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Data-Based Parametric Biomechanical Models for Cyclic Motions

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Abstract. We present a method to convert motion capture data and anthropometric statistics into parametric biomechanical models of cyclic motions, such as walking, cycling and running. The motivation is ease of modelling and the desire to make models prospective. We have developed a data processing pipeline, which pre-compiles a large amount of motion capture trials into a parametric model relying on the correlations between the input variables. The compilation converts optical motion capture data into anatomical joint angle variations and anatomical body dimensions. Finally, a quadratic programming method with a closed-form solution is developed to predict motion patterns meeting subject-specific requirements. The method is demonstrated on running models, and we conclude that the method can facilitate new uses of biomechanical models.

Keywords. Running, Anthropometry, Statistics, Principal Component Analysis

1. Introduction

One of the trends in biomechanics from the past two decades is individualization of model to specific subjects or patients. The importance of this topic was illustrated by the "Grand Challenge Competition to Predict in Vivo Knee Loads": a blinded conference competition to predict measured forces in knee implants [1]. Such carefully implemented subject-specific models typically require advanced medical imaging input to obtain correct geometries of internal anatomical structures. Despite recent advances in automatic processing of medical image data [2], this process tends to be cumbersome and not tractable for clinical workflows.

In terms of movement, such models typically require subject-specific motion capture data. The prior collection of motion data means that subject-specific models can only be retrospective, in the sense that they represent movements that happened in the past in a laboratory. This contradicts the purpose of many models, which is to predict what will happen if a prospective intervention is performed.

There are many applications of human models which do not require accurate representations of single individuals but rather statistical representations of populations;

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in terms of anthropometry, digital human models for ergonomics and product design have successfully relied on population statistics for decades [3].

While skilled and repetitive movements, such as walking, running and cycling, differ between people, they do seem to show more similarity than difference, and there may be notable connections between movement patterns and anthropometry. For instance, a positive correlation between leg length and step length seems plausible. Such correlations are important to recover, because they can potentially reduce the need for subject-specific model input and thereby facilitate the development of truly predictive models. The idea of investigating skilled movements based on many motion capture trials was pursued successfully in the HUMOSIM framework from the University of Michigan [4]. In this paper, we report on the development of a unified statistical model for anthropometry and movement patterns for cyclic motions exemplified by running.

2. Methods

Kinematics of a total of 285 treadmill running trials were collected from 80 subjects using an optical motion capture system (Qualisys AB, Gothenburg, Sweden). 180 trials were from male subjects, and 105 trials were from female subjects. The subjects were recreational and skilled runners. Informed consent was obtained, and the data were handled in accordance with the GDPR regulations. Statistical summaries are presented in Table 1.

Table 1. Summary of data of running trials.

Property	Mean	Standard deviation	Range
Velocity [km/h]	12.48	2.79	6-20
Subject age [years]	35.8	12.0	19-65
Body Mass [kg]	73.0	10.7	51-105
Stature [m]	1.77	0.0807	1.58-1.95

The marker trajectories were imported into the AnyBody Modelling System ver. 7.2 (AnyBody Technology, Aalborg, Denmark) [5] for the initial compilation. Using an algorithm for identification of model kinematics and segment parameters [6], each trial was converted into an individualized, full-body musculoskeletal model. The model comprises 67 anatomical segments and 52 anatomical joints with a total of 104 joint degrees-of-freedom. The variation of each joint degree-of-freedom over a typical running cycle was recovered from the model, and these time functions are parameterized with Fourier series truncated to 11 terms.

Each running trial is now represented by parameters, which are the Fourier coefficients for each degree-of-freedom, subject-specific segment lengths identified from the motion capture data, and meta data, such as gender, age, body weight, stature and running speed. This comprises a total of 1224 parameters from which each trial can be recreated. Parameters from all trials are collected into a standard-scaled matrix, $\mathbf{X}$, where each row represents a trial, and each column is a parameter. The matrix is subjected to principal component analysis (PCA):

$$\mathbf{y} = \mathbf{A}(\mathbf{x} - \boldsymbol{\mu}) \tag{1}$$

where $\mathbf{A}$ is the PCA transformation matrix, $\mathbf{x}$ is a set of running parameters, $\boldsymbol{\mu}$ is the vector of mean values of $\mathbf{X}$.

The orthonormal properties of $\mathbf{A}$ enable the opposite transformation:

$$\mathbf{x} = \mathbf{A}^{\mathbf{T}}\mathbf{y} + \boldsymbol{\mu} \tag{2}$$

The principal components can be ordered in terms of variance, thus offering an opportunity to investigate which generic features of the running style and anthropometry primarily distinguish runners from each other.

Performing PCA leads to a convenient parametric running model, because the components of $\mathbf{y}$, unlike the primal parameters in $\mathbf{x}$, are orthogonal and therefore can be varied independently to create new running patterns. The procedure is to select a set of transformed parameters, $\mathbf{y}$, within a reasonable statistical range, transform them back to primal space, $\mathbf{x}$, through (2), feed $\mathbf{x}$ back into the biomechanical simulation model and recreate the running style.

However, the transformed parameters, $\mathbf{y}$, are linear combinations of $\mathbf{x}$ and may or may not lend themselves to physical interpretation. From a user's perspective, it would be more practical to be able to specify primal parameters, $\mathbf{x}$, with a physical or physiological interpretation, for instance running speed, step length, leg length, gender or BMI. However, changing a single parameter in $\mathbf{x}$ is not immediately possible because the parameters in $\mathbf{x}$ are statistically correlated, i.e. changing a single primal parameter will lead to unrealistic combinations. To combine the benefits of the primal and transformed space, we formulate parameter identification as an optimization problem. We first observe that the average runner corresponds to $\mathbf{y} = \mathbf{0}$. Minimizing a weighted norm of $\mathbf{y}$ given one or more constraints on the primal parameters will therefore lead to a running pattern that is as probable as possible, given the constraints on primal variables:

Minimize

$$\mathbf{y}^{\boldsymbol{T}}\mathbf{C}^{-\mathbf{1}}\mathbf{y} \tag{3}$$

Subject to

$$x_j = f_j \text{ for } j \in \boldsymbol{J} \tag{4}$$

where $\mathbf{C}$ is a diagonal matrix of eigenvalues of $\mathbf{X}$, f_j is a prescribed value of primal parameter x_j and $\boldsymbol{J}$ is the set of primal variables that are constrained. We express x_j in terms of $\mathbf{y}$ using (2) and obtain a quadratic optimization problem with linear constraints in the transformed variables:

Minimize

$$\mathbf{y}^{\boldsymbol{T}}\mathbf{C}^{-\mathbf{1}}\mathbf{y} \tag{5}$$

Subject to

$$\sum_i a_{ij} y_i + \mu_j = f_j \text{ for } j \in \boldsymbol{J} \tag{6}$$

where a_{ij} is the ij^{th} entry in **A.** Defining **B** as the subset of **A** corresponding to the indices $\boldsymbol{J}$, this mathematical program has a closed form solution:

$$\begin{bmatrix} \mathbf{C}^{-1} & \mathbf{B}^T \\ \mathbf{B} & \mathbf{0} \end{bmatrix} \begin{Bmatrix} \mathbf{y} \\ \boldsymbol{\lambda} \end{Bmatrix} = \begin{Bmatrix} \mathbf{0} \\ \boldsymbol{f} - \boldsymbol{\mu} \end{Bmatrix} \tag{7}$$

where $\boldsymbol{\lambda}$ is a vector of Lagrange multipliers corresponding to the constraints on primal parameters. Equation (7) makes it possible to specify constraints on primal parameters in the transformed, orthogonal space.

2.1. Software implementation

For the purpose of demonstration, the technology has been encapsulated into a demonstrator app, Runover, working as a front end to the AnyBody Modeling System. Runover is programmed in Python using the cross-platform user interface framework kivy [7], so it is theoretically deployable on mobile devices running Android or iOS. Runover collects user input, executes the biomechanical analysis, displays the running animation, and reports key figures for the running pattern biomechanics, for instance ground reaction forces, Achilles tendon forces or patella ligament forces.

3. Results

3.1. Data processing

The processed running trials show differences as well as similarities. Figure 1 illustrates these differences with selected joint angle variations resulting from the compilation process.

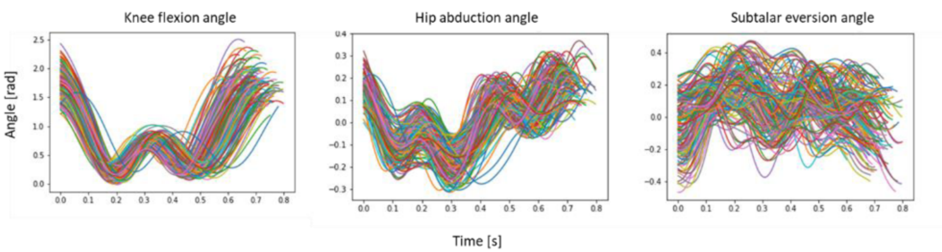

Figure 1. Populations of selected anatomical angles.

The explained variance from the principal components is illustrated in Figure 2, which shows that 40 principal components explain 90% of the total variance of the 1224 primal parameters. Although the figure is truncated after 40 parameters, PCA was not used to reduce the dimensionality of the system. There is no practical reason to do so since the PCA analysis is easily manageable on an ordinary desktop computer.

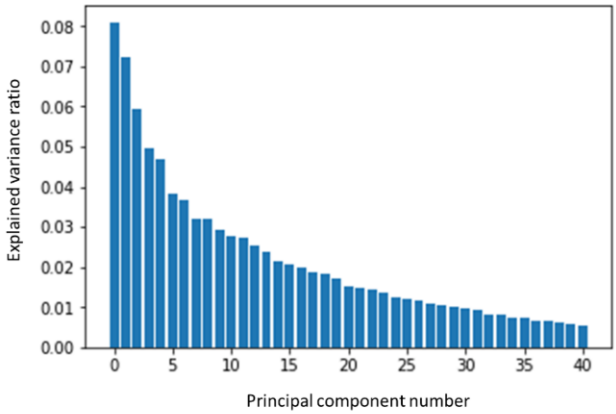

Figure 2. Explained variance ratio from the principal component analysis.

The average runner corresponding to the mean values listed in Table 1, and the runner's biomechanics output are depicted in Figure 3. Please notice that the computed parameters are slightly asymmetric because the runners compiled into the model were also asymmetric to some extent.

Figure 3. Average runner and computed biomechanical parameters.

3.2. Interpretation of principal components

Direct variation of each parameter in transformed space reveals, by visual inspection of the model animations, that the first principal component is primarily associated with running speed, while the second appears to be related mostly to the stature of the runner. Subsequent parameters are more difficult to interpret visually but seem to concentrate their influence on movements of specific body regions: core movements for the third principal component, shoulder and arm movements for the fourth component and leg movements—specifically knee extension—for the fifth component.

3.3. Control of primal parameters

Any subset of the primal parameters, **x**, i.e. the 1224 parameters for each runner, can be specified as constraints in (6). Constraining the running speed to 6 and 30 km/h respectively for the otherwise average runner leads to the running styles depicted in Figure 4.

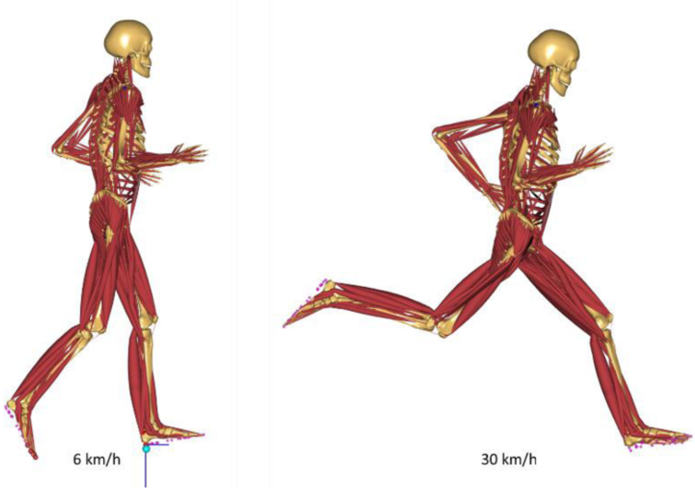

Figure 4. Synthesized running patterns for speeds of 6 km/h (left) and 30 km/h (right).

A debated issue in running biomechanics is whether forefoot running might entail biomechanical advantages with respect to running with heel strike [8]. During the processing of the statistical data, the angle of the foot with respect to the ground at foot strike is registered and stored as a primal parameter in **X**. It is therefore subsequently possible to constrain the foot strike angle along with the running speed as primal parameters and obtain models that are similar, except for the foot strike pattern. Such models running at 13 km/h are depicted in Figure 5, and their simulated biomechanical parameters are compared in Table 2. The peak ground reaction forces are, perhaps surprisingly, a bit higher for forefoot running, while the patella ligament force is reduced at the cost of increasing the Achilles tendon load. The running economy in terms of metabolism seems to be slightly better for the heel strike running pattern.

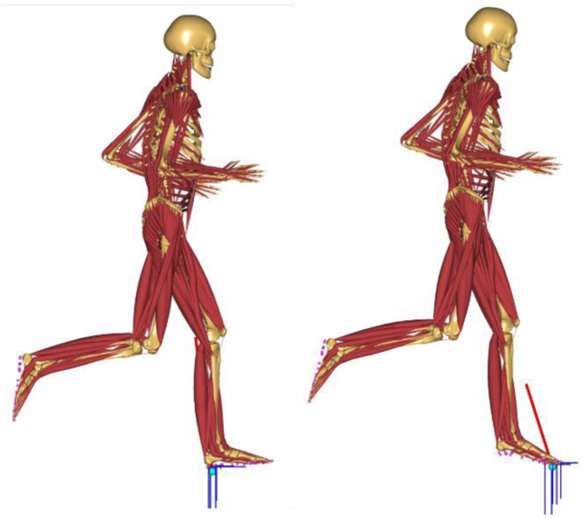

Figure 5. Synthesized running patterns for heel strike (left) and forefoot running (right) at 13 km/h.

Table 2. Simulated biomechanical parameters of heel strike and forefoot running at 13 km/h.

Property	Heel strike	Forefoot
Peak GRF [BW]	2.03	2.17
Peak patella lig. force [BW]	6.6	5.84
Peak Achilles tend. force [BW]	7.38	9.05
Metabolism [J/(kg km)]	3714.0	3858.0

4. Discussion

The proposed method can be regarded as a machine learning algorithm, which appears to be able to generate a statistical variation of plausible running models. The underlying PCA approach is not confined to normally distributed data, but the optimization problem formulation relies on an assumption of normality. It is certain that this condition is not fulfilled for all of the underlying data in the sense that male and female trials are mixed, and the gender variable is categorical. Other gender-dependent variables, such as anthropometrical dimensions, probably do not meet the criteria for normal distribution in their merged form.

Despite these reservations, the method seems to work well, even to the extent of producing surprisingly good results in some cases. The fastest speed in the empirical data is 20 km/h, but the model reproduces notable features of sprint running, such as high heel elevation in the forward swing, when the speed is extrapolated to sprint at 30 km/h as shown in Figure 4.

It is obvious that the validity of the synthetically generated running styles is inferior to recorded empirical data. However, for comparison of related but different conditions, the synthetic approach offers the advantage that selected parameters can be changed while keeping other parameters constant, which is rarely possible in empirical studies. While doing so, users should observe that the optimization problem in the interest of orthogonality is formulated in the set of transformed parameters, $\mathbf{y}$. The effect of this choice is that unconstrained primal variables will change during the solution of the optimization problem, so it is necessary to explicitly constrain the variables that must remain unchanged between conditions. This should also be done with caution, because constraining too many or unlikely combinations of primal variables can lead to improbable running patterns.

The method has the potential to facilitate the use of digital human models for prospective purposes because it allows for generation of anthropometry and motion with minimal subject-specific input. The method should be directly extensible to other cyclic motions, where walking will probably be the more important application.

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