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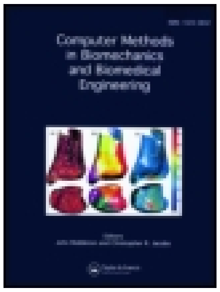

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Marker-based classification of young-elderly gait pattern differences via direct PCA feature extraction and SVMs

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Marker-based classification of young–elderly gait pattern differences via direct PCA feature extraction and SVMs

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The classification of gait patterns has great potential as a diagnostic tool, for example, for the diagnosis of injury or to identify at-risk gait in the elderly. The purpose of the paper is to present a method for classifying group differences in gait pattern by using the complete spatial and temporal information of the segment motion quantified by the markers. The classification rates that are obtained are compared with previous studies using conventional classification features. For our analysis, 37 three-dimensional marker trajectories were collected from each of our 24 young and 24 elderly female subjects while they were walking on a treadmill. Principal component analysis was carried out on these trajectories to retain the spatial and temporal information in the markers. Using a Support Vector Machine with a linear kernel, a classification rate of 95.8% was obtained. This classification approach also allowed visualisation of the contribution of individual markers to group differentiation in position and time. The approach made no specific assumptions and did not require prior knowledge of specific time points in the gait cycle. It is therefore directly applicable for group classification tasks in any study involving marker measurements.

Keywords: biomechanical data classification; PCA feature extraction; difference visualisation; young–elderly gait classification; support vector machines

1. Introduction

The automated recognition of gait patterns may be of importance because of the potential applications in medical diagnostics, e.g. for the identification of at-risk gait in the elderly. In such clinical gait analyses, 3D positions of markers attached to the human body are typically measured to determine joint angles and range of motion.

Previous studies used pattern classification methods to differentiate gait patterns of young–elderly groups based on such kinematic variables (Wu et al. 2006) or the combination of kinematic and spatio-temporal variables (Wu et al. 2007) with classification rates of 89.6% and 91%, respectively. While these classification rates indicate the ability of pattern classification to differentiate the group gait patterns, a possible loss of information may have been introduced by the methods that were applied to the data. First, the calculation of the kinematic variables required combining marker information. Therefore, the amount of spatial information was reduced. Second, only specific time points of the gait cycle (e.g. touch-down, toe-off) were considered in the evaluation. Thus, a substantial part of the available temporal information was discarded (Chau 2001).

It is suggested that more information is available for group differentiation if the 3D marker trajectories, which represent the complete available temporal information, are used for feature computation and classification. Such a method for the classification of gait has not been presented in the literature. It is postulated that higher group classification rates will be obtained by using such an approach.

Therefore, the purpose of this study is to present a method for classifying group differences in gait pattern by using a more complete representation of the spatial and temporal information of the individual markers. The resulting classification rates were compared with previous studies using conventional classification features.

2. Methods

2.1 Data preparation

2.1.1 Collected data

Kinematic data were collected from 48 healthy female subjects (Table 1). The age of 24 subjects was between 55 and 70 years (elderly group) and the age of the other 24 subjects was between 21 and 30 years (young group). All subjects gave informed written consent according to the

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Table 1. Characteristics of the 48 subjects that were used for analysis purposes.

	n	Age (years)	Height (m)	Mass (kg)	Treadmill speed (m/s)
Elderly group	24	59.9 (4.5)	1.61 (0.05)	68.8 (10.9)	1.24 (0.27)
Young group	24	25.3 (2.4)	1.66 (0.07)	67.2 (13.0)	1.53 (0.17)
Ranges					
Elderly group		[55.0;70.0]	[1.50;1.75]	[51.1;89.4]	[0.76;1.67]
Young group		[21.0;30.0]	[1.52;1.78]	[50.5;101.0]	[1.07;1.79]

Notes: Values in the first two rows are presented as mean (SD). Values in the last two rows indicate the ranges of the different parameters.

guidelines of the University of Calgary's Conjoint Health Research Ethics Board, which approved the study.

All subjects were equipped with 37 reflective markers that were placed on the head, trunk, arms, hands, legs and feet consistent with Vicon's (Oxford Metrics, Oxford, UK) Plug-In-Gait model (e.g. Orendurff et al. 2006; Buckley et al. 2009).

Of the 37 originally collected markers, 28 were at anatomical landmarks (Table 2). These markers were selected for the current study as they represented comparable body locations. The remaining nine markers were needed in the Plug-In-Gait model for the determination of joint angles; however, these markers were not located on anatomically well-defined locations and were therefore not used for the purposes of classification.

Table 2. Identifiers of the 28 markers that were used for classification purposes.

Marker no.	Marker identifier	Marker position
1	'LTOE'	Left toe
2	'LANK'	Left ankle
3	'LHEE'	Left heel
4	'LKNE'	Left knee
5	'RTOE'	Right toe
6	'RANK'	Right ankle
7	'RHEE'	Right heel
8	'RKNE'	Right knee
9	'RASIS'	Right anterior superior iliac spine
10	'LASIS'	Left anterior superior iliac spine
11	'RPSI'	Right posterior superior iliac spine
12	'LPSI'	Left posterior superior iliac spine
13	'STRN'	Sternum
14	'CLAV'	Clavicle
15	'C7'	7th cervical vertebrae
16	'T10'	10th thoracic vertebrae
17	'RSHO'	Right shoulder
18	'RELB'	Right elbow
19	'RWRA'	Right wrist thumb side
20	'RWRB'	Right wrist pinkie side
21	'LSHO'	Left shoulder
22	'LELB'	Left elbow
23	'LWRA'	Left wrist thumb side
24	'LWRB'	Left wrist pinkie side
25	'LFHEAD'	Left front head
26	'RFHEAD'	Right front head
27	'LBHEAD'	Left back head
28	'RBHEAD'	Right back head

Note: The identifiers were in accordance with Vicon's plug-in-gait marker set.

Before data collection, all subjects walked for 5 min on a treadmill in order to warm up and to select a comfortable walking speed. During data collection, the subjects walked for 80 s on the same treadmill at a self-selected speed (Table 1). The walking speed remained constant for each subject throughout data collection.

Marker positions were recorded at 240 frames/s using a system of eight synchronised digital infrared high-speed cameras (Eagle and Hawk, Motion Analysis Corp., Santa Rosa, CA, USA). The coordinate system defined by the calibration of the camera system had the subjects walk along the y-axis (anterior–posterior direction). The x-axis was aligned with the medial-lateral direction and the z-axis was aligned with the vertical direction.

The trajectories of individual markers were reconstructed using the software Eva Real-Time (EVaRT, Motion Analysis Corp.). The data were not filtered. Short gaps in the dataset (1–10 frames) were filled using cubic interpolation. Gaps up to 0.1 s rarely appeared in the hip marker trajectories and could be reconstructed by determining the position of the missing marker from adjacent markers. Longer gaps were not present in the data. All subsequent analyses were performed using customised MATLAB (version 7.6.0.324, The MathWorks, Inc., Natick, MA, USA) software.

2.1.2 Gait cycle extraction

For each of the 48 subjects, 10 consecutive gait cycles were extracted from the collected walking gait data. For this purpose, gait phases without artefacts in the gait were used. Artefacts were defined as any measurements that deviated from a subject's automated (unconscious) gait pattern; for example, when the subjects scratched themselves or moved their head in an unusual way.

For the purpose of artefact detection, eight markers were selected: the two wrist markers of the left and right hand and the four head markers. The data were analysed in x- and z-axis components, information about artefacts in

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the y-coordinate was considered redundant. The 16 resulting time sequences were individually normalised to mean $\mu = 0$ and standard deviation $\sigma = 1$. This was only done for the purpose of artefact detection to allow a fair comparison between markers. A 20-s window was then extracted from the start of all 16 sequences. For each of the windows, it was then tested whether any point was more than $\sigma = 2$ away from the mean. If such a point was detected in any sequence, the latest was set as new starting point for another window extraction. If the end of the sequence was reached without success, the standard deviation criterion was increased by 0.1 and the process was repeated. As a maximum value, $\sigma = 3$ was set. However, this maximum value was not reached for any of the 36 subjects. Each resulting window was also visually inspected and no remaining artefacts were found.

From the artefact-free 20-s windows, 10 complete gait sequences were extracted for subsequent analysis. The beginning of a new gait cycle was arbitrarily defined as the point in the time sequence when the left heel marker reached its lowest z-axis position. This point allowed unambiguous splitting of gait cycles.

The 10 extracted gait cycles were then prepared for classification in three steps. First, they were individually time normalised. For this purpose, a normalisation to 101 time steps from 0% to 100% was performed using a cubic spline interpolation (De Boor 1978). Second, anthropometric differences between the subjects were eliminated by calculating the mean position of each of the 84 marker time sequences (28 markers in three axes each) for each subject and by subtracting them from the respective time sequence. Third, the classification was designated to use a mean gait cycle representation from each subject. For that reason, the mean of the 10 consecutive gait cycles that were extracted was computed.

The 84 marker sequences were then concatenated into one movement pattern vector $\mathbf{m}_i$ per subject $i = 1, \ldots, 48$, which was of dimension 8484 (84 marker sequences $\times$ 101 time steps).

The movement pattern vectors $\mathbf{m}_i$ were visualised in Figure 1, where the mean movement pattern vector $\bar{\mathbf{m}} \in \Re^{8484\times1}$ of all subjects is illustrated for four positions of the gait cycle. In each time point the marker positions were

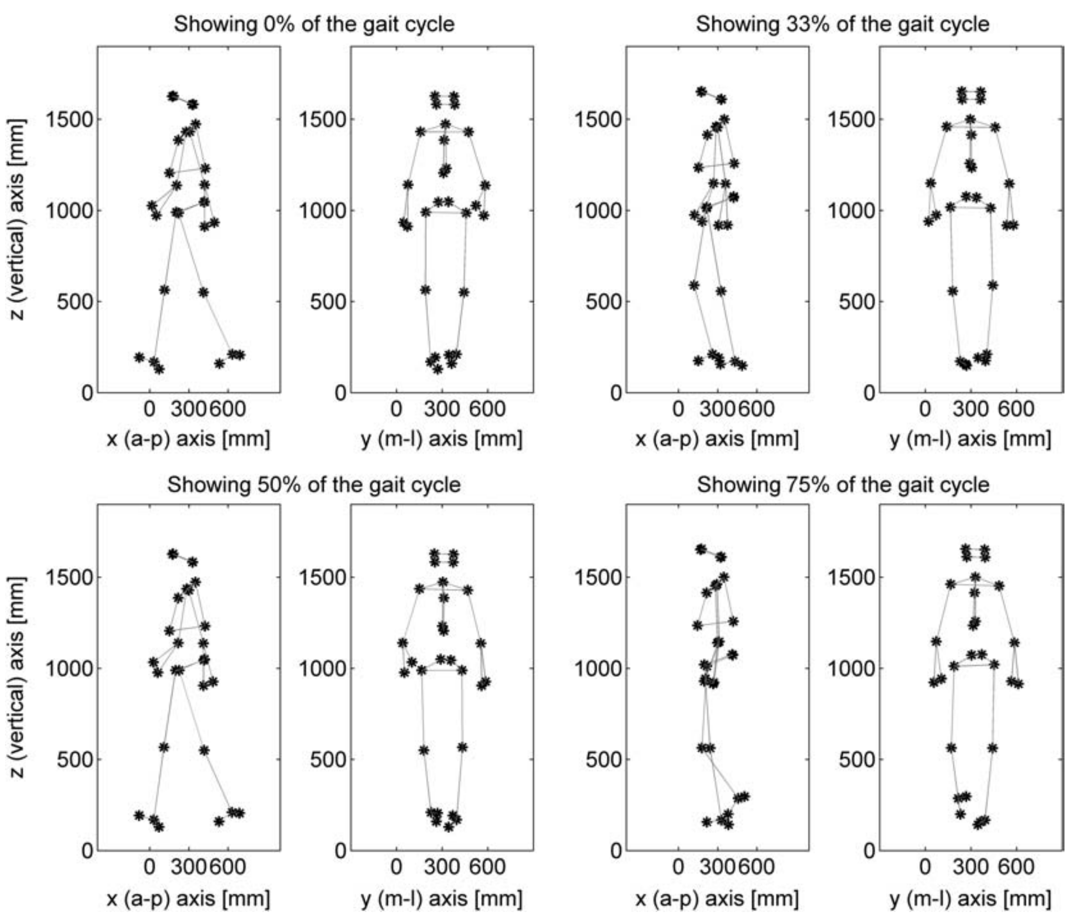

Figure 1. Mean marker position of all subjects at different time points of the gait cycle. For each time point, the sagittal plane is shown on the left and the frontal plane on the right. Each star represents the position of one of the 28 markers that were used for classification.

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visualised in the *x*-*z* plane (sagittal plane) on the left and the *y*-*z* plane (frontal plane) on the right.

2.2 Group classification algorithm

2.2.1 Feature extraction

The purpose of feature extraction was to retain as much of the spatial and temporal information of the movement patterns as possible. Therefore, direct feature extraction from the movement patterns by principal component analysis (PCA; Fukunaga 1990) was carried out. The important characteristic of the PCA was that it conducted a transformation of the marker movement space that still incorporated all the available information. Furthermore, the PCA feature representation is known to be suitable for classification (Theodoridis and Koutroumbas 2009).

To carry out the PCA, the movement pattern vectors $\mathbf{m}_i \in \Re^{8484\times1}$ from all subjects were arranged in the data matrix $\mathbf{M} \in \Re^{8484\times48}$. As the number of individual samples (48) was smaller than the number of dimensions (8484), the PCA algorithm for a small sample size (Fukunaga 1990) was used. In this algorithm an eigenvalue decomposition of the sample correlation matrix $\mathbf{M}^t\mathbf{M}\,(\in \Re^{48\times48})$ was performed first. The eigenvectors $\mathbf{e}_k\,(\in \Re^{48\times1}, k = 1, \ldots, 48)$ of this matrix were then multiplied with the data matrix $\mathbf{M}$ to compute the corresponding principal movements $\mathbf{p}_k\,(\in \Re^{8484\times1})$. The 48 principal movement vectors were ordered according to the magnitude of their corresponding eigenvalues, which encoded the amount of gait variability captured by this specific principal movement. Therefore, the first few principal movements corresponded to the largest overall gait variability and described the main variations in the movement over time.

As a next step each movement pattern vector $\mathbf{m}_i$ was projected onto the 48 principal movements $\mathbf{p}_k$, resulting in 48 principal movement features $x_i^k\,(\in \Re^{1\times1})$ per subject, where

$k = 1,\ldots,48$, the number of principal movements
$i = 1,\ldots,48$, the number of subjects.

Due to the properties of the PCA the movement patterns $\mathbf{m}_i$ of each subject could now be represented as a weighted linear combination of up to 48 principal movements $\mathbf{p}_k$ using the principal movement features x_i^k as weights.

The principal movement features x_i^k were directly used as features for classification. For the evaluation of the classifier, an increasing number $d = 1,\ldots,48$ of principal movement features x_i^k were combined into a principal movement pattern vector $\mathbf{x}_i\,(\in \Re^{d\times1})$. This process was also conducted in a way that the principal movement features were ordered corresponding to the eigenvalues of the PCA. This is a standard procedure for classification (Theodoridis and Koutroumbas 2009), as every PCA component adds additional information for group classification according to overall data variability.

2.2.2 Group classification

For group differentiation, a support vector machine (SVM) classifier (Vapnik 1998) was used. The SVM classifier (e.g. Begg et al. 2005; Wu and Wang 2008) has, to the knowledge of the authors, not been applied previously to principal movement patterns of gait. Important characteristics of the SVM classifier for this project were (a) that it typically obtained high classification rates (Sapankevych and Sankar 2009), (b) that the SVM implementation that was used (C-SVM; Chang and Lin 2001) only possessed one free parameter that had to be set and (c) that the application of SVM with a linear kernel allowed further analysis of group differences with respect to spatial and temporal information of individual marker movement.

To obtain high group classification rates, the SVM had to find an optimal decision hyperplane (Figure 2) that separated the principal movements of subjects from different groups with a maximal margin, i.e. the distance of the hyperplane to any principal movement was as large as possible.

The parameter that needed to be set for SVM classification was the cost parameter C (Schölkopf and Smola 2002). It determined the trade-off between the classification performance on the training set and the generalisation ability, i.e. the ability of the classifier to correctly classify new samples. Since no general rule for setting the C-parameter existed (Vapnik 1998; Chang and Lin 2001), the classification results when using different

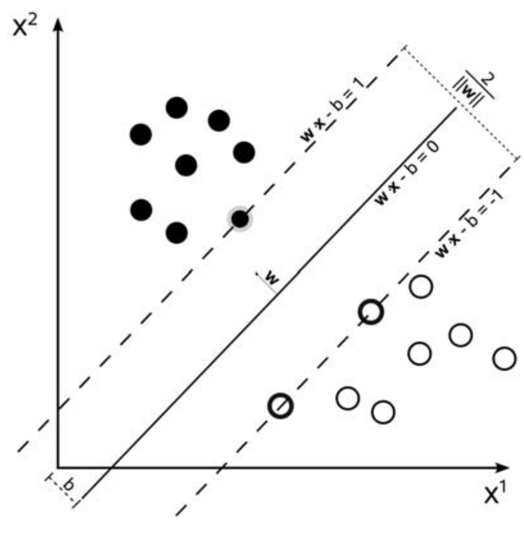

Figure 2. An SVM example group classification for a two class problem. Class 1 is represented by white circles and labels −1 and class 2 by black circles and labels +1. The class representatives are shown for two feature dimensions x^1 and x^2. The decision hyperplane is represented by the normal vector $\mathbf{w}$ and the distance to the origin b.

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settings for C were experimentally evaluated (e.g. Begg and Kamruzzaman 2005). For the evaluation, a logarithmic range ($C = 10^n$, $n = -3, -2.5, -2, \ldots, 3$) was employed.

The SVM operated by first subjecting the principal movements $\mathbf{x}_i^d$ to implicit mapping to a higher-dimensional space (Vapnik 1998). For this purpose, different kernel functions (Schölkopf and Smola 2002) were available. In the present study a linear kernel was chosen because it allowed functional analysis of the contribution of individual markers to group differences. The visualisation of group differences, which was used for this purpose, also allowed investigating what spatial and what temporal information was needed for group differentiation.

With the linear kernel that was employed, the hyperplane that separated the groups was parameterised by its normal vector $\mathbf{w} \in \Re^{d\times 1}$ and by its distance to the origin b (Figure 2). The vector $\mathbf{w}$ pointed in the direction of difference between the two groups on either side of the decision boundary (Figure 2). Its length was defined by the mean distance to the individual group cluster centroids. As the vector $\mathbf{w}$ was an element of the principal movement space, it could be projected back onto the original marker movement space for further analysis of group differences. For this purpose, a linear combination of the PCA eigenvectors using the components of $\mathbf{w}$ as weights was computed. This back-projection of the vector $\mathbf{w}$ was called difference marker movement vector $\mathbf{m}_\mathbf{w} \in \Re^{8484\times 1}$. It represented the spatial and temporal contribution of each individual marker movement to group differentiation. To show these individual contributions, the difference marker movement vector $\mathbf{m}_\mathbf{w}$ was added (elderly group, labels $+1$) and subtracted (young group, labels -1) from the mean movement $\bar{\mathbf{m}}$ of all subjects, which is shown in Figure 1.

For the evaluation of the classification rate, a leave-one-subject-out cross-validation was conducted with all trials from one subject being removed for classifier training. Then, the left-out trials were classified and tested for correctness. This was repeated until each subject was left out once. The number of correctly classified trials divided by the total number of trials then gave the classification rate.

3. Results

The maximum classification rate of 95.8% was reached when using $d = 36, \ldots, 39$ principal movements (Figure 3). In this case, two subjects that belonged to the elderly class were incorrectly classified during cross-validation. The drop in classification accuracy when using more than 39 principal movements (Figure 3) was attributed mainly to the fact that PCA components that belong to smaller eigenvalues mainly contain noise (Theodoridis and Koutroumbas 2009).

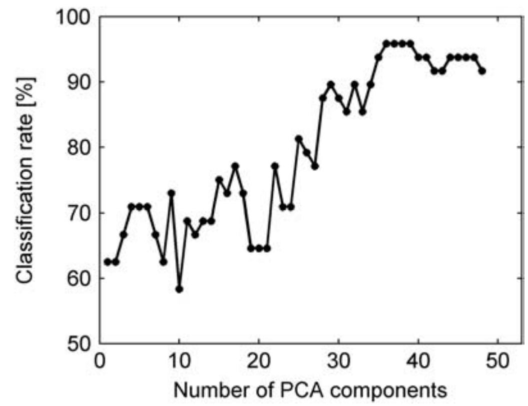

Figure 3. Classification rate in percent when using $d = 1, \ldots, 48$ principal movement pattern features and $C = 0.1$.

The setting of the cost parameter C did not affect the maximum classification rate or its locations. The mean classification rates over all $d = 1, \ldots, 48$ cross-validation runs for different cost parameters C varied slightly (Table 3). The minimum and maximum mean classification rate were 79.1% for $C = 1000$ and 80.5% for $C = 0.1$, respectively.

The computation of the contribution of individual markers to group differentiation in position and time was performed at the point of the maximum classification rate using 36 principal movement features (Figure 3). The resulting difference information is illustrated for four time points of the gait cycle (Figure 4). A video of the difference information for all time points of the gait cycle can be found at http://tinyurl.com/group-diff.

Table 3. Mean classification rates for different C-parameter settings.

Parameter n	Mean classification rate (%)
-3	80
-2.5	80
-2	80
-1.5	80.1
-1	**80.5**
-0.5	79.7
0	79.5
0.5	79.2
1	79.1
1.5	79.3
2	79.2
2.5	79.2
3	79.1

Notes: The C-parameter was evaluated over a logarithmic range ($C = 10^n$, $n = -3, \ldots, 3$). The parameter n is given within the table. The mean classification rates were computed over all $d = 1, \ldots, 48$ cross-validation runs. The best result (printed bold) of 80.5% mean classification rate is obtained when using $n = -1$.

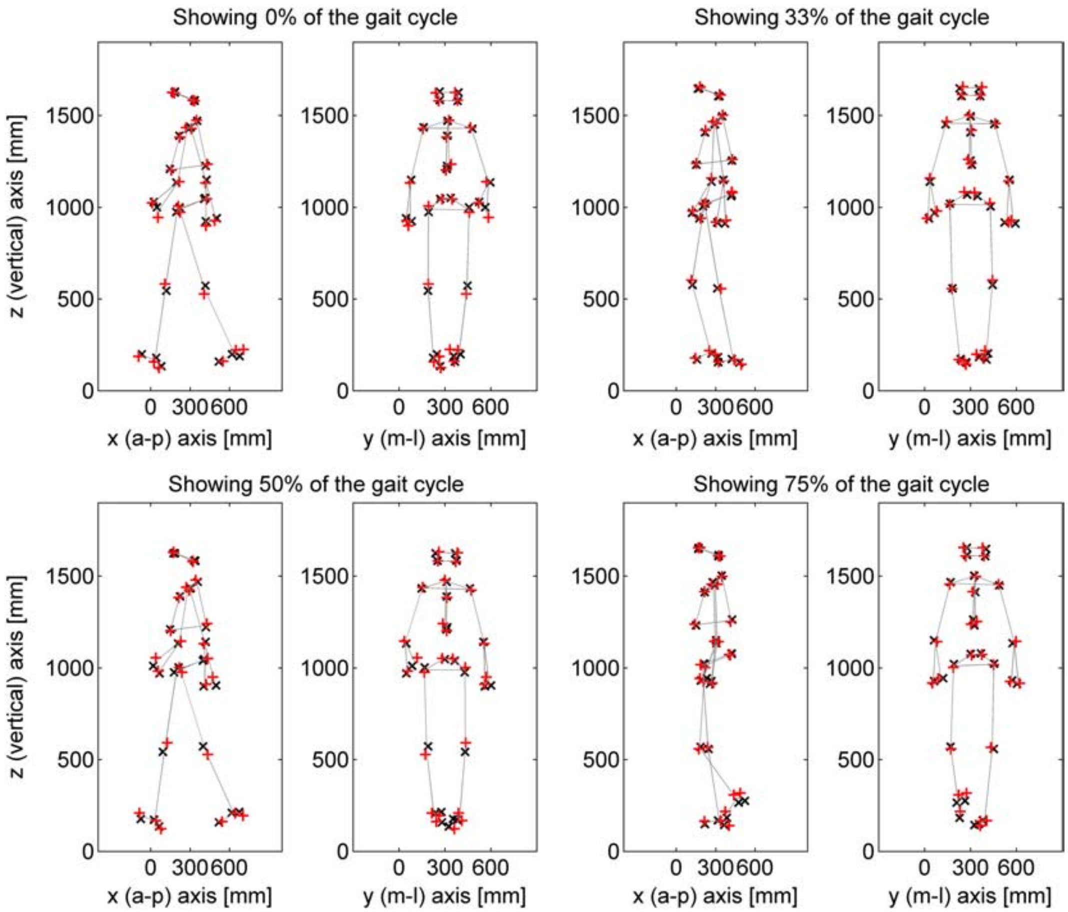

Figure 4. Visualisation of the contributions of individual markers to group differentiability at different time points of the gait cycle. The marker location differences in relation to the overall mean movement of all subjects (Figure 1) is shown for the elderly group (black cross) and the young group (red plus).

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4. Discussion

The results demonstrated that the proposed method was capable of obtaining higher classification rates compared to previous studies that differentiated the young–elderly gait based on 3D marker data. The previous studies reported classification rates of 89.6% based on kinematic variables (Wu et al. 2006) and of 91.0% based on the combination of kinematic and spatio-temporal variables (Wu et al. 2007). Based on the proposed approach in the current paper, a classification rate of 95.8% (Figure 3) was obtained. This increased classification of power may be attributed to the more complete availability of spatial and temporal information, which was achieved by direct feature computation via PCA from the 3D marker data.

A direct PCA analysis of group marker information for gait classification had, to the knowledge of the authors, not been attempted earlier. PCA was, however, applied to the analysis of the movement of individuals. Previous results showed that the gait patterns of individual subjects could be efficiently modelled using four principal components (Troje 2002). In this light the number of principal movement patterns needed for a sufficient classification (36–39) in the present study may seem high. However, the current study did not focus on principal components of the movement of individual subjects, but on the movement differences between groups of subjects. Human gait comprises high inter-individual variance (Sadeghi et al. 2000). As opposed to the modelling of the movement of individuals, a higher number of principal movement patterns were therefore needed in the current study to efficiently generalise and classify the differences between groups.

Each of the individual principal movement patterns represented a combination of spatial and temporal information about the movement of the individuals. Both aspects contributed to group differentiation (Figure 4). The illustration showed the differences in individual marker positions that led to the classification. One example of the combination of the spatial and temporal aspect of group differentiation could be seen by examining the knee markers. During the swing phase (Figure 4, 33% and 75% gait cycle), the knee markers of both groups did not exhibit a large difference. However, during the double support phase (Figure 4, 0% and 50% gait cycle), both knee markers exhibited a large difference. Thus, both the spatial and the temporal aspects of the movement were important for classification. The authors are not aware of a similar technique that allowed the analysis of the contribution of individual markers to group differentiation by taking both the position and time aspects into account.

For the age-related example, previous findings could be reproduced by this analysis of the contribution of individual markers to group differentiation. Notable differences visible in Figure 4 were foot clearance and stride length of the young and the elderly. In the representations of the swing phase (Figure 4, 33% and 75% gait cycle), it could be seen that the young group had a higher position of the swinging foot than the elderly group. This observation of higher foot clearance in the young group was consistent with previous results (Begg et al. 2005). In the representations of the double support phase (Figure 4, 0% and 50% gait cycle), it could be seen that the markers representing the feet were farther outwards for the young group than for the elderly group. This increase of stride width in gait of young subjects has also been reported previously (Blanke and Hageman 1989). Naturally, several of the parameters mentioned can be directly attributed to the effects of different walking speeds. However, since we let the subjects choose their preferred movement speed themselves, the changes in those parameters can still be attributed to differences in the natural gait pattern of the groups under investigation.

Other previously reported positional and temporal differences in young–elderly gait could be reproduced as well. These were, for instance, an increased range of motion in the arm movement (Elble et al. 1991) and in the plantar–dorsiflexion of the foot (Nigg et al. 1994). In the same manner, differences in individual body part movements could be observed by examining individual markers over time. In principle, the representation of group difference in the original marker space also allowed further functional analyses by calculating kinematic variables.

Limitations of the proposed methodology were in the necessity for a time normalisation of the gait cycles due to the equal sample length requirements for the PCA. Information about the different walking speeds (Table 1) was therefore lost. Future work could include this information as an additional feature for classification.

As an additional algorithmic limitation, the *C*-parameter of the SVM had to be set correctly. However, this setting could easily be determined by an experimental parameter search. Even with a non-optimal *C*-parameter, the algorithm converged with a high classification rate (Table 3).

When compared with more traditional approaches that used discrete kinematic variables at specific time points of the gait cycle for group differentiation, some further limitations existed. Given that the selection of variables and time points for the discrete approach was appropriate and functional, direct functional conclusions could be drawn about group differences. In the approach for the current paper, these conclusions were not as straightforward to draw, but required careful additional analysis of the reasons that led to group differentiation.

However, not to perform the classification on discrete functional variables at specific time points of the gait cycle also had several advantages. First, the selection of functional features for the classification procedures is usually based on prior knowledge of the researchers. The method presented here extracts the features based on a mathematical algorithm. The classification result therefore identifies group differences independently of prior knowledge. Second, the calculation of kinematic and kinetic variables typically requires assumptions (e.g. about the direction of joint axes), which are often difficult to validate. Third, the computation of these variables might lead to error amplification (e.g. when marker positions are affected by skin movement). Fourth, the process is often time consuming. Last, the incorporation of a more complete representation of the temporal information prevents discarding a substantial part of the available time-dependent information (Chau 2001).

Since the presented methodology made no special assumptions, it could be applied for group classification tasks to any study involving marker measurements. Examples include analysis of pathological gait differences that are due to injuries, for medical pre-diagnosis of gait diseases and for the evaluation of the outcome of treatment and rehabilitation.

5. Summary

The current study proposed a method for group classification that directly extracted spatial and temporal information from the 3D marker trajectories collected during human gait. Thus, this method did not require prior knowledge or assumptions, which are required when biomechanical features such as joint angles are determined in additional post-processing steps. The classification using the SVM classifier yielded better group classification rates for the young–elderly group example than those reported in previous studies. The group discriminator could be visualised, which allowed identification of functional differences between the groups.

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