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Research Article

Gait Recognition Using Joint Moments, Joint Angles, and Segment Angles

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Abstract Recognition of gait patterns has been studied only moderately during the last decades. Different gait strategies have been described by applying different waveform analysis techniques to biomechanical gait data and it has been shown that individuals can be identified using joint angles in the sagittal plane. However, little is known about additional variables for gait recognition. We examined which biomechanical variables (joint moments, joint angles, and segment angles from the lower extremities) obtained in a gait lab could be used to distinguish between 21 subjects on two different days. A systematic "dc-offset" between days was often observed. This could be removed by taking the *first derivative* to the displacement data. Especially the joint angular and segment angular "velocities" (*first derivative*) in the sagittal and frontal planes provided high recognition rates and 100% subjects could be recognized by combining three of these variables.

Keywords correlation analysis, intraclass correlation, clinical gait analysis, forensic medicine

1 Introduction

The detailed time course pattern of net joint moments during human walking exhibits almost unique "finger prints" of individual subjects. Even during increasing load carrying, this pattern is consistent [22]. For most people, it is a common experience that people known to them can be identified solely by the sound of their walking. Identification using gait was already mentioned by Shakespeare in "The Tempest," where Ceres identified Juno saying "Great Juno, comes; I know her by her gait...", and psychological studies have shown that man is able to recognize for example, the gender of a walker [16] as well as friends and colleagues [14].

Most often, scientific studies focus on differences between groups. Clinically, it would be beneficial if much more detailed information could be obtained about the walking characteristics of individual patients [19]. Within the area of forensic medicine, such analyses could entail that criminals or terrorists may be identified from surveillance cameras by their gait pattern [17, 24]. Schöllhorn et al. [19] found that individuals could be discriminated by combining joint moments, ground reaction forces, and kinematic variables of the lower extremities. Model-based approaches within research disciplines of automated image or pattern recognition (*Cyber Vision*) have shown that it is possible to achieve high recognition rates using angular rotations of the lower extremities in the sagittal plane [5, 7]. However, it would be valuable to examine the contribution of single variables to the recognition process. This would enhance the use of gait analysis in forensic medicine, where typically only a limited number of gait variables are available for examination [17]. In addition, it will help selecting input variables in models to analyze gait such as principal component analysis. Baofeng and Nixon [3] examined the importance of 73 features for recognition. Among them were joint angle rotations of the lower extremities in the sagittal plane together with anthropological measurements and temporal parameters such as gait frequency. They found that ankle, knee, and hip rotations could be placed on a top 15 list among the 73 features. The relevance of other biomechanical variables in recognition remains to be established.

The aim of this study was therefore to examine the ability of recognition of individual joint moments, joint angles (anatomical), and segment angles (relative to horizontal) in the sagittal, frontal, and transverse planes using a well-known laboratory setup including several video cameras, reflective markers at anatomical landmarks on the subjects as well as multiple force plates.

	Hip			Knee			Ankle		
Subject	*FE*	*AA*	*IE*	*FE*	*AA*	*IE*	*FE*	*AA*	*IE*
1	3	1	2	9	1	9	1	1	1
2	1	2	2	1	3	9	1	11	6
3	1	1	1	4	1	1	2	2	2
4	1	1	3	1	1	17	1	1	7
5	1	1	1	1	4	1	4	1	3
6	1	1	1	1	1	1	1	1	15
7	11	1	5	5	1	1	13	1	18
8	1	4	7	1	5	1	1	1	2
9	1	1	9	1	7	4	1	1	3
10	2	1	10	1	3	2	3	2	1
11	1	3	1	1	1	1	1	1	1
12	1	1	11	2	7	7	4	5	2
13	4	17	1	4	5	7	5	3	1
14	11	2	18	8	2	2	2	5	14
15	1	7	10	1	17	11	4	5	11
16	1	1	2	1	18	4	9	1	6
17	1	1	1	1	4	2	1	1	1
18	1	1	14	8	2	9	1	2	10
19	1	2	1	2	1	5	13	1	5
20	11	1	3	4	16	1	3	1	6
21	1	6	3	1	1	2	1	5	2
Rate	71%	62%	33%	57%	38%	33%	48%	57%	24%

FE: flexion/extension angle.
AA: abduction/adduction angle.
IE: internal/external rotation angle.
The first value in the *Hip FE* column shows that the correlation between the right hip flexion/extension angle on the two different test days for subject 1 was the third best compared to the correlations between subject 1 and the 20 other subjects. The second row (subject 2) shows a successful match (the correlation between the right hip flexion/extension angle on the two different test days for subject 2 was the best compared to the correlations between subject 2 and the 20 other subjects). The recognition rate (last row) is calculated as percent of successful matches.

Table 1: Recognition rate obtained using Pearson's correlation for the joint angles of the right leg.

2 Materials and methods

Subjects. Six women and 15 men were recruited to the study. The women mean age, height, and weight were 34 years (SD: 9, range: 25–46), 170 cm (SD: 6, range: 164–178), and 61 kg (SD: 9, range: 55–76), respectively. The men mean age, height, and weight were 30 years (SD: 10, range: 20–58), 182 cm (SD: 7, range: 166–192), and 81 kg (SD: 12, range: 52–102), respectively. No subjects had record of prior injuries or pathology related to the lower extremities.

Test protocol. All subjects arrived at the laboratory and went through the same test protocol on two different days separated by at least two days. Fifteen spherical markers (12 mm) were positioned on anatomical landmarks on the lower extremities according to the marker setup proposed by Vaughan et al. [26]. The same operator mounted the markers on the same subjects on both test days. The subjects were taught to walk at a velocity of 1.25 m/s ($\pm$10%) across two force plates (model OR6-5-1, AMTI, Watertown, Mass., USA). The duration of one gait cycle across the two platforms was measured by two sets of photocells and immediately returned to the subject in terms of velocity. Fifteen trials were recorded, but only the six trials closest to the desired walking velocity were selected for further analysis.

The force plate sampling rate was 1000 Hz. The subjects were allowed to carry out test trials to become acquainted with the gait lab and the fixed velocity. Six trials from each subject were recorded each test day using five Canon MV 600 digital video cameras operating at 50 Hz. Photocells were placed before and after the force plates to record the walking speed. When the first photocell was passed, an electronic audio signal was sent to each of the cameras and the sampling of the force plates was triggered in order to synchronize the cameras with each other and the force plates.

Data analysis. One right gait cycle (swing phase, then stance phase) and one left gait cycle (stance phase, then swing phase) were derived from each trial for each subject and each test day. Heel strike (HS) and second toe off

(TO) for the right leg and first HS and TO for the left leg occurred on the force plates, hence HS was defined as the time when the vertical ground reaction force exceeded 10 N and second TO was defined at the instant where the vertical force fell below 5 N (values of thresholds were adopted from O'Connor et al. [18]). The first TO for the right leg and the second HS for the left leg were predicted using the method proposed by O'Connor et al. [18], where HS and TO are determined by local peaks of the velocity of a foot center calculated as the midpoint of a vector formed by the heel-marker and the marker on the second metatarsal. The duration of the step cycles varied between 53 and 65 sample points (time duration: 1.04 s–1.28 s).

For each trial, 3D coordinates of the markers were obtained with the Ariel Performance Analysis System, (Ariel Dynamics Inc., Calif., USA) and filtered with a 4th-order Butterworth filter with a cutoff frequency of 6 Hz. A custom-build calibration frame with eight non-coplanar points was placed in the middle of the walkway covering both force plates and digitized to calibrate each of the video sequences. The filtered time-position data were numerically differentiated to velocity and acceleration using three data points at a time to avoid any phase shift.

The 1000 Hz signals from the force plates were down sampled to 50 Hz to match the video signals. A local coordinate system was applied to the center of mass of the pelvis and each segment of the lower extremities based on the markers and used to calculate anatomical joint angles of the ankle, knee, and hip joints and segment angles of the thigh, shank, and foot in relation to the global coordinate system. Segment angles were calculated separately for the pelvis, thigh, shank, and foot as the angle between the longitudinal axis of the segment and the sagittal, frontal, and transverse planes of the laboratory coordinate system. Joint angles were defined as the smaller angle between two adjacent segments, often also termed anatomical angles.The position of the joint centers was calculated based on the position of the markers [26], and net internal joint moments of the ankle, knee, and hip joints were calculated using a 3D inverse dynamics approach according to Vaughan et al. [26] using custom-made software. The most important biomechanical output parameters are listed in Table 2.

Joint moments were normalized to a dimensionless number as proposed by Hof [11]:

$$\text{Moment}_{\text{normalized}} = \text{Moment}/\left(\text{bm}^* g^* l_0\right),$$

where bm is body mass, g is acceleration of gravity and l_0 is leg length (from greater trochanter to floor while standing).

For each subject, each of the six trials recorded each of the two days were normalized to 100% step cycle and averaged.

Gait recognition. The time course pattern of each variable for each of the 21 subjects from the first day was used as reference. The matching variables from the second day for each subject were tested against the 21 references in order to identify the same subject on the second day. This is illustrated in Table 1, where matches of joint angles for the right leg obtained with Pearson's correlation analysis are presented with recognition rates.

	Hip/thigh	Knee/shank	Ankle/foot
Joint angles			
Flexion/extension	**71%**	57%	48%
Flex/ext *first derivative*	**76%**	**67%**	**76%**
Abduction/adduction	**62%**	38%	57%
Abd/add *first derivative*	**90%**	43%	**76%**
Internal/external rotation	33%	33%	24%
Int/ext *first derivative*	48%	57%	33%
Segment Angles			
Flexion/extension	52%	48%	38%
Flex/ext *first derivative*	**67%**	**71%**	57%
Abduction/adduction	48%	**67%**	57%
Abd/add *first derivative*	**81%**	**81%**	**81%**
Internal/external rotation	52%	**67%**	24%
Int/ext *first derivative*	43%	**76%**	43%
Joint moments			
Flexion/extension	43%	52%	29%
Flex/ext *first derivative*	52%	52%	**62%**
Abduction/adduction	**62%**	48%	19%
Abd/add *first derivative*	**76%**	**67%**	38%
Internal/external rotation	52%	43%	29%
Int/ext *first derivative*	52%	52%	29%

Recognition rates higher than 60% are in bold.

Table 2: Recognition rates for the right leg obtained with the Pearson correlation.

Statistics. Only data from the right leg are presented. Four different statistical measures were used to compare the time course patterns of each variable. The first three were relative reliability measures: (1) the intraclass correlation coefficient (ICC 2,1) [20], (2) the lower bound of the 95% confidence interval of the ICC (lb_ICC), and (3) Pearson's correlation analysis. The fourth measure was the mean square residual from the repeated measures ANOVA (resid_ICC), which was used as a measure of absolute reliability [2]. The statistical package SPSS 15.0 was used.

Ethics. The experiments were approved by the local ethics committee.

3 Results

We compared one subject at a time from day one with all subjects including himself from day two. Figure 1 displays hip abduction/adduction angle of subject 1 obtained on day one plotted against the same angle of all the subjects

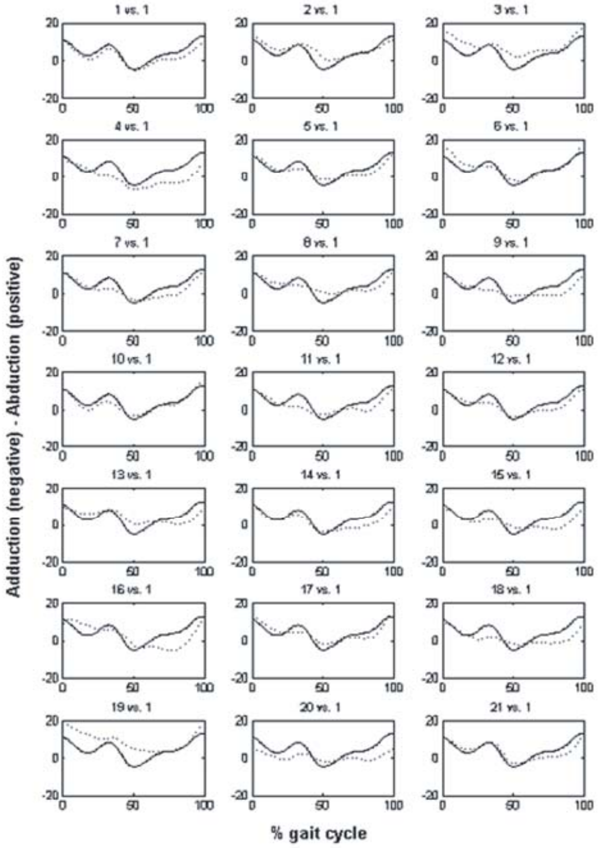

Figure 1: Abduction/adduction hip joint angle displacement in degrees. The time course pattern for day 1, subject 1 (solid curve) is plotted against the time pattern for day 2 (dotted curve) for every subject in each of the graphs.

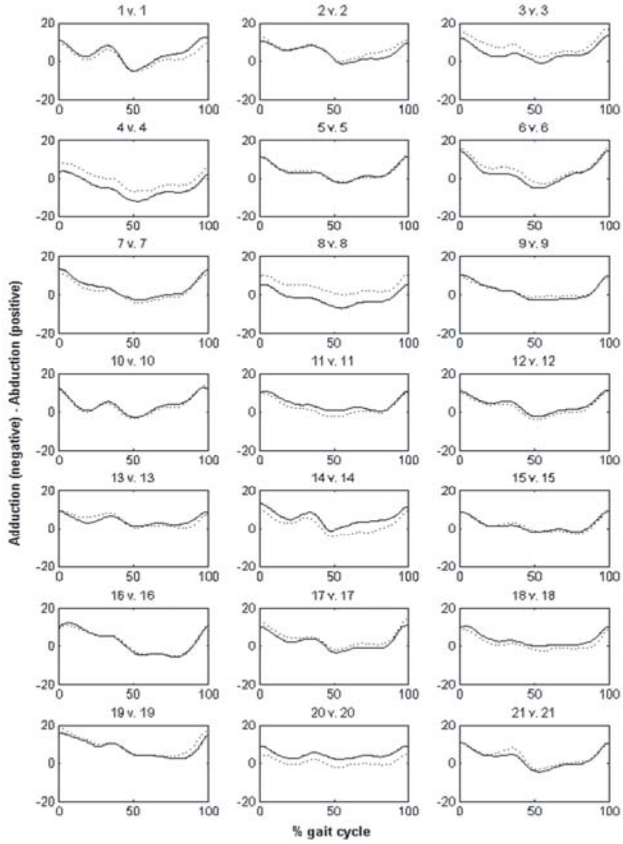

Figure 2: Abduction/adduction hip joint angle displacement in degrees. The time course pattern for day 1 (solid curve) for each subject is plotted against the time pattern for day 2 (dotted curve) for the same subject in each of the graphs.

obtained on day two in order to recognize this particular subject (subject 1). Although the overall time course pattern could be identified easily by visual inspection, a kind of "DC-offset" was observed in many cases. The term refers to the fact that the same time-course pattern can be observed but at a different level of numerical values. This is illustrated in Figure 2, where the same joint angle is plotted for each subject recorded on day one versus day two. It is clear that the time-course pattern was very similar between the days, but it is evident that the average joint angle in many cases was different between days. We believed that these differences primarily were due to small differences in marker placement on the anatomical landmarks of the subjects, which is known to be a common source of error in gait analysis. Therefore, we chose to differentiate the time course pattern of all variables. In this way, we obtained a *first derivative*, which excluded any offset due to marker placement. This is illustrated in Figure 3, where each subject is plotted against itself between day one and two. The differentiation allowed the exact time-course pattern of the variables to be compared numerically.

The upper part of Table 2 shows the recognition rates for the joint angles of the right leg for all subjects obtained with the Pearson correlation. The *first derivative* provided a higher recognition rate for all joint angles and the joint angles in the sagittal plane, and the hip and knee joint angles in the frontal plane appeared to provide the highest recognition rates, which were up to 90%, i.e., that 18 subjects out of 21 could be recognized. The angles in the transverse plane seemed to provide the lowest recognition rates.

The recognition rates for the segment angles are shown in the middle part of Table 2. Generally, the same pattern was seen as for joint angles although it is noteworthy that the shank had high recognition rates in all three planes.

The recognition rates for the joint moments are shown in the lower part of the table and these appeared to be lower than for the joint angles and segment angles. Nevertheless, the recognition rates for the joint moments also appeared to be highest in the sagittal and frontal planes.

If the *first derivative* profile of two segment angles and a joint angle, all from the frontal plane, were combined,

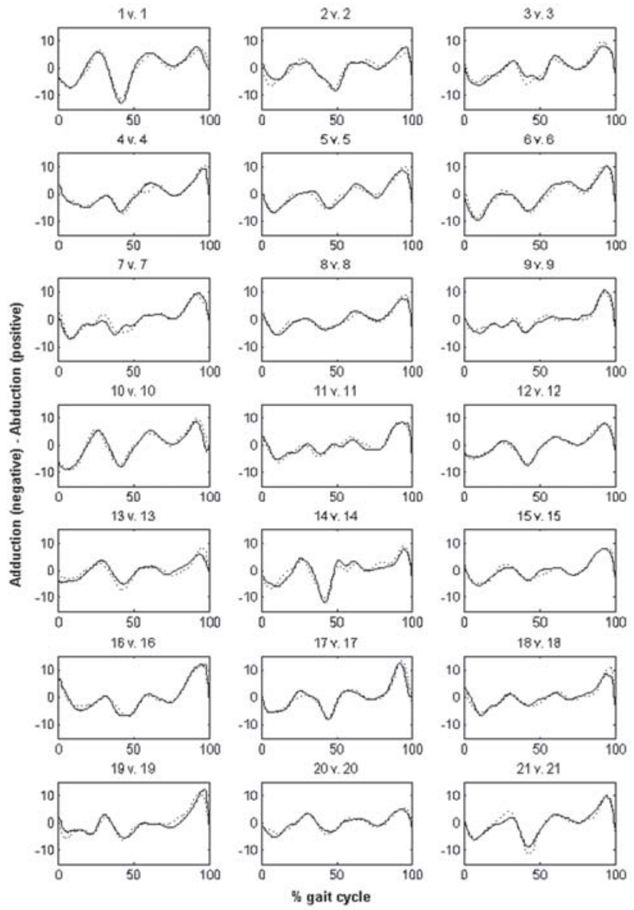

Figure 3: Abduction/adduction hip joint angular velocity in degrees/seconds (*first derivative*). The time course pattern for day 1 (solid curve) for each subject is plotted against the time pattern for day 2 (dotted curve) for the same subject in each of the graphs.

a recognition rate of 100% was obtained. These angles were the thigh angle, the shank angle, and the hip joint angle.

Additionally, the *second derivative* profile of the joint angles was calculated. This did not provide better recognition rates than the *first derivative* profiles.

The recognition rates for the right leg as analyzed by each of the four statistical methods divided in joint angles, segment angles, joint moments for all variables are shown in Table 3. ICC_LB seemed to result in the lowest recognition rates for the displacement patterns, while resid_ICC and the Pearson had a tendency to provide the highest recognition rates. The lower part of the table shows that all four methods generally resulted in similar recognition rates when using the *first derivative* patterns.

4 Discussion

In this study, we examined recognition rates of individual 3D biomechanical gait variables obtained on two different days using correlation analysis. It was found that several variables provided high recognition rates when discriminating between 21 subjects, and by combining three joint angles and segment angles, we could recognize all subjects. This is in concordance with other studies [3, 7, 19], which found that combining more variables leads to better discrimination.

The *first derivative* profiles seemed to produce higher recognition rates than the displacement profiles due to a "DC-offset" between days in the displacement patterns. Kadaba et al. [15] reported similar offsets and found lower reproducibility between days than within days. The discrepancy was explained with differences in marker placement. Several studies [9, 12, 23] have found that variability in placement of markers results in kinematic as well as kinetic errors. Furthermore, Della Croce et al. [8] found that low reproducibility of placement of markers was the major source of error compared to instrumental errors and skin movement artifacts. A markerless 3D approach might be the optimal solution to overcome this problem. Such models have for example been developed in *Cyber Vision* [10, 25] and commercial markerless systems such as MaMoCa (www.mamoca.com) and Organic Motion (www.organicmotion.com) have been developed for biomechanical use. However, these systems remain to be validated against traditional marker-based approaches.

We used four statistical methods to assess recognition rates. The "DC-offsets" discovered in the displacement profiles may explain why the ICC and thereby also lb_ICC seemed to provide lower recognition rates. When data from two observations are plotted against each other, ICC assesses the proximity of the data points to a straight line passing through the origin of a coordinate system with a gradient of 1, on one hand. Any systematic bias like the observed "off-sets" will therefore affect the ICC. Pearson's correlation analysis, on the other hand, assesses the proximity to any straight line and is thereby unaffected by systematic bias [13]. The resid_ICC derived from the repeated measures ANOVA provides a measure of the amount of variation remains to be explained between the two variables so a systematic bias should not affect this measure either. After differentiation, the four statistical methods provided similar recognition rates when testing the *first derivative* profiles of the variables suggesting that they can be used interchangeably when data contains no systematic bias.

The variables in the sagittal and frontal planes seemed to provide higher recognition rates than the variables in the transverse plane. The relatively high recognition rate for each variable is encouraging for the use of gait analysis in forensic medicine, where less optimal setup of surveillance systems often restricts the number of gait variables that can be analyzed [17]. By comparing the variables for subject

Method	Joint angles (%)		Segment angles (%)		Joint moments (%)		All (%)	
Displacement patterns								
ICC	29	(24–41)	38	(27–46)	33	(24–43)	33	(29–43)
Lb_ICC	19	(5–24)	19	(14–24)	24	(17–31)	19	(14–24)
Resid_ICC	57	(31–62)	52	(48–60)	38	(34–52)	52	(38–57)
Pearson	48	(33–60)	52	(43–62)	43	(29–52)	48	(33–57)
First derivative patterns								
ICC	62	(41–79)	67	(60–81)	57	(41–65)	62	(43–76)
Lb_ICC	62	(41–79)	67	(60–81)	57	(41–65)	62	(43–76)
Resid_ICC	62	(46–79)	67	(65–79)	48	(43–62)	62	(48–71)
Pearson	67	(46–76)	71	(50–81)	52	(45–65)	62	(48–76)

ICC: Intraclass Correlations Coefficient.
lb_ICC: 95% lower bound of the ICC.
resid_ICC: the within people mean square residual obtained with a repeated ANOVA analysis.
Pearson: Pearson's correlation analysis.

Table 3: Right leg – median and quartiles for the recognition rates obtained with each of the four methods for joint moments, joint angles, and segment angles.

1 and subject 5 in Figure 4, it is noticeable that there is a higher between subject variation in the curve patterns in the frontal plane than in the sagittal plane. The between subject variation in the frontal plane was also found by Borghese et al. [4] and could be an explanation for the relatively high recognition rates in this plane. This should be investigated further and the use of variables in the frontal plane should be considered in models using, e.g., principal component analysis to examine differences between groups in biomechanical research.

The recognition rates for joint angles and segment angles were generally higher than the recognition rates for joint moments. This could partly be due to the fact that segment angles and joint angles are only calculated on the basis of markers mounted on anatomical landmarks of the subjects while the calculation of joint moments also includes ground reaction forces obtained from force plates as well as anthropometric measurements of the lower extremities used to calculate inertia of the segments [26]. These parameters could be subject to variations caused by measurement error or variations in gait pattern between days. This is supported by Simonsen et al. [21] who concluded that ground reaction forces by far dominated the calculation of joint moments compared to segment displacements and anthropometric measures

Limitations. The recognition rates found in this study give an indication of which biomechanical variables contribute most to the individual gait pattern. However, it should be taken into account that the variables are related to each other. It can be mentioned as an example that the foot segment angle in the frontal plane has been shown to be related to stance phase knee adduction and hip joint moments in the frontal and sagittal planes [1, 6].

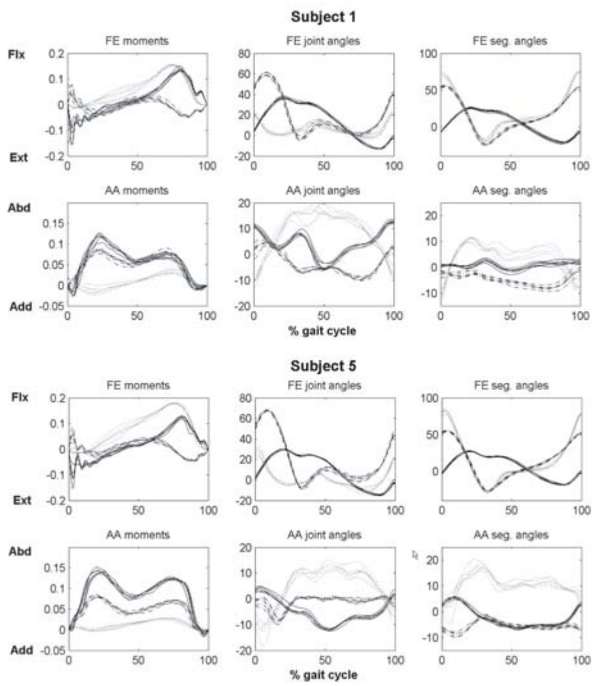

Figure 4: Right leg displacement patterns for 6 trials for joint moments (left), joint angles (middle), and segment angles (right) in the sagittal (FE) and frontal (AA) planes. Hip/thigh: solid curve. Knee/shank: slash/dotted curve. Ankle/foot: dotted curve. Joint moments are normalized to bodyweight and leg length. Joint angles and segment angles are in degrees.

Eventually, it will be more relevant within forensic biomechanics to try to recognize singular gait cycles. In this study, we intentionally averaged six gait cycles to reduce small casual variations from step to step because the main purpose of the study was to see whether or not a basic walking pattern could be recognized between days.

The choice of a fixed walking speed may seem as a limitation, but if we had let the subjects walk at self-selected speed, we would have run the risk that the individual subjects would be recognized more by his/her particular velocity than a basic movement pattern, that is of course provided the subjects could reproduce their self-selected velocity on two days. If the subjects would have chosen a different velocity on both days, which could happen, the individual subject may not be recognized, mostly due to a difference in walking speed. Finally, it has never been our impression that we force subjects into something "unnatural" as long as we use velocities within normal limits.

5 Conclusions

We have found high recognition rates especially for the joint angles and segment angles in the sagittal and frontal planes using correlation analysis. We could identify all 21 subjects in this sample by combining recognition rates of three joint angular and segment angular velocities. The variables in the frontal plane showed larger interindividual differences in the shape of the curve patterns than in the sagittal plane and should be studied further for use in forensic medicine and taken into consideration for use in models analyzing differences between groups and individuals.

Conflicts of interest

None of the authors have any conflicts of interest regarding this manuscript.

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References

[1] M. Andrews, F. R. Noyes, T. E. Hewett, and T. P. Andriacchi, *Lower limb alignment and foot angle are related to stance phase knee adduction in normal subjects: a critical analysis of the reliability of gait analysis data*, J Orthop Res, 14 (1996), pp. 289–295.

[2] G. Atkinson and A. M. Nevill, *Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine*, Sports Med, 26 (1998), pp. 217–238.

[3] G. Baofeng and M. S. Nixon, *Gait feature subset selection by mutual information*, in Proceedings 1st IEEE International Conference on Biometrics: Theory, Applications, and Systems, IEEE, Washington, DC, 2007, pp. 1–6.

[4] N. A. Borghese, L. Bianchi, and F. Lacquaniti, *Kinematic determinants of human locomotion*, J Physiol, 494 (Pt. 3) (1996), pp. 863–879.

[5] I. Bouchrika and M. S. Nixon, *Model-based feature extraction for gait analysis and recognition*, in Computer Vision/Computer Graphics Collaboration Techniques, vol. 4418 of Lecture Notes in Computer Science, Springer, Berlin, 2007, pp. 150–160.

[6] K. A. Bowsher and C. L. Vaughan, *Effect of foot-progression angle on hip joint moments during gait*, J Biomech, 28 (1995), pp. 759–762.

[7] D. Cunado, M. S. Nixon, and J. N. Carter, *Automatic extraction and description of human gait models for recognition purposes*, Comput Vis Image Underst, 90 (2003), pp. 1–41.

[8] U. Della, Croce, A. Cappozzo, D. C. Kerrigan, and L. Lucchetti, *Bone position and orientation errors: pelvis and lower limb anatomical landmark identification reliability*, Gait Posture, 5 (1997), pp. 156–157.

[9] U. Della Croce, A. Cappozzo, and D. C. Kerrigan, *Pelvis and lower limb anatomical landmark calibration precision and its propagation to bone geometry and joint angles*, Med Biol Eng Comput, 37 (1999), pp. 155–161.

[10] Z. Guoying, L. Guoyi, L. Hua, and M. Pietikainen, *3D gait recognition using multiple camera*, in Proceedings 7th International Conference on Automatic Face and Gesture Recognition, University of Southampton, Southampton, UK, 2006, pp. 529–534.

[11] A. L. Hof, *Scaling gait data to body size*, Gait Posture, 4 (1996), pp. 222–223.

[12] J. P. Holden and S. J. Stanhope, *The effect of variation in knee center location estimates on net knee joint moments*, Gait Posture, 7 (1998), pp. 1–6.

[13] A. M. Holmback, M. M. Porter, D. Downham, J. L. Andersen, and J. Lexell, *Structure and function of the ankle dorsiflexor muscles in young and moderately active men and women*, J Appl Physiol, 95 (2003), pp. 2416–2424.

[14] D. Jokisch, I. Daum, and N. F. Troje, *Self recognition versus recognition of others by biological motion: viewpoint-dependent effects*, Perception, 35 (2006), pp. 911–920.

[15] M. P. Kadaba, H. K. Ramakrishnan, M. E. Wootten, J. Gainey, G. Gorton, and G. V. Cochran, *Repeatability of kinematic, kinetic, and electromyographic data in normal adult gait*, J Orthop Res, 7 (1989), pp. 849–860.

[16] L. T. Kozlowski and J. E. Cutting, *Recognizing the sex of a walker from a dynamic point-light display*, Percept Psychophys, 21 (1977), pp. 575–580.

[17] P. K. Larsen, E. B. Simonsen, and N. Lynnerup, *Gait analysis in forensic medicine*, J Forensic Sci, 53 (2008), pp. 1149–1153.

[18] C. M. O'Connor, S. K. Thorpe, M. J. O'Malley, and C. L. Vaughan, *Automatic detection of gait events using kinematic data*, Gait Posture, 25 (2007), pp. 469–474.

[19] W. I. Schöllhorn, B. M. Nigg, D. J. Stefanyshyn, and W. Liu, *Identification of individual walking patterns using time discrete and time continuous data sets*, Gait Posture, 15 (2002), pp. 180–186.

[20] P. E. Shrout and J. L. Fleiss, *Intraclass correlations: Uses in assessing rater reliability*, Psychol Bull, 86 (1979), pp. 420–428.

[21] E. B. Simonsen, P. Dyhre-Poulsen, M. Voigt, P. Aagaard, and N. Fallentin, *Mechanisms contributing to different joint moments observed during human walking*, Scand J Med Sci Sports, 7 (1997), pp. 1–13.

[22] E. B. Simonsen, P. Dyhre-Poulsen, M. Voigt, P. Aagaard, G. Sjøgaard, and F. Bojsen-Møller, *Bone-on-bone forces during loaded and unloaded walking*, Acta Anat (Basel), 152 (1995), pp. 133–142.

[23] R. Stagni, A. Leardini, A. Cappozzo, M. Grazia Benedetti, and A. Cappello, *Effects of hip joint centre mislocation on gait analysis results*, J Biomech, 33 (2000), pp. 1479–1487.

[24] S. V. Stevenage, M. S. Nixon, and M. Voigt, *Visual analysis of gait as a cue to identity*, Appl Cogn Psychol, 13 (1999), pp. 513–516.

[25] R. Urtasun and P. Fua, *3D tracking for gait characterization and recognition*, in Proc. 6th IEEE International Conference on Automatic Face and Gesture Recognition, IEEE, Korea University, Seoul, 2004, pp. 17–22.

[26] C. L. Vaughan, B. L. Davis, and C. M. O'Connor, *Dynamics of Human Gait*, vol. 2, Human Kinetics Publishers, Champaign, IL, 1992.