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Speed-dependent reference joint trajectory generation for robotic gait support

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ABSTRACT

For the control of actuated orthoses, or gait rehabilitation robotics, kinematic reference trajectories are often required. These trajectories, consisting of joint angles, angular velocities and accelerations, are highly dependent on walking-speed. We present and evaluate a novel method to reconstruct body-height and speed-dependent joint trajectories. First, we collected gait kinematics in fifteen healthy (middle) aged subjects (47–68), at a wide range of walking-speeds (0.5–5 kph). For each joint trajectory multiple key-events were selected (among which its extremes). Second, we derived regression-models that predict the timing, angle, angular velocity and acceleration for each key-event, based on walking-speed and the subject's body-height. Finally, quintic splines were fitted between the predicted key-events to reconstruct a full gait cycle. Regression-models were obtained for hip ab-/adduction, hip flexion/extension, knee flexion/extension and ankle plantar-/dorsiflexion. Results showed that the majority of the key-events were dependent on walking-speed, both in terms of timing and amplitude, whereas the body-height had less effect. The reconstructed trajectories matched the measured trajectories very well, in terms of angle, angular velocity and acceleration. For the angles the RMSE between the reconstructed and measured trajectories was 2.6°. The mean correlation coefficient between the reconstructed and measured angular trajectories was 0.91. The method and the data presented in this paper can be used to generate speed-dependent gait patterns. These patterns can be used for the control of several robotic gait applications. Alternatively they can assist the assessment of pathological gait, where they can serve as a reference for "normal" gait.

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1. Introduction

During the last decade a lot of effort has been put in the development of actuated orthoses. They can enable neurological patients to walk again, assist physical therapy, or increase human performance above normal levels (Diaz et al., 2011; Dollar and Herr, 2008; Ferris et al., 2005; Pennycott et al., 2012). Independent of whether these devices are position or force controlled they often require reference trajectories to define the motion, or determine the amount of assistance.

Generally, these reference patterns are based on pre-recorded trajectories from unimpaired volunteers walking on a treadmill or walkway (Banala et al., 2009; Riener et al., 2005; Stauffer et al., 2009; Yano et al., 2003), or based on walking in the device while it is operated in a transparent mode (Aoyagi et al., 2007; Emken et al., 2008) or with the motors removed (Colombo et al., 2000). Others create patient specific patterns by recording the gait trajectory while the patient walks with manual assistance (Aoyagi et al., 2007; Emken et al., 2008), or by reconstructing joint patterns based on movements of the unimpaired limb (Vallery et al., 2009).

Most methodologies however, have certain considerations that limit the use of the recorded trajectories to specific applications. First, due to the mass and inertia of a device and/or imperfections of the transparent mode, gait patterns recorded in the device might not match with the ones recorded during free walking (Emken et al., 2006; van Asseldonk et al., 2008). Second, the recorded patterns obtained during manual assistance will only be valid for that specific subject (and speed) and still require initial manual support from the therapist. Third, coupling the movement of the disabled leg to the movement of the unimpaired leg is only applicable to patients with one affected leg, which is often true for stroke survivors, but not for many other neurological injuries. Thus, obtaining pre-recorded trajectories from unimpaired volunteers seems the most suitable approach to create a set of reference patterns that can be used in a variety of gait-support applications.

Still, their use is constrained to the limited number of speeds they are recorded on. Most studies include slow, normal and fast walking (Hanlon and Anderson, 2006; Lelas et al., 2003; Oberg et al., 1994), while the progress of the patients' preferred walking-

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speed can be as small as 0.1 kph. Additionally, even the slow walking-speeds of healthy controls, ranging from 0.9 to 1.4 m/s (Hanlon and Anderson, 2006; Oberg et al., 1994), are typically higher than the preferred walking-speed of patients with neurological injuries like stroke, ISCI or Parkinson (0.5–1.1 m/s) (Beaman et al., 2010; Delval et al., 2008; Goldie et al., 1996; van Hedel et al., 2007; Witte and Carlsson, 1997).

To eliminate the need to record joint trajectories at a high number of different walking-speeds a method is required that can reconstruct joint trajectories for any given speed. Several studies already tried to quantify the speed-dependencies of joint trajectories for some key features like peak sagittal plane parameters (Hanlon and Anderson, 2006; Kirtley et al., 1985; Lelas et al., 2003; Stansfield et al., 2006).

However, for robotic control purposes these peak parameters, consisting of one or two specific key-events per joint, are not sufficient to reconstruct a full gait cycle. Information about the velocity and acceleration of these key-events, which are never reported, would also allow for more accurate joint trajectory reconstruction. Additionally, the relative timing of these peak parameters, which is not included in most regression-models, is also shown to be largely dependent on speed (Stoquart et al., 2008). Finally, all studies that provide regression-models for the speed-dependency of kinematic gait parameters are limited to the sagittal plane kinematics, whereas also hip ab-/adduction is incorporated in the more advanced orthoses.

The objective of this study was to present and evaluate a novel method for reconstructing body-height and speed-dependent angular trajectories (sagittal and frontal). We propose to use piece-wise quintic spline fitting between different key-events. The key-events consist of a selection of extreme values in position and velocity data. The timing, angle, angular velocity and acceleration of these key-events are predicted, based on walking-speed and body-height, using regression-models. The presented method and data provide a reference for generating speed-dependent joint trajectories for several robotic gait applications.

2. Methods

2.1. Subjects

Fifteen healthy (middle) aged subjects in the age range 47–68 (age 59.3 ± 6.4, seven men, eight women, weight 74.0 kg ± 11.0, body-height 1.69 m ± 0.10, BMI 25.8 ± 2.4) participated in this study. No subject had symptoms of orthopedic or neurological disorders and all gave informed consent, according to the recommendations of the declaration of Helsinki.

2.2. Experimental protocol and recordings

Subjects walked on a treadmill, starting with a familiarization period of 3 min followed by a 3 min walking trial. This was repeated for seven different speeds (0.5, 1, 1.5, 2, 3, 4 and 5 kph) with 1-min breaks between trials. No specific instructions on how to walk on the treadmill were given. Gait kinematics were recorded with an optical tracking system (Vicon Oxford Metrics, Oxford, UK) at a frequency of 120 Hz. To track the motion of the subject, 21 passive reflective markers were attached to bony landmarks and segments on the legs and trunk (Fig. 1).

2.3. Data analysis

Conventional methods that determine normative gait patterns take the average across individual subjects. This may result in an underestimation of the extremes in the gait pattern, when subjects have a different distribution of the extremes throughout the gait cycle (Molloy et al., 2008; Sadeghi et al., 2003). Therefore, we developed a method where the pattern is parameterized with different key-events (minima, maxima etc.). This way, the extreme value in the reconstructed pattern is actually the mean of the extreme values of the individual patterns, even when the extremes occur at another percentage in the gait cycle. A piece-wise quintic spline is fitted between the different key-events to create subject- and speed-dependent reference patterns. The following paragraphs describe these different steps in more detail

Fig. 1. Marker placement. To track the motion of the subject, twenty one passive reflective markers (gray circles) were attached to bony landmarks and segments on the legs and trunk. Joint angles are defined according to the classical method used in clinical examination, where (dorsi-) flexion and abduction are defined positive.

2.3.1. Kinematics

Custom-written Matlab software was used to convert the marker positions into hip ab-/adduction, hip flexion/extension, knee flexion/extension and ankle plantar-/dorsiflexion (Fig. 1). This program can be seen as a variant of the Conventional Gait Model. It uses the minimum number of markers possible to determine 3-dimensional kinematics. All joints are modeled as potential ball-hinges, with three independent rotational degrees of freedom. The model is hierarchical, indicating that the proximal segments have to be detected before the distal segments can be defined. Joint positions are based on the location of some anatomical landmarks and regression equations. In the software additional constrains, primarily during the double stance phase, and optimization routines are used to reduce measurement errors (Koopman et al., 1995).

To prevent habituation from affecting the gait patterns, only the last minute of each trial was selected for data analysis. The joint angular data was split into individual strides, and normalized as a percentage of the gait cycle, 0% corresponding to heel contact of the concerned leg. Heel-contact and toe-off events were detected with a phase detection method developed by (Zeni et al., 2008) that used the local maxima in the anterio-posterior position of the heel marker. Outliers, due to missing marker data, bad interpolation or a misplaced step by the subject, were removed. A step was defined as outlier when the whole trajectory, or part of it, fell outside the boundaries, which was set at 3 times the interquartile range away from the 25 and 75 percentile. Because the intra-subject variation (in amplitude and timing) was small we calculated average trajectories for each individual subject. Still, average trajectories were calculated for the left and right leg separately.

The detected heel-contact and toe-off events were also used to calculate other spatiotemporal parameters like cadence, stride length and relative gait phases. Although one can walk with infinite combinations of stride lengths and cadences, (Sekiya and Nagasaki, 1998) demonstrated that step-length divided by step-rate ("step-ratio") is relatively constant over a wide range of walking-speeds. Therefore we used this ratio as a simple descriptor for temporal and spatial co-ordination. The step-ratio is calculated according to:

$$\text{step ratio} = \frac{\text{step length (m)}}{\text{step frequency}\,\frac{\text{steps}}{s}} = \frac{1}{4}\frac{\text{stride length}}{\text{stride frequency}} \tag{1}$$

2.3.2. Key-events

From each joint trajectory we extracted 6 key-events, including the start of the joint trajectory (heel contact) and a selection of extreme values in position and velocity data (Fig. 2). We parameterized each key-event with an x parameter, representing the percentage of the gait cycle at which the key-event occurred, its angle (y), angular velocity (dy/dx) and acceleration (d^2y/dx^2).

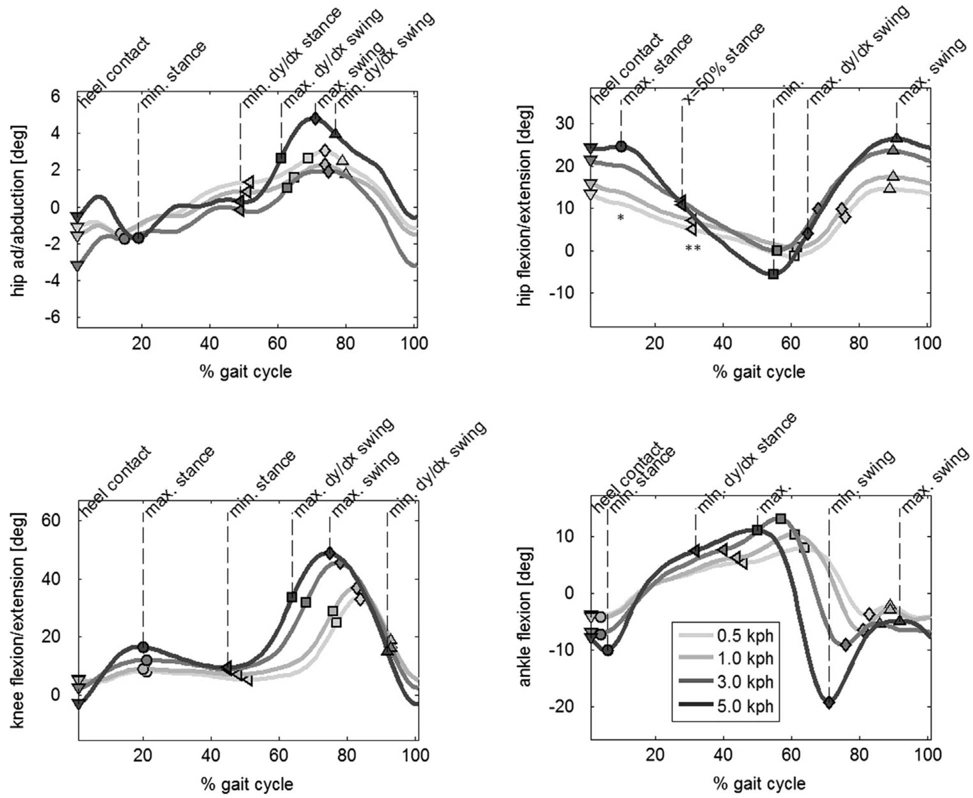

Fig. 2. Selected key-events for the different joint trajectories. Example of the average trajectories of a typical subject at 0.5, 1, 3 and 5 kph, together with the extracted key-events. We selected 6 key-events that described the individual's gait pattern. The key-events include the start of the gait cycle (heel contact) and its extreme values. Between some extreme values additional key-events were placed at maxima/minima in velocity data to obtain an adequate distribution of key-events throughout the gait cycle. The key-events of the average left and right joint trajectories were extracted separately. * At lower walking-speeds this key-event is not present for every subject. If this is true for the majority the subjects (at a specific speed), then this particular key-event is not included in the spline fitting procedure at that speed (Table 2). ** Key-event added to improve spline fitting. This key-event does not represent a maxima or minima in position or velocity, but is defined at the middle of the stance phase.

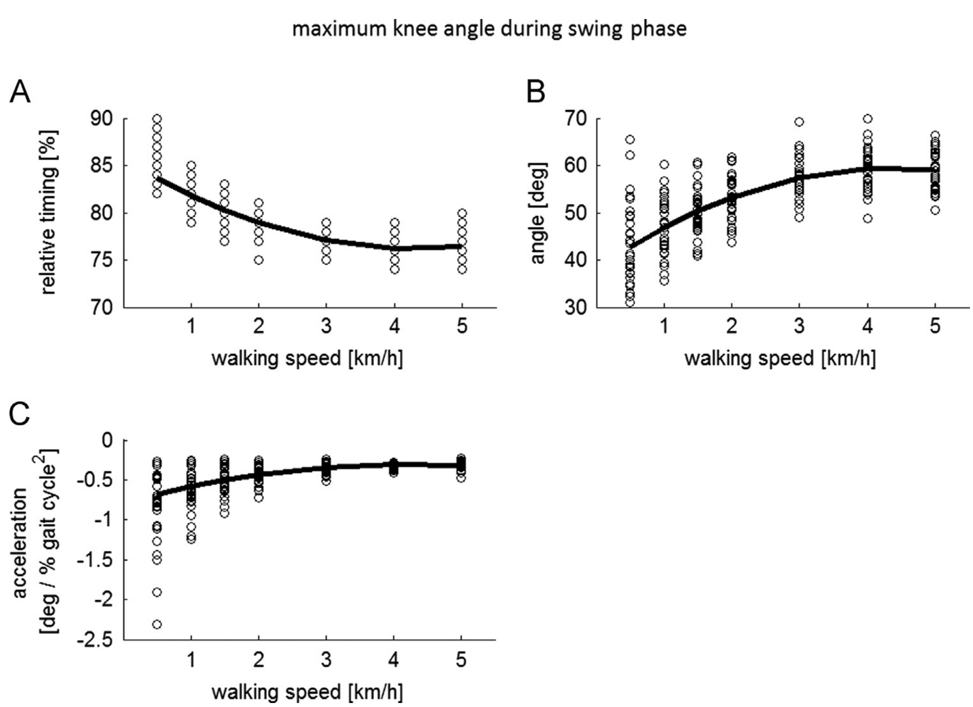

Fig. 3. Typical example of speed- and body-height dependency of the parameters of a key-event. Relation between walking-speed and the relative timing (A), angle (B), and angular acceleration (C) of the “max. swing” key-event of the knee joint, referring to the maximum knee flexion during the swing phase. Each circle represents the parameter value of the key-event at a specified walking-speed for one subject. The solid line indicates the fitted regression-model. Since this key-event represents a maximum in the joint angular data, the angular velocity parameter is zero by definition, and is not shown. For the parameters of this key-event the body-height did not significantly add to the predictability of the regression-model (Table 3).

2.3.3. Regression-models

The extracted parameters of the key-events were used to construct a set of regression-models. These models were used to predict the parameter values for each key-event, based on a set of predictor variables. We used the following regression formula.

$$Y = \beta_0 + \beta_1 v + \beta_2 v^2 + \beta_3 l \tag{2}$$

where v represents walking-speed, l body-height and Y represents the x, y, dy/dx, or d^2y/dx^2 parameter of a particular key-event. Both v and v^2 are included in the regression formula, since (Lelas et al., 2003) already showed that most common peak sagittal plane parameters have a linear and/or quadratic relationship with walking-speed. We used stepwise regression (Draper and Smith, 1998) to test the statistical significance of the predictor variables, using entrance/exit tolerances with $p < 0.01$. After selecting the appropriate predictor variables for the regression-model, we used robust regression (Street et al., 1988), with a 'bisquare' weighing function, to retrieve the final set of regression coefficients (β_x). Regression-models (Fig. 3) were derived for all 4 parameters of all 6 key-events, creating 24 regression-models for each joint. We also obtained regression-models for the step-ratio and the relative duration of the different gait phases, using the same predictor variables.

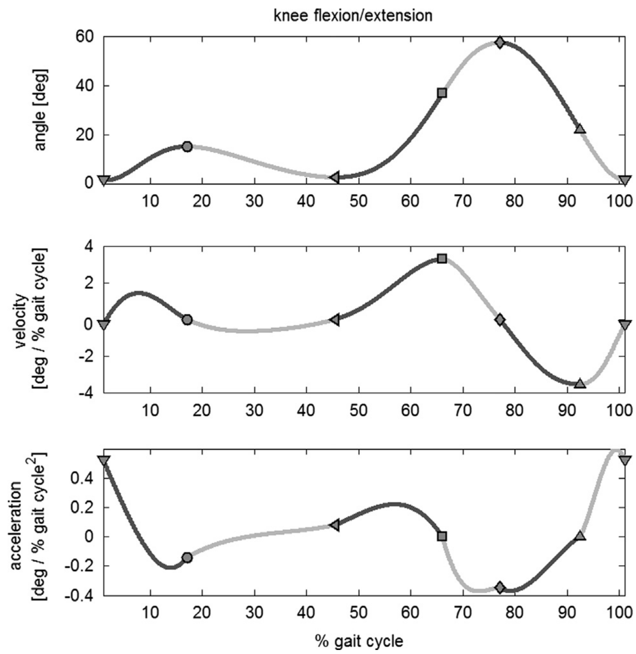

Fig. 4. Reconstruction of the joint trajectories. Typical example of the reconstruction of a joint trajectory using piece-wise quintic splines. Here a trajectory for the knee joint is reconstructed. Six quintic splines are fitted between the 7 key-events. The values for the x, y, dy/dx, and d^2y/dx^2 parameter of the first 6 key-events are calculated for a specific speed and body-height with the regression equations provided in Table 3. To ensure continuity in the reconstructed trajectory the y, dy/dx, and d^2y/dx^2 parameter of the 7th key-event (at 100% of the gait cycle) is equal to the first 1st key-event (at 0% of the gait cycle). The resulting trajectory is continuous in the position (A), velocity (B) and acceleration (C).

2.3.4. Spline fitting

The obtained regression-models were used to reconstruct the reference patterns (for each subject and walking-speed). First, the x, y, dy/dx, and d^2y/dx^2 parameters of the key-events (for a certain speed and body-height) were calculated. Subsequently, a quintic spline was fitted between every pair of consecutive key-events, resulting in 6 (5th order) polynomials (Fig. 4 and Supplementary material A). Piece-wise quintic spline fitting was used because it creates continuous trajectories (in terms of position, velocity and acceleration), which is preferable for robotic control.

2.3.5. Validation

To determine the accurateness of the spline fitting procedure we evaluated the root mean square error (RMSE) and the correlation coefficient (r) between the actual (left and right) joint trajectories and the reconstructed spline, using the leave-one-out method of cross-validation (or rotation estimation) (Geisser, 1993; Stone, 1974) (Fig. 5). Next, the results were averaged over left and right trajectories and across subjects ($RMSE_{act\text{-}rec}$ and $r_{act\text{-}rec}$) and reported for every walking-speed (Fig. 6). To assess the quality of the fit during the different gait phases, the RMSE between the actual and reconstructed trajectories was also expressed as a percentage of the gait cycle. As a reference for the obtained model error, we calculated the natural deviation ($RMSD_{l-r}$) and correlation coefficient (r_{l-r}) between the left and right joint trajectories. Another reference for the model error was provided by the inter-subject variability, which was calculated by the standard deviation (STD) across subjects, for every percentage of the gait cycle.

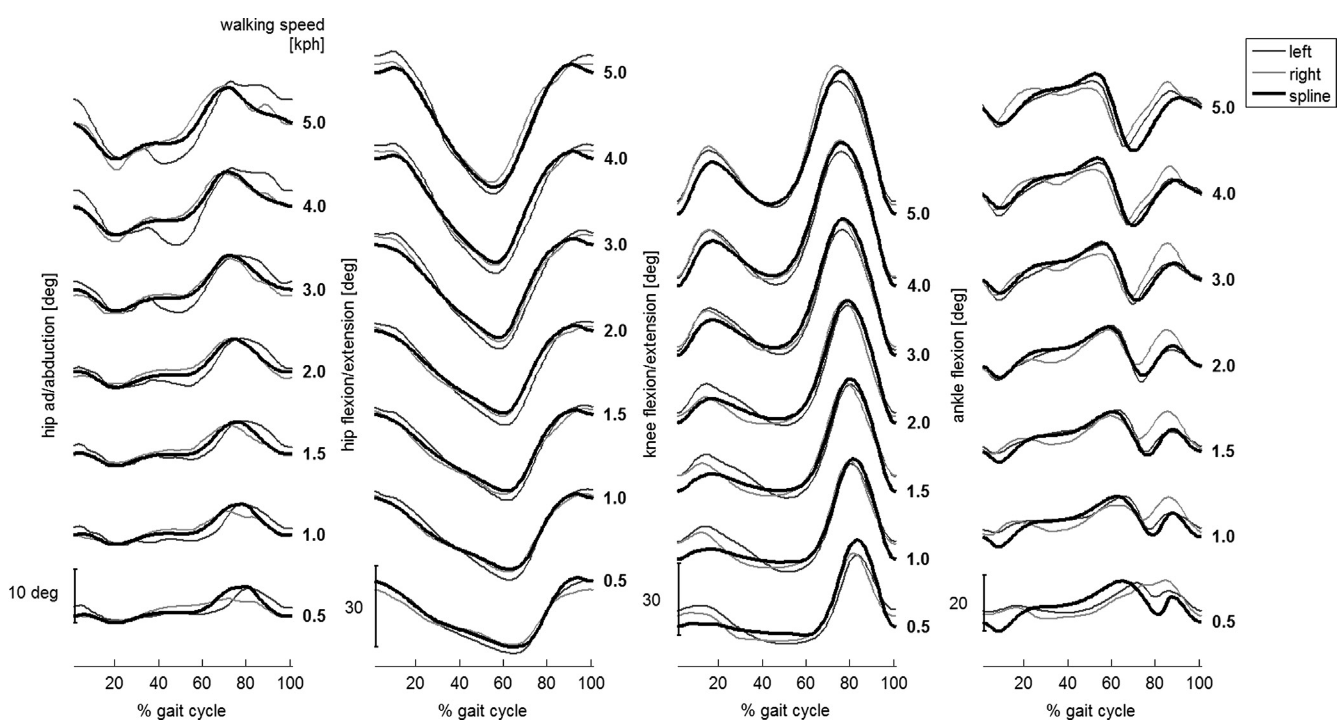

Fig. 5. Cross-validation of the reconstructed trajectories. Example of the results of one round of cross-validation for a typical subject. It shows the left (thin light gray line) and right (thin dark gray line) joint trajectories, together with the reconstructed trajectories (thick black line). Here the key-events for the splines are based on regression-models that do not include data from this particular subject. Subsequently, the $RMSE_{act\text{-}rec}$ and correlation coefficient ($r_{act\text{-}rec}$) are calculated for every speed. This procedure was repeated 15 times (once for each subject), and the results were averaged over the rounds.

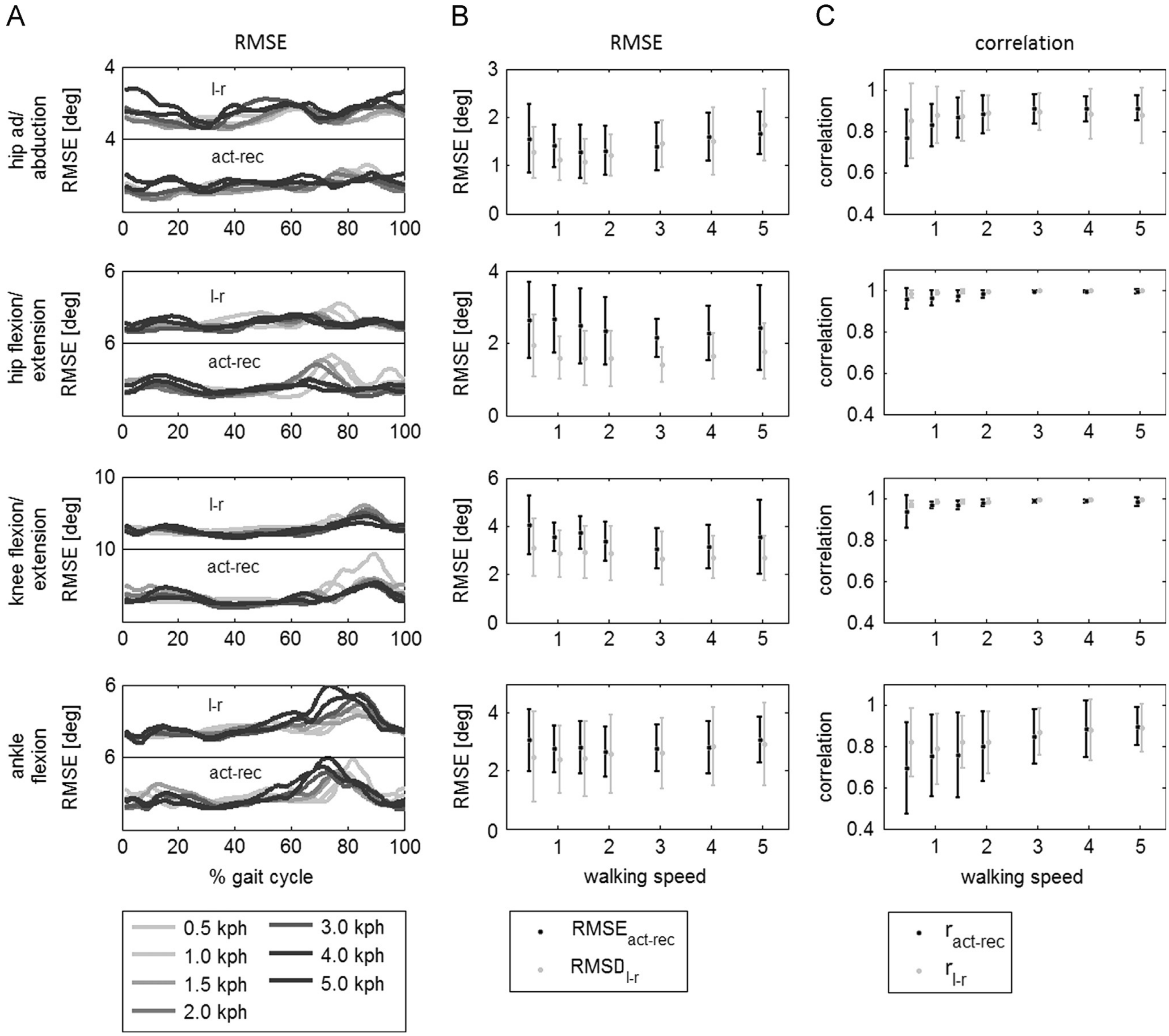

Fig. 6. Validation of the reconstructed reference trajectories. (A) RMSE between actual and reconstructed trajectories for the different joints ("act-rec", bottom part of the graphs), expressed as a function of the gait cycle for every walking-speed. As a reference for the model error the natural deviation between the left and right joint trajectories are also provided ("l − r", top part of the graphs). (B) RMSE between actual and reconstructed trajectories ($RMSE_{act\text{-}rec}$, black lines) and natural deviation between the left and right joint trajectories ($RMSD_{l-r}$, gray lines). Both measures are averaged across subjects for each walking-speed. The error bars indicate the standard deviation. (C) Correlation coefficients between actual and reconstructed trajectories ($r_{act\text{-}rec}$, black lines) and correlation coefficients between the left and right joint trajectories (r_{l-r}, gray lines).

3. Results

3.1. Regression-models

Most key-events showed a dependency on walking-speed, whereas body-height influenced the parameters of the key-events to a lesser extent (Tables 1–4). For the angle (y) only 7 of the 24 key-events were dependent ($p < 0.01$, see "Regression-models") on body-height, whereas 19 key-events were linearly and/or quadratically dependent on speed. For the timing (x), only 10 key-events were dependent on body-height, whereas 15 key-events were linearly and/or quadratically dependent on speed.

For instance, the maximal knee flexion during swing, which is a commonly reported gait feature, showed a decrease in relative timing at higher walking-speeds, whereas the maximum angle itself, and its acceleration, increased with speed (Fig. 3). Stepwise regression showed that these effects are nonlinear and that the body-height has no significant contribution to the predictability of any of the parameters of this key-event. Therefore, the regression-models for the x, y, and d^2y/dx^2 parameter of this particular key-event only include coefficients for the walking-speed and walking-speed squared (Table 3).

The regression-models for the parameter values of the individual key-events for the different joints are presented in Tables 1–4. Generally, different subjects show similar dependencies. However, there was considerable variation between subjects in the parameter values of the key-events (Fig. 3), as reflected by the RMSE of the prediction of the different parameter values of the key-events (Tables 1–4).

To determine the time in which a reference trajectory needs to be replayed (for robotic control), or transform the relative duration of the different gait phases (% of gait cycle), to absolute timing (s),

Table 1
Regression equations and RMSE for the parameter values of the key-events of the hip ab-/adduction.

	Hip ab-/adduction					
	Key-event	β_0 (Intercept)	β_1 (Speed)	β_1 (Speed^2)	β_1 (Body-height)	RMSE
Index (x parameter)	Heel contact	1	–	–	–	
	Min. stance	33.360	–	–	−7.319	4.206
	Min. dy/dx stance	30.158	−2.038	–	11.832	4.494
	Max. dy/dx swing	52.727	−1.613	–	9.393	3.704
	Max. swing	83.318	−6.031	0.762	–	2.840
	Min. dy/dx swing	68.490	−1.847	–	10.898	3.523
Angle (y parameter)	Heel contact	−0.783	–	0.056	–	1.457
	Min. stance	−1.641	−0.879	–	–	1.129
	Min. dy/dx stance	0.121	−0.652	–	–	1.403
	Max. dy/dx swing	3.090	–	–	–	1.419
	Max. swing	4.441	0.557	–	–	1.820
	Min. dy/dx swing	1.860	0.657	–	–	1.674
Velocity ($\frac{dy}{dx}$ parameter)	Heel contact	−0.689	–	−0.010	0.424	0.119
	Min. stance	0	–	–	–	
	Min. dy/dx stance	−0.015	–	–	–	0.092
	Max. dy/dx swing	0.350	0.075	–	–	0.215
	Max. swing	0	–	–	–	
	Min. dy/dx swing	−0.399	–	–	–	0.153
Acceleration ($\frac{d^2y}{dx^2}$ parameter)	Heel contact	0.019	–	–	–	0.047
	Min. stance	0.043	–	0.002	–	0.027
	Min. dy/dx stance	0	–	–	–	
	Max. dy/dx swing	0	–	–	–	
	Max. swing	−0.082	–	–	–	0.039
	Min. dy/dx swing	0	–	–	–	

Here the regression formulas are shows that include the data from all 15 subjects.
Speed is defined in kph.
1 (One) by default (% of gait cycle of heel contact key-event), 0 (zero) by default (minimum or maximum in joint angle or angular velocity), - no significant contribution to the regression-model.

the cycle time is required. The cycle time can be obtained from the regression-models for the step-ratio (Table 5) according to:

$$\text{cycle time} = 2\sqrt{\frac{\text{step ratio}}{v/3,6}}, (\text{with } v \text{ in kph}) \tag{3}$$

3.2. Validation

With the obtained regression-models a set of reference trajectories was reconstructed for every subject (at each walking-speed). The reconstructed patterns matched the measured data well (Fig. 5). Generally, the largest errors are found at the lower walking-speeds, and are located during the parts of the gait cycle where the joint excursions are largest or where joint angles change rapidly (Fig. 6A). The quality of the fit was also reflected in the calculated RMSE (Fig. 6B). For the hip abduction the $\text{RMSE}_{\text{act-rec}}$ (averaged over all walking-speeds) was smallest ($\pm 1.5°$). This joint also had the smallest range of motion of the considered joints ($\pm 10°$, Table 6). Reversely, the knee joint, which has the largest range of motion ($\pm 53°$), shows the highest average $\text{RMSE}_{\text{act-rec}}$ ($\pm 3.5°$). The $\text{RMSE}_{\text{act-rec}}$ results are in line with the RMSE values of the predicted angles of the key-events. That is; the RMSE in the predicted angles (y) of the key-events ($\text{RMSE}_{\text{y key-event}}$) is very similar to the $\text{RMSE}_{\text{act-rec}}$ for all joints (Table 6).

Additionally, the correlation coefficient was used to quantify the similarity between the reconstructed and actual patterns. For hip- and knee flexion the $r_{\text{act-rec}}$ was above 0.93 at low walking-speeds, with even larger correlations for higher speeds (Fig. 6C). For hip abduction and ankle flexion, the $r_{\text{act-rec}}$ was lowest, ranging from 0.69 at 0.5 kph to 0.89 at 5 kph. The $r_{\text{act-rec}}$ of the different joints are in line with the RMSE values in predicting the relative timing of the key-events. That is; the RMSE in the predicted timing (x) of the key-events ($\text{RMSE}_{\text{x key-event}}$) is also highest for the ankle flexion and hip abduction (Table 6).

As a reference for the obtained fitting quality, we compared the model error with the natural deviation between the left and right leg. Here the model error ($\text{RMSE}_{\text{act-rec}}$) was only slightly higher than the left–right deviation ($\text{RMSD}_{\text{l-r}}$) and the $r_{\text{act-rec}}$ was only slightly lower than the $r_{\text{l-r}}$ (Fig. 6, Table 6). Both measures indicates that the error in the reconstructed spline is only marginally larger compared to the error when the trajectory of one leg is taken as a reference for the other. Similar results were obtained for the reconstructed angular velocity and acceleration profiles (Fig. 7), though the correlation measures decrease for the velocity and acceleration. Another reference for the model error was provided by the inter-subject variability (STD). Generally, the model error is close to the natural variability between subjects (Table 6).

The spline fitting methodology was also compared to the traditional averaging method, where we calculated the average trajectories across subjects. Generally, the amplitude of the average trajectories was smaller than the amplitude of the reconstructed trajectories (Fig. 8), especially for the hip abduction and ankle flexion.

4. Discussion and conclusion

In this study we present a method to parameterize joint trajectories and generate walking-speed- and body-height dependent reference joint trajectories. The generated trajectories are

Table 2
Regression equations and RMSE for the parameter values of the key-events of the hip flexion/extension.

	Hip flexion/extension					
	Key-event	β_0 (Intercept)	β_1 (Speed)	β_1 (Speed^2)	β_1 (Body-height)	RMSE
Index (x parameter)	Heel contact	1	–	–	–	
	Max. stance[a]	−10.809	–	–	11.762	1.755
	x=50% Stance[b]	24.512	−2.021	0.195	5.109	1.017
	Min.	48.879	−3.854	0.355	9.891	1.943
	Max. dy/dx swing	80.562	−6.432	0.885	–	2.058
	Max. swing	94.280	−0.601	–	–	2.183
Angle (y parameter)	Heel contact	20.354	1.934	–	–	2.424
	Max. stance[a]	18.917	2.583	–	–	2.022
	x=50% Stance[b]	4.845	1.718	–	–	1.964
	Min.	−2.026	−2.090	–	–	2.328
	Max. dy/dx swing	20.030	–	–	−7.732	2.508
	Max. swing	21.447	2.318	–	–	2.388
Velocity ($\frac{dy}{dx}$ parameter)	Heel contact	−2.062	–	–	1.112	0.234
	Max. stance[a]	0	–	–	–	
	x=50% Stance[b]	−0.240	−0.224	–	–	0.149
	Min.	0	–	–	–	
	Max. dy/dx swing	0.472	0.096	–	0.633	0.246
	Max. swing	0	–	–	–	
Acceleration ($\frac{d^2y}{dx^2}$ parameter)	Heel contact	−0.068	0.031	–	–	0.059
	Max. stance[a]	−0.112	–	–	–	0.041
	x=50% Stance[b]	0.026	−0.010	–	–	0.024
	Min.	−0.117	0.059	−0.007	0.098	0.036
	Max. dy/dx swing	0	–	–	–	
	Max. swing	−0.083	–	−0.002	–	0.044

[a] For walking-speeds below 3.5 kph this key-event is not included in the spline fitting procedure.
[b] Key-event added to improve spline fitting. This key does not represent a maxima or minima in position or velocity, but is defined at the middle of the stance phase.

Table 3
Regression equations and RMSE for the parameter values of the key-events of the knee flexion/extension.

	Knee flexion/extension					
	Key-event	β_0 (Intercept)	β_1 (Speed)	β_1 (Speed^2)	β_1 (Body-height)	RMSE
Index (x parameter)	Heel contact	1	–	–	–	
	Max. stance	17.103	–	–	–	2.487
	Min. stance	48.542	−0.998	–	–	2.789
	Max. dy/dx swing	68.947	−6.096	0.611	5.967	1.623
	Max. swing	85.816	−4.480	0.519	–	1.301
	Min. dy/dx swing	92.489	–	–	–	1.553
Angle (y parameter)	Heel contact	31.595	−4.311	0.494	−13.050	3.596
	Max. stance	5.995	3.028	–	–	3.481
	Min. stance	−10.037	–	–	7.594	2.291
	Max. dy/dx swing	29.618	3.803	−0.486	–	3.556
	Max. swing	38.110	9.744	−1.105	–	4.354
	Min. dy/dx swing	24.631	−0.967	–	–	3.866
Velocity (dy/dx parameter)	Heel contact	−3.581	–	–	1.977	0.525
	Max. stance	0	–	–	–	
	Min. stance	0	–	–	–	
	Max. dy/dx swing	3.276	–	–	–	0.447
	Max. swing	0	–	–	–	
	Min. dy/dx swing	−0.446		−0.032	−1.696	0.629
Acceleration (d^2y/dx^2 parameter)	Heel contact	0.301	0.073	–	–	0.171
	Max. stance	−0.094	–	−0.005	–	0.051
	Min. stance	0.042	–	0.004	–	0.029
	Max. dy/dx swing	0	–	–	–	
	Max. swing	−0.784	0.225	−0.026	–	0.125
	Min. dy/dx swing	0	–	–	–	

Table 4
Regression equations and RMSE for the parameter values of the key-events of the ankle plantar-/dorsiflexion.

	Ankle plantar-/dorsiflexion					
	Key-event	β_0 (Intercept)	β_1 (Speed)	β_1 (Speed^2)	β_1 (Body-height)	RMSE
Index (x parameter)	Heel contact	1	–	–	–	
	Min. stance	8.145	0.331		–	1.915
	Min. dy/dx stance	12.005	–	–	13.754	4.307
	Max.	67.686	−5.469	0.493	–	3.333
	Min. swing	73.460	−6.699	0.744	6.463	1.673
	Max. swing	87.621	–	0.132	–	3.150
Angle (y parameter)	Heel contact	18.645	0.554	–	−13.246	2.357
	Min. stance	17.309	–	–	−14.173	2.517
	Min. dy/dx stance	0.836	0.812	–	–	2.328
	Max.	−15.523	–	–	14.494	2.494
	Min. swing	21.984	−3.425	–	−12.522	4.848
	Max. swing	4.860	−0.655	–	–	2.687
Velocity (dy/dx parameter)	Heel contact	−0.145	–	−0.020	–	0.267
	Min. stance	0	–	–	–	
	Min. dy/dx stance	−0.991	–	–	0.620	0.172
	Max.	0	–	–	–	
	Min. swing	0	–	–	–	
	Max. swing	0	–	–	–	
Acceleration (d^2y/dx^2 parameter)	Heel contact	0.145	−0.137	0.015	–	0.109
	Min. stance	−0.556	–	–	0.492	0.111
	Min. dy/dx stance	0	–	–	–	
	Max.	0.055	−0.019	–	−0.089	0.059
	Min. swing	0.433	–	–	–	0.235
	Max. swing	0.412	0.087	−0.012	−0.425	0.098

Table 5
Regression equations and RMSE for spatiotemporal parameters.

		Spatiotemporal parameters				
		β_0 (Intercept)	β_1 (Speed)	β_1 (Speed^2)	β_1 (Body-height)	RMSE
Spatiotemporal parameters	Step-ratio	−0.532	0.020	–	0.47	0.073
	Relative double support phase (%)	26.485	−7.230	0.795	–	1.771

continuous in terms of position, velocity and acceleration, and especially suitable for the control of robotic gait applications. The method is based on fitting quintic splines between different key-events, which are estimated with regression-models. The reconstructed trajectories matched the measured trajectories very well. The obtained regression-models also show that: (1) the majority of the key-events are speed dependent, both in terms of amplitude and timing, (2) walking-speed has a larger effect on the key-events than body-height, (3) there is considerable inter-subject variability in the extracted key-events, especially at lower walking-speeds. This section discusses these findings in further detail.

4.1. Extreme values in joint angles

Previous studies on walking-speed dependencies in joint trajectories mainly focused on the extreme values. In this study we observed similar changes in all commonly reported extreme values (Kerrigan et al., 1998b; Kirtley et al., 1985; Lelas et al., 2003; Oberg et al., 1994; Pepin et al., 2003; Silder et al., 2008; Stoquart et al., 2008). For the knee joint we found a speed-dependent increase in knee flexion during the swing phase, as well as during the loading response. Maximum hip flexion and extension also increased with walking-speed, in a similar manner as reported by others. The ankle joint also contained multiple extreme values that changed with walking-speed, like an increase in maximum plantar flexion and a reduction in dorsiflexion during swing. Generally, the effect of speed on these kinematic changes was largest at lower walking-speeds (Van Hedel et al., 2006). An in-depth comparison between our findings and related studies, for all commonly reported extreme values, is provided in Supplementary material B. For the extreme values in the hip ab/adduction we observed an increase with speed. (Schwartz et al., 2008) are one of the few reporting hip ab/adduction angular patterns at different speeds. Although they focused on growing children, rather than elderly, they report similar changes in terms of angular amplitude at increasing speeds.

4.2. Timing of extreme values in joint angles

The relative timing of the majority of the extreme values showed a clear dependency on walking-speed. They occurred earlier during the gait cycle with increasing speed. These changes in timing are strongly related to changes in the duration of the different gait phases. At higher walking-speeds the relative duration of the double support phase decreases (Table 5), shifting most extreme values forward. (Stoquart et al., 2008) are one of the few who reported the relative timing of the maximum hip extension, maximum knee flexion and maximum ankle plantar flexion, and demonstrated similar changes (Supplementary material B). (Van Hedel et al., 2006) did not quantify the changes in timing, still their normalized joint trajectories showed very similar trends in relative timing at increasing speeds.

Table 6
RMSE for the reconstructed trajectories and the estimated key-events.

	$RMSE_{y\ key\text{-}event}$ [a]	$RMSE_{act\text{-}rec}$ [c]	$RMSD_{l-r}$ [c]	STD [d]	ROM [c]
Hip ab-/adduction	1.48	1.46	1.35	1.41	9.94
Hip flexion/extension	2.27	2.42	1.64	2.34	34.22
Knee flexion/extension	3.52	3.49	2.82	3.42	52.76
Ankle plantar-/dorsiflexion	2.87	2.84	2.60	2.79	20.04
Average	2.53	2.55	2.10	2.49	
	$RMSE_{x\ key\text{-}event}$ [b]	$r_{act\text{-}rec}$ [c]	r_{l-r} [c]		
Hip ab-/adduction	3.75	0.87	0.88		
Hip flexion/extension	1.79	0.98	0.99		
Knee flexion/extension	1.95	0.97	0.98		
Ankle plantar-/dorsiflexion	2.88	0.80	0.84		
Average	2.59	0.91	0.92		

[a] $RMSE_{y\ key\text{-}event}$ Mean RMSE between measured y -parameters of the key-events and the y -parameters estimated with the regression-models (Tables 1–4). The $RMSE_{y\ key\text{-}event}$ is averaged over the 6 key-events for every joint.
[b] $RMSE_{x\ key\text{-}event}$ Mean RMSE between measured x -parameters of the key-events and the x -parameters estimated with the regression-models (averaged over the 6 key-events).
[c] These measures are averaged over the different walking-speeds.
[d] The standards deviation (STD) is averaged across the gait cycle and subsequently over the different walking-speeds.

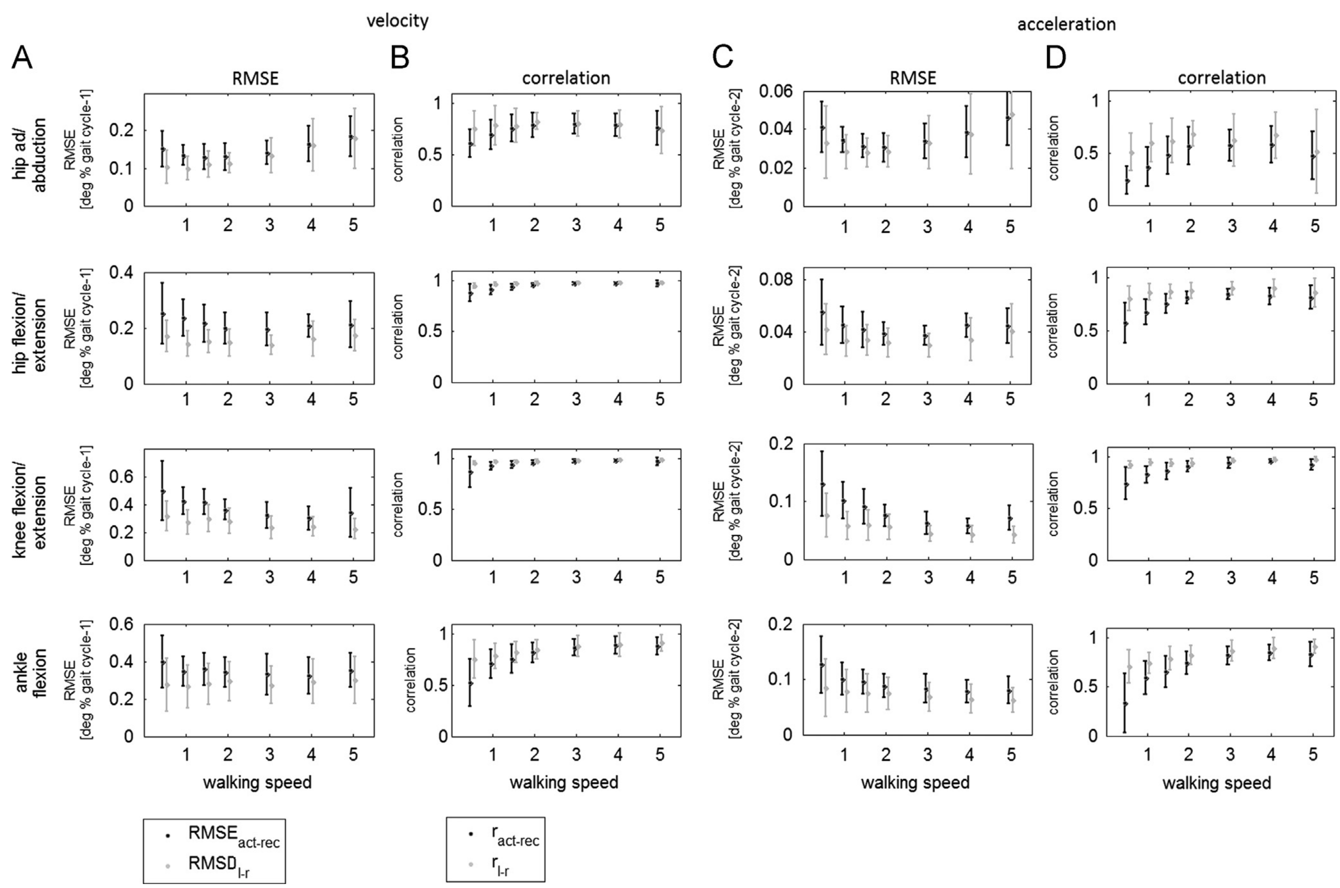

Fig. 7. Validation of the reconstructed reference velocity and acceleration trajectories. (A) RMSE between actual and reconstructed angular velocity profiles ($RMSE_{act\text{-}rec}$, black lines) and natural deviation between left and right angular velocity profiles ($RMSD_{l-r}$, gray lines). Both measures are averaged across subjects for each walking-speed. The error bars indicate the standard deviation. (B) Correlation coefficients between actual and reconstructed angular velocity profiles ($r_{act\text{-}rec}$, black lines) and correlation coefficients between the left and right joint angular velocity profiles (r_{l-r}, gray lines). (C)–(D) RMSE and correlation coefficient measures for the actual and reconstructed angular acceleration profiles.

4.3. Inter-subject variability in the extracted key-events

We clearly demonstrated the speed-dependency of the key-events, but the RMSE between the measured and predicted key-events was considerable, up to 15% of the mean ROM for the hip abduction. This is primarily caused by the high inter-subject variability, which was also reported by others (Hanlon and Anderson, 2006; Kirtley et al., 1985; Lelas et al., 2003; Oberg et al., 1994; Stansfield et al., 2006). For most key-events the variation in the parameters decreased with walking-speed, suggesting a more consistent walking pattern at higher speeds. Nonetheless, most key-events show significant correlations with walking-speed, underlining the need to adjust angular trajectories to walking-speed.

4.4. Influence of body-height on key-events

In accordance with other studies we found that body-height has a limited effect on the key-events, compared to walking-speed. (Hanlon and Anderson, 2006) did not demonstrate any improvement in the correlation between gait patterns and walking-speed when using normalized walking-speed (normalized to leg length), compared to using absolute speed. Additionally, (Lelas et al., 2003), who performed regressions with normalized walking-speed, and multiple regression with walking-speed and leg-length, did not show overall improvement compared to regressing on walking-speed only. Finally, (Kirtley et al., 1985) did not find significant correlation between body-height and any of their reported kinematic parameters. Still, it should be mentioned that, in most studies, including ours, the variability in body-height is much smaller than the variability in walking-speed. If a wider range of body-heights were included, for instance by including extremely short or tall persons, the effect of body-height may be larger.

4.5. Comparison with traditional averaging methods

As mentioned before, most studies that report normative gait patterns take the average of individual normalized datasets. Molloy et al. (2008) and Sadeghi et al. (2003) showed that averaging over subjects can have a dampening effect on the extremes in the gait pattern, when the datasets have a different distribution of the extremes throughout the gait cycle. Fig. 8 demonstrates that the method proposed here compensates for this effect, which is most noticeable in joint trajectories that have large inter-subject variability in the timing of the key-events (hip abduction and ankle flexion, Table 6). Molloy et al., who did not assess hip abduction, also reported that the largest errors were found for the ankle joint (maximum plantar flexion).

4.6. Limitations

This study is not without limitations. Due to the small number of subjects (15), we did not derive separate regression equations for male and female subjects, although small gender differences have been reported. Females are reported to have a moderately increased hip flexion (Kerrigan et al., 1998a; Oberg et al., 1994), and less knee flexion during swing (Oberg et al., 1994) and loading response (Kettelkamp et al., 1970; Oberg et al., 1994). Here, we focused on (middle) aged subjects, since many neurological gait disorders occur in this group. Studies on age-related gait alterations demonstrated a moderate increase in knee flexion at mid-stance, a decrease of the maximum knee flexion (Oberg et al., 1994), reduced hip extension (Crowinshield et al., 1978; Kerrigan et al., 1998b), and reduced ankle plantar flexion (Kerrigan et al., 1998b; Silder et al., 2008). Others, however, reported no clear effect of age (Murray et al., 1964). Although most of the reported changes in gait kinematics in elderly are related to aging per se, and not to reduced walking-speed, they are small and inconsistent. Therefore, we suggest that, in practice, the same reference data can be used for all adults. In future studies (including more subjects), all these variables can be added to the regression-models in order to investigate their potential contribution towards more accurate joint trajectory estimations.

In this study 6 key-events were selected for every joint. These key-events (Fig. 2) were chosen based on the experience of the authors. Visual comparison of the reconstructed patterns and the measured patterns showed that these key-events sufficed to capture the main characteristics of the joint trajectories. We did not perform an optimization on the number of key-events to achieve the best possible fit. Consequently, another set (or

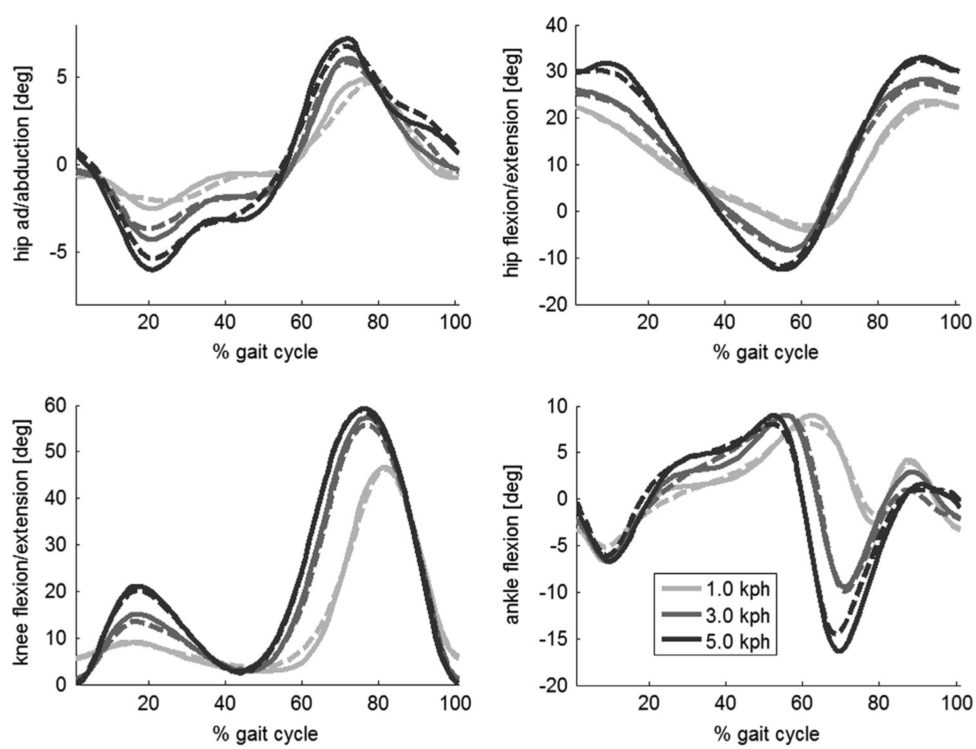

Fig. 8. Reconstructed trajectories versus averaged trajectories. The reconstructed trajectories (solid line) are based on the predicted key-events and the average trajectories are averaged across subjects (dashed line). The trajectories are presented at 3 different speeds. Averaging over multiple subjects has a dampening effect on the extreme values in the average pattern, especially for the hip abduction and ankle flexion. The reconstructed trajectories are generated for a subject with a body-height that equals the mean body-height of our subject population (1.69 m).

amount) of key-events could possibly produce a better fit. However, based on the high correlation coefficients and low RMSE values, we do not see much room for improvement.

Another potential limitation of this study is that the gait kinematics were recorded on a treadmill. Although small kinematic (and spatio-temporal) differences have been recorded in the past (Alton et al., 1998; Strathy et al., 1983), more recent studies show that these differences are typically smaller than 3°, and fall within the normal variability and repeatability of these kinematic parameters (Lee and Hidler, 2008; Parvataneni et al., 2009; Riley et al., 2007). They concluded that humans do not make any significant gait adjustments when walking on a treadmill, taking into account an appropriate familiarization period (Matsas et al., 2000; Wass et al., 2005). Therefore, we suggest that, in practice, the same reference data can be used for overground- and treadmill-walking.

4.7. Utility

The obtained regression-models (Tables 1–4) can be used to reconstruct subject- and speed-dependent reference trajectories, within the provided range (0.5–5 kph). For the control of robotic orthoses, the trajectories can be replayed with a user specific cycle time, or with an estimate of the cycle time (Table 5). The fitted splines also provide continuous angular velocity and acceleration patterns, which can be used for friction and/or inertia compensation of a robotic device. Although our primary goal was to create reference trajectories that can be used for robotic gait applications they can also serve a clinical purpose. They can help discriminating between gait changes due to a reduction in self-selected walking-speed and effects actually caused by underlying pathologies. Supplementary material C discusses the clinical and robotic applications (and limitations) in more detail.

Conflict of interest statement

None of the authors have any financial or personal conflict of interest with regard to this study.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jbiomech.2014.01.037.

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