KNEE ABDUCTION/ADDUCTION ANGLE PATTERNS IDENTIFICATION IN ASYMPTOMATIC GAIT BY PRINCIPAL COMPONENT CLUSTERING

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SUMMARY

The purpose of this study is to identify meaningful gait patterns in the wide array of abduction/adduction (abd/add) time sequence signals from a large population of asymptomatic individuals. We investigate principal component (PC) clustering to identify these representative gait patterns. PCs are obtained by projecting the original abd/add gait cycle data onto a subspace of much lower dimension but which still contains most of the relevant information concerning the shape of the gait curves. The PC signs are then clustered to provide an effective and computationally efficient method to separate the individuals gait into homogenous groups. Four descriptive gait patterns were identified and validated by the clustering silhouette width and statistical hypothesis testing, as well as by a clinical interpretation. The first pattern is close to neutral during the stance phase and in adduction during the swing phase (Cluster 1). The second pattern is in abduction during the stance phase and tends into adduction during the swing phase (Cluster 2). The third pattern is close to neutral during the stance phase and in abduction during the swing phase (Cluster 3). Finally, the fourth pattern is in abduction during both the stance and the swing phase (Cluster 4).

INTRODUCTION

Gait analysis provides valuable information about an individual's locomotion function based on biomechanical characteristics, i.e., electromyographic, kinematic, and kinetic data. A characterization of asymptomatic gait, also called normal gait, by a few patterns representative of clearly distinct gait categories, is necessary to understand locomotion function. However, such a characterization can be difficult for two reasons. First, there is a significant variability in the biomechanical data of asymptomatic gait. Second, these data are given, for each subject, in the form of a measurement vector of high dimension. Both the variability and the high dimensionality are illustrated in Figure 1, which shows the graph of a sample of 213 distinct asymptomatic abduction/adduction (abd/add) curves, each composed of 100 measurement points corresponding the gait cycle percentage. The identification of knee descriptive abd/add patterns by visual analysis is very difficult. As a result, pattern recognition and machine learning techniques are required to extract characteristic gait patterns. There have been a few studies in the field of biomechanics in this respect. In particular, various clustering techniques have been applied [1,3,4,5,6,7]. However, these studies have, in general, focused on pathological gait, rather than asymptomatic which may be due to the insufficient sample sizes investigated. The purpose of our study is to extract a few patterns, which would separate the abd/add into meaningful homogeneous groups. The problem we are facing when trying to determine characteristic patterns in curve bundles, such as the one in Figure 1, is basically clustering a large set of *unlabeled* patterns which exhibit significant *overlap*.

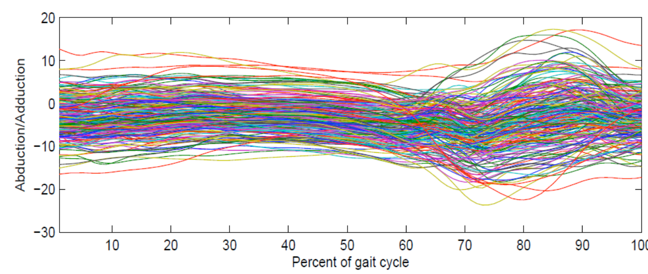

Figure 1: Abduction/adduction angle curves over gait cycle of the database: The signals were interpolated and resampled from 1% to 100% (100 points) of the gait cycle.

METHODS

In its general meaning, clustering is a non parametric technique which consists of dividing a data sample into groups of similar elements: the elements in a group are more similar to each other than they are to the elements of the other groups. Clustering, as any other pattern classification technique, suffers from the curse of dimensionality: unless the amount of high dimensional data is very large, it will be sparse in space and, therefore, difficult to separate into meaningful groups. We address this problem by principal component analysis (PCA): the original data is projected onto a low dimensional subspace of relevant variables, called principal components (PC), without affecting the inherent information it contains about the meaningful groups in the sample. Doing so reveals that the signs of the PCs of the abd/add vector data form clusters and thus provide an effective and computationally efficient method to determine distinct patterns descriptive of the asymptomatic gait. Further analysis shows that PCA also identifies a relationship between the clustered abd/add data and the significant segments in the gait cycle.

The abd/add data were recorded while the participant was walking on a conventional treadmill at a self-selected comfortable speed. Data collection was performed on each knee separately. For nine of the participants, measurements were only collected on one knee, giving a total of 213 data set elements. Each participant took part in a 10 minute treadmill walking adaptation period to ensure reproducible knee kinematics prior to data acquisition. A knee marker attachment system, developed to reduce skin motion artifact [2], was installed on the participant's knee to record the 3D kinematics. The position and orientation of the markers were recorded using an electromagnetic motion tracking system (Fastrack, Polhemus, USA) at a sampling frequency of 60 Hz. A number of representative gait cycles, generally fifteen, were averaged to obtain a mean pattern per subject. This was followed by interpolation and resampling from 1% to 100% of the gait cycle, therefore giving a 100 measurement points for each participant (Figure 1).

The clustered abd/add data have been validated by clinical experts to ascertain that a clinical interpretation can be drawn from the cluster waveform pattern.

RESULTS AND DISCUSSION

The four clusters, which the PCs sign yields, are shown in Figure 2 and their corresponding mean patterns are shown in Figure 3. Each curve in a cluster in Figure 2 corresponds to an abd/add subject in the original data space. Note that Cluster 1 and Cluster 2 mean curves have similar shapes with an evident vertical displacement at every point. This is the same for Cluster 3 and Cluster 4 mean curves. The four clusters clearly correspond to four specific gait patterns during both the stance phase (neutral vs. abduction) and the swing phase (abduction vs. adduction): The first pattern is close to neutral during the stance phase and in adduction during the swing phase (Cluster 1). The second pattern is in abduction during the stance phase and tends into adduction during the swing phase (Cluster 2). The third pattern is close to neutral during the stance phase and in abduction during the swing phase (Cluster 3), and the last pattern is in abduction during both the stance and the swing phase (Cluster 4).

CONCLUSION

In summary, this study has identified four distinct normal gait patterns by PCA of knee abd/add angle data and PC sign clustering thereof. It can be extended to the analysis of the sagittal plane (tibial internal/external rotation) and transverse plane (flexion/extension) kinematic data. These results can be integrated into studies of pathological gait detection and characterization for therapy treatment.

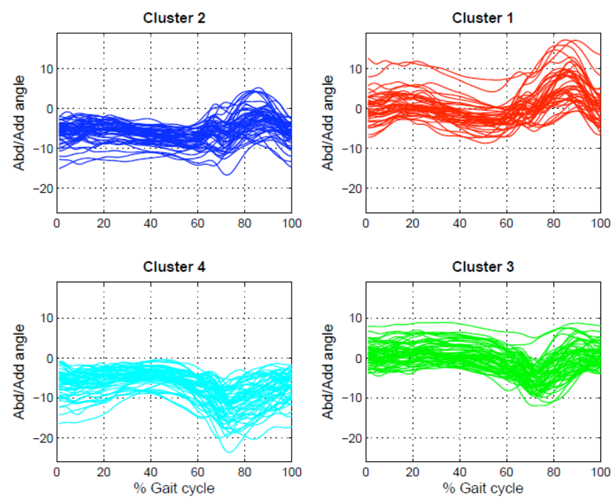

Figure 2: The clustered 213 abd/add samples. Each curve corresponds to a subject in the original data space.

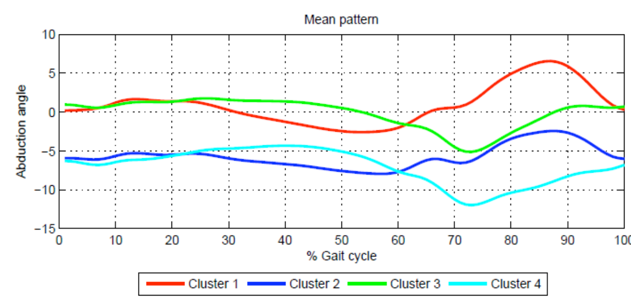

Figure 3: The mean pattern of the four clusters.

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