Gait Recognition by Two-Stage Principal Component Analysis

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Abstract

We describe a methodology for classification of gait (walk, run, jog, etc.) and recognition of individuals based on gait using two successive stages of principal component analysis (PCA) on kinematic data. In psychophysical studies we have found that observers are sensitive to specific "motion features" that characterize human gait. These spatiotemporal motion features closely correspond to the first few principal components (PC) of the kinematic data. The first few PCs provide a representation of an individual gait as trajectory along a low-dimensional manifold in PC space. A second stage of PCA captures variability in the shape of this manifold across individuals or gaits. This simple eigenspace based analysis yields excellent classification across subjects.

Keywords

Gait recognition, principal component analysis, motion features.

INTRODUCTION

Biological motion—the characteristic movements of humans and animals—provides a challenging paradigm for understanding spatiotemporal pattern recognition. Human gait is characterized by a pattern of relative motions of the articulated parts of the body, each of which has constrained relative positions and ranges of motion. Much remains to be understood concerning the intermediate and high level visual features used for recognition. However, evidence suggests that both form and motion features are used for recognition. The ability to recognize human movements from motion cues was demonstrated by Johansson [1] who introduced the study of point-light walkers. Small lights are attached to different body parts (shoulders, elbows, hands, hips, knees, feet, and head) of subjects moving in a dark room--from the motion of these "point-lights" observers can robustly discriminate different gaits (walking, strutting, limping, running), the direction of gait, and to some degree the gender [2] and identity of the walker [3]. Structural information is minimized in a point-light video—in a single static frame, no form is recognizable. Nevertheless, observers are able to detect a walker or runner in such videos within a small fraction of the gait cycle [4]. Gait recognition is an area of extensive research in computer vision as well. Research in detection and tracking of people from real videos have employed different approaches ([5], [6], [7] [8]). The use of gait as a biometric has also received attention, particularly as part of the HumanID research initiative [9]. Both Silhouette based ([10], [11], [12], [13]) and marker based ([14], [15]) approaches have been used.

Most gait recognition research has concentrated either on image processing/machine learning methodology, or on psychophysical aspects of the perception of biological motion (such as the role temporal information [16], or the contributions of structural vs. kinematic cues [3]). A key to progress will be to identify human psychophysical mechanisms and incorporate efficient versions of these mechanisms into recognition systems [12].

In psychophysical studies [17], we have found that the perception of human gait depends upon the detection of specific "motion features" that characterize the relative motion of body parts. Focusing on the legs, we identified three particular motion features that are necessary and sufficient to identify gait: (1) anti–symmetrical movement of the thighs, (2) knee flexion followed by extension during the swing phase of gait, and (3) relative absence of knee movement during the pivot phase of gait. Interestingly, these three features are the core features of Cutting's [18] algorithm for generating realistic looking point light displays of human gait. While the visual system most likely makes use of additional motion features, these three motion features define a low-dimensional manifold of motion parameters that can be used for accurate recognition and classification.

We tested human observers' sensitivity to perturbations in these motion features in upright vs. inverted point-light walker displays. Since it is well known that display inversion impedes recognition [19], we hypothesized that observers should be more sensitive to features used for recognition in upright displays than in inverted displays. This is indeed what we found psychophysically [17]. In these experiments, perturbations to a variety of potential motion features were introduced. Perturbations that led to distortions of the low-dimensional manifold were detectable at much lower thresholds than similar motion perturbations that did not distort the manifold—suggesting that the low-dimensional manifold represents critical information used by the visual system for recognition. Most critically for the present study, we found that the first two principal components of gait data have close correspondence with the identified motion features [20]. It has been shown that PCA can be successfully employed to represent movement data in a low-dimensional space ([21, 22]). We can therefore use the low-dimensional manifold defined by the first few principal components to perform a *second stage* of principal component analysis that describes deviations in the manifold across individuals or types of gait. This second PCA stage primarily distinguishes the temporal characteristics of the motion. We demonstrate high accuracy for gait and identity discrimination tasks, and show that the two-stage PC representation yields insights into the contributions of various parameters to different recognition tasks.

METHODS

Gait data was obtained using the ReActor2 motion capture system (http://www.ascension-tech.com). Six human subjects (3 male, 3 female) walked, jogged, ran and limped on a Quinton Hyperdrive Club Track treadmill. Limping was simulated by tying weights to one ankle of the subject. Infrared emitters placed at 30 body positions provided 3D spatial positions of markers at 33 frames/s with a spatial resolution of 3 mm. The locations of 13 major body parts (shoulders, elbows, hands, hips, knees, feet, and head) were calculated from this data and projected to the sagittal plane. Angles and angular velocities were calculated from the data using angles as defined in

Figure 1. We concentrate on the lower limbs, as they provide more salient information on gait than other body parts [23]. An example of how the thigh and knee angles vary with time during two consecutive gait cycles is shown in Figure 2.

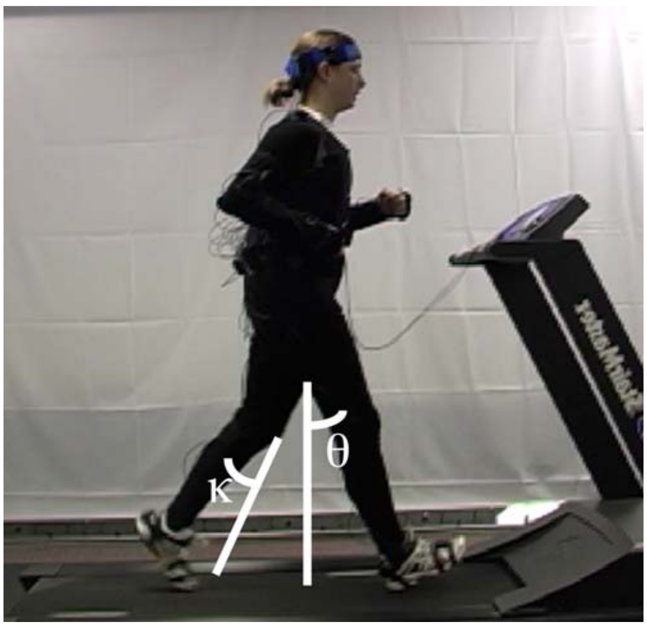

Figure 1. Subject running on a treadmill. The thigh angle θ is defined as the relative orientation of the thigh with respect to the vertical – it is negative for thigh behind the torso and positive for thigh in front of the torso. The knee angle κ is defined as the joint angle at the knee – zero means a fully extended knee, a positive angle means flexed knee.

Two Stage PCA

In the first stage, we performed principal component analysis [24] on a 6-dimensional dataset consisting of left and right thigh angles, the inter-thigh angle and inter-thigh angular velocity, and the knee angle and knee angular velocity. 60 seconds of data for each subject was used for each treadmill speed and type of gait (running, walking etc.). Each data point is a 6-dimensional vector consisting of values x_{ij} of variable i (= 1, 2, …, 6) at time j. If each such data point is denoted by $X_j = [x_{1j}, x_{2j},\ldots,x_{6j}]$ and the principal components are denoted by P_k (k = 1..6), then the projections Y_{kj} of X_j on P_k are given by

$$Y_{kj} = \left\langle X_j, P_k \right\rangle \qquad ..(1)$$

where $\langle\, , \rangle$ represents the dot product. For every 60 second segment, P_k and Y_{kj} were calculated separately.

In the second stage, the projections Y_{1j} and Y_{2j} of the original data onto the first two principal components were considered. Y_{1j} and Y_{2j} represent a "D" shaped 2D manifold (Figure 3). In order to capture information about the temporal variability of the data throughout the gait cycle, the projection values for each cycle of gait were considered as a time series. If we represent the gait cycle by N uniformly spaced time points, each data point $\hat{Y}^l$ constructed from the l^{th} gait cycle for the second PCA is given by

$$\hat{Y}^l = [\hat{Y}_1^l \;\; \hat{Y}_2^l] \qquad ..(2)$$

where we have introduced the variables $\hat{Y}_1^l = [Y_{11}^l \; Y_{12}^l \ldots \; Y_{1N}^l]$ and $\hat{Y}_2^l = [Y_{21}^l \; Y_{22}^l \ldots \; Y_{2N}^l]$ which represent the time series of projections onto the first and second PCA dimensions.

We now perform a second PCA decomposition with each data point $\hat{Y}^l$ representing a gait cycle. The principal components thus obtained after the second stage of PCA are denoted by

$$\hat{Q}^m = [\hat{Q}_1^m \;\; \hat{Q}_2^m] \qquad ..(3)$$

where m = 1..2N is the second stage principal component number and $\hat{Q}_1^m = [Q_{11}^m \; Q_{12}^m \ldots \; Q_{1N}^m]$ is the part of component $\hat{Q}^m$ that acts on the first dimension (i.e. $\hat{Y}_1^l$) and $\hat{Q}_2^m = [Q_{21}^m \; Q_{22}^m \ldots \; Q_{2N}^m]$ is the part that acts on the second dimension, $\hat{Y}_2^l$. Therefore, the projection $\hat{Z}^{lm}$ of $\hat{Y}^l$ on $\hat{Q}^m$ is given by

$$\begin{aligned} \hat{Z}^{lm} &= \left\langle \hat{Y}^l, \hat{Q}^m \right\rangle \\ &= \left\langle \hat{Y}_1^l, \hat{Q}_1^m \right\rangle + \left\langle \hat{Y}_2^l, \hat{Q}_2^m \right\rangle \end{aligned} \qquad ..(4)$$

All results presented here are based on projections onto the first three principal components of this second PCA stage, *viz.* $\hat{Z}^{l1}$, $\hat{Z}^{l2}$, and $\hat{Z}^{l3}$. A similar two-stage PCA method has been used for classification of spatiotemporal patterns of neuronal activity in turtle cortex [25].

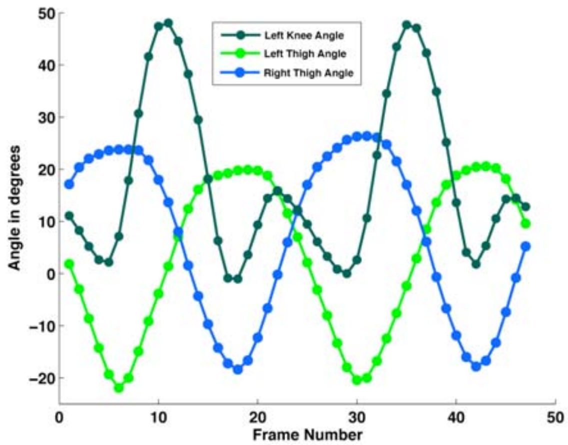

Figure 2. Thigh and knee angles over one gait cycle. The left and right thigh angles vary antisymmetrically. The knee angle flexes then extends during the swing phase.

RESULTS

We used projections in the eigenspace after two-stage PCA to perform various classification tasks. For all the results reported here, linear discriminant analysis [26] based on the first three principal components was performed. Figure 3 shows the variation of the projections Y_{1j} and Y_{2j} after the first stage of PCA. The appearance of the "D" like manifold contains information about the type of gait, the identity of the subject, etc. The manifolds are aligned so that the stems of the "D" are parallel to each other. The "D" is traversed in the counterclockwise direction once every gait cycle indicated by the color change from deep blue to deep red. The vertical stem of the "D" corresponds to the pivot phase and the semicircular arc corresponds to the swing phase of gait [27].

Gait Classification

The presence of a "D"-like manifold in PC space is the signature of a gait-like motion. The "D" manifolds for walking versus running, shown in figure 3, differ subtly in their shape characteristics. Differentiation between similar manifolds representing gaits or individuals is extracted by a second stage of PCA. Figure 4 shows the results of gait classification for four types of gait – walking, running, jogging and limping for one subject. There are distinguishable clusters representing different gaits.

Identity Recognition

Figure 5 shows results of identity classification on 6 running subjects. The variations in the appearance of the "D" manifold and the temporal dynamics of how the manifold is traversed during a gait cycle are even more subtle in this case (compare the two panels in the top row of Figure 3). Nevertheless, more than 90% accuracy in classification was obtained in most cases.

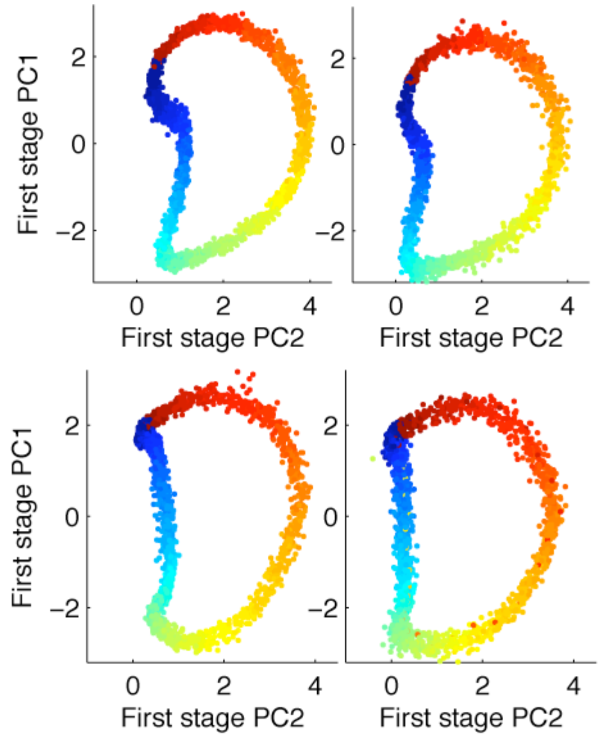

Figure 3. Manifolds in PC space after first stage of PCA. Top row running, bottom row walking. Left column subject 1, right column subject 2. Manifold is traversed once every gait cycle in the counterclockwise direction, color represents the phase of gait cycle. 2000 frames of gait data were used in each panel.

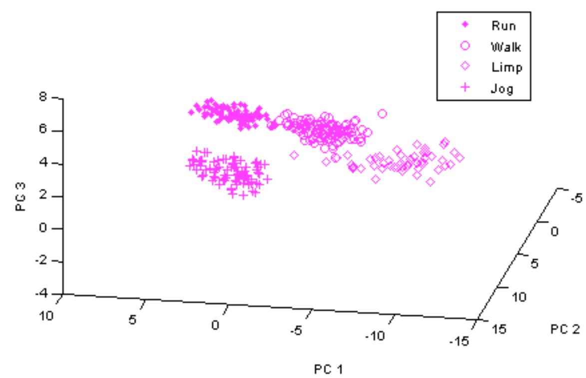

Figure 4 Clusters for gait classification. The classification rate was 99% in this case.

It is informative to consider the characteristics of the "D" manifold that are relevant for identity recognition. For example, each panel in Figure 6 plots the *same* 2D manifold defined by the projections $\hat{Y}_1$ (y axis) and $\hat{Y}_2$ (x axis) of 528 gait cycles from 6 different people. However, the different panels have different color codings proportional to $\hat{Q}^1_{1j}$ (top left), $\hat{Q}^1_{2j}$ (top right), $\hat{Q}^2_{1j}$

(bottom left), and $\hat{Q}^2_{2j}$ (bottom right) respectively, where $j = 1..N$.

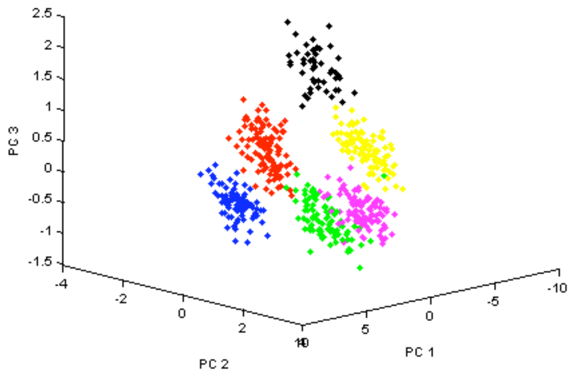

Figure 5. Recognition of different people from their running gaits. Points corresponding to gait cycles of each individual are color coded in the second-stage PC space—points for each individual are distinguishably clustered. Classification accuracy for 528 gait cycles in these 6 subjects was 96.7%.

Specifically, color codings in the top left panel signify relative contributions of y locations ($\hat{Y}_1$ values) on the manifold towards projection $\hat{Z}^{l1}$. The top right panel shows relative contributions of x locations ($\hat{Y}_2$ values) towards $\hat{Z}^{l1}$. The bottom left panel shows relative contributions of y locations ($\hat{Y}_1$ values) towards $\hat{Z}^{l2}$. Finally, the bottom right panel shows relative contributions of x locations ($\hat{Y}_2$ values) towards $\hat{Z}^{l2}$.

Hence, as we traverse the gait cycle on the manifold at N equally spaced time points, the color coded loadings convey the relative importance of information at different phases that is crucial for recognition. Red shades indicate positive loadings and blue shades indicate negative loadings – both of which contribute significantly towards $\hat{Z}^{lm}$ values that aid discrimination. Green indicates loadings close to zero – signifying little contribution to discrimination.

Observe that $\hat{Q}^1$ has high positive loadings on the y locations during the mid-swing part of the gait cycle (top left). This would correspond to a measure of variability of limb positions around the midpoint of the swing. $\hat{Q}^1$ has significant positive and negative loadings on the x locations around the bottom and top extremities of the manifold (top right) respectively. Since the x coordinates ($\hat{Y}_2$ values) at both of these manifold locations are positive, this would produce an estimate of the amount of tilt in the semi-circular part of the "D". On the other hand, $\hat{Q}^2$ has a high positive loading on the stem of the "D" – this would correspond to a measure of how the leg moves during the pivot phase (bottom left).

Thus, by looking at the loadings of the PCs on the information available at different phases of the gait cycle, one can infer the information present in the data that is useful for a particular recognition task.

Figure 7 depicts the relationship between a specific manifold shape (given by $\hat{Y}^l$) and its projections $\hat{Z}^{l1}$ and $\hat{Z}^{l2}$ on the first two PCs, $\hat{Q}^1$ and $\hat{Q}^2$ respectively. The left panel shows the $\hat{Z}$ plane on which different clusters of individual running gaits have been projected. To see what happens as we span the axes on the projection space, we consider four points approximately located at four corners of the rectangular region enclosing the actual data set. The corresponding manifolds back-projected onto the $\hat{Y}$ space are shown on the right panel. Color coding in the right panel represents the phase of the gait cycle. The gamut of shapes and the variation in the location of a given color across the different manifolds capture the discriminating power of the principal components.

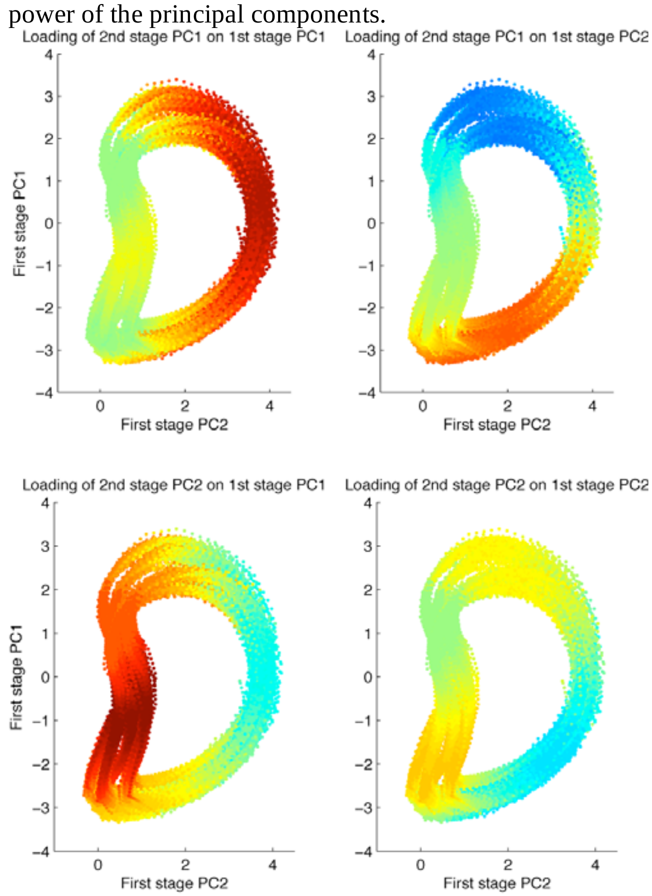

Figure 6. Loadings of first two of the second stage principal components on different parts of the "D" manifold (i.e. different times in the gait cycle) for identity recognition from running gaits. Red saturation levels indicate positive loadings and blue saturation levels indicate negative loadings. Green indicates loadings close to zero. We can see that the second stage PCs combine the variability of first stage PC projections at different phases of the gait cycle with different weights.

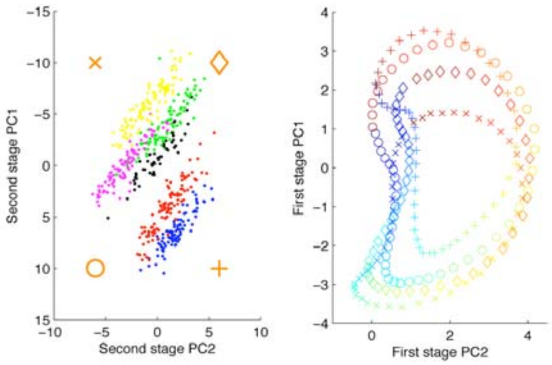

Figure 7. Left panel shows the projection plane defined by the first two PCs of second stage that discriminate subjects from their run. Different colored clusters represent different people. The four orange markers denote approximate boundary points of the classification space. Their back-projections to "D" manifold space are plotted on the right panel with corresponding marker types.

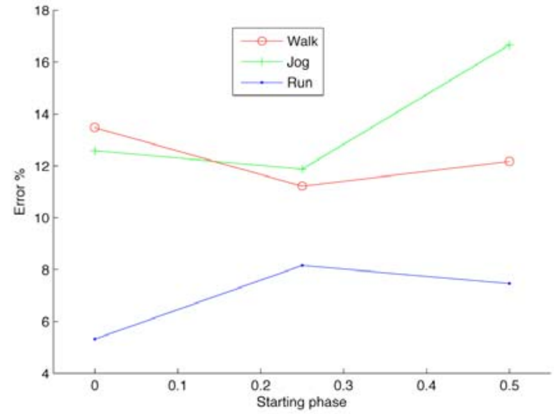

Figure 8. Average identity recognition error rates using different gaits when data were taken from early (starting phase = 0), middle (starting phase = 0.25), and late (starting phase = 0.5) half of the gait cycle.

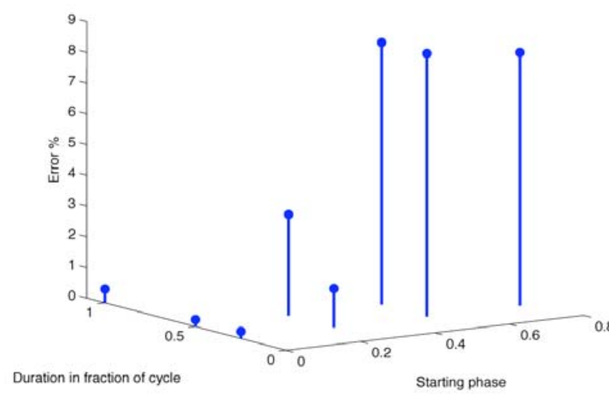

Figure 9. Error rates for gait type recognition when different starting phases and different fractions of gait cycle were used. Note that the error increases as we go towards later parts of the cycle.

It is also interesting to note that depending on the type of gait used for identity recognition, different parts of the gait cycle and/or different properties of the manifold contain discriminating information. One way to look at the importance of different parts of the gait cycle for recognition is to use data from only part of the gait cycle in the second stage PCA. The results for this for identity recognition using only half of the gait cycle are shown in Figure 8. Observe that discriminating individuals from their running gait is in general easier than from other gaits. Also, the first half of the gait cycle seems to contain more discriminating information for running compared to walking or jogging (lower error rates). Note that the relatively higher error rates for certain conditions are due to only half of the gait cycle being used.

A similar analysis can be done for gait type recognition. In Figure 9, data was provided for different fractions of a gait cycle, with the cycle beginning at various phases of gait (e.g., start of swing, midway through swing, etc..). The initial portions of the cycle contain more discriminatory information about the type of gait than the later parts.

DISCUSSION

We have developed a PCA-based gait representation that arises from psychophysically-identified features used in visual recognition of biological motion. We perform a two-stage principal component analysis where the first stage extracts salient information, in the form of the "D" manifold, concerning the relative motion of limbs. This is followed by a second PCA stage that discriminates differences in the temporal trajectory of data points along the manifold. Despite this straightforward eigen-approach, promising recognition accuracies are obtained for classifying both gait type and identity, and informative task-specific discriminating properties emerge.

Note that our manifold representation normalizes the range of original angle variables as well as temporal evolution of PCs in a gait cycle. This makes the representation time-warp invariant ([28]) but throws away potentially discriminating information like stride length – instead focusing on the relative motion of limbs on a normalized time scale – yet the classification performance is good.

A more sophisticated classification technique may improve performance further. The set of variables used are a minimal set that describes the relative motions of limb segments. Including more variables may also improve performance. Our dataset is relatively small, and for large-scale biometric applications, the representations and/or algorithms may have to be extended, for example by including more form information, to achieve maximal performance. Also, we have used motion capture data, with the assumption that accurate joint position and gait cycle data are available. Our intention is to present a proof of concept based on the use of perceptually salient information. This two-stage analysis can be applied to any spatiotemporal sequence dataset. Future work may reveal that this approach has utility for a wider class of problems in motion-based recognition.

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