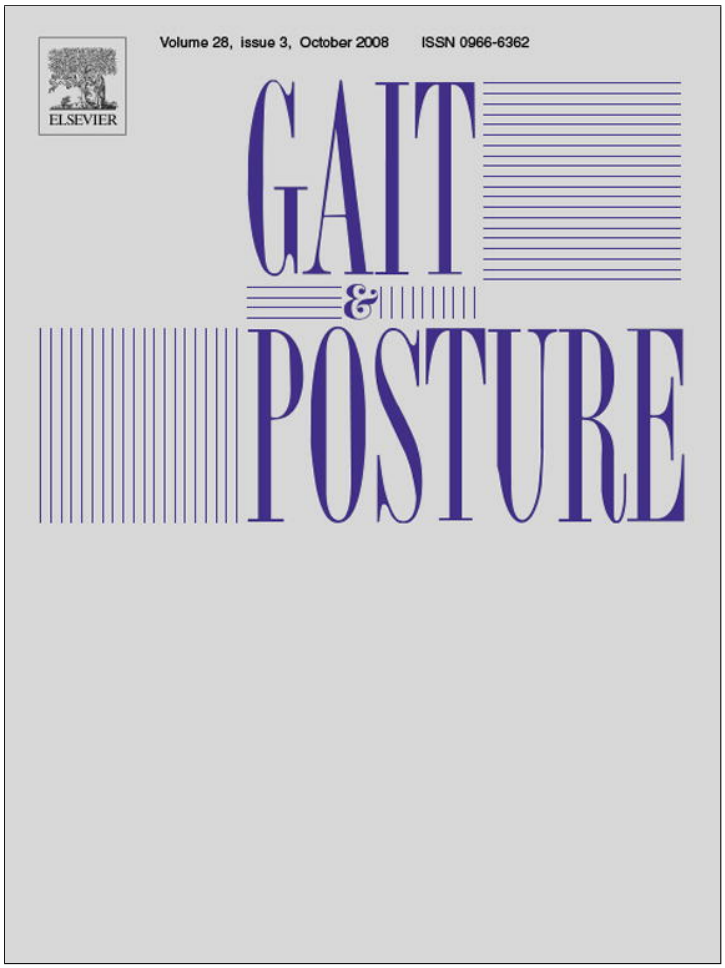

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The gait deviation index: A new comprehensive index of gait pathology

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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-

structed gait vector onto the original gait vector, normalized by the original gait vector,

$$\Phi = \frac{\mathbf{g} \cdot \tilde{\mathbf{g}}^m}{||\mathbf{g}||^2}. \quad (6)$$

The value of Φ is 1.0 when $\tilde{\mathbf{g}}^m = \mathbf{g}$, and decreases to a minimum of 0.0 as $\tilde{\mathbf{g}}^m$ deviates from $\mathbf{g}$. Note that $||\tilde{\mathbf{g}}^m|| \leq ||\mathbf{g}|| \Rightarrow \Phi \leq 1.0$.

Finally, to test whether the reconstruction was efficient on non-native data, 1000 strides not among the original 6702 (non-native) were reconstructed to various orders $m = \{1\text{–}459\}$. The quality of these reconstructions, as measured by VAF and Φ, was compared to that of the native data at the same order of reconstruction.

2.3. Proximity of gait data

Given any two subjects α and β, the Euclidean distance ($d^{\alpha\beta}$) between the gait vectors of the subjects ($\tilde{\mathbf{g}}^\alpha$ and $\tilde{\mathbf{g}}^\beta$)[1] can be defined as

$$d^{\alpha,\beta} = ||\mathbf{c}^\alpha - \mathbf{c}^\beta||. \quad (7)$$

The distance metric applies to any pair of gait vectors. With this in mind, consider a control group (*e.g.* typically developing – or TD – children). Let $\bar{\mathbf{c}}^{\mathrm{TD}}$ be the average of the feature components over the TD control group. The feature components $\bar{\mathbf{c}}^{\mathrm{TD}}$ thus describe the average TD gait. The distance of a subject α from the average TD gait is

$$d^{\alpha,\mathrm{TD}} = ||\mathbf{c}^\alpha - \bar{\mathbf{c}}^{\mathrm{TD}}||. \quad (8)$$

2.4. The Gait Deviation Index

Given the distance between subject α and the average control, the *raw* GDI for subject α is defined as

$$\mathrm{GDI}^\alpha_{\mathrm{raw}} = \ln(d^{\alpha,\mathrm{TD}}). \quad (9)$$

This measure can be used in its raw format as a measure of pathology. To improve interpretability the GDI can be scaled as follows [27]. First compute $\mathrm{GDI}^k_{\mathrm{raw}}$ for each subject in the control group ($k = 1$, N_{control})

$$\begin{aligned} \mathrm{GDI}^k_{\mathrm{raw}} &= \ln(d^{k,\mathrm{TD}}) \\ &= \ln(||\mathbf{c}^k - \bar{\mathbf{c}}^{\mathrm{TD}}||) \end{aligned} \quad (10)$$

Next, compute the sample mean and standard deviation of $\mathrm{GDI}^k_{\mathrm{raw}}$ ($\mathrm{Mean}(\mathrm{GDI}^{\mathrm{TD}}_{\mathrm{raw}})$, $\mathrm{S.D.}(\mathrm{GDI}^{\mathrm{TD}}_{\mathrm{raw}})$). Then compute the z-score with respect to the TD control for subject α,

$$z\mathrm{GDI}^\alpha_{\mathrm{raw}} = \frac{\mathrm{GDI}^\alpha_{\mathrm{raw}} - \mathrm{Mean}(\mathrm{GDI}^{\mathrm{TD}}_{\mathrm{raw}})}{\mathrm{S.D.}(\mathrm{GDI}^{\mathrm{TD}}_{\mathrm{raw}})}. \quad (11)$$

Finally, multiply these z-scores by 10 and subtract them from 100 to give the GDI for subject α,

$$\mathrm{GDI}^\alpha = 100 - 10 \times z\mathrm{GDI}^\alpha_{\mathrm{raw}} \quad (12)$$

Keeping in mind that the GDI measures a (scaled) distance away from the average TD gait, the resulting GDI can be interpreted as follows:

- GDI $\geq$ 100 indicates a subject whose gait is at least as close to the TD average as that of a randomly selected TD individual. In other words, a GDI of 100 or higher indicates the absence of gait pathology.
- Every 10 points that the GDI falls below 100 corresponds one standard deviation away from the TD mean. So, for example, $\mathrm{GDI}^\alpha = 75$ means that the gait of subject α is 2.5 × S.D.$(\mathrm{GDI}^{\mathrm{TD}}_{\mathrm{raw}})$ away from the TD mean.

2.5. Concurrent and face validity

The concurrent and face validity of the GDI was evaluated by examining its behavior with respect to several established overall pathology measures: The GGI, FAQ, and topographic classification for the sub-set of subjects with a diagnosis of Cerebral Palsy (CP).

3. Results

3.1. Order of reconstruction

Examination of VAF and Φ showed that 15 features accounted for 98% of the total variation and produced a 98% faithful gait vector as measured by the mean Φ (Fig. 1). Further examination showed that 99% of all subjects exhibited a $\Phi > 95\%$. The difference in reconstruction efficiency between native and non-native data was trivial (<0.1%) at $m = 15$. Based on these results, 15 features ($m_{\mathrm{crit}} = 15$) was deemed to provide a ''sufficiently'' faithful reconstruction of the native and non-native data.

A typical example of a 95% faithful ($\Phi = 0.95$) 15 feature reconstruction is provided for a subject with GDI = 70, which is three standard deviations away from TD (Fig. 2). It was noteworthy that significant timing differences were captured by the reconstructed data (*e.g.* peak swing phase knee flexion, dorsi/plantarflexion), as were large shifts in level (*e.g.* pelvic rotation and tilt, dorsi/plantarflexion, foot progression), along with radical alterations in pattern (*e.g.*

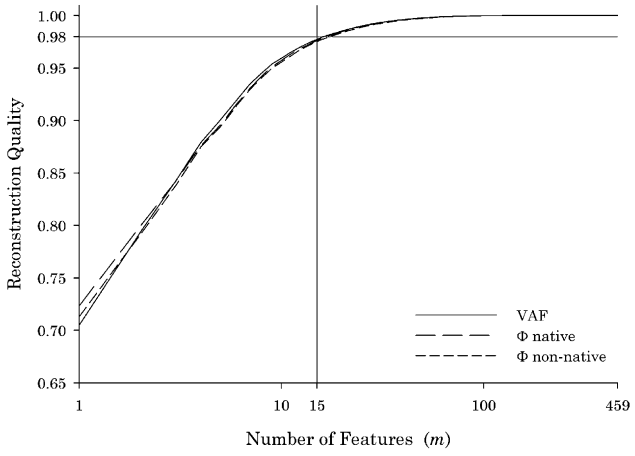

Fig. 1. A 98% complete reconstruction is attained with 15 features, as measured by both variance accounted for (VAF) and reconstruction fidelity (Φ). Note that Φ for the 6702 native strides (used to generate the gait features) and 1000 non-native strides are essentially identical.

[1] The Greek superscript now refers to the subject, not the level of reconstruction as was the case in Eq. (3). This convention will hold for the remainder of the text, unless otherwise noted.

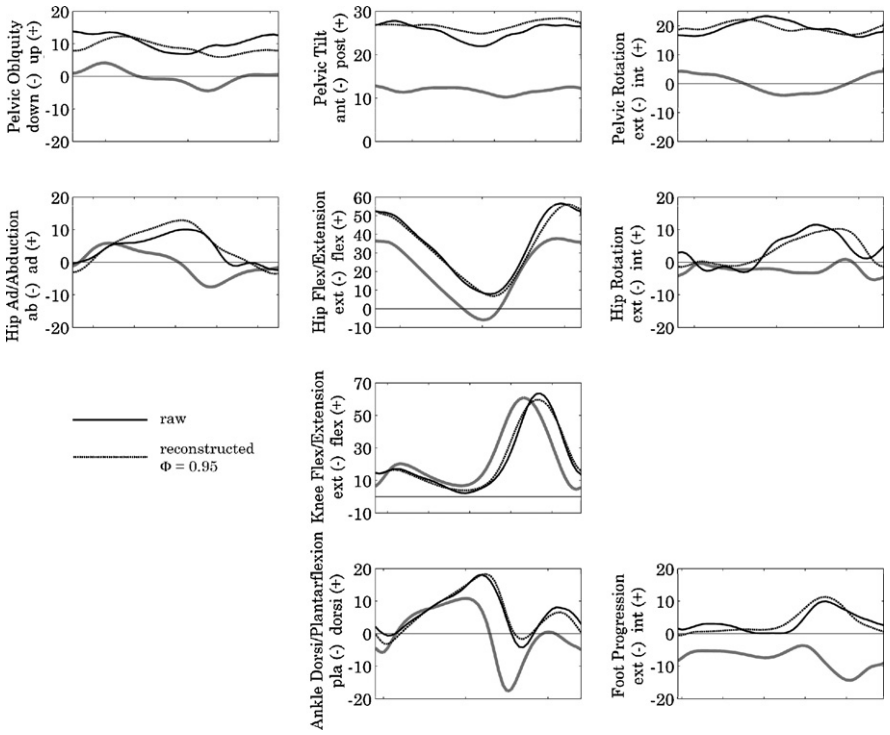

Fig. 2. An example of a 15 feature reconstruction ($\Phi = 0.95$) shows the ability to model complex gait deviations with a significantly reduced order approximation. The solid line is the original data for the subject, the dotted line is the subject's 15 feature reconstructed data, and the heavy grey line is the typically developing control data mean. The example is representative of the overall performance, and shows data for a subject with a GDI = 70 (three standard deviations from the control group). Deviations in timing, level, and pattern are all captured.

hip rotation, hip adduction). Most of the reconstruction errors were on the order of 1°, and the shapes of the kinematics were largely preserved. It should be noted that the size and location of reconstruction errors will vary from subject-to-subject.

3.2. Comparison to the GGI

Both the GDI and the GGI compare a subject's gait to the mean gait pattern of a control group (TD subjects, in this study). Because the GGI reflects a distance squared, it was necessary to perform a transformation in order to compare it to the GDI,

$$\mathrm{GGI}^{*} = \ln(\sqrt{\mathrm{GGI}}) \tag{13}$$

The GDI was compared to the GGI* (Fig. 3). There was a moderately strong linear relationship ($r^2 = 0.56$) between the two measures, suggesting that both measures are associated with the same basic underlying content (gait pathology). However, there was also a relatively large spread in the data, indicating that the two measures reflect different aspects of gait pathology.

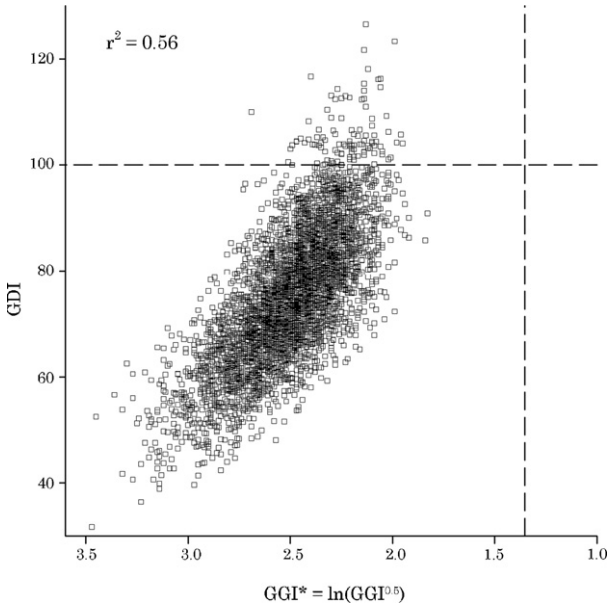

Fig. 3. A scatter plot of the GDI versus $\ln(\sqrt{\mathrm{GGI}})$ shows a strong relationship between the two measures ($r^2 = 0.56$). There is, however, a significant spread, suggesting that the GDI and GGI measure different aspects of gait pathology. The dashed lines indicate the average level for typically developing (TD) subjects.

3.3. Comparison to the FAQ

The GDI was stratified by FAQ walking level, from six (limit of community ambulation) to ten (keeps up with

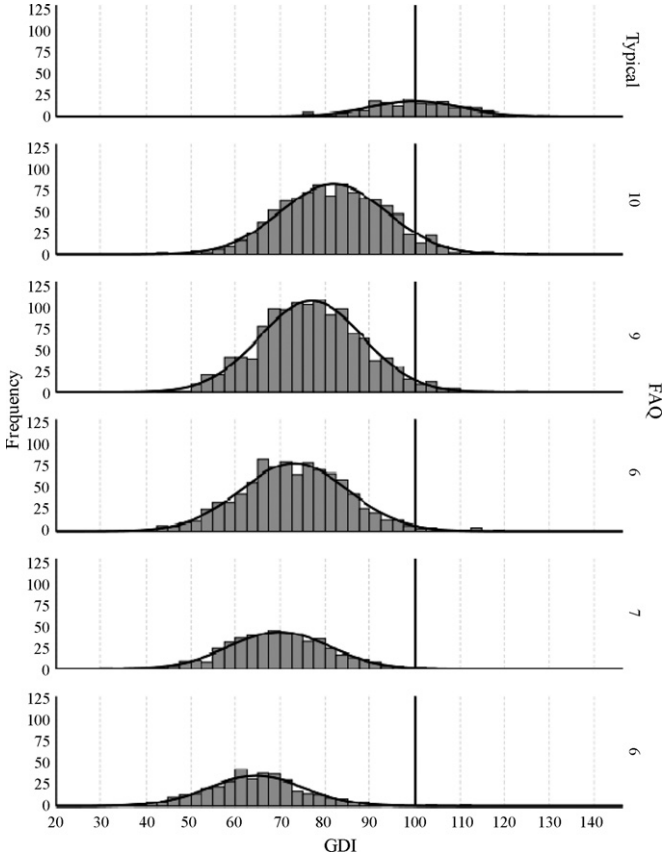

Fig. 4. Histograms of the GDI stratified by FAQ level show that (i) the GDI is normally distributed across a wide range of walking abilities, and (ii) the GDI differentiates between various overall walking abilities (see Table 1 for additional details). The normal distribution curve is shown for comparison, and a heavy vertical line indicates the control mean (GDI = 100).

peers). There were 3922 such subject-strides out of the original 6702 within this FAQ range. The GDI distribution with respect to FAQ was examined to evaluate the effect of function on the pathology measures (Fig. 4, Table 1). Two things were noteworthy about these results. First, Kolomogorov–Smirnov tests found that the GDI was normally distributed at each FAQ level and for the TD control. Second, an ANOVA showed that the GDI distinguished between each pair of levels, including TD ($p < 0.05$). These findings strongly suggest that the overall level of gait pathology, as measured by the GDI, is related to functional walking ability. This conclusion supports the notion of using an overall gait pathology index as a patient stratification and outcome assessment tool.

3.4. Analysis by Cerebral Palsy sub-type

The 3128 strides from subjects with CP were grouped into topographic classifications according to Gage [29]. There was a clear trend of decreasing GDI with increasing severity of involvement (see electronic addendum Fig. S1). The TD mean was 100 (by definition), while the next closest group was the unaffected side for Type I Hemiplegia (just below 90). The so-called ‘‘unaffected’’ side was thus one full standard deviation away from the TD mean. This finding reaffirmed the prevalent clinical impression that the contralateral side of a person with Hemipligia is affected by a crossover/coupling effect from the involved side.

4. Discussion

A new measure of overall gait pathology, the Gait Deviation Index (GDI), has been introduced along with concurrent and face validity data. The GDI scales with overall gait function, is well behaved statistically, and can be implemented easily using the Supplemental data provided with this article.

The GDI was strongly correlated ($r^2 = 0.56$) with the previously validated and widely used GGI. This suggests that the GDI and GGI are both measures of the same underlying construct, though the large spread at any given level indicates that they measure different aspects of gait pathology. It remains to be determined what accounts for this spread.

The GDI scaled monotonically with FAQ, and was normally distributed for FAQ levels six to ten and TD children. The GDI was sensitive enough to differentiate between every pair of FAQ levels based on an ANOVA. Coincidentally, the decrement in mean GDI with decreasing FAQ level (*e.g.* FAQ = 10 → FAQ = 9, FAQ = 8 → FAQ = 7, *etc.*) was quite consistent, with a mean decrement of 4.3 and a standard deviation of 0.9. Recalling that the GDI is measured in ten-fold standard deviation units, this means that each FAQ level was separated from its neighbor by about 0.43 ± 0.09 standard deviations. The FAQ was not designed to provide equally spaced functional intervals, however, it appears to do so, at least as measured by the GDI.

Table 1
GDI by FAQ level

FAQ	N	Mean	Std. deviation	Minimum	Maximum	Normally distributed (K–S test)
6 (7,8,9,10,TD)	382	64.6	10.9	39.9	112.4	True
7 (6,8,9,10,TD)	471	69.8	11.1	31.7	103.8	True
8 (6,7,9,10,TD)	916	73.1	11.8	38.9	118.1	True
9 (6,7,8,10,TD)	1205	76.9	11.5	44.8	123.3	True
10 (6,7,8,9,TD)	948	81.8	11.8	44.0	126.5	True
TD (6,7,8,9,10)	166	100.0	10.0	73.9	129.9	True

Numbers in parentheses indicate statistically significant differences as determined from an ANOVA with $p < 0.05$.

The effect of diagnostic sub-type within the CP group was similarly compelling—the GDI decreased steadily as the overall level of clinical severity increased. Furthermore, the GDI distinguished between the affected and contralateral side for Hemipligia, while also confirming that the contralateral side does not exhibit a typical gait pattern (*i.e.* $GDI_{contra} < 100$). While the gait deviations for the affected side got progressively larger for Hemiplegia Types I–IV, the contralateral sides for Type I–III showed essentially the same amount of pathology (about 1 1/2 standard deviations from TD), however, this was not the case for Type IV Hemiplegia, where the contralateral side was almost two standard deviations away from TD.

The analysis of VAF and reconstruction fidelity (Φ) showed that 15 features provided a sufficiently accurate approximation to the original gait vector. This amounts to a 459/15 = 30.6-fold reduction in data. This sizeable compression reflects the high degree of underlying interdependence in the original data. The reconstructed data were able to capture deviations in timing, level, and shape; lending credence to the notion that the 15 features can give overall measure of gait deviation. A similarly high level of Φ was found for non-native data, though it should be noted that the non-native data was collected at the same center as the native data. Similar results would be expected for non-native data from other centers. This conclusion is based on the underlying principles of the SVD method, and holds as long as the non-native data can be closely approximated by a linear combination of gait cycles from the native data.

The number of features to preserve (m_{crit}) is clearly a subjective assessment. It may be the case that for some applications a closer approximation of the original gait data may be desired, in which case more features can be used. It may also be the case that for a different set of gait data (*e.g.* only sagittal plane angles), fewer features may provide sufficiently accurate reconstruction. For the GDI as described here, this specific set of kinematic data and a 15-feature reconstruction are strictly assumed.

The GDI methodology incorporates three-dimensional rotation angles for the pelvis and the hip. At the knee, only the sagittal plane was used, since the coronal plane is prone to artifact (cross-talk from poor knee axis alignment) and the transverse plane of less clinical relevance in most centers. At the ankle, the sagittal plane was also chosen for reasons of clinical utility and practicality; namely the fact that few centers regularly collect three-dimensional hind foot data required to compute coronal and transverse plane ankle rotations. Finally, foot progression was selected as it tends to be the most commonly used transverse plane foot orientation measure. It should be noted, however, that the same general steps outlined above can be used to derive similar indices based on different sets of kinematics (*e.g.* a hip score, or a sagittal plane score), as well as on combinations of kinematics, kinetics, and enveloped electromyographic data, though scaling considerations would be required in these latter cases.

The GDI is straightforward to implement. A center merely needs to carry out a matrix multiplication, along with a few elementary statistical and arithmetic operations. All of these steps can be accomplished using the provided electronic addendum. While the GDI has not been extensively evaluated on non-native data, early indications are that the index works well in other centers [30].

The underlying feature extraction methodology and gait proximity measure have many other possible applications. One such application currently under development is to use the proximity metric (Eq. (7)) to aid in problem identification and treatment planning. The scheme under development is as follows:

- A center collects gait data for a new patient ($\mathbf{g}^{patient}$).
- All existing gait vectors within the center's database are sorted based on proximity to $\mathbf{g}^{patient}$. Additional sorting criteria, such as age, diagnosis, or prior surgery can also be used.
- A set of closely matched patients are selected, and the previously determined gait problems, surgeries, and outcomes are compiled.
- Treatment and/or patient characteristics exhibiting good and bad outcomes are then extracted, and this information is used guide treatment decisions on the patient at hand.

Future work will focus on further validation of the GDI, extension to kinetics and EMG data, multi-center study considerations, along with exploring additional applications of the basic methodology.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gaitpost.2008.05.001.

Conflict of interest

None of the authors had any financial or personal relationships with other people or organizations that could inappropriately influence this work.

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