Angular Features Analysis for Gait Recognition

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***Abstract*—Automatic gait recognition is an emergent biometrics identification system for recognizing humans by the way they walk. Its system is non-invasive because it operates from a distance via video cameras. The videos cum image frames are manually labeled to extract angular displacements of thigh's and lower leg's rotation, and foot flexion. The angular displacements data is analyzed using standard approach of Principal Component Analysis (PCA) and Canonical Analysis (CA). A cycle extraction procedure consisting of cubic-spline interpolation in SVR (Support Vector machine for Regression) and resampling within zero crossings is performed beforehand for an invariant analysis due to difference in walking speed of subjects. Combined dataset, is proposed for analyzing features that provide the most variations in gait recognition. Results have shown that the hip accounts for most variations among the three limbs' displacements data. Also, difference in temporal information of gait's signal does affect the recognition performance.**

Automatic gait recognition; angular kinematics features; cubic- spline interpolation; Support Vector machine for Regression (SVR); Principal Component Analysis (PCA); Canonical Analysis (CA);

I. INTRODUCTION

As a biometric, gait may be defined as a means of identifying individuals by the way they walk [1]. Automatic gait recognition is an attractive identification system since it operates on video cameras, thus it is non-invasive and recognizable over a distance. It has symmetrical and periodic structure that allow for reconstruction of 'missing' or 'noisy' views due to occlusions and noises in the video cameras.

Gait motion pattern can be described by its kinematics characteristics, which concern the geometry of its motion. Angular displacements data contains angular displacements of thigh's and lower leg's rotation for they are consistent with many studies [2] [3] [4] [5], which shows that they are quantifiable. The work extends into investigating the flexion of the foot throughout a gait cycle and the combination of the angular displacements. A cycle extraction procedure is proposed for extracting the gait cycles from the discrete signal representing the gait kinematics motion pattern. The procedure involves first a cubic spline interpolation in SVR and then resampling between two consecutive zero crossings with similar phase direction of the signal. This procedure is performed for making the analysis invariant to differences in walking speed of subjects. Then a data-driven approach is employed for investigation, namely using the standard approach of combining PCA and CA.

II. DATA ACQUISITION

The inputs are side-viewed video clips of walking subjects, which are digitized into individual image frames. These frames are manually labeled corresponding to the leg at front at four locations; the hip S_H, the knee S_K, the ankle S_A, and the toe S_{OE} as in Fig. 1. These points are gathered and used to calculate the angular displacements data, which are the hip angle θ (the angle of inclination between the thigh and the vertical), the knee angle ϕ (the angle of inclination between the lower leg and the vertical), and the ankle angle ρ (the angle of foot flexion with respect to horizontal).

III. CYCLE EXTRACTION FORMULATION

Gait data is observational, in which they are finitely sampled and thus the representation signal of its raw data is discrete. A cubic-spline interpolation guarantees a smooth curve to pass through two endpoints for better estimation within finite intervals of the gait cycle. Its interpolation in SVR allows high dimensional data calculations based around kernels, which gives rigorous formulation and good generalization [6]. Based on a priori knowledge of gait signal, which are its periodicity and continuity, cubic-splines are the kernel function that best reflects gait motion. Resampling at zero crossings is chosen, as they are the easiest to extract. Also resampling can be used to deal with phase difference of each gait motion signal for it has been shown that there are significant variations of phase features with individual gaits [7]. This cycle extraction procedure also relieves the analysis from dependence upon heel-strike, which was employed previously. Thus adding flexibility in gait analysis.

A. Mathematical Formulation

Given vectors of raw data for each sequence of length L,

$$\boldsymbol{\theta} = [\theta_1 \ \theta_2 \ \dots \ \theta_L]^T \ , \quad \boldsymbol{\theta} \in [0, 2\pi]^L \tag{1}$$

$$\boldsymbol{\phi} = [\phi_1 \ \phi_2 \ \dots \ \phi_L]^T \ , \quad \boldsymbol{\phi} \in [0, 2\pi]^L \tag{2}$$

$$\boldsymbol{\rho} = [\rho_1 \ \rho_2 \ \dots \ \rho_L]^T \ , \quad \boldsymbol{\rho} \in [0, 2\pi]^L \tag{3}$$

where $\theta_i = \theta(t_i)$, $\phi_i = \phi(t_i)$, and $\rho_i = \rho(t_i)$ are the angular displacements of thigh, leg, and foot at time t_i, respectively.

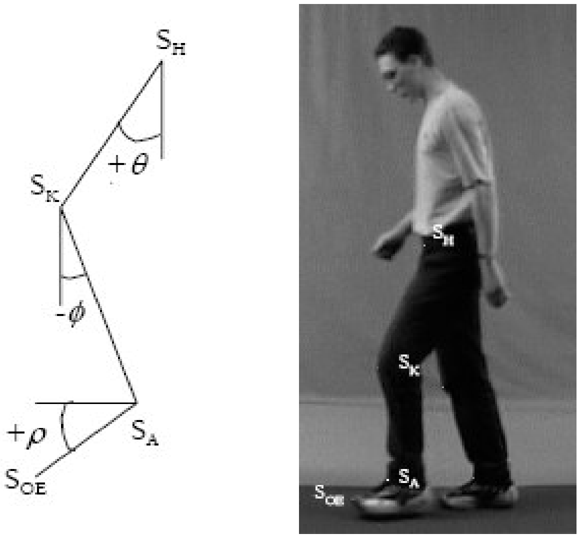

Figure 1. Points and angles location on a subject.

The interpolation estimate in an SVM for (3) is,

$$\hat{\rho}(t) = \sum_{i=1}^{L} \alpha_i K(t_i, t) \tag{4}$$

where, $\alpha_i \in \Re$ are the support vectors, $K(t_i, t)$ is a kernel function and t_i are the training input space points.

The preferred kernel function is the cubic spline,

$$K(t_i, t) = 1 + t_i t + \frac{1}{2} t_i t \ \min(t_i, t) - \frac{1}{6}(\min(t_i, t))^3 \tag{5}$$

This estimate applies to angular displacements of thigh (θ), and leg (ϕ) as well.

The resampled vector estimate is of length r, which makes up a dataset of r x S_T matrix containing vectors of length r representing S_T as total sequences,

$$\mathbf{X}_\theta = [\hat{\boldsymbol{\theta}}_1 \ \hat{\boldsymbol{\theta}}_2 \ldots \hat{\boldsymbol{\theta}}_{S_T}] \tag{6}$$

$$\mathbf{X}_\phi = [\hat{\boldsymbol{\phi}}_1 \ \hat{\boldsymbol{\phi}}_2 \ldots \hat{\boldsymbol{\phi}}_{S_T}] \tag{7}$$

$$\mathbf{X}_\rho = [\hat{\boldsymbol{\rho}}_1 \ \hat{\boldsymbol{\rho}}_2 \ldots \hat{\boldsymbol{\rho}}_{S_T}] \tag{8}$$

IV. Definitions of Extracted Data

- **Hip Angle** (θ_i). Angular displacements data of the thigh extracted between two consecutive zero crossings independently.
- **Knee Angle** (ϕ_i). Angular displacements data of the leg extracted between two consecutive zero crossings independently.
- **Ankle Angle** (ρ_i). Angular displacements data of the foot extracted between two consecutive zero crossings independently.
- **Hip+Knee+Ankle Independent** (**Dataset HKAI**). The three angular displacements data, each has been extracted between two consecutive zero crossings independently and combined by stacking each angular displacements onto a column feature vector with the uppermost body part on top.
- **Hip+Knee+Ankle Hip-Dependent** (**Dataset HKAD**). The angular displacements of lower body parts (leg and foot) are extracted respective to the zero crossings of angular displacements of uppermost body part (thigh) and combined.
- **Hip+Knee Independent** (**Dataset HKI**) and **Knee+Ankle Independent** (**Dataset KAI**). The angular displacements of two body parts data, each has been extracted between two consecutive zero crossings independently and combined.
- **Hip+Knee Hip-Dependent** (**Dataset HKD**) and **Knee+Ankle Knee-Dependent** (**Dataset KAD**). The angular displacements of body part (the ones lower) are extracted respective to the zero crossings of angular displacements of its upper body part and are combined.

V. Summary of Results

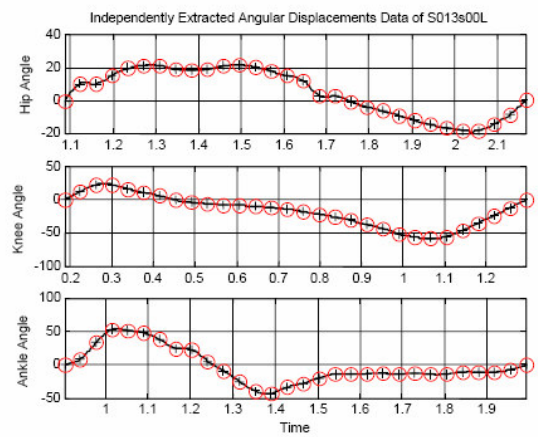

Figure 2. Independent extraction of hip, knee, ankle cycles.

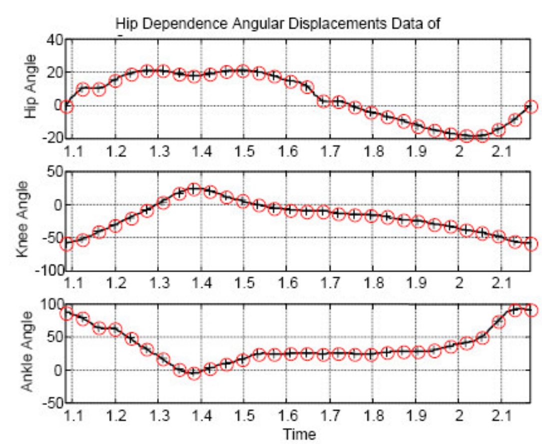

Figure 3. Knee and ankle cycles are extracted based on hip cycle's zero crossings.

TABLE I. AVERAGE CORRECT CLASSIFICATION OF ANGULAR DISPLACEMENTS DATA (%)

How Data is Combined	**Dataset Name**	***k* = 1**	***k* = 3**	***k* = 5**
Independent Extraction	HKAI	95.0	94.3	91.4
	HKI	88.6	85.7	79.3
	KAI	79.3	77.9	68.6
Based on Hip	**HKAD**	**97.9**	**97.9**	**95.0**
	HKD	92.1	91.4	84.3
Based on Knee	KAD	84.3	77.1	68.6
Individual Extraction	Hip	79.3	76.4	65.0
	Knee	70.7	66.4	65.7
	Ankle	62.9	63.6	45.7

The cubic-spline interpolation in SVR has fitted a smooth curve, which describes the curves well. Resampling within two consecutive zero crossings has uniformly aligned the temporal information of gait's motion signal. For recognition purposes, the feature dataset after cycle extraction is divided into test and training sets. A leave-one-out cross validation process is applied for each test set for 10 subjects. First, the training set is applied into PCA and CA algorithm where it is projected into a feature space by transformation matrices. Then, the test set is projected into that feature space using the similar transformation matrices. A k-nearest neighbor is applied for calculation of the recognition rate.

From Table 1, it is apparent that the upper leg dataset produces higher average recognition rate than the lower leg dataset. This may indicate that the upper leg, which is the hip angle, accounts for most variations in walking patterns. In fact, the average recognition rate is higher when the hip angle is involved in the combination datasets than combination of only knee and ankle angle. Other studies in biomechanical science further strengthen this finding [8] [9] [10].

Additionally a person can be recognized through combined angle dataset. They can be independently or dependently extracted and both give a higher recognition rate than the individual angular dataset. Results also shows that whenever the combined dataset is dependently extracted, which is extracted based on the most upper limb in the combination, the recognition rate is higher than the independent combined dataset. Combined dataset that has been dependently extracted uses similar temporal information, which makes it invariant to difference in time of start and end points leading to a better recognition. Hence, this paper has been able to show that a difference in temporal information for different angular displacements does affect the recognition performance. This is further supported by other gait's research [4] [11] [12].

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