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The gait deviation index: A new comprehensive index of gait pathology

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Abstract

This article describes a new multivariate measure of overall gait pathology called the Gait Deviation Index (GDI). The first step in developing the GDI was to use kinematic data from a large number of walking strides to derive a set of mutually independent joint rotation patterns that efficiently describe gait. These patterns are called *gait features*. Linear combinations of the first 15 gait features produced a 98% faithful reconstruction of both the data from which they were derived and 1000 validation strides not used in the derivation. The GDI was then defined as a scaled distance between the 15 gait feature scores for a subject and the average of the same 15 gait feature scores for a control group of typically developing (TD) children. Concurrent and face validity data for the GDI are presented through comparisons with the Gillette Gait Index (GGI), Gillette Functional Assessment Questionnaire Walking Scale (FAQ), and topographic classifications within the diagnosis of Cerebral Palsy (CP). The GDI and GGI are strongly correlated ($r^2 = 0.56$). The GDI scales with FAQ level, distinguishes levels from one another, and is normally distributed across FAQ levels six to ten and among TD children. The GDI also scales with respect to clinical involvement based on topographic CP classification in Hemiplegia Types I–IV, Diplegia, Triplegia and Quadriplegia. The GDI offers an alternative to the GGI as a comprehensive quantitative gait pathology index, and can be readily computed using the electronic addendum provided with this article.

Keywords: Gait pathology; Gillette gait index; Normalcy index; Outcome; Singular value decomposition

1. Introduction

Comprehensive measures of gait pathology are useful in clinical practice. They allow stratification of severity, give an overall impression of gait quality, and aid in objective evaluation of treatment outcome. There are many ways to gauge overall gait pathology. Parent report questionnaires such as the Gillette Functional Assessment Walking Scale (FAQ), observational video analysis schemes like the Edinburgh Gait Score, or rating systems such as the Functional Mobility Scale (FMS), can provide a general picture of gait impairment [1–3]. While parent and caregiver assessments are useful and practical, they lack the precision and objectivity provided by three-dimensional quantitative gait data.

Gait data can be used to assess pathology in a variety of ways. For example, stride parameters such as walking speed, step length, and cadence provide an overall picture of gait quality. These parameters are especially useful when non-dimensionalized to account for differences in stature [4]. It is possible, however, to walk with adequate stride parameters and still have significantly atypical joint motions and orientations. This suggests a need for three-dimensional gait data in assessing overall gait pathology. Interpreting three-dimensional gait data in a global sense is not a simple task.

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Difficulties arise from the complexity of gait, and from the interdependent nature of gait data. For example, to assess the motions of the lower extremities during a single stride requires the analysis of multiple joints and body segments in multiple planes at multiple instants of time. Furthermore, these motions are coupled across joints, planes, and time. Motions of one joint affect the motions of adjacent or remote joints. Motions of a joint in one plane are coupled to motions in other planes. Finally, positions of a joint at one time affect positions at a later instant. Combining these effects, it can be surmised that the motion of a joint in a given plane at one instant can affect the position of a different joint, in a different plane, at a different instant. It is clear, therefore, that some method for dealing with this complexity and interdependence is necessary to gain an overall sense of gait pathology.

A number of multivariate statistical methods have been developed for dealing with the complexity and interdependence of gait data [5–20]. While some of these methods focus primarily on identifying gait patterns and relationships among variables, several aim to develop either joint-specific or overall indexes of gait pathology [7,8,10,12–14,19]. Among these, the Gillette Gait Index (GGI) appears to be the most extensively validated, commonly cited (based on a SCOPUS™ citation search), and is widely used in clinical gait research and practice [3,12,13,21–25]. While the GGI has been shown to be useful, a number of limitations have also been noted [26,27]. These include the arbitrary, unbalanced, and incomplete nature of the 16 univariate parameters that comprise the index, uncertainty surrounding principal component scaling, non-normality of the index, lack of physical meaning for the multivariate components, and difficulties in implementation—including excessive sensitivity to lab-specific control data.

This article describes a new measure of overall gait pathology—the Gait Deviation Index (GDI). Face and concurrent validity data for the GDI are presented through comparisons with the GGI, FAQ, and topographic classifications within the diagnosis of Cerebral Palsy (CP).

2. Methods

2.1. Motivation

The method used in constructing the GDI was motivated by a biometric method used for face identification—the so-called "eigenface" method [28]. In the eigenface method, a large collection of faces is digitized and the resulting arrays of grayscale values are converted to vectors. This collection of vectors is then subjected to principal component analysis. A small number of the extracted eigenvectors (called eigenfaces) that account for a large percentage of the information in the original collection of faces are preserved. These are then combined in a linear manner to create a reduced order approximation of any given face. A distance metric is defined to measure the similarity (proximity) of one face to another. Translating this procedure to gait analysis, the digitized face is replaced by a set of kinematic plots (digitized gait) and the grayscale levels are replaced by joint angles. Given these substitutions, the principles, methods, and proximity measure follow directly.

2.2. Reduced order approximation of gait data

One barefoot stride was selected from each side of subjects seen in the Gillette Children's Specialty Healthcare Center for Gait and Motion Analysis between Feb-1994 and Apr-2007 ($N_{\text{sides}} = 6702$). All data had been processed using either the Vicon Clinical Manager or Vicon Plug-in-gait model. Pelvic and Hip angles in all three planes, Knee Flex/Extension, Ankle Dorsi/Plantarflexion, and Foot Progression were extracted at 2% increments throughout the entire gait cycle (9 angles × 51 points = 459 datum). The data were then arranged in 459 × 1 *gait vectors* (**g**).

$$\begin{aligned}\mathbf{g} &= [\{\text{pel tilt}\}, \{\text{pel obliq}\}, \ldots, \{\text{foot prog}\}]^{\mathrm{T}} \\ &= [\{g_{1-51}\}, \{g_{52-102}\}, \ldots \{g_{358-408}\}, \{g_{409-459}\}]^{\mathrm{T}}\end{aligned} \tag{1}$$

The vectors from every subject side were concatenated to form a 459 × 6702 gait matrix **G**

$$\mathbf{G} = \left[\begin{pmatrix} g_1^1 \\ g_2^1 \\ \vdots \\ g_{459}^1 \end{pmatrix} \begin{pmatrix} g_1^2 \\ g_2^2 \\ \vdots \\ g_{459}^2 \end{pmatrix} \cdots \begin{pmatrix} g_1^{6702} \\ g_2^{6702} \\ \vdots \\ g_{459}^{6702} \end{pmatrix} \right]. \tag{2}$$

The singular value decomposition (SVD) of **G** was computed, and the unit length singular vectors $\{\hat{\mathbf{f}}_1, \hat{\mathbf{f}}_2, \hat{\mathbf{f}}_3, \ldots, \hat{\mathbf{f}}_{459}\}$ and singular values $\{\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_{459}\}$ were preserved. These singular vectors, referred to henceforth as *gait features*, form an optimal orthonormal basis (*f-basis*) for reconstructing the gait data. The *f-basis* is optimal in that it maximizes variance accounted for (VAF) using the minimum number of features.

Given the *f-basis*, an *m*th order approximation of any gait vector can be computed as

$$\tilde{\mathbf{g}}^m = \sum_{k=1}^{m} c_k \hat{\mathbf{f}}_k, \tag{3}$$

where the feature components c_k are

$$c_k = \mathbf{g} \cdot \hat{\mathbf{f}}_k. \tag{4}$$

The feature components can be arranged as a vector $\mathbf{c} = (c_1, c_2, \ldots, c_m)$, and thought of as the gait vector projected onto the *k*th feature directions.

In order to choose an appropriate order of reconstruction – that is to choose $m = m_{\text{crit}}$ from Eq. (3) that yields $\tilde{\mathbf{g}}^m$ "sufficiently" close to **g** – two different criteria were examined. The first of these was an evaluation of the portion of overall variation accounted for by the first *m* features (VAF_m). It is straightforward to show that this can be computed as

$$\text{VAF}_m = \frac{\sum_{i=1}^{m} \lambda_i^2}{\sum_{j=1}^{459} \lambda_j^2}. \tag{5}$$

The second criterion was to measure the fidelity of the reconstructed gait vector ($\tilde{\mathbf{g}}^m$) to the original gait vector (**g**). This can be expressed by (among other options) the projection of the recon-