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Predicting body movements for person identification under different walking conditions

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ABSTRACT

Human motion during walking provides biometric information which can be utilized to quantify the similarity between two persons or identify a person. The purpose of this study was to develop a method for identifying a person using their walking motion when another walking motion under different conditions is given. This type of situation occurs frequently in forensic gait science. Twenty-eight subjects were asked to walk in a gait laboratory, and the positions of their joints were tracked using a three-dimensional motion capture system. The subjects repeated their walking motion both without a weight and with a tote bag weighing a total of 5% of their body weight in their right hand. The positions of 17 anatomical landmarks during two cycles of a gait trial were generated to form a gait vector. We developed two different linear transformation methods to determine the functional relationship between the normal gait vectors and the tote-bag gait vectors from the collected gait data, one using linear transformations and the other using partial least squares regression. These methods were validated by predicting the tote-bag gait vector given a normal gait vector of a person, accomplished by calculating the Euclidean distance between the predicted vector to the measured tote-bag gait vector of the same person. The mean values of the prediction scores for the two methods were 96.4 and 95.0, respectively. This study demonstrated the potential for identifying a person based on their walking motion, even under different walking conditions.

1. Introduction

Human motion plays an important role in understanding personal motion characteristics [1]. Human motions are a repetitious sequence of smaller motions with a cycle-to-cycle variation, which are complex activities comprising numerous interactions between multi-segments of the body [2]. Human motion provides important biometric information [3], thus it has been widely investigated in laboratories for applications in human identification [4,5], human activity classification [6], emotion detection [7], and gender classification [8]. Human walking motion or gait analyses have long been investigated and have produced various promising applications such as human identification, human recognition, and human motion synthesis. Specifically, walking motions can be analyzed for forensics purposes to provide similarity measurements [9], similar to finger prints, in order to complement other identifying information.

Identifying a person based on gait for use in surveillance applications was inspired from the fact that motions can be collected without contacting the subjects via non-invasive characteristics [4]. Moreover, human motion has been utilized as evidence to identify criminals in forensics in Denmark and the UK [10]. Two bank robbers were identified by Lynnerup et al. through a similarity index by matching their motions with the motions from collected surveillance systems [11]. To identify a person, inter and intra similarity scores were estimated by Nixon et al. for different subjects and the same subject, respectively [12]. Josiński et al. [13] applied multiple classifiers to identify a person, including naive Bayes, k-nearest neighbors, a radial basis function network, and multilayer perceptron, by processing gait motion capture data. Lugwig et al. [14] quantified the gait pattern in various situations based on joint angle measurements via two-dimensional sagittal-view images. Recent advances in deep neural networks and computer vision techniques have allowed estimation of human joints in images and two-dimensional poses without human intervention [15] and estimation of three-dimensional human poses from single camera videos such as CCTV [16,17]. As

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these techniques mature, a method of comparing three-dimensional walking poses that allows for calculating the similarity between known and unknown persons in CCTV videos for forensic gait analysis is needed. However, there is still only a paucity of information regarding the changes in three-dimensional (3D) walking motion of a subject under different walking conditions, which is important for human identification and quantifying the similarity between two walking motions.

Previous studies have presented walking motions as coordinates of joint positions or joint angles, while some of the studies applied frequency analyses to the motions to transform the human motion between different styles. Unuma et al. [18] transformed the time series of joint angles into the frequency domain and presented human motions using Fourier coefficients. A linear coefficient was utilized to interpolate and extrapolate between two styles for the same subject. Meanwhile, Pullen and Bregler [19] applied Laplacian Pyramid decomposition using middle to high frequencies, and subsequently transferred the motion. In other studies, Yumer and Mitra [20] applied a discrete Fourier transform to decompose the joint position in the time domain signals into the spectral domain and transfer the motion into the spectral domain. In addition, Troje et al. [21] synthesized the motions of males and females as a combination of sinusoidal functions and presented a linear transformation method to transfer the motions of a generalized model.

Various other approaches have investigated dynamic models. For example, a linear time-invariant algorithm was introduced by Hsu et al. [22] to transform one motion into a motion of another style, specifically they transformed normal walking into a sneaky crouch-style walking. Multi-linear analysis techniques were utilized by Min et al. [23] to synthesize the personalized stylistic motions of a person and transfer such motions of one subject to another with a large dataset using an angle coordinate system.

Recently, state-of-the-art deep learning techniques have be applied for motion synthesis. Taylor and Hinton [24] and Nair and Hinton [25] utilized restricted Boltzmann machines to produce human motion synthesis and prediction. Furthermore, Fragkiadaki et al. [26] utilized deep learning with a feedforward neural network model using a loss network with a convolutional auto-encoder to transform the locomotion. In general, deep learning requires a voluminous motion dataset for training.

The objectives of this study were to develop a method for identifying a person using their walking motion when given a different walking motion under different walking conditions and to test its performance. We used a biomechanical approach by calculating the 3D joint kinematics and finding their linear transformation for different environmental conditions. The study contributes to understanding the potential application of human motion-based identification as admissible evidence, especially when other strong traditional features such as DNA, face data, and fingerprints are not available [27].

2. Method

2.1. Data acquisition

Three-dimensional coordinates of the joint positions were recorded using an optical motion capture system (MX T-10, Vicon Motion Systems, Oxford, UK) with eight cameras. The study was approved by the Institutional Review Board at ** Blinded for review **. Informed consent was obtained from each subject prior to testing. Twenty-eight male subjects (23.9 ± 1.8 years old, 172.2 ± 4.6 cm in height, and 66.9 ± 5.9 kg in weight) volunteered for the study. Forty-three retroreflective markers were attached to the anatomical landmarks of the body according to the Vicon plug-in-gait marker-set protocol (Vicon, Oxford, UK) [28], as shown in Fig. 1. All motion data were obtained on the same day and marker placements remained at the same positions throughout all gait trials. Each subject practiced walking on a 6.4-m-long walkway with his sport shoes and performed a walking trial at their self-selected walking speed. A tote-bag with size 30 cm by 28 cm was prepared, which contained weights totaling 5% of the subject's body weight. The subject performed normal walking again but instead while carrying the tote-bag in his right hand. The subject repeated both normal and tote-bag walking trials twice. Three-dimensional trajectories of the 43 body markers were recorded at 100 Hz.

2.2. Data processing

Trajectories of the 43 retroreflective markers were processed using the Vicon Nexus software (Vicon Motion Systems, Oxford, UK) to extract the temporal positions of 17 anatomical landmarks in the body, including the head, heels, toes and joints such as shoulders,

Fig. 1. Forty-three retroreflective markers were attached to the anatomical landmarks of each subject and their positions were recorded using a motion capture system.

elbows, wrists, hips, knees and ankles joints. The positions of the right heel marker with respect to the ground were used to identify two gait cycles in each walking trial. A walking motion was represented as time-series pose data, which were the trajectories of the 17 anatomical landmarks for the frames during two gait cycles. The number of frames for the two gait cycles varied among the subjects and trials. Here, we assumed that the two gait cycles were representative of the gait style of a person; however, note that human gait can be perturbed by various environmental variables.

In pattern recognition and prediction, data normalization helps to remove noise and determine the underlying relationships between variables [29]. To find the relationship between the two cycles of normal walking and the two cycles of tote-bag walking, all walking data were normalized. First, there were variations in walking locations and directions in the laboratory space between subjects for the two cycles of walking trials. Second, walking speed and the number of frames for the two gait cycles varied. The average walking distance and time for the two cycles of normal walking were 2860 mm and 2.19 s, respectively, and those of tote-bag walking were 2848 mm and 2.18 s, respectively. After aligning the progression line of all walking trials, all marker positions were subtracted from the pelvis position, making the motion stationary [21]. The number of frames from heel-strike to heel-strike were resampled to be 50 frames, thus the total number of frames was 201 frames.

A gait vector with 10251 components was constructed for a gait trial from the 3D trajectories of the 17 markers for 201 frames. The gait vectors from 28 subjects with two trials for normal walking were concatenated to create a normal gait matrix of 10251×56. The tote-bag gait matrix was created in the same way. Subsequently, a principal component analysis (PCA) was applied to represent each gait vector as n principal components and their weights maintaining the substantial gait information [30], as illustrated in Fig. 2.

Method 1—linear transformation between two walking motions: We assumed that a linear transformation exists that can map a normal walking motion to a tote-bag walking motion. Using an average gait vector and n principal components, each of the normal and tote-bag gait vectors can be represented as a vector with n components, namely, a reduced gait vector, where n is the number of the meaningful principal components. Therefore, the linear transformation between two walking motions can be found using the reduced gait vectors of both the normal gait vectors $\boldsymbol{K}_N(\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_{56})$ and the tote-bag gait vectors $\boldsymbol{K}_T(\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_{56})$. The linear transformation was estimated as:

$$\boldsymbol{y}_i = \boldsymbol{B} + \boldsymbol{A}\boldsymbol{x}_i, i = 1.56.$$

In matrix form, this is written as:

$$K_T = B + AK_N$$

$$\boldsymbol{K}_T = [\boldsymbol{B} \quad \boldsymbol{A}] \begin{bmatrix} 1 \\ \boldsymbol{K}_N \end{bmatrix},$$

where $[\boldsymbol{B} \quad \boldsymbol{A}]$ is the linear transformation, which can be estimated using a QR decomposition [31].

Method 2—partial least squares regression between two walking motions: Partial least squares (PLS) regression [32,33] was used for predicting a tote-bag gait vector from a given normal gait vector as the second method, which is also called two-block PLS regression. Each of the 56 normal gait vectors $(\boldsymbol{w}_{N1}, \boldsymbol{w}_{N2}, \ldots, \boldsymbol{w}_{N56})$ and 56 tote-bag gait vectors $(\boldsymbol{w}_{T1}, \boldsymbol{w}_{T2}, \ldots, \boldsymbol{w}_{T56})$ is a 10251-dimensional column vector made from three-dimensional trajectories of the 17 anatomical landmarks for 201 frames. First, we concatenated the normal gait vectors to their corresponding tote-bag gait vectors of the same subject to make a column vector $\boldsymbol{w}_{Ci}^T = [\boldsymbol{w}_{Ni}^T, \boldsymbol{w}_{Ti}^T]$ of size $20{,}502 \times 1$, where the superscript T represents a transpose. Second, a PCA was applied to decompose the concatenated gait matrix $\boldsymbol{W}_C = [\boldsymbol{w}_{C1}, \ldots, \boldsymbol{w}_{C56}]$ into an average gait matrix $\boldsymbol{W}_{AC} = \left[\boldsymbol{W}_{AN}^T, \boldsymbol{W}_{AT}^T\right]^T$, the principal components $\boldsymbol{V}_C = \left[\boldsymbol{V}_{CN}^T, \boldsymbol{V}_{CT}^T\right]^T$, and the weight matrix K.

The idea of this method is using the same weight vector for both normal gait vectors and tote-bag gait vectors. In a prediction process, a new normal gait vector, w_{Nnew}, is provided. The weight vector k_{new} in Fig. 3 can be calculated using the average normal gait vector, w_{AN}, and the upper part of the principal components, V_N, as shown below.

$$\boldsymbol{k}_{new} = (\boldsymbol{w}_{Nnew} - \boldsymbol{w}_{AN})\boldsymbol{V}_N$$

Consequently, a tote-bag gait vector can be estimated from the weight vector k_{new}, the average gait vector w_{AT} of the tote-bag gait vector, and the lower part of the principal components, V_T.

$$\boldsymbol{w}_{Tnew} = \boldsymbol{w}_{AT} + \boldsymbol{k}_{new}\boldsymbol{V}_T^T$$

Validation of the two prediction methods: The leave-one-out algorithm was utilized to validate the two prediction methods. That is, the normal and tote-bag gait vectors from 27 subjects were used for training. For the two normal gait vectors of the 28th subject, their tote-bag gait vectors were predicted. This was repeated for the remaining 27 subjects. The prediction performance was quantified as the Euclidean distance of the 17 landmark positions between the predicted tote-bag gait vector and the measured tote-bag gait vector in each frame:

$$e_i = \sqrt{\left(x_i^{(m)} - x_i^{(p)}\right)^2 + \left(y_i^{(m)} - y_i^{(p)}\right)^2 + \left(z_i^{(m)} - z_i^{(p)}\right)^2},$$

where $i = 1, 2, \ldots, 17$ represents the 17 landmark positions and p and m represent the predicted and measured tote-bag gaits, respectively.

The predicted tote-bag gait vector was used to identify a subject when given the measured tote-bag gait vectors from a population. The Euclidean distances between the predicted tote-bag gait vector and the measured tote-bag gait vectors of the 28 subjects, or 56

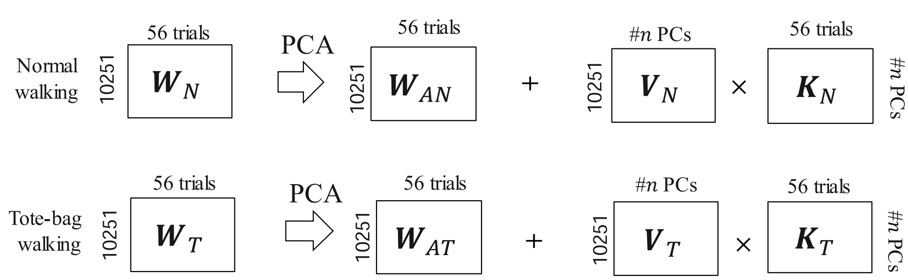

Fig. 2. A principal component analysis (PCA) was applied to the normal gait matrix ($\boldsymbol{W}_N$) and tote-bag gait matrix ($\boldsymbol{W}_T$) to represent them as a combination of the average gait matrix ($\boldsymbol{W}_{AN}$ and $\boldsymbol{W}_{AT}$), the first n meaningful principal components ($\boldsymbol{V}_N$ and $\boldsymbol{V}_T$), and the weights ($\boldsymbol{K}_N$ and $\boldsymbol{K}_T$).

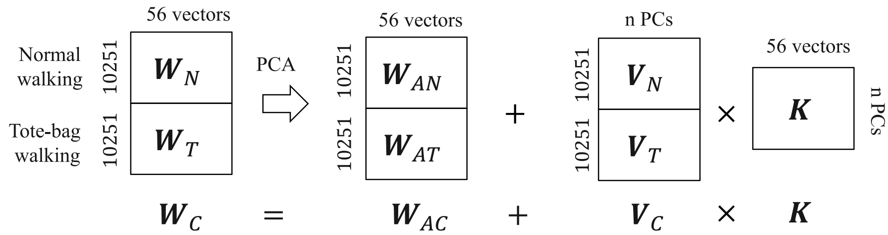

Fig. 3. The PCA decomposed matrix $\boldsymbol{W}_C$ consisting of 56 concatenated gait vectors into an average concatenated gait matrix $\boldsymbol{W}_{AC}$, a matrix of the principal components $\boldsymbol{V}_C$, and a matrix of the respective weight vectors $\boldsymbol{K}$.

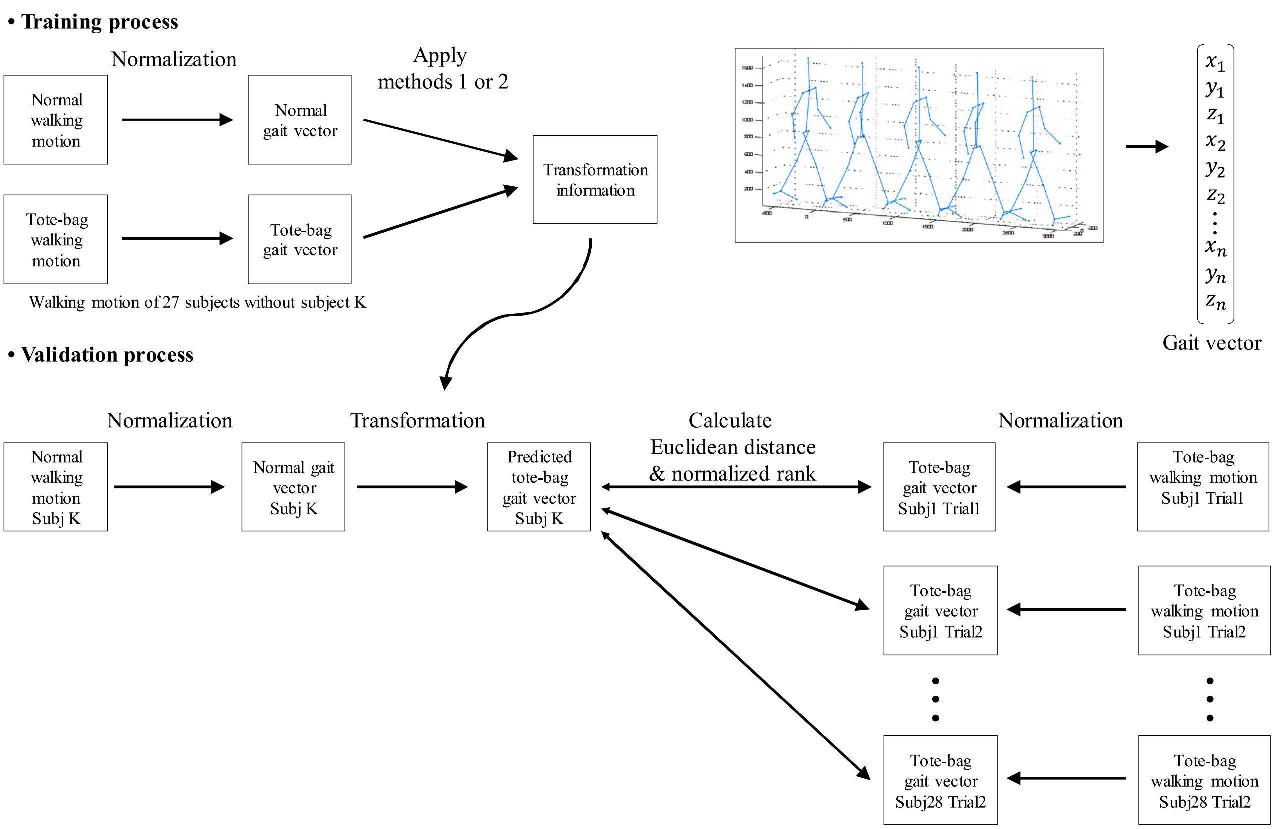

Fig. 4. With the training of methods 1 and 2, the normal and tote-bag walking motion data from 27 subjects, i.e., excluding one, were used to calculate the transformation information between the two motions. To validate the two methods, the Euclidean distances and normalized ranks were calculated for the target subject versus all other subjects.

trials, were calculated. The Euclidean distances were sorted in descending order to calculate the normalized ranks of the two measured tote-bag gait vectors of the target subject. The average value of the two normalized ranks were used as the prediction power of the method. For example, as the best case, the Euclidean distances of the two measured tote-bag gait vectors of a target subject were ranked as 55th and 56th. The prediction score was then calculated as below.

$$\textit{prediction score} = \frac{\left(\frac{55}{56} + \frac{56}{56}\right)}{2} \times 100 = 99.1\%$$

The overall process for training the first and second methods and validating them using the prediction score described in this study, are summarized in Fig. 4.

3. Results

The mean (one standard deviation) position prediction errors of the two suggested methods were calculated for the 17 anatomical landmarks during two gait cycles, as shown in Fig. 5. The linear transformation method showed a smaller mean error than the PLS regression method in all frames (mean error of 30.0 ± 6.7 mm versus 34.0 ± 8.7 mm) according to a student's t-test at a significance level of $p < 0.05$.

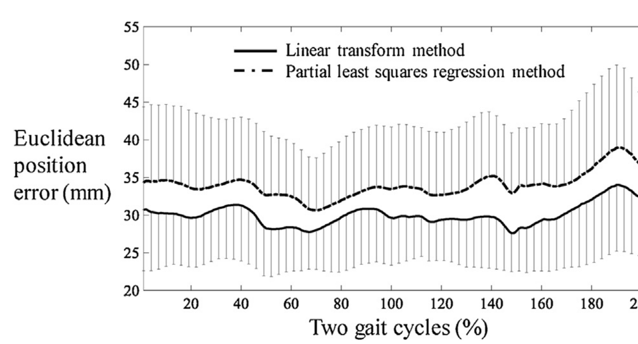

Fig. 5. The means and standard deviations of the position prediction errors for the 17 anatomical landmarks were calculated for each frame during two gait cycles using a linear transformation method and partial least squares regression.

Table 1
The mean and standard deviation of position prediction errors of 17 landmark positions for two gait cycles.

Joint position	Linear transformation method (mm)	Partial least squares method (mm)	*p*-Value
Top head	28.8 ± 9.4	37.9 ± 14.7	<0.001
Left shoulder	23.7 ± 10.7	31.3 ± 14.9	<0.001
Left elbow	32.1 ± 9.7	39.3 ± 11.7	<0.001
Left wrist	51.2 ± 18.7	55.8 ± 21.9	0.008
Right shoulder	26.1 ± 9.8	31.7 ± 14.4	0.003
Right elbow	25.3 ± 8.8	29.5 ± 10.4	0.001
Right wrist	30.8 ± 9.8	34.7 ± 10.8	0.003
Left hip	13.9 ± 6.2	19.0 ± 12.4	0.004
Left knee	26.5 ± 7.4	27.7 ± 9.4	0.181
Left ankle	32.8 ± 8.8	34.1 ± 8.6	0.148
Left heel	36.5 ± 8.5	37.4 ± 8.7	0.341
Left toe	36.5 ± 9.5	38.3 ± 9.4	0.106
Right hip	14.2 ± 5.8	18.7 ± 11.8	0.006
Right knee	28.7 ± 8.8	29.9 ± 9.3	0.149
Right ankle	33.0 ± 9.5	34.8 ± 11.0	0.029
Right heel	35.2 ± 9.1	38.3 ± 11.2	0.003
Right toe	35.5 ± 11.3	39.0 ± 12.8	0.004

The differences in the mean position prediction were calculated for every joint using the two methods, as shown in Table 1. The smallest error was observed at the hips for both methods (13.9–19.0 mm) and the left wrist, where the joint position has a large swing during walking, had the largest error of 51.2–55.8 mm. The linear transformation method showed a generally smaller prediction error than the PLS regression method in most of the joints, and significant differences were observed in 12 out of the 17 anatomical landmarks, as summarized in Table 1.

The prediction scores of the two methods were calculated for the 56 trials, and their histograms are shown in Fig. 6. The mean prediction score of the linear transformation method was higher than that of the PLS regression method, which was 96.4 (±4.3) and 95.0 (±3.8), respectively. In further analyses, 24 trials (42.9%) and 13 trials (23.2%) scored a 99 for the linear transformation method and PLS regression methods, respectively. A total of 53 (94.6%) and 47 (89.3%) trials received a score of 92 and above for the two methods, respectively.

4. Discussion

We developed two gait motion transformation methods to identify the walking motions from the same person and then evaluated the performances of the methods, focusing on potential applications for person identification. Prediction of the joint trajectories of walking with a tote bag from those of normal walking for both of our methods showed a superior performance than in previous studies [20,22,34]. Yumer and Mitra applied a discrete Fourier transform on the joint positions between two walking styles. Although the frequency can be used to describe a human motion, it may distort the representation of the motion with a significant loss of motion information, resulting in a mean error of around 50 mm. The methods by Hsu et al. [22] and Xia et al. [34] resulted in mean errors of around 80 and 50 mm, respectively, when tested by Yumer and Mitra [20].

The linear transformation method for predicting a tote-bag gait vector from a given normal gait vector is based on the linear relationship between the weight vector of the two motions when applying a PCA. This method is also similar to a PCA regression method for predicting data from other given data, as stated by Geladi and Kowalski [32]. However, a PCA was separately applied for the tote-bag and normal gait vectors, resulting in a weak relationship between the weight vectors of the tote-bag and normal walking motions. The weight vectors for the first thirteen principal components of normal gait vectors were strongly correlated with those of the tote-bag gait vectors.

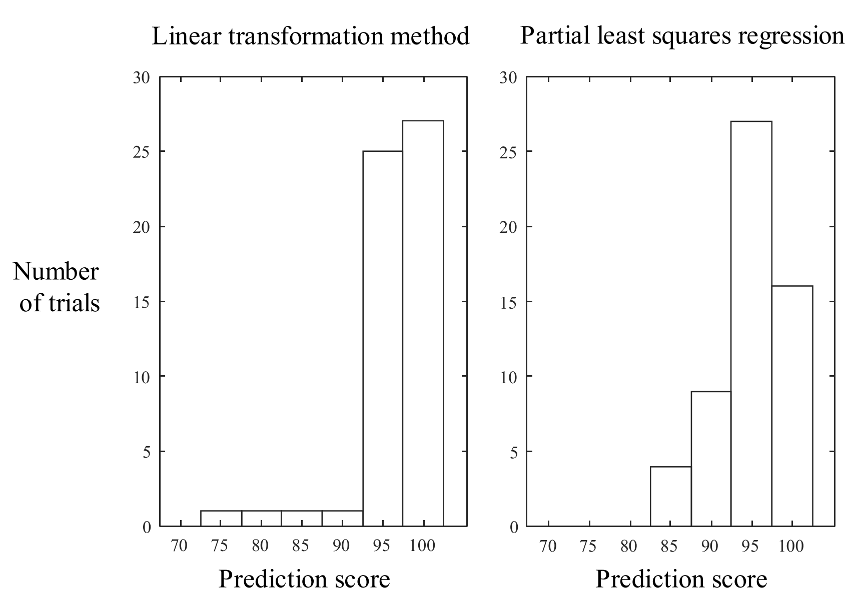

Fig. 6. The prediction score and corresponding frequency of the linear transformation and partial least squares regression methods.

With the PLS regression method, an inner relation [32] is found between two motions by taking the same weight vector for both motions. However, this makes the principal components from the PLS regression different from the principal components obtained separately from the two motions. Thus, the first five principal components from the PLS regression could explain only 64–67% of the variance of the individual gait vectors.

In this study, we conducted temporal and spatial normalizations. A linear interpolation was utilized for the temporal normalization, which equalized the number of frames to describe two gait cycles for every gait. Although this normalization assists in equalizing the feature vector size or the personalized speed, the prediction method was unable to predict the absolute temporal speed. Moreover, spatial normalization was conducted by fixing the pelvis of a walking individual. Although the suggested spatial normalization method can produce a more accurate prediction of human motion, it cannot be applied to a reconstruction of the absolute spatial position of walking subjects.

The effectiveness of the two motion prediction methods was tested by re-identifying a person walking under different conditions, resulting in mean prediction scores of 96.4 and 95.0, respectively. The normalized rank of 95.0 indicates that the method can find the appropriate person within the top-five ranked persons out of 100, which is comparable to previous studies [35,36]. Xu et al. [35] achieved a 96% recognition accuracy in finding a correct subject. They used a discriminant analysis with a tensor representation and a coupled subspaces analysis to extract the features from the gait data, represented as binary images. The Mahalanobis distance was then calculated between two motions to determine the recognition accuracy based on the nearest neighbor rule. The method by Sarkar et al. [36] resulted in an accuracy of 93% for finding a correct subject when tested by Xu et al. [35].

Gait is a result of complex neuromusculoskeletal coordination and interaction with the environment, thus it has inherent step-to-step and day-to-day variability [14]. However, gait contains a significant amount of biomedical and biometric information to evaluate pathologic conditions [37]. We assumed that two cycles of walking taken in the middle of the walkway are representative of the walking motion under the weight condition. Interestingly, the two gait cycles could be used to find the variation at different weight conditions for the same person with high probability, suggesting that the gait contains identifiable information. A limitation of this study is that we performed tests with only two different walking conditions.

We used 43 body markers and eight high-speed cameras to extract the spatiotemporal positions of the anatomical landmarks, which is unrealistic from a forensic perspective. A single, low-speed (~15 frames per second) camera with a night-time video sequence would be more realistic. However, recent developments in computer vision, image processing, and deep neural network techniques can provide techniques to improve image resolution [38], automatic identification of human joints in two-dimensional images [15], and three-dimensional gait pose estimation from a two-dimensional video sequence [16,17]. This study suggests that three-dimensional joint kinematics during gait can be used for person identification, and its practicability in forensics should be further studied using three-dimensional gait poses estimated from single camera video sequences.

5. Conclusions

In this study, a framework was proposed to calculate the similarity of walking motions when a person walked under two different conditions (normal and tote-bag walking trials) for identification. We developed a method of predicting the tote-bag walking motion from an individual's normal walking, one using linear transformations and the other using partial least squares regression. The performance demonstrated the use of 56 pairs of normal and tote-bag walking motion data from 28 subjects, indicating its promise for practical use in forensic gait analysis. Our study showed that three-dimensional motions during walking contain biometric information which is identifiable to a high probability, even when a person walks at different weight conditions.

Data statement

We are not submitting the data in our manuscript. Our data are temporal three-dimensional coordinates of body joints during walking from 28 subjects which are actually four-dimensional data. This raw data is very complicated and requires intensive programming to view the data.

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