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Principal Component Analysis of Temporal and Spatial Information for Human Gait Recognition

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Abstract—**Principal component analysis was applied to human gait patterns to investigate the role and relative importance of temporal versus spatial features. Datasets consisted of various limb and body angles sampled over increasingly long time intervals. We find that spatial and temporal cues may be useful for different aspects of recognition. Temporal cues contain information that can distinguish the phase of the gait cycle; spatial cues are useful for distinguishing running from walking. PCA and related techniques may be useful for identifying features used by the visual system for recognizing biological motion.**

Keywords— **spatiotemporal pattern recognition, point-light figures, gait analysis,**

I. Introduction

Biological motion--the characteristic movements of humans and animals—provides an intriguing paradigm for understanding spatiotemporal pattern recognition. A human gait, for example, is characterized by a pattern of relative motions of the articulated parts of the body, each of which has a defined relative position and range of motion. For categorical discrimination, e.g., walking vs. running, many details of these motions do not seem to matter, rather it is the general aspects of relative angles, directions, phases and timings that affect categorization [1-3]. Hochstein and Ahissar [4] have observed that the use of more abstract, relative, and categorical-type descriptors—as opposed to detailed, precise parameter values—may be the hallmark of computation in higher sensory centers, and they propose such categorical descriptions are employed in rapid recognition, with the details filled in later.

A great deal has been learned about the neural pathways involved in biological motion recognition. Electrophysiological studies [5], lesion studies [6], and fMRI investigations [7] indicate involvement of higher visual centers in the superior temporal sulcus (STS) and elsewhere. These higher centers receive inputs from both motion and spatial centers in extrastriate cortex [8]. Giese and Poggio [9] have proposed an elegant model of gait recognition, based on evidence (reviewed therein) that spatial and temporal information arrive via separate streams to STS, and are each separately capable of inducing biological motion perception.

However, much remains to be understood concerning the relative roles and importance of spatial versus temporal information in gait recognition. This question was first addressed by Johannson [10] who introduced the study of point-light walkers. Small lights are attached to selected body parts (shoulders, elbows, hands, hips, knees, feet, and head) and the motion of these lights is the only stimulus seen (the walker wears a black outfit against a black background), in addition to whatever randomly moving dots are introduced as noise. Ostensibly, spatial 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 [11]. Psychophysical studies document our ability to rapidly discriminate different gaits (walking, strutting, limping, running), direction of gait, gender of the walker, and sometimes even the identity of the walker simply from the motion of the point-lights. Yet, even point-light walkers contain some spatial/structural information. For example, the point-lights on the feet always remain below those for the hips.

Several psychophysical studies have attempted to dissect what information is most useful for various recognition tasks, e.g., gender identification [12], or direction of motion [13]. We used principal component analysis (PCA) on point-light walker datasets containing varying amounts of temporal information (from 0 to 600 ms of data) in order to determine the relative contributions of spatial versus temporal information in several gait discrimination tasks.

II. Methodology

Gait data was obtained using the ReActor motion capture system with markers at 13 joints of 4 human subjects. 3D spatial positions of markers were acquired at 33 frames/s with a spatial resolution of 3 mm. The orientation of limb segments with respect to the absolute vertical axis was calculated from the marker coordinates.

Each data point for PCA consisted of a vector of nxm dimensions, where n is the number of angle variables considered, and m is the number of time frames spanned by the data. A sliding time window of length m (frames) is used for every walk or run data sequence in the database to generate the data point as described above—so that each sequence of frame length p generates (p - m +1) data points.

We obtained a total of 66 walking and 45 running sequences from the 4 subjects. Principal components were found using 75% of the data; then the remaining 25%

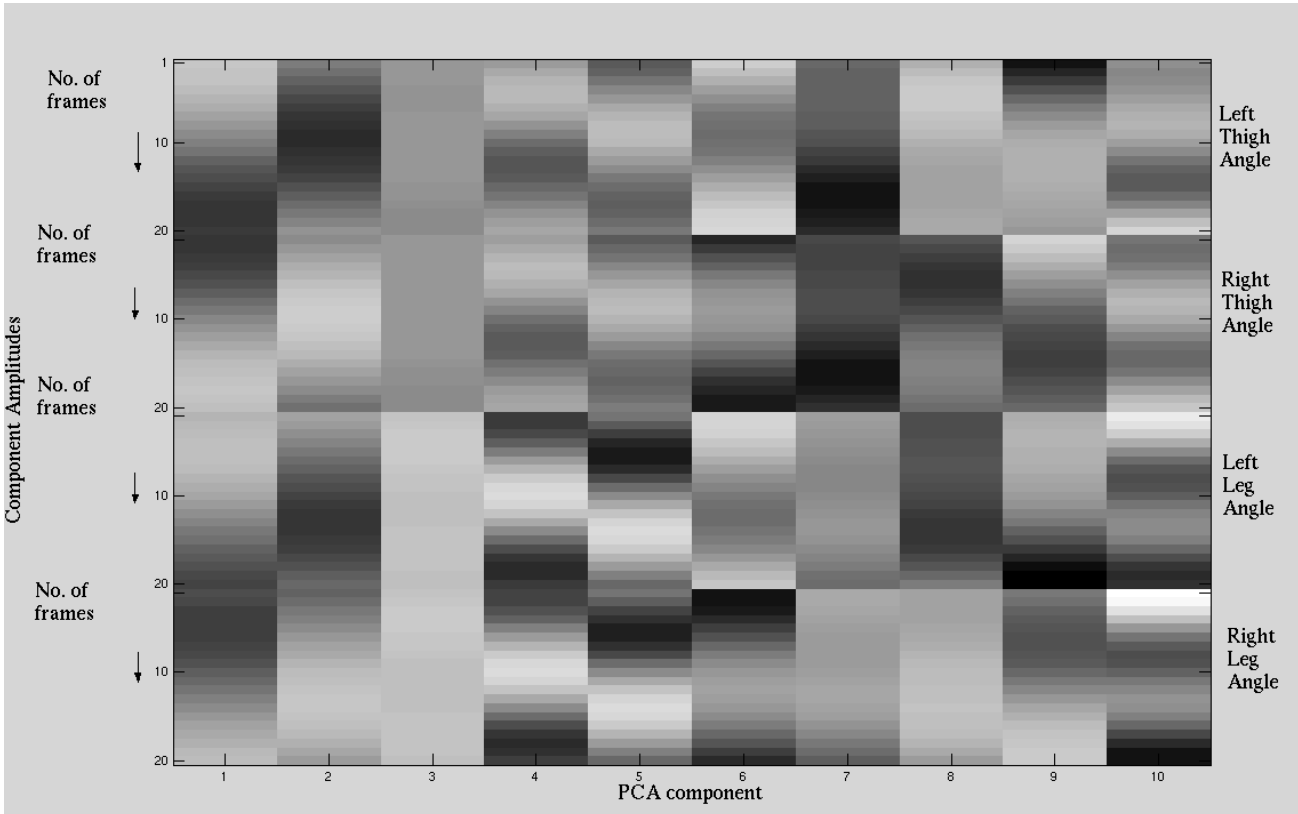

Fig. 1. First ten principal components obtained with a time window of 20 frames. Each column represents a different principal component (4 angles and 20 frames). Rows represent consecutive frames. Changes in greyscale shading within a block of 20 rows indicates the principal component is time-dependent.

of the data sequences were projected onto the principal component axes. The projected coordinates of the validation data points were then used as input to a linear classifier to differentiate walking and running.

III. Results

PCA was performed on the limb orientation angles of subjects. Three sets of angles were tested - upper limb angles, lower limb angles and both upper and lower limb angles. Each datapoint contained data from a time window (TW) which was varied from 1 (single frame) to 20 frames. All gaits were recorded in pure profile view with subjects moving from left to right across the visual field.

Figure 1 shows the first 10 principal components obtained when lower limb data spanning 20 consecutive frames was used, so that there were 20 frames x 4 angles = 80 dimensions for each input datapoint. The amplitudes of many of the principal components vary with time (vertical dimension in fig. 1). This reflects the time evolution of the limb angles as the gait cycle proceeds.

Figure 2 shows the 4 principal components obtained when

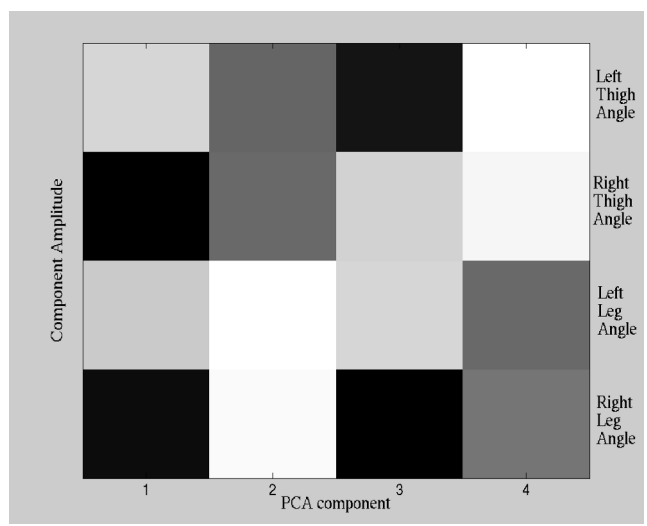

Fig. 2. Principal components obtained with a time window of 1 frame. Each column represents the coefficients of a principal component along each of the four dimensions (limb angles) of the input data.

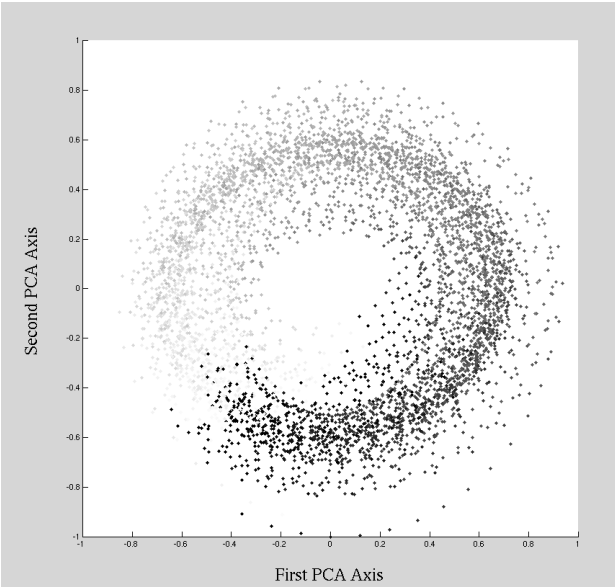

Fig. 3. Projection of all data points onto the plane defined by the first two principal components. Shades of gray indicate the phase of the gate cycle from which the datapoint was obtained. Shows that phase information is captured by first two principal components.

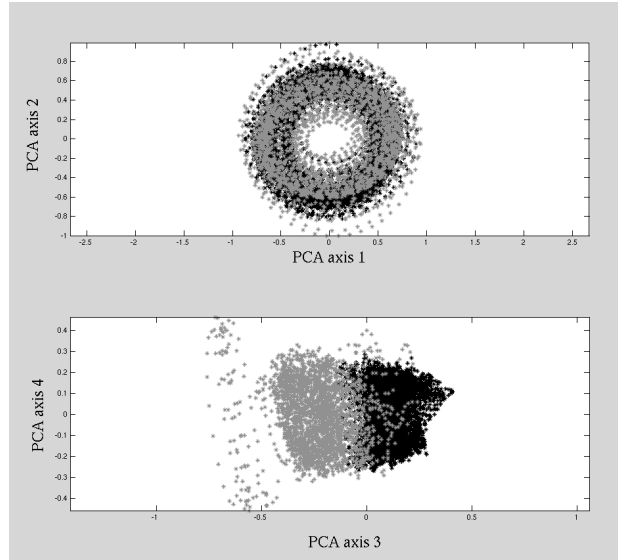

Fig. 4. Projection of all data points onto different pairs of principal components. Black points are data from a walking sequence and gray points from a running sequence. (top) Projections onto the first and second principal components. These components do not contain information about the type of gait. (bottom) Projections onto the third and fourth principal components. Walking and running data are linearly separable. (black marker = walk; gray marker = run)

lower limb data spanning single time frames was used. Here, time evolution of the angles within the gait cycle cannot be captured because each datapoint (1 frame x 4 angles = 4 dimensional) spans a single point in time (see discussion).

Once the principal components were determined, datasets not previously used were projected onto the axes defined by various principal components. Figure 3 shows the amplitude of these "validation" data points projected onto the first and second principal components (lower limb angles over 20 frames). The shade of gray indicates the phase of the gait cycle from which the datapoint originated. It can be seen that the projection of a data point onto the first two principal components encodes information about the phase of the gait. However, the first two components do not preserve information about the type of gait (walk or run) as can be seen in Figure 4a. Data points coming from walking (black stars) and running (gray stars) are not separable. In Figure 4b, the data are projected onto the 3rd and 4th principal components. One can clearly use a linear classifier to distinguish run from walk on the basis of these projection amplitudes. The classification error rates (for walking vs. running) under different time window lengths and angle variables are given in Table 1. Table entries marked by an asterisk (*) indicated cases in which the first two principal components captured information regarding the phase of the gate (as in fig. 3). The lower limbs apparently provide phase information in shorter time windows, thus are more useful for determining phase.

TABLE I
Error Rates (%) in Classifying Walk vs. Run

	Length of Time Window (TW)		
	TW=1	TW=10	TW=20
Upper limbs	3.68±0.24	1.96±0.21	4.71±0.90*
Lower limbs	26.37±1.04	14.16±0.51*	4.09±0.36*
Both upper & lower limbs	5.22±0.43	3.05±0.30*	1.80±0.20*

*Phase of gait captured by first two principal components

DISCUSSION and CONSCLUSIONS

We used PCA to determine the relative role of temporal and spatial information in discriminating walking from running in visual displays. We report four main findings: (1) When temporal information is explicitly provided in each datapoint, principal components are obtained that differentially weight inputs over time. The temporal structure of these components is somewhat reminiscent of the components obtained from independent component analysis of spatial or chromatic images [14] in that some components contain Gabor-like structures. (2) Some components, in particular the first two components, appear to capture the phase of the gait. These first two components together account for ~70% of the variance in the data. However, the first two components are

not useful for discriminating between gaits, as shown by our run vs. walk discrimination results. (3) Other components, particularly the third component, are useful in discriminating between gaits. Using a simple linear discriminator and just the third and fourth components, discrimination accuracy of over 98% is obtained. No attempt was made to further improve these results. It is interesting that the third component, which provides nearly all of the gait discrimination, is the least time-dependent of the first 10 components. (4) The lower limbs are more useful for determining the phase of the gait, the upper limbs are more useful for distinguishing running vs. walking, use of both upper and lower limbs yields better gait discrimination than either alone.

Troje [15] has used PCA to analyze human gait, and reported that a series of "eigen postures" are obtained which allow accurate reconstruction of the gait when the component amplitudes are sequenced sinusoidally in time. These basis functions correspond to various static poses along the gait sequence. Our findings complement Troje's in that our first two principal components tend to describe the phase of the gait. Our approach differs in the introduction of temporal information, and the finding that higher order components emerge that are critical in discriminating different gaits.

Use of PCA and related techniques only address what information is available in the stimulus—psychophysical studies are required to determine whether the visual system makes use of such information. Many recent studies have found visual function is close to that of an ideal Bayesian observer [16], thus our findings may have direct implications for human biological recognition.

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