduction, all runners are individual and is able to move differently. Therefore, runners must be considered individually to provide the best possible feedback to optimize their running pattern. However, there appears not be a generalized optimal running pattern applying to all types of runners. Therefore, we created a parametric running model in AMS to describe the individual runner with a minimal set of parameters, able to provide different types of running patterns. Further, the model enabled the possibility to adjust the simulated running pattern to optimize kinematics and hereby provide a strategy for offloading injury prone areas.

The parametric running model was based on kinematic data obtained from the company, Kaiser Sport & Orthopedics. A representation of the joint degrees-of-freedom and anthropometrics by Fourier coefficients, successfully drove the parametric running model. PCA resulted in 90 % of the total variance was explained by the first 39 PCs and 50% was explained by the first 10 PCs. Exploring the first 10 PCs, was done individually by offsetting the principal components by three and negative three standard deviations. This enabled the creation of pseudo running models representing the statistical variation of each PC to evaluate their physical impact. Eigenvectors acted means of translating the influence of the given PC to physical parameters such as running techniques and anthropometry of the model.

PC1 explained approximately 9 % of the total variance and was associated with hip, knee and ankle kinematics, and the video of the pseudo models for this PC showed that it influences running velocity. This is in agreement with previous findings by Orendurff et al. (2018), who found change in hip, knee and ankle kinematics and kinetics, when participants ran by self-selected baseline velocities and hereafter increased their running velocity. PC1 results matched PC2 results in order to consider the group of subjects as heterogeneous, as PC2 parameters were predominantly anthropometric. It was known that subject height varied from 1.60 m to 1.95 m in respect to variation of PC2. It was known from experimental trials, that running velocities varied from 8 km/h to 20 km/h. Thus, a great variation in running velocity was noted from experimental trials and explained by PC1 variance.

Results from PC4 seemed to mainly express movement in the sternoclavicular joint. Further, according to figure 7, when looking at the a pseudo-generated models in the frontal plane, the models deviated from the average runner by having noticeably more knee abduction. Moreover, the pseudo-models appear to differ in both upper body rotation and thorax lean. The pseudo-generated model with noteworthy knee abduction had less upper body rotation and were more upright in respect to trunk lean. This is in agreement with biomechanical analysis from a sagittal plane, as a forward trunk lean will result in an increased load at the hip and decrease the knee load and vice versa (Powers 2010), probably because a shift forward of the center-of-mass reduces the moment arm of gravity around the knee. Moreover, excessive knee valgus has been linked to hip strength (Claiborne 2003; Jacobs 2007) and can lead to osteoarthritis (Felson et al. 2013). Therefore, a preventive strategy could be to strengthen the gluteus maximus and medius that have been linked to knee valgus (Hollman et al. 2009).

Earlier studies have found a correlation between trunk lean and patellofemoral joint stress. A study by Teng & Powers (2014) revealed that increased trunk flexion leads to decrease of patellofemoral joint stress, without influencing ankle and hip kinematics. Knee extensor moment was significantly decreased and has the potential to reduce injury risk by changing trunk kinematics. In this study, PC6 described the variation of the trunk and pelvis angle/rotation in the created pseudo models as seen in figure 8. Furthermore, elbow flexion acted as an important parameter in PC6. The link is interpreted as increased elbow flexion and general increased elbow movement range will lead to an increased forward lean of thorax. Another factor contributing to patellofemoral injuries is excessive hip adduction (Noehren et al. 2013), which also can lead to iliotibial band syndrome (Noehren et al. 2007). The primary parameters in PC3 were hip adduction, pelvic rotation in frontal plane, but also knee flexion and hip flexion. Like PC1, the pseudo-generated model for PC3 also seemed to differ in running velocity, which corresponds to the change in knee and hip kinematics. Consequently, a strategy for rehabilitation could be to decrease running velocity resulting in reduced hip adduction.

In the best practice used by KSO, a major parameter linked to overuse injuries concern ankle eversion. The practical experience from KSO is in agreement with studies regarding ankle rear foot eversion/hyper pronation that has been linked to different types of injuries (Ryan et al. 1990; Viitasalo & Kvist 1983). Ankle eversion was one of the main parameters along with hip rotation and hip adduction in PC8. Additionally, when offsetting PC8 with standard deviation +/-3, the pseudo-generated running model showed that one model had severe ankle eversion, knee abduction and heel strike. The other model ran striking on the midfoot, leading to more stability in the foot and knee. Thus, midfoot landing seem to have a steady impact on the pelvis in frontal plane, knee adduction and ankle eversion.

As presented earlier, two training physiotherapist at KSO were interviewed with to recover their best practice for screening of running customers and interpretation the parameters of the model in view of this. Similarities between observed characteristics of KSO customers and PC parameters were identified. The frequently detected clinical biomechanics at KSO were the following. Firstly, the pelvic movement/rotation in all three planes were connected to PC3, PC5 and PC6. Secondly, upper body movement in frontal and sagittal planes, but not in the transversal plane, where arm movement in the sagittal plane were considered a greater influence. Lateral bending of the thorax was observed as a parameter in PC8, and trunk lean was a noteworthy parameter in PC4 and PC6. Thirdly, horizontal movement of the feet in frontal plane during swing phase, which from customer experience showed connection to pelvic movement in frontal and sagittal plane. PC4 and PC8 both supported these observations, as pelvic rotation and horizontal foot movement in frontal plane were visually detected. Finally, step length, step frequency and foot contact time were often-considered parameters. However, none of the final clinical observations were noticed as key parameters in any of the first 10 PCs.

There exists a link between running kinematics and injuries. The parametric running model created in this study has the ability to be applied to runners based on a few parameters and thereby provide information that could prevent injuries or help overcome them. However, the results require interpretation by coaches or physiotherapists to establish the parameters that has to be changed. The parametric running model is able to simulate a proposed alternative running pattern based on the runner's need. However, the adaption to an alternative running style also demands guidance from professionals. Further, a study from Tartaruga et al. (2012) presented a link between running kinematics, such as stride length, elbow range of motion, ankle angle at foot strike etc., and running economy. Hence, the properties of the parametric running model also applies for runners who seek to improve their performance and not just for injury prevention purposes.

The pipeline structure of data-input will allow the model to evolve and improve over time. For now, 39 subjects and 149 trials define the parametric running model according to the running technique and anthropometrics. However, a greater population size will contribute to a greater variation of parameters and influence the existing running styles. In the study previously mentioned by Kloster & Iversen (2017), a number of the trials that were used to develop the parametric running model comprised less than a full period of the running cycle. Thus, to construct a full stride cycle, they had to assume symmetry in their model. However, this limitation was not an issue in this study, as we had a minimum of five second coherent recordings for each trial. Asymmetry was noticed in the results of multiple PCs, e.g. PC5 and PC9. At KSO, this is a noticeable parameter when working with injury rehabilitation and optimization of running kinematics. This is addressed as asymmetry is associated with running compensatory patterns caused by previous injuries (Zifchock & Davis 2005). However, the consequences of running kinematics and kinetics have not been fully studied scientifically. Carpes et al. (2010) performed a review among asymmetry in running and found multiple articles that reporting significant kinematic and kinetic asymmetry, but there are no or few connections between injured runners and asymmetry. However, according to practical use at KSO, asymmetry is caused by previous injuries and runners often adapt a compensatory pattern, which increases loading in a non-injured areas.

The next step in the development of the parametric running model, is to add moments, muscle activity and reaction forces. Therefore, it was needed to predict ground reaction forces in AMS. A method provided by Fluit et al. (2014) enables estimation of ground reaction forces. This method introduces muscle-like actuators with 12 contact nodes under each foot. For every contact node, normal forces in the vertical direction is detected and medio-lateral and anterior-posterior are added as static friction forces.

It was by hypothesized by KSO physiotherapists that the parametric running model has great potential with respect to their field of work. However, an obstacle in the practical application was assumed to be the adaptation of a new running technique of the customers. This would require a serious of attention to ensure that the correct running style was trained. Still, the possibilities of the parametric running model are attractive, as simulating running kinematics with a few parameters would be less time consuming than the current possibilities. Further, the value propositions of KSO entailed developing knowledge regarding coaching and treatment strategies, whereas the model also can simulate kinematics and kinetics that is currently unavailable information to the employees at KSO.

Acknowledgement

I would like to express my gratitude towards Kaiser Sport & Orthopedics for their cooperativeness and Morten Lund from AnyBody Technology A/S for his assistance. Especially, I would like to thank John Rasmussen for his guidance throughout the project.

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Supplementary material

Musculoskeletal modelling

Simulation of different physical phenomena can provide insight into the workings of nature, including biomechanics. Computer-Aided Engineering (CAE) simulates physical processes and phenomena, and in biomechanics it is a tool to increase the understanding of human movements. There are, however, some complex elements to simulate, as the simulation has to account for soft tissue and bones. Furthermore, the movement of the human skeleton is controlled by muscles and activated by the central nervous system (CNS). As the human body consists of more muscles than total degrees of freedom, a kinetic redundancy issue arises. The redundancy issue can be resolved by introducing an optimality criterion regarding the distribution by the CNS to the muscles (Rasmussen et al. 2001). The muscle recruitment strategy is based on the body's ability to survive. Therefore, simulation presumes that the muscles activate in order to reduce energy levels and fatigue. This is formulated as $G(f^m)$, provided $Cf = r$, where *C* is a coefficient matrix, f a vector of internal forces and *r* a vector of external forces.

In biomechanics, inverse dynamics can be used to estimate muscle activation and other kinetics factors based on kinematic data. Inverse dynamics is based on equation solving from Newton's second law: $F = m * a$, where mass is known by the weight of the subjects, acceleration is given by measuring markers during motion capture and force is to be solved. In realistic musculoskeletal models, the problem to solve is large and complicated and requires computer simulation. Inverse dynamics entails assumptions that limit its application field to skilled and non-explosive movements, but it has a computational efficiency that allows for models with a realistic level of detail (Damsgaard et al. 2006).

Fourier series

Fourier series was chosen as representation of data, as the data can be written as periodic functions and can be used to describe data to infinite accuracy from sine and cosine waves. Essentially, Fourier series breaks

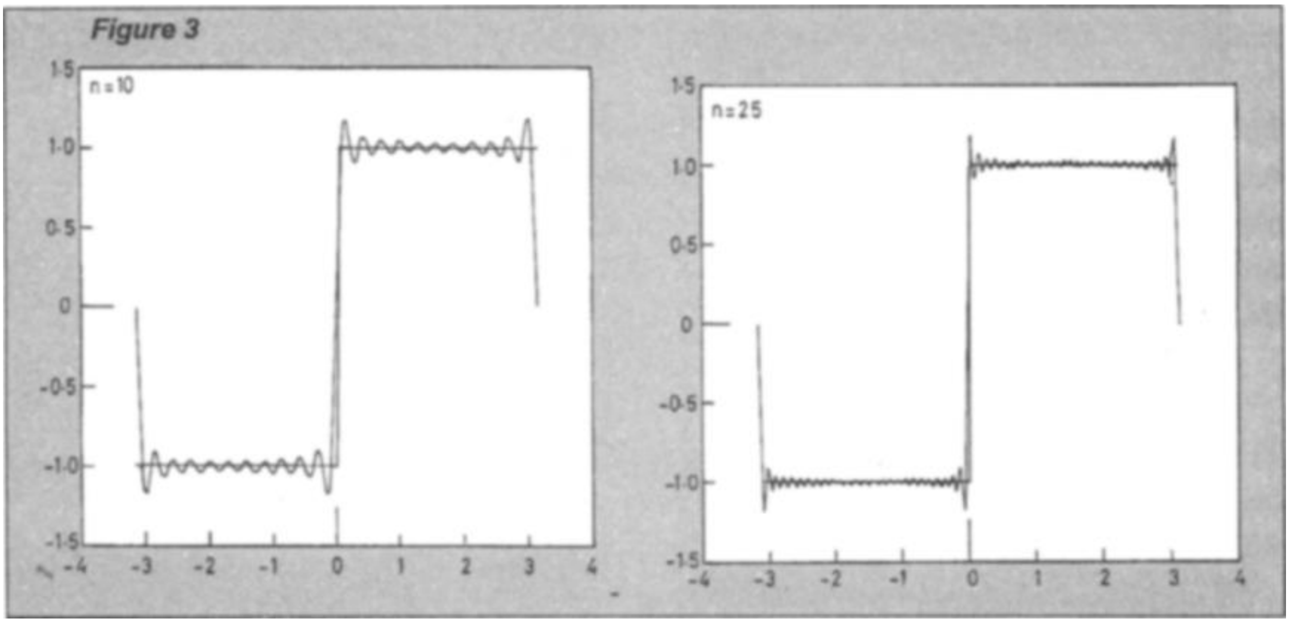

Figure 1 – Fourier series with different Fourier terms (Thangavelu 1996)

down any periodic function into a convergent series. The time-based pattern in Fourie series, has the purpose of returning/synchronizing the function according to offset and amplitude for every cycle.

Fourier coefficients act as weights (amplitudes) on the periodic step function, which figure 1 provides a graphic representation of how two signals are represented as a Fourier series. The major difference between the two step functions are the numbers of Fourier terms. As more terms are added the sine and cosine functions will approximate the step function. However, in this study it was hypothesized that having Fourier coefficients a0, a1-5 and b1-5 was a good compensation between the Fourie series representation and reducing the amount of data.

Running test setup

Nine infrared Qualisys M3 cameras were setup surrounding the treadmill (see figure 2). All of them were positioned at a 2.5 meters height above ground level, except the two frontal cameras in front of the treadmill (the arrow shows the directions that the subject is running in), they were set at 50 cm height above ground level. All cameras were positioned strategically so markers could be detected from every possible angle. If the markers were not fully detected, the function '*Polynomial Gapfill with trajectory preview*' was used to gapfill the markers. However, if the markers had several fall-outs or were missing for a longer period, the trial was discarded. Reflexes from clothing or footwear were covered with non-reflective tape, so it would not influence the capture of markers. Prior to every test, the area around the treadmill was calibrated with a wand provided by Qualisys.

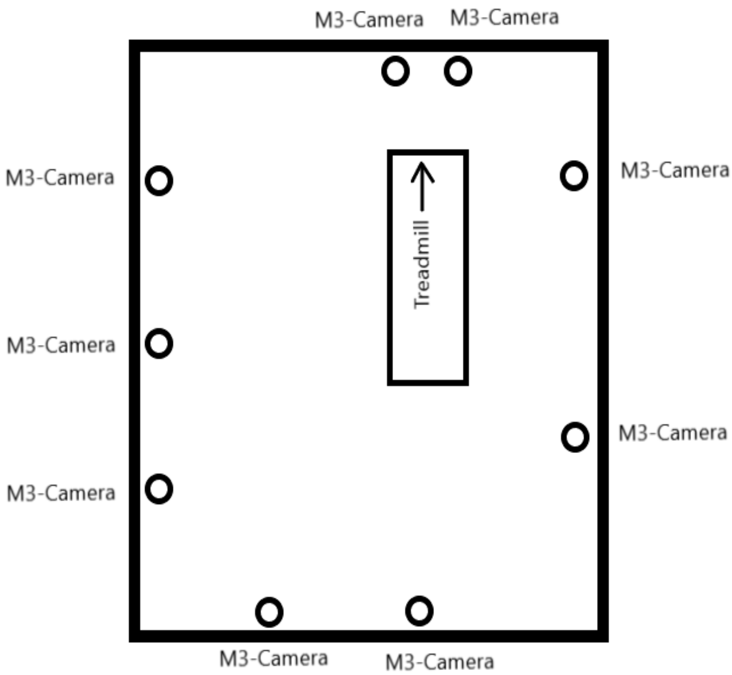

Figure 2 - Camera setup in Kaiser Sports Lab

Marker protocol

35 markers were attached to the full body and the anatomical placements of the markers are described in the following table.

Marker name	Marker position
R_HEAD	Right side of the skull
L_HEAD	Left side of the skull
SGL (were not used in AMS)	Center frontal of the skull
R_SAE	Right acromioclavicular joint
L_SAE	Left acromioclavicular joint
SME	Sternoclavicular joint
R_AIS	Right anterior superior iliac
L_AIS	Left anterior superior iliac
TV2	Thoracic vertebra, 2^{nd}
TV12	Thoracic vertebra, 12^{th}
SACR	Sacrum, S1
R_HLE	Right humerus lateral epicondyle
L_HLE	Left humerus lateral epicondyle
R_HME	Right humerus medial epicondyle
L_HME	Left humerus medial epicondyle
R_RSP	Right hand radialis
L_RSP	Left hand radialis
R_USP	Right hand ulnaris
L_USP	Left hand ulnaris
R_HM2	Right metacarpal 2^{nd}
L_HM2	Left metacarpal 2^{nd}
R_PAS	Right thigh, 5 cm above patella
L_PAS	Left thigh, 5 cm above patella
R_FLE	Right lateral condyle of femur
L_FLE	Left lateral condyle of femur
R_TTC	Right tibial tuberosity
L_TTC	Left tibial tuberosity
R_FAL	Right lateral malleolus of tibia
L_FAL	Left lateral malleolus of tibia
R_FCC	Right calcaneal tubercle
L_FCC	Left calcaneal tubercle
R_FM5	Right metatarsal 5^{th}
L_FM5	Left metatarsal 5^{th}
R_FM2	Right metatarsal 2^{nd}
L_FM2	Left metatarsal 2^{nd}

Table 1 - Marker names and their anatomical position

Results

In this supplementary result section, the remaining top 10 PC pseudo-generated running models are displayed. As noted in the rapport, the average model was tested by offsetting three and negative three standard deviation, to illustrate the parameters influence on each PC.

Figure 3 – PC1

Figure 4 - PC3

Figure 5 - PC5

Figure 6 - PC7

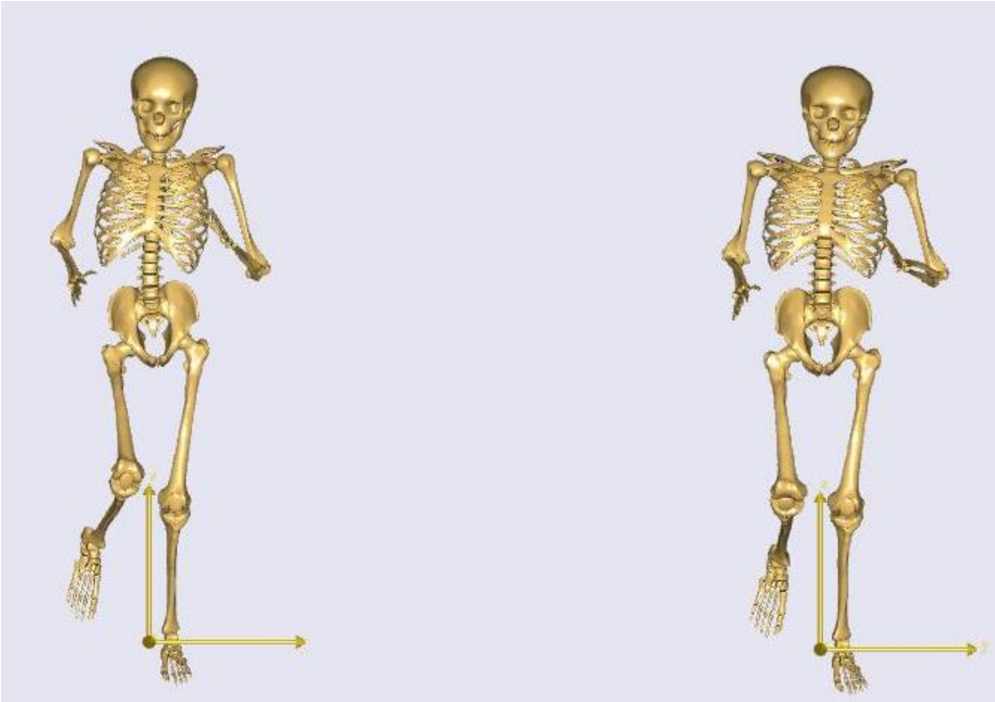

Figure 7 - PC8

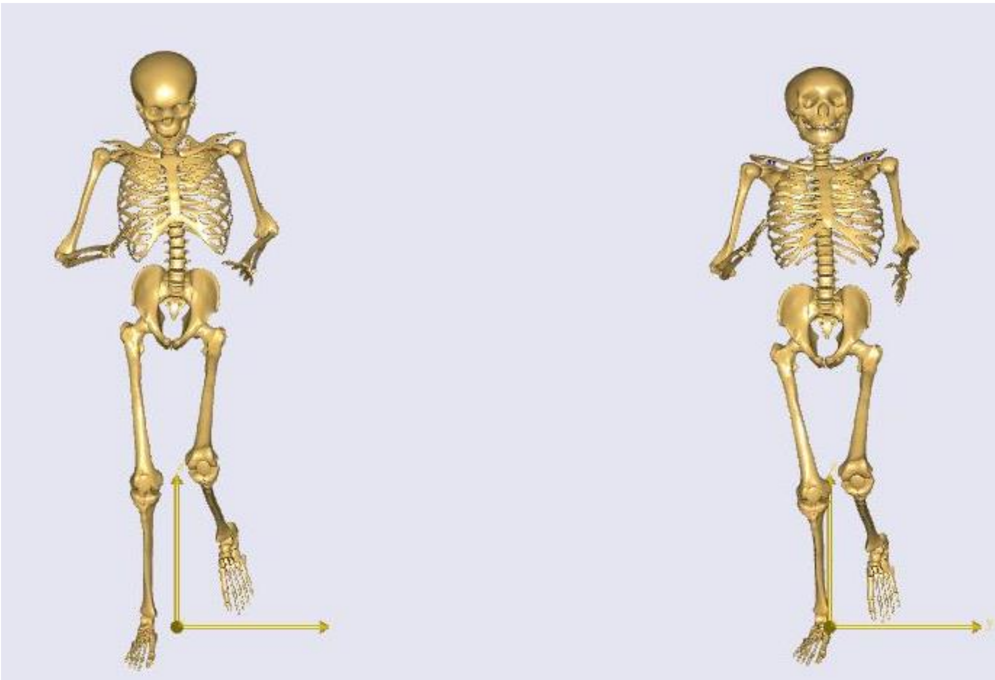

Figure 8 - PC9

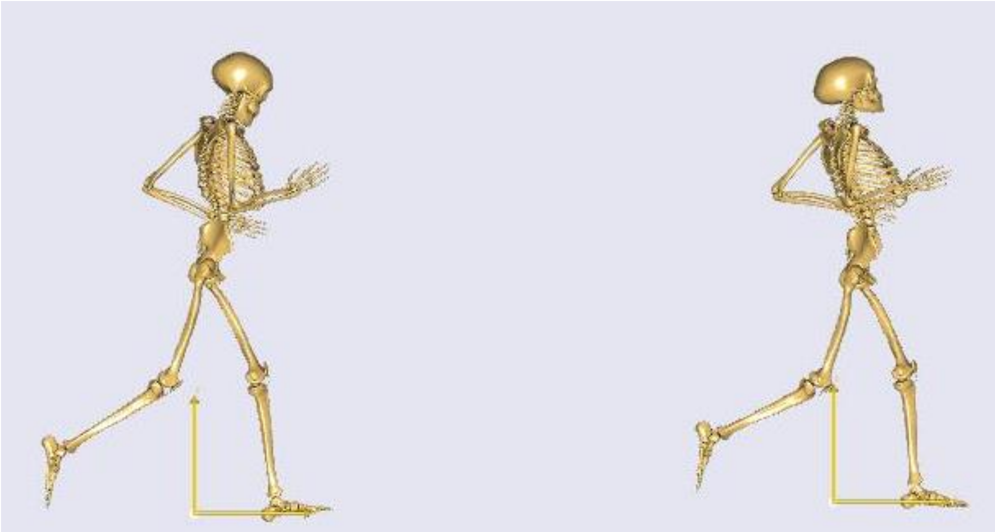

Figure 9 - PC10

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