Development and Testing of Decision Support Tools in Gait Analysis

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Abstract

Objectives

Clinical gait analysis, as commonly prescribed for children with Cerebral Palsy, is a complex set of procedures which include examining data from several sources. The tools developed with this project will use that data to provide robust, repeatable, evidence-based guidance to highlight the most effective treatments for children with CP. These tools will also supply objective measures that can be included in outcome analysis.

Methods

Several mathematical techniques are used to find patterns within the gait date including: singular value decomposition of kinematic and kinetic data to measure gait pathology; k-means cluster analysis of those results to find recurring patterns; principal components analysis of physical exam findings to relate the gait patterns to physical function; and non-negative matrix factorization of electromyography data to measure motor control.

Results

The decomposition and scaling of the kinematic and kinetic data resulted in a set of indexes that are able to quantify gait pathology. The k-means cluster analysis reveals that there are repeatable patterns within the gait pathology. These patterns are related to clinical findings as calculated from principal components analysis. Clinical interpretations of motor control can be quantified as muscle synergies using non-negative matrix factorization.

Interpretation

These tools have proven to provide important quantitative information on treatment outcomes. When implemented in routine clinical gait analysis, these tools have the ability to provide evidence based guidance in treatment decisions.

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Chapter 1

1. Introduction

Cerebral palsy results from a brain injury at, or around, birth. The injury is static, that is, the disorder itself does not progress. However, the expression of the disorder evolves as the child grows. Cerebral palsy is a movement disorder and one of the primary effects on the musculoskeletal system is abnormal muscle tone, often in the form of spasticity. Spasticity is a velocity dependent response to passive stretch that makes it very difficult for the child to move her joints through the typical range of motion. This, in turn, leads to growth problems such as boney deformities (through Wolff's law) and muscle contractures, as well as muscle weakness, poor selective motor control, and poor balance. It is the interaction of all of these deficits that lead to the movement patterns that are seen in children with CP [1].

There is currently no treatment for the static brain injury that causes CP. Therefore, treatments focus on the expressions of the disorder: rhizotomy, Botulinum Toxin A, or baclofen to directly treat spasticity; orthopedic surgery to correct musculoskeletal deformities; and physical therapy to address weakness and poor selective motor control. It is important that the correct treatment be given at the correct time and in the correct dose for the outcome to be positive. However, with the multiple interactions between the deficits in the neural and musculoskeletal systems, treatment decisions can be difficult to make. Often times these decisions are made in an inconsistent manner, which makes it exceedingly difficult to determine which treatments are most effective.

Clinical gait analysis is commonly used as a way to objectively measure movement patterns. "Gait analysis", as used here, refers to three-dimensional movement analysis, a physical exam and an examination of the patient's medical history that are used in

conjunction to give a comprehensive and objective assessment of function. This provides the information that clinicians can use to determine which treatments would be best for any specific patient. Gait analysis also provides the data needed to determine how consistently certain treatment decisions are being made. If the gait analysis is repeated sometime after the treatment, the specific treatment outcome can also be evaluated.

One of the challenges of gait analysis is the vast amount of data that is generated. Joint angles, moments, and powers are routinely calculated in each anatomical plane for the ankle, knee, hip, pelvis, and trunk. This data can be collected under multiple conditions and analyzed using multiple musculoskeletal models. Data can also be derived from the kinematics, including muscle lengths and lengthening rates. Physical exam and patient history data is also documented. With all of this data, making objective and consistent treatment decisions can be challenging. Thus the need for automated and objective decision support tools for gait analysis.

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.

The main objective of this thesis was to develop and evaluate decision support tools in gait analysis that can help deal with this complexity in order to guide clinical decisions. In today's healthcare environment, the objective analysis of clinical data is more important than ever. The tools developed with this project are to provide robust, repeatable, evidence-based guidance to highlight the most effective treatments for children with CP. This was accomplished through three specific aims.

Specific Aim 1: Development and evaluation of improved outcome measures

Specific Aim 2: Objective analysis of the clinical decision making process

Specific Aim 3: Examination of motor control in gait to improve surgical outcome prediction

Specific Aim 1

Current outcome assessment tools include questionnaires like the Gillette Functional Assessment Questionnaire and the Pediatric Outcomes Data Collection Instrument [2,3]. These tools can be used to provide a subjective assessment of a child's function before and after treatment. More objective measures of outcome include walking speed and range of motion of effected joints. However these tools do not provide a full picture of the gait pathology. Comprehensive tools to describe gait pathology are not new to gait analysis and a number of multivariate statistical methods have been developed for dealing with the complexity and interdependence of gait data [4–18]. 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 [5,6,13,15–18]. 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 [5,18–24]. While the GGI has been shown to be useful, a number of limitations have also been noted [25,26]. 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. Specific Aim 1 focused on overcoming the weaknesses of the GGI by developing a novel, robust, and flexible tool for quantifying gait pathology. Furthermore, the quantification of gait pathology before and after treatment has provided an objective assessment of outcome. Our hypothesis was that an objective, robust and intuitive measure for assessing gait pathology will improve outcome assessment.

RELATED CHAPTERS

2. Gait features and the Gait Deviation Index

3. Extension of the GDI to the hip and pelvis

4. The Gait Deviation Index for Kinetics

Specific Aim 2

Generally, surgical decisions are made based on each surgeon's experience and varying physical exam and technical data points. The existing literature on this subject suffers from limited sample sizes, lack of control groups, and lack of clarity regarding surgical indications. Specific Aim 2 focused on examining patterns in gait analysis that can be used to guide the clinical decision making process.

Building on the methods of Specific Aim 1, this next part of the project objectively analyzed and classified the gait patterns of children with CP who walked in a flexed position ("crouch gait"). Several methods to classify gait in children with CP currently exist. The strengths and weaknesses of these methods have been discussed in a review by Dobson *et al.* [27]. Traditional classification schemes use a wide variety of gait variables to define their classification, including kinematics, kinetics, EMG, energy consumption and temporal spatial parameters. The review found that the "overall methodological quality of the studies evaluated … was low". This was due to poor description of the methods, small sample sizes and limited validity. The first part of Specific Aim 2 demonstrates that meaningful distinctions, both in pattern and underlying pathology, can be found objectively and that these patterns relate to historical treatment decisions. Evaluating those historical treatment decisions was the focus of the second part of Specific Aim 2. Intramuscular psoas lengthening (IMPL) has been shown to improve dynamic hip function when included as part of a single event multi- level surgery (SEMLS) for children with cerebral palsy [28,29]. However, in previous analyses, there have been no control subjects to which outcomes could be compared [28,29]. Thus, there is still debate about which patients would benefit most from the procedure, given the risks that do exist, and conversely, which patients would do poorly following such an intervention.
Distal rectus femoris transfer (RFT) is widely considered an effective treatment for stiff knee gait (SKG) in ambulatory individuals with CP [30]. However, controversy exists regarding the expected outcomes [31,32]. Reinbolt *et al.* hypothesized that the inconsistency of outcomes was due to a lack of an optimal patient selection criterion. To address this,

supervised learning was used to derive a score capable of correctly predicting outcomes after RFT 80% of the time [33]. No control group was tested in Reinbolt's study, thus it is unclear whether the score was specific to the RFT, or merely predicted subjects likely to benefit from single event multi-level surgery (SEMLS).

The second part of Specific Aim 2 focused on the outcomes of a large retrospective cohort of subjects who underwent SEMLS treatment, all of whom met purported kinematic criteria for treatment (either IMPL or RFT). Because of a lack uniform decision-making regarding treatment at the time of the surgical intervention, not all patients who met the criterial had undergone the treatment, thereby providing a retrospectively identified control group. The goal of this part of the project was to determine if there is a beneficial effect to following specific, objective surgical criteria. Our hypothesis was that objectively identifiable patterns will emerge in the gait data and that these patterns will be related to treatment. Also, strict adherence to known clinical guidelines will improve patient outcome.

RELATED CHAPTERS

3. Extension of the GDI to the hip and pelvis

5. Objective Classification of Crouch Gait

6. Crouch gait clusters are related to treatment decisions

7. Assessment of Surgical Criteria

Specific Aim 3

It is clear that the process of making surgical decisions for children with CP is quite complex and not well documented. Still, improvement in gait after surgical treatment including SEMLS or selective dorsal rhizotomy (SDR) is generally quite good. At

Gillette Children's Specialty Healthcare, the average change in kinematics 1-2 years after surgical treatment is nearly a full standard deviation closer to normal, which is a statistically and functionally significant improvement. However, the range in the changes seen after surgery is quite large. Many patients (35%) do not improve significantly and 25% actually get worse. Further evidence is needed to develop a system that can provide a warning if a patient is at risk for not improving their gait after surgery.

Clinicians believe that there are many factors that contribute to the outcome of surgical treatment. Proper patient selection, surgical technique and dedicated rehabilitation are all important. Gait analysis, which consists of gathering data from many different sources, including patient history, physical exam, oxygen consumption and motion capture data, can play an integral role in the patient selection aspect. This is true both for determining the specific surgeries to include (by identifying deviations from normal) and potentially for screening which patients are likely to do well after surgery (by finding combinations of data that are consistent with previous good outcomes). Retrospectively identifying optimal patient selection criteria can be quite useful, but designing a prospective test will allow for the ability to control the conditions in which the data is collected and create extra challenges that can differentiate patients that will do well with surgery and patients that will not.

One hypothesis is that motor control plays an important role in determining the response to surgical treatment [34]. Recent research suggests that the central nervous system (CNS) uses a modular approach to controlling movement [35–37]. These modules reduce the number of degrees of freedom the CNS needs to control by allowing groups of muscles to

be recruited together as one unit. These groups of muscles are commonly referred to as synergies or modes. It has been shown that similar synergies are recruited during many different physical activities (*e.g.*, walking, running, cycling, etc.)[38,39]. However, it is still unclear whether these synergies are neurological in origin (*i.e.*, the neurological pathways exist specifically to recruit muscles together) or mechanical in origin (*i.e.*, mechanical constraints dictate certain patterns of muscle coordination)[40,41].

Individuals with neurological deficits (*e.g.*, stroke or cerebral palsy) use fewer synergies in order to complete a movement task [42–45]. If synergies truly have a neural origin, this could be an adaptation to the injury that further simplifies control. However, this simplification comes at a cost. The movement patterns of individuals with neurological deficits are significantly different from, and less efficient than, the movement patterns of intact individuals [1]. If synergies are mechanical in origin, the reduction in the number of synergies could be explained by the fact that the simplified movement pattern favors a certain muscle activation pattern independent of neural control [40]. Understanding the etiology of synergies is important for interpreting the impact that altered synergies may have in cerebral palsy and other neurological disorders. These factors may help guide treatment decisions in these patient populations.

Specific Aim 3 investigated whether synergies change when unimpaired individuals walk on a treadmill at different speeds and slopes. This treadmill task required adaptations of both the position of the joints, and the force produced by the various muscle groups. Our hypothesis was that the significant changes in movement pattern associated with the slopes and speeds will not be accompanied by significant changes in synergies. Specific

Aim 3 focused on determining the neural or mechanical origins of synergies which may be important in the clinical recommendations and rehabilitation strategies for individuals with neurological deficits.

RELATED CHAPTERS

8. Assessment of muscle synergies during treadmill gait

Chapter 2

2. Gait features and the Gait Deviation Index

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Summary

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.

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 [2,23,46]. 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 [47]. 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. 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[4–16,18,48]. 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 [5,6,13,15–18].

Among these, the Gillette Gait Index (GGI) appears to be the most extensively validated, commonly cited (based on a ScopusTM citation search), and is widely used in clinical gait research and practice [5,18–24]. While the GGI has been shown to be useful, a number of limitations have also been noted [25,26]. 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).

Methods

Motivation

The method used in constructing the GDI was motivated by a biometric method used for face identification—the so-called ‘‘eigenface’’ method [49]. 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.

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 February, 1994 and April, 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**).

$$\begin{aligned} \mathrm{g} &= [\{\text{pel tilt}\}, \{\text{pel obliq}\}, \ldots, \{\text{foot prog}\}]^{\mathrm{T}} \\ &= [\{\mathrm{g}_1 - \mathrm{g}_{51}\}, \{\mathrm{g}_{52} - \mathrm{g}_{102}\}, \ldots \{\mathrm{g}_{409} - \mathrm{g}_{459}\}]^{\mathrm{T}} \end{aligned} \qquad \text{Eq 2.1}$$

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

$$\mathbf{G} = \left[\begin{pmatrix} \mathrm{g}_1^1 \\ \mathrm{g}_2^1 \\ \vdots \\ \mathrm{g}_{459}^1 \end{pmatrix} \begin{pmatrix} \mathrm{g}_1^2 \\ \mathrm{g}_2^2 \\ \vdots \\ \mathrm{g}_{459}^2 \end{pmatrix} \ldots \begin{pmatrix} \mathrm{g}_1^{6702} \\ \mathrm{g}_2^{6702} \\ \vdots \\ \mathrm{g}_{459}^{6702} \end{pmatrix} \right]. \qquad \text{Eq 2.2}$$

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 $\{\hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3 \ldots \hat{\lambda}_{459}\}$ 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

$$\tilde{\mathbf{g}}^m = \sum_{k=1}^{m} c_k \hat{\mathbf{f}}_k \,, \qquad \text{Eq 2.3}$$

where the feature components c_k are

$$c_k = \mathbf{g} \cdot \hat{\mathbf{f}}_k \,. \qquad \text{Eq 2.4}$$

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 $m = m_{crit}$ from $\tilde{g}^m = \sum_{k=1}^{m} c_k \hat{f}_k$,Eq 2.3 that yields $\tilde{\mathbf{g}}^m$ ''sufficiently'' close to **g** – two different criteria were examined. T

$$\mathrm{VAF}_m = \frac{\sum_{i=1}^{m} \lambda_i^2}{\sum_{j=1}^{459} \lambda_j^2} \,. \qquad \text{Eq 2.5}$$

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

$$\phi = \frac{\mathbf{g} \cdot \tilde{\mathbf{g}}^m}{\|\mathbf{g}\|^2} \,. \qquad \text{Eq 2.6}$$

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 **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 $m = \{1–459\}$. 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.

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 $\tilde{\mathbf{g}}^{\beta}$) can be defined as [Note: The Greek superscript now refers to the subject, not the level of reconstruction as was the case in ,Eq 2.3. This convention will hold for the rema

$$d^{\alpha,\beta} = \left\| \mathbf{c}^{\alpha} - \mathbf{c}^{\beta} \right\| . \qquad \text{Eq 2.7}$$

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

$$d^{\alpha,\mathrm{TD}} = \left\| \mathbf{c}^{\alpha} - \bar{\mathbf{c}}^{\mathrm{TD}} \right\| . \qquad \text{Eq 2.8}$$

The Gait Deviation Index

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

$$\mathrm{GDI}_{\mathrm{raw}}^{\alpha} = \ln(d^{\alpha,\mathrm{TD}}) \,. \qquad \text{Eq 2.9}$$

This measure can be used in its raw format as a measure of pathology. To improve interpretability the GDI can be scaled as follows [25]. First compute $\mathrm{GDI}_{\mathrm{raw}}^{k}$ for each subject in the control group (k = 1, N_{control})

$$\begin{aligned}\mathrm{GDI}_{\mathrm{raw}}^{k} &= \ln(d^{k,\mathrm{TD}}) \\ &= \ln(\|\mathbf{c}^{k} - \bar{\mathbf{c}}^{\mathrm{TD}}\|) \,. \qquad \text{Eq 2.10}\end{aligned}$$

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

$$z\mathrm{GDI}_{\mathrm{raw}}^{\alpha} = \frac{\mathrm{GDI}_{\mathrm{raw}}^{\alpha} - \mathrm{Mean}(\mathrm{GDI}_{\mathrm{raw}}^{\mathrm{TD}})}{\mathrm{S.D.}(\mathrm{GDI}_{\mathrm{raw}}^{\mathrm{TD}})} \,. \qquad \text{Eq 2.11}$$

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

$$\mathrm{GDI}^{\alpha} = 100 - 10 \times z\mathrm{GDI}_{\mathrm{raw}}^{\alpha} \,. \qquad \text{Eq 2.12}$$

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 ≥ 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, GDI^{α} = 75 means that the gait of subject α is 2.5 × S.D.($\mathrm{GDI}_{\mathrm{raw}}^{\mathrm{TD}}$) away from the TD mean.

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).

Results

Order of reconstruction

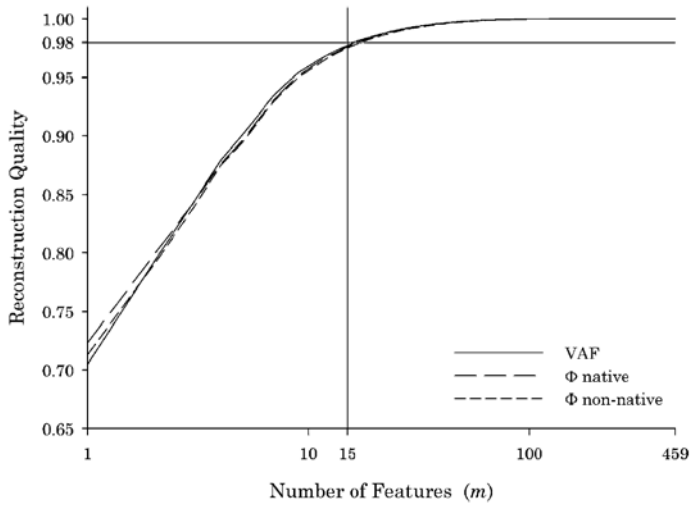

Figure 2.1 A 98% complete reconstruction is attained with 15 features, as measured by both variance accounted for (VAF) and reconstruction fidelity ($\boldsymbol{\phi}$). Note that $\boldsymbol{\phi}$ for the 6702 native strides (used to generate the gait features) and 1000 non-native strides are essentially identical.

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. Further examination showed that 99% of all subjects exhibited a ϕ > 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_{crit} = 15) was deemed to provide a ‘‘sufficiently’’ faithful reconstruction of the native and non-native data.

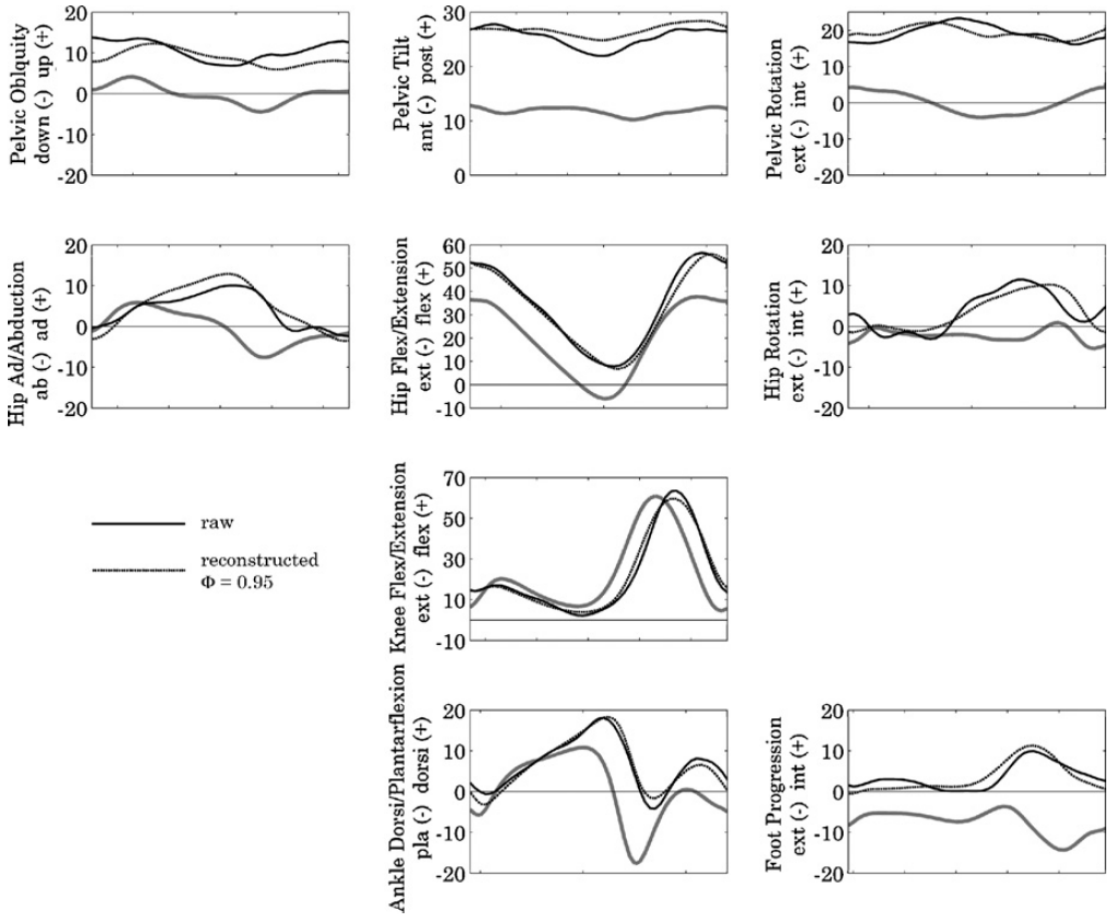

Figure 2.2 An example of a 15 feature reconstruction (F = 0.95) shows the ability to model complex gait deviations with a significantly reduced order approximation. The solid line is the original data for the subject, the dotted line is the subject’s 15 feature reconstructed data, and the heavy grey 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.

A typical example of a 95% faithful (ϕ = 0.95) 15 feature reconstruction is provided for a subject with GDI = 70, which is three standard deviations away from TD (Figure 2.2). 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. 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.

Comparison to the GGI

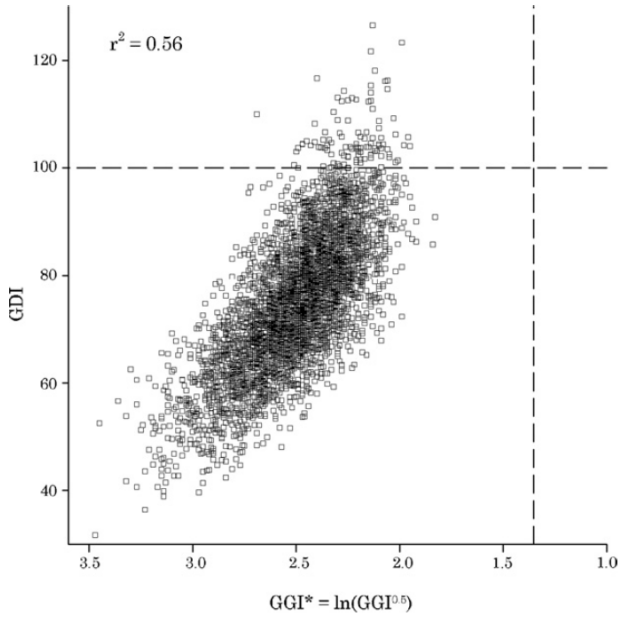

Figure 2.3 A scatter plot of the GDI versus $\sqrt{\text{GDI}}$ shows a strong relationship between the two measures (r^2 = 0.56). There is, however, a significant spread, suggesting that the GDI and GGI measure different aspects of gait pathology. The dashed lines indicate the average level for typically developing (TD) subjects.

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,

$$\text{GDI}^* = \ln\left(\sqrt{\text{GGI}}\right) \qquad \text{Eq 2.13}$$

The GDI was compared to the GGI* (Figure 2.3). 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.

Comparison to the FAQ

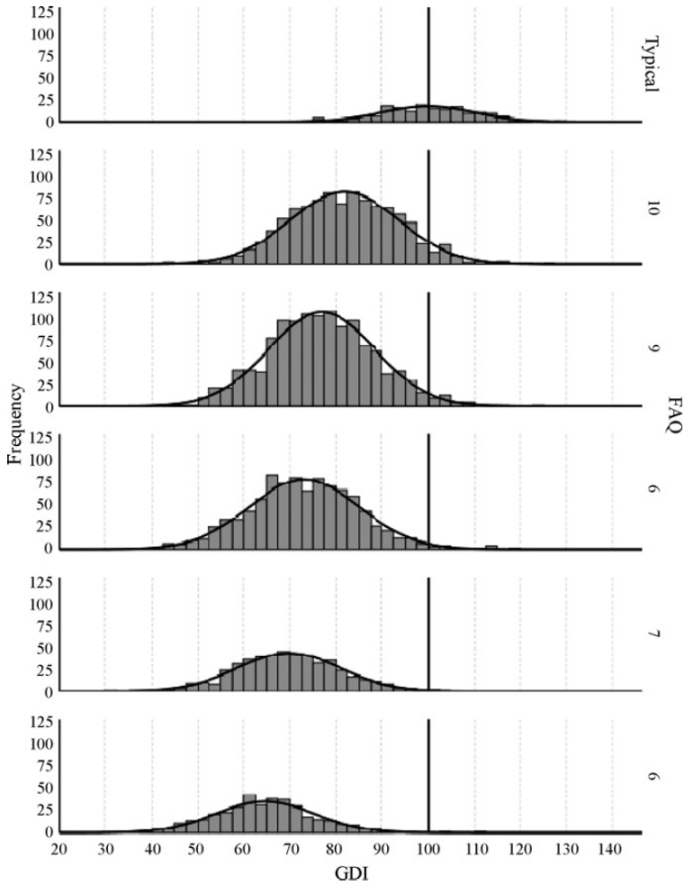

Figure 2.4 Histograms of the GDI stratified by FAQ level show that (i) the GDI is normally distributed across a wide range of walking abilities, and (ii) the GDI differentiates between various overall walking abilities (see Table 1 for additional details). The normal distribution curve is shown for comparison, and a heavy vertical line indicates the control mean (GDI = 100).

The GDI was stratified by FAQ walking level, from six (limit of community ambulation) to ten (keeps up with 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 (Figure 2.4,**Table 2.1**). 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 ($p < 0.05$).

Table 2.1 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	126.5	True
TD (6 7 8 9 10)	166	100	10	73.9	129.9	True

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

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.

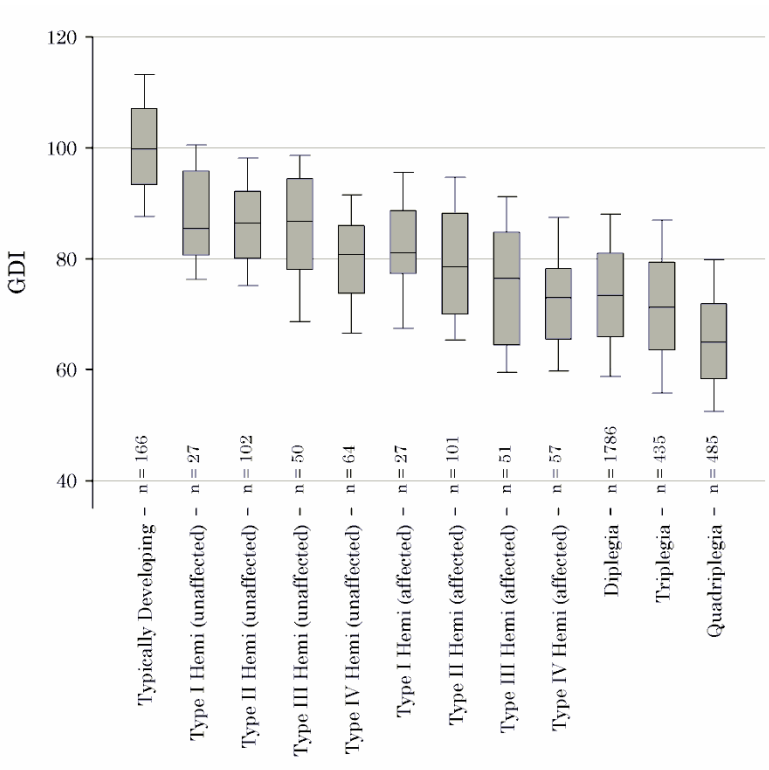

Figure 2.5 Distribution of the GDI by topographical classification.

Analysis by Cerebral Palsy sub-type

The 3128 strides from subjects with CP were grouped into topographic classifications according to Gage [50]. There was a clear trend of decreasing GDI with increasing

severity of involvement (Figure 2.5). 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 Hemiplegia is affected by a crossover/coupling effect from the involved side.

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.

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 Hemiplegia, 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 [51].

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.

Chapter 3

3. Extension of the GDI to the hip and pelvis

Presented as:

Explicit Kinematic Criteria Predict Postoperative Improvements Following Surgical Lengthening of the Psoas Tendon in Patients with Cerebral Palsy

Adam Rozumalski, Walter H. Truong, Michael H. Schwartz, Cammie Beattie, Tom F. Novacheck

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Gait & Posture 30 (2009) S57-S58

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Introduction

Intramuscular psoas lengthening has been shown to improve dynamic hip function when included as part of a single event multi-level surgery (SEMLS) for children with cerebral palsy [28,29]. However, in previous analyses, there have been no control subjects to which outcomes could be compared [28,29]. The procedure remains somewhat controversial due to a lack of clear indications for patient selection, as well as concerns about postoperative weakness and safety of the procedure. This study reports on a large retrospective cohort of subjects who underwent SEMLS treatment, with or without psoas lengthening, in order to determine if appropriate patient selection can optimize functional outcomes.

Methods

A retrospective analysis was performed on children with cerebral palsy, ages 3 to 18, who underwent SEMLS (± intramuscular psoas lengthening) at Gillette Children's Specialty Healthcare after January 1994. Each child had an initial gait analysis no more than 18 months before the SEMLS and a follow up gait analysis between 6 and 24 months after the SEMLS. Average kinematics were computed for each side for each child and treated as a separate case. SEMLS was defined as 2 or more major surgical procedures for any one side (*e.g.* osteotomy, muscle lengthening, muscle transfer). Subjects who underwent selective dorsal rhizotomy were excluded from the study. Children were further categorized by whether they had undergone previous major surgery.

Children meeting two-out-of-three of the following criteria were considered appropriate for psoas surgery: 1) maximum hip extension greater than 8°, 2) maximum pelvic tilt

greater than 24°, and 3) pelvic tilt range of motion greater than 8°. These levels represent two standard deviations from normal values. To quantify the outcome of the intervention, the change in overall gait pattern, as measured by the gait deviation index (GDI), was calculated [52]. In addition, the change in pelvic and hip kinematics was measured using a modified version of the GDI (the pelvis and hip deviation index or PHiDI) that only includes sagittal plane pelvis and hip kinematics. The PHiDI scores can be interpreted in the same manner as the GDI scores; a score of ≥100 means normal kinematics, and each 10 points below 100 is one standard deviation away from normal kinematics.

Results

The inclusion criteria produced 412 sides, 211 of which had no prior surgery. These 211 sides will be the focus of the present analysis. Of these 211, 55 went on to have a psoas lengthening as part of their SEMLS treatment. Measures of kinematic function before and after intervention are shown (**Table 3.1**).

Table 3.1 Mean GDI and PHiDI, pre and post

	Met Kinematic Criteria	Psoas Lengthening Included	
		Yes	No
PHiDI pre	Yes	74	77
	No	87	90
PHiDI post	Yes	84	84
	No	89	91
GDI pre	Yes	62	61
	No	69	71
GDI post	Yes	75	72
	No	76	80

The most dramatic improvement in hip function (as measured by PHiDI) occurred in the group that met the kinematic criteria and went on to have psoas lengthening (Figure 3.1a). This was a larger improvement than the group that met the criteria but did not have surgery,

although this latter comparison was not statistically significant. The PHiDI was improved (ΔPhiDI > 0) for all subjects who met the kinematic criteria ($p < 0.001$) and was statistically unchanged for those who did not ($p > 0.15$), regardless of whether they underwent psoas lengthening (Figure 3.1a).

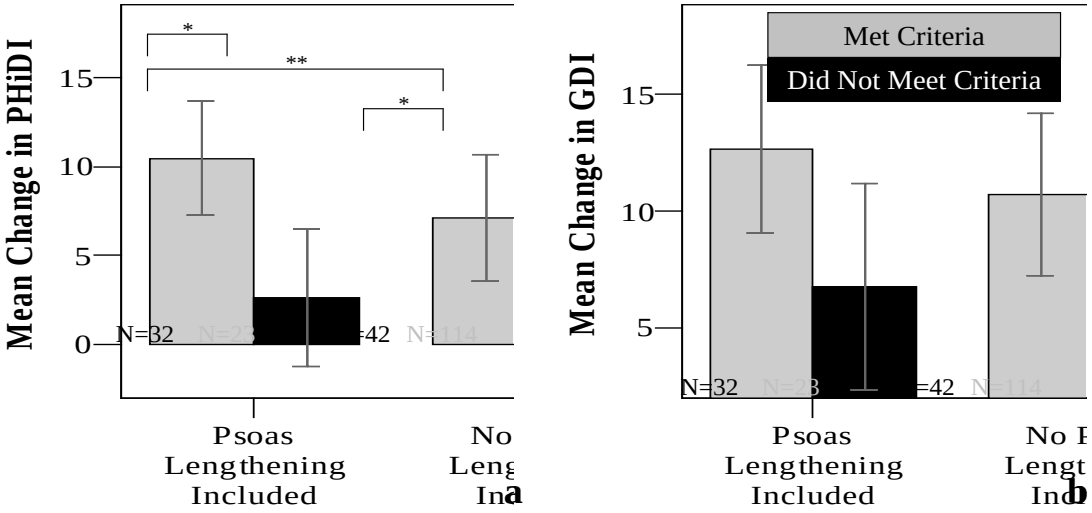

Figure 3.1 Change in a) PHiDI and b) GDI after a SEMLS procedure. Error bars show the 95% confidence interval. The largest changes occurred for the group that met the criteria and had a psoas lengthening. (* = $p < 0.05$, ** = $p < 0.001$)

The GDI improved after surgery (ΔGDI > 0, $p < 0.01$) regardless of whether psoas lengthening was included in the SEMLS, or whether the side met the kinematic criteria for psoas lengthening (Figure 3.1b). The greatest improvement was for the group that met the kinematic criteria and had psoas lengthening, while the group with the least improvement met the criteria but did not have the surgery. There was no significant difference between any of the groups for mean change in GDI.

Discussion

Overall kinematics improved for children undergoing SEMLS treatment. When deciding whether or not to include a psoas lengthening in the procedure, pelvis and hip kinematics in the sagittal plane can give guidance. Subjects who met the kinematic criteria for psoas surgery exhibited significantly more improvement in pelvis and hip kinematics than those who did not meet the criteria (Figure 3.1). The overall and hip-specific results imply that, for children who meet the kinematic criteria, the best results are realized when psoas lengthening is included as part of a SEMLS procedure. The converse is also true; children who do not meet the kinematic criteria tend to achieve the best results when psoas lengthening is left out of the SEMLS procedure. Further study will focus on examining safety, as well as investigating whether there are other criteria that can more definitively guide the decision making process.

Chapter 4

4. The Gait Deviation Index for Kinetics

Published as:

The GDI-Kinetic: A new index for quantifying kinetic deviations from normal gait

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Summary

This article introduces a new index, the GDI-Kinetic; a direct analog of the GDI based on joint kinetics rather than kinematics. The method consists of: 1) identifying "features" of the raw gait kinetic data using singular value decomposition, 2) identifying a subset of features that account for a large percentage of the information in the raw gait kinetic data, 3) expressing the raw data from a group of typically developing children as a linear combination of these features, 4) expressing a subject's raw data as a linear combination of these features, 5) calculating the magnitude of the difference between the *subject* and the mean of the *control*, and 6) scaling and transforming the difference, in order to provide a simple, and statistically well-behaved, measure. Linear combinations of the first 20 gait features produced a 91% faithful reconstruction of the data. Concurrent and face validity for the GDI-Kinetic are presented through comparisons with the GDI, Gillette Functional Assessment Questionnaire Walking Scale (FAQ), and topographic classifications within the diagnosis of Cerebral Palsy (CP). The GDI-Kinetic and GDI are linearly related but not strongly correlated ($r^2 = 0.24$). Like the GDI, the GDI-Kinetic scales with FAQ level, distinguishes levels from one another, and is normally distributed across FAQ levels six to ten, and among typically developing children. The GDI-Kinetic also scales with respect to clinical involvement based on topographic CP classification in Hemiplegia Types I–IV, Diplegia, Triplegia, and Quadriplegia. The GDI-Kinetic complements the GDI in order to give a more comprehensive measure of gait pathology.

Introduction

There is a need for, and interest in, methods to quantify the amount of pathology present in the gait of patients. The needs range from gait classification to objective assessment of outcome. The interest can be seen in the number of techniques that have been proposed [6,15,53,54]. Recently, the gait deviation index (GDI) was introduced as a measure of overall gait pathology [55]. The GDI is an intuitively scaled distance between the kinematics of a pathological gait pattern and those of the average normal gait pattern; based on a reduced-order approximation of the gait cycle. The GDI has been shown to be valid, robust, and practical [56–58]. The method used to derive the GDI can be applied to a broad range of waveform signals, including gait kinetics.

The following study introduces a new index, the GDI-Kinetic*;* a direct analog of the GDI; based on joint kinetics rather than kinematics.

Methods

The methodology used to develop the GDI was applied to kinetic variables to calculate the GDI-Kinetic [55]. Briefly, the method consists of:

1. Identifying “features” of the raw gait kinetic data using singular value decomposition. This step is described in detail below.
2. Identifying a subset of features that account for a large percentage of the information in the raw gait kinetic data.
3. Expressing the raw data from a group of typically developing children as a linear combination of the features chosen in step 2 (*control feature scores*).
4. Expressing a subject’s raw data as a linear combination of the features chosen in step 2 (*subject feature scores*).

5. Calculating the magnitude of the difference between the *subject feature scores* and the mean of the *control feature scores*.
6. Scaling and transforming the difference found in the step 5, in order to provide a simple, and statistically well-behaved, measure.

The data used to identify the features in steps 1 and 2 were compiled from subjects seen in our center between February 1994 and January 2010, who completed gait trials without the use of assistive devices. In each session, for each side, barefoot strides that included a clean force plate strike were averaged. This resulted in at most two strides per session for each subject, for a total of $N_{strides}$ = 8488 strides from 2792 subjects (some subjects were evaluated during multiple sessions). All data had been processed using either the Vicon Clinical Manager or Plug-in-Gait model. There was no explicit filtering of the kinetics. However, cubic splines were fit to the marker trajectories which facilitates algebraic differentiation of the spatial data over time. This results in smoother kinetics than if numerical differentiation of the raw data was used and essentially acts as a low-pass filter. Coronal and sagittal plane moments, and total joint power at the hip, knee, and ankle were normalized to body mass. The moments and powers were extracted at 2% increments throughout the gait cycle (6 moments × 51 points + 3 powers × 51 points = 459 datum). The data were then arranged in 459 × 1 gait vectors ($\mathbf{k}^i$, i = 1, $N_{strides}$)

$$\mathbf{k} = \begin{bmatrix} \{\text{sagittal hip moment}\},\{\text{coronal hip moment}\}, \\ \{\text{sagittal knee moment}\},\{\text{coronal knee moment}\}, \\ \{\text{sagittal ankle moment}\},\{\text{coronal ankle moment}\}, \\ \{\text{hip power}\},\{\text{knee power}\},\{\text{ankle power}\} \end{bmatrix} \quad \text{Eq 4.1}$$

$$\mathbf{k} = [\{\boldsymbol{k}_{\mathbf{1-51}}\}, \{\boldsymbol{k}_{\mathbf{52-102}}\}, \dots, \{\boldsymbol{k}_{\mathbf{358-408}}\}, \{\boldsymbol{k}_{\mathbf{409-459}}\},] \quad \text{Eq 4.2}$$

The vectors from every subject×side were concatenated to form a 459 × 8488 matrix **K**.

$$\mathbf{K} = \left[\begin{pmatrix} k_1^1 \\ k_2^1 \\ \vdots \\ k_{459}^1 \end{pmatrix} \begin{pmatrix} k_1^2 \\ k_2^2 \\ \vdots \\ k_{459}^2 \end{pmatrix} \cdots \begin{pmatrix} k_1^i \\ k_2^i \\ \vdots \\ k_{459}^i \end{pmatrix} \cdots \begin{pmatrix} k_1^{8488} \\ k_2^{8488} \\ \vdots \\ k_{459}^{8488} \end{pmatrix} \right] \quad \text{Eq 4.3}$$

The singular value decomposition of **K** was computed and unit length singular vectors $\{\widehat{\boldsymbol{\kappa}}_1, \widehat{\boldsymbol{\kappa}}_2, \widehat{\boldsymbol{\kappa}}_3, \ldots, \widehat{\boldsymbol{\kappa}}_{459}\}$ and singular values $\{\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_{459}\}$ were preserved. These singular vectors form an optimal orthonormal basis (*κ-basis*) for reconstructing the kinetic gait data and are the "features" referred to in steps 1 and 2 above. The *κ-basis* is optimal in that it maximizes the variance accounted for using the minimum number of features.

From this point, the derivation of the GDI-Kinetic then proceeds exactly as described in equations 3-12 by Schwartz and Rozumalski [55].

The resulting GDI-Kinetic is a scaled measure of the distance between a subject's gait and the average gait of a control group. The GDI-Kinetic can be interpreted as follows:

- GDI-Kinetic ≥ 100 indicates a subject who's kinetics are no further away from the mean control than would be expected of a subject with normal gait. In other words, a GDI-Kinetic of ≥ 100 indicates normal kinetics.
- Every 10 points that the GDI-Kinetic falls below 100 is one standard deviation further away from the control group mean. For example, a GDI-Kinetic = 86 is $1.4\times$S.D. further away from the control group mean than would be expected of a subject with normal gait.

The behavior of the new index for a sub-set of subjects with a diagnosis of Cerebral Palsy (CP) was examined relative to several other established measures of overall gait pathology (GDI, FAQ, and topographical classification as described by Gage [50]).

Results

Using 20 gait features accounted for 91% of the variance exhibited in the 8488 strides. This was deemed sufficient for the reconstruction of the kinetic data as it provides ~23× data compression without introducing significant reconstruction error (Figure 4.1).

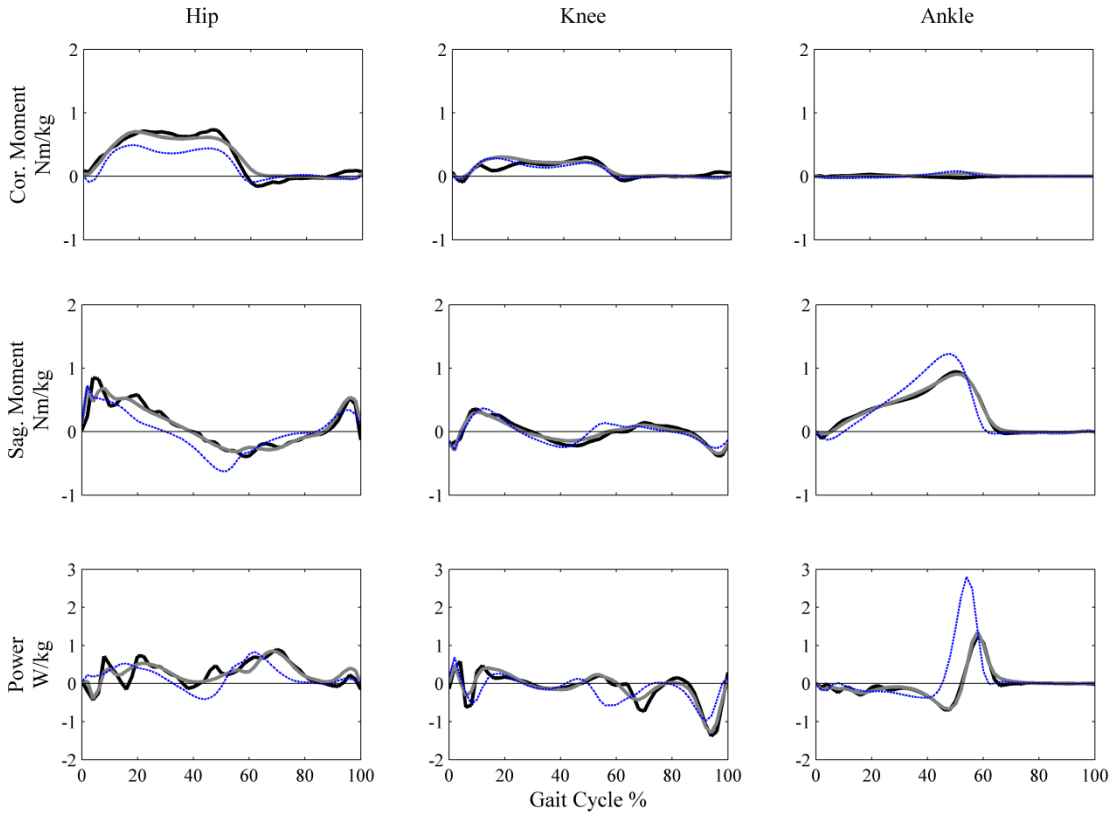

Figure 4.1 Moment and power graphs from one subject with GDI-Kinetic = 86. Black Solid (▬▬▬): original data, Grey Solid (▬▬▬): reconstructed data, Blue Dotted (·····): average normal kinetics. The reduced-order approximation faithfully reproduces most of the important elements of the kinetics (peaks, timing, ranges). Some filtering affects can be seen (e.g. in the Hip Power graph). These may be desirable, as in the case of noisy data, or undesirable, as in the case of rarely arising kinetic deviations.

The GDI and GDI-Kinetic exhibit a statistically significant linear relationship ($p < 0.01$), however strength of this relationship is relatively weak ($r^2 = 0.24$) (Figure 4.2).

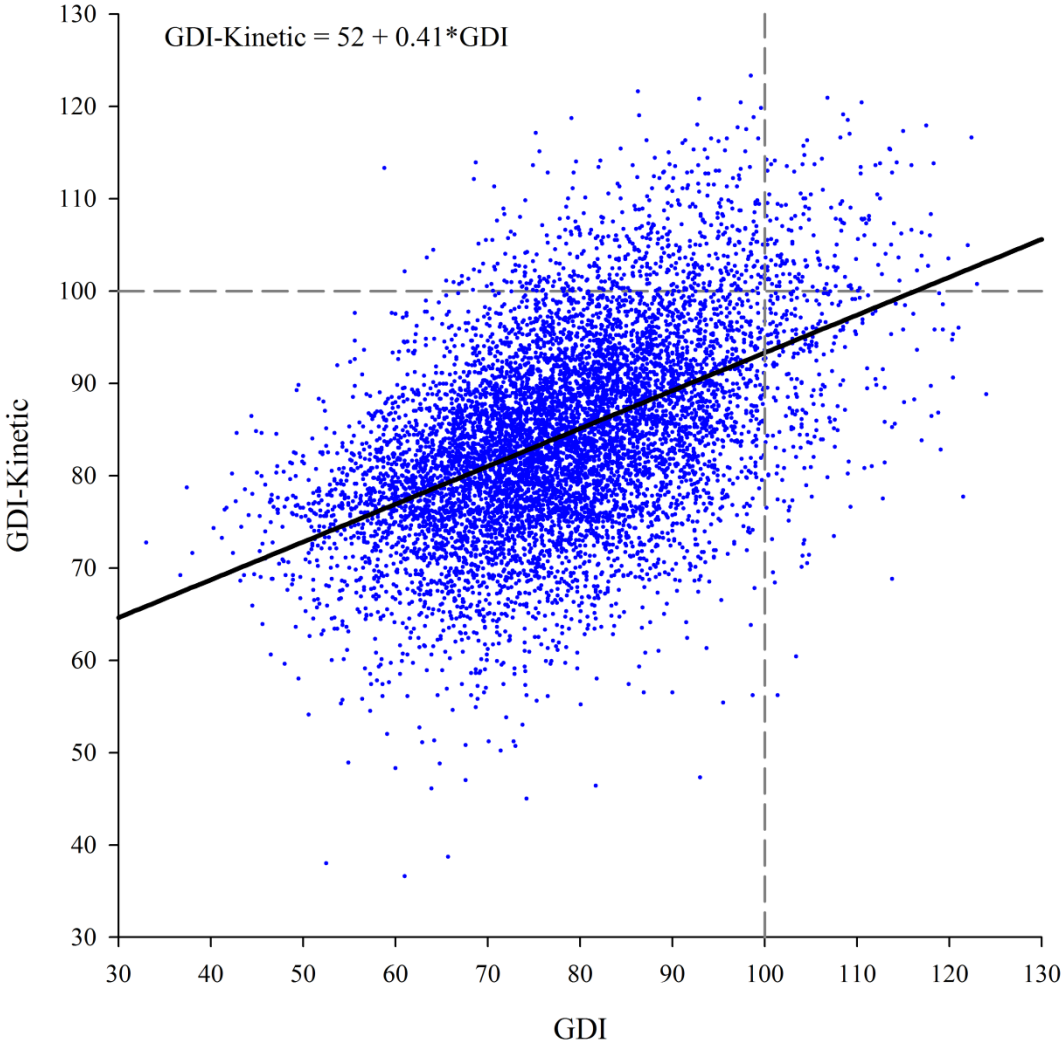

Figure 4.2 Scatter plot of the GDI vs. the GDI-Kinetic. The linear relationship (thick black line) shows that the two indexes are related, however, the spread in the data indicates that the indexes measure different aspects of gait pathology. A value of ≥ 100 indicates absence of pathology (dashed lines).

The GDI-Kinetic is normally distributed among subjects with gait pathology, as well as within separate functional walking levels as measured by the FAQ. The mean GDI-Kinetic values decrease monotonically for subjects in FAQ levels 10 through 6 (Table 4.1). The average decrement from level 10 to level 7 is 2.4 (SD 1.2).

Table 4.1 GDI-Kinetic by FAQ Level

FAQ	N	Mean GDI-Kinetic
10 (9,8,7,6)	2041	87.4
9 (10,8,7,6)	2807	85.0
8 (10,9,6)	1620	81.6
7 (10,9)	841	80.5
6 (10,9,8)	308	79.0

Parentheses indicate FAQ levels that are statistically different from the given level ($p < .01$).

When examining the mean GDI-Kinetic values for the different CP sub-types, there is the expected decrease from Hemiplegia → Diplegia → Triplegia → Quadriplegia.

Table 4.2 GDI-Kinetic by Topographic Sub-Type

Diagnosis	N	Mean GDI-Kinetic
Hemiplegia Type I (unaffected side)	52	88.6
Hemiplegia Type I (affected side)	52	91.2
Hemiplegia Type II (unaffected side)	194	85.8
Hemiplegia Type II (affected side)	192	86.6
Hemiplegia Type III (unaffected side)	115	83.1
Hemiplegia Type III (affected side)	111	85.6
Hemiplegia Type IV (unaffected side)	160	77.7
Hemiplegia Type IV (affected side)	159	84.2
Diplegia	3536	82.6
Triplegia	785	81.6
Quadriplegia	548	80.4

Interestingly, for Hemiplegia types I-IV, the unaffected limb has a lower GDI-Kinetic score than the affected limb on average (Table 4.2).

Discussion

The choice of 20 gait features an arbitrary one. However, with 20 kinetic gait features the patterns were faithfully reconstructed, even when subjects had significant kinetic pathology. The reconstructed data is smoother than the original, while maintaining most of the information related to peaks, ranges, and timing. This is a consequence of the fact that the reduced-order approximation acts as a filter: selectively removing kinetic data that accounts for only a small amount of total variance in the sample. This selectively removed data may be “noise” in the kinetics arising from numerical differentiation, in which case important information is emphasized by the filtering effect. On the other hand, the removed data may reflect rare kinetic patterns, in which case potentially valuable information is lost.

The relatively low correlation coefficient between the GDI and the GDI-Kinetic indicates that for any given level of GDI-Kinetic, there can be a wide variety of kinematic patterns and *vice-versa*; suggesting each index is measuring a different aspect of gait pathology. Like the GDI, the mean of the GDI-Kinetic decreases monotonically as the FAQ level decreases. There is a larger difference between levels 8, 9, and 10 than between levels 6, 7, and 8. Subjects whose walking ability is classified as level 6 or 7 often require assistive devices when walking in the community. In this study, only subjects who were able to walk without assistive devices during their gait analysis were included. This means that

the number of subjects available in the lower FAQ levels was greatly reduced, possibly impacting this result.

An interesting finding relative to diagnostic subtype is that for subjects diagnosed as Hemiplegia types I-IV, the unaffected limb had lower GDI-Kinetic scores than the affected side. This indicates that compensations in the unaffected limb result in greater deviations from normal gait than are seen in the affected limb.

The GDI-Kinetic was developed analogously to the GDI, using gait kinetics instead of kinematics. Although each index provides a global measure of gait pathology, there are distinct differences between them. The GDI-Kinetic thus complements the GDI, giving a more comprehensive measure of gait pathology.

Chapter 5

5. Objective Classification of Crouch Gait

Published as:

Crouch gait patterns defined using k-means cluster analysis are related to underlying clinical pathology

Adam Rozumalski, Michael H. Schwartz

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Runner-Up ESMAC 2008 Best Paper Award

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Summary

In this study a gait classification method was developed and applied to subjects with Cerebral Palsy who walk with excessive knee flexion at initial contact. Sagittal plane gait data, simplified using the gait features method, is used as input into a k-means cluster analysis to determine homogeneous groups. Several clinical domains were explored to determine if the clusters are related to underlying pathology. These domains included age, joint range of motion, strength, selective motor control, and spasticity. Principal component analysis is used to determine one overall score for each of the multi-joint domains (strength, selective motor control, and spasticity). The current study shows that there are five clusters among children with excessive knee flexion at initial contact. These clusters were labeled, in order of increasing gait pathology: 1) mild crouch with mild equinus, 2) mild crouch, 3) crouch with anterior pelvic tilt, 4) crouch with equinus, and 5) severe crouch. Further analysis showed that age, range-of-motion, strength, selective motor control, and spasticity were significantly different between the clusters ($p < 0.001$). The general tendency was for the clinical domains to worsen as gait pathology increased. This new classification tool can be used to define homogeneous groups of subjects in crouch gait, which can help guide treatment decisions and outcomes assessment.

Introduction

Clinical gait analysis, as commonly prescribed for children with Cerebral Palsy (CP), is a complex procedure which includes examining data from several sources. Patient history, physical examination, and three-dimensional motion analysis all supply data related to the patient's gait impairments. Distinguishing patterns and tendencies within this large set of data can be difficult. However, subjective pattern recognition is the most common way

that clinicians interpret the results of a clinical gait analysis, and make treatment decisions [1]. For this reason, a method for objectively classifying gait data would be useful, by identifying groups of patients with common underlying clinical problems. Several methods have been introduced to classify gait in children with CP. The strengths and weaknesses of these methods have been discussed in a review by Dobson *et al.* [27]. Traditional classification schemes use a wide variety of gait variables to define their classification, including kinematics, kinetics, EMG, energy consumption and temporal spatial parameters. The review found that the "overall methodological quality of the studies evaluated … was low". This was due to poor description of the methods, small sample sizes and limited validity.

Gait data must be simplified to facilitate classification. This simplification ranges from selecting only a small number of clinically meaningful variables to using mathematical algorithms that automatically determine the relevant data [59,60]. For simplification to be effective, it needs to preserve the underlying information in the data so that the inherent relationships between data points are still valid

An efficient method of gait data simplification using *gait features* has previously been described [55]. The *gait features* approach allows for a significant reduction in the amount of data (more than 30 fold reduction) while preserving nearly all of the meaningful content (98% of the variance of the original data is accounted for). The current study seeks to take advantage of the *gait features* technique to develop a new, objective crouch gait classification scheme for children with CP.

The focus of the current study is on subjects who walk with excessive knee flexion at

initial contact. Among this group of subjects are those who, in addition to their poor landing position, fail to extend their knee during mid-stance. Such subjects are typically said to be walking in crouch gait. There are also subjects who, despite their excessive knee flexion at initial contact, manage to get their knees fully (or nearly fully) extended during stance. This pattern would not typically be called crouch. In fact, other labels have been applied, such as jump knee gait [59–61]. Both the "true" crouch and the jump knee gait pattern share the common problem of knee hyperflexion at initial contact. In fact, there may be reason to believe that jump knee gait may eventually lead to crouch gait if hamstrings contractures worsen, or plantarflexion power diminishes [1,62]. For this study, all patterns of gait that include knee hyperflexion at initial contact will be loosely referred to as "crouch". The point of the study, however, is to demonstrate that meaningful distinctions, both in pattern and underlying pathology, can be found within this general class of gait deviations.

Methods

Reduced order approximation of gait data

The use of singular value decomposition (SVD) to compute a reduced order approximation of gait data has previously been described [49,52]. The relevant elements of the method are summarized below:

1. Choose a continuous set of time series data of interest (such as kinematics, kinetics, and/or EMG), and rearrange the data as a "gait vector", **g**.
2. Collect a large sample (n) of vectors, representative of the population as a whole, and arrange as a matrix $\mathbf{G} = [\mathbf{g}^1, \mathbf{g}^2, \ldots, \mathbf{g}^n]$.
3. Compute the SVD of **G** to produce an optimal basis for the data, called "*gait*

features" [$\mathbf{f}^1, \mathbf{f}^2, \ldots, \mathbf{f}^n$].

4. Approximate the original data using the first *m* basis vectors; $\tilde{\mathbf{g}} = \sum_{\beta=1}^{m} (\mathbf{g} \cdot \hat{\mathbf{f}}_{\boldsymbol{\beta}})\, \hat{\mathbf{f}}_{\boldsymbol{\beta}}$.

Expressing the gait vector relative to the optimal basis maximizes the variance accounted for (VAF) in the gait data while minimizing the dimensionality. The *feature scores* $(\mathbf{g} \cdot \hat{\mathbf{f}}_{\boldsymbol{\beta}})$ are thus the projections of the original gait vector onto the first *m* directions of the optimal basis.

The number of *gait features* needed to adequately describe the data will vary depending on the amount of data being represented and the amount of detail required. For example, the Gait Deviation Index (GDI) is a multivariate measure representing the overall gait pathology of a patient. As a result, accurately representing a set of nine joint kinematic curves was required. This application required 15 features, accounting for 98% of the variance in the original data. Applications which require fewer gait variables or a less precise representation or may use fewer *gait features*.

Sagittal plane kinematics

As crouch is mainly a sagittal plane phenomenon, pelvic tilt, hip flex/extension, knee flex/extension and ankle dorsi/plantarflexion were used to comprise the gait vector **g** for this study. One stride per visit from each side of every patient seen in the motion lab between February 1994 and February 2007 was extracted from the database. This resulted in 6066 strides from 2159 patients. Patient ages ranged widely, and diagnoses were varied (Table 5.1).

Table 5.1 Subject Diagnoses

Cerebral palsy	71.2%

Developmental variants	4.3%
Traumatic/acquired brain deficit	3.4%
Normal	3.3%
Myelomeningocele	2.4%
Genetic disorder	1.3%
Neuromuscular unspecified	1.1%
Childhood CVA	1.1%
28 Other diagnoses ≤ 1%	11.9%

Thus it was reasonable to conclude that this set was a representative sample of the population of gait patterns, though it is biased towards those patterns exhibited by children with CP due to the nature of the clinical service at our center.

To determine the number of features needed to adequately represent each stride, the critical value for the VAF was set at 95%. This represents a compromise between fidelity (*e.g.* in the GDI, a 98% threshold was used) and complexity. Since the goal was to derive broad categories of gait patterns, additional detail was felt to be unnecessary.

Crouch

The data was further examined to determine which strides were considered to be in crouch. Strides were classified as being in crouch if knee flexion at initial contact was greater than 2 standard deviations above the average control value. This translated to knee flexion at initial contact greater than 20°. Once these strides were identified, the sagittal plane features scores were calculated.

Cluster analysis

A k-means cluster analysis was conducted on the *feature scores* to identify groups that occurred within the crouch data. The first four *gait features* derived from the sagittal plane kinematics explained 95.6% of the total variance in the data. Therefore, the first four *feature scores* for each stride were considered sufficient as input to the subsequent cluster analysis. K-means cluster analysis requires that the number of clusters be pre-determined, and that each stride belongs to only one cluster (“crisp” clusters). The

number of clusters was iteratively increased from 2 to 20 and the Dunn index was calculated for each iteration [63]. The Dunn index reaches a maximum for the configuration which optimizes the combination of inter-subject distances within a cluster and inter-cluster distances.

The distance of each subject's gait to each cluster center was determined, and membership was assigned to the closest cluster. To determine how robust the cluster configurations were, a v-fold cross-validation was conducted for each configuration (2 – 20 clusters). Details of the v-fold cross-validation are as follows:

- For each configuration (2-20 clusters), the k-means cluster analysis was performed using all of the crouch strides. This analysis determined a *reference* membership for each stride.
- The collection of all strides was then randomly split into 10 equal size sets (or folds).
- The k-means cluster analysis was repeated using 9 of the folds.
- Cluster membership for the strides in the fold that was held out was calculated based on the new clusters to determine a test membership for each stride. This process was repeated 10 times, holding out a different fold each time. All of the strides then had both a reference and test membership.
- The misclassification rate was calculated as the number of strides for which there was a difference in reference and test membership, divided by the total number of strides.

Clinical Parameters

Relevant clinical data was also compiled from several different domains, and used to

characterize the subjects' underlying pathology. This data included:

- Age at initial visit
- Range of Motion of the hip flexors, knee flexors and plantarflexors: contracted defined as lacking 10° from full range, otherwise sufficient.
- Strength at the hip, knee, and ankle using the Kendall scale: trace-1, poor-2, fair (anti-gravity)-3, good-4, normal-5.
- Selective motor control of the hip, knee and ankle: patterned-0, partially isolated-1, completely isolated-2
- Spasticity of the hip flexors, hamstrings, rectus femoris, and plantarflexors using a modified Ashworth score: no spasticity-1, sight increase in tone-2, more marked increase in tone-3, considerable increase in tone-4, rigid-5.

It was hypothesized that strength at the ankle would be correlated with strength at the knee and hip. To address the interrelationship between the strength at the various joints, a principal component analysis (PCA) was applied to the strength measures, and a single score describing the overall ankle, knee, and hip strength was defined [64]. The same inter-joint dependence was hypothesized for selective motor control and spasticity, and thus PCA was used to define a single score for each of these domains as well.

Comparison to normal kinematics

The first four *feature scores* of the sagittal plane kinematics were extracted for 83 subjects with normal gait, and these scores were averaged. The distance from this average to the center of each crouch cluster was computed. These distances reflect the overall level of sagittal plane gait pathology found in each crouch cluster; analogous to the measure of overall gait pathology embodied in the GDI. The further the cluster is away

from the average normal kinematic *feature scores*, the greater the pathology.

Results

Of the 6066 strides selected from the database, 2956 were from children with a diagnosis of CP who walked with greater than 20° of knee flexion at initial contact (*i.e.* were in crouch). These 2956 strides were included in the study.

Cluster analysis

The maximum Dunn index corresponded to the 5 cluster configuration. It is worth noting that the value was much less than one, indicating that the clusters were not compact and well separated. The stability of the clusters centers was quite high, based on cross fold validation; with a misclassification rate less than 5%. Taken together, these two findings suggest that although individual strides fall along a continuum between the clusters, there are repeatable sub-groupings within the overall pattern of crouch as defined here.

The sagittal plane gait pathology for the center of each cluster shows that as the distance from normal kinematics increases, so too does the amount of knee flexion at initial contact, with associated changes at each of the other joints. This allows the clusters to be ordered in terms of increasing pathology (**Figure 5.1**). Clusters are labeled as follows:

Cluster 1. Mild crouch with mild equinus

Cluster 2. Mild crouch

Cluster 3. Crouch with anterior pelvic tilt

Cluster 4. Crouch with equinus

Cluster 5. Severe crouch.

It should be noted that clusters 3-5 would be considered by most to be forms of “true crouch”. That is, subjects in these clusters present with persistent excessive stance-phase knee flexion, whereas subjects in clusters 1 and 2 have excessive knee flexion at initial contact, but reasonably well extended knees in mid-stance.

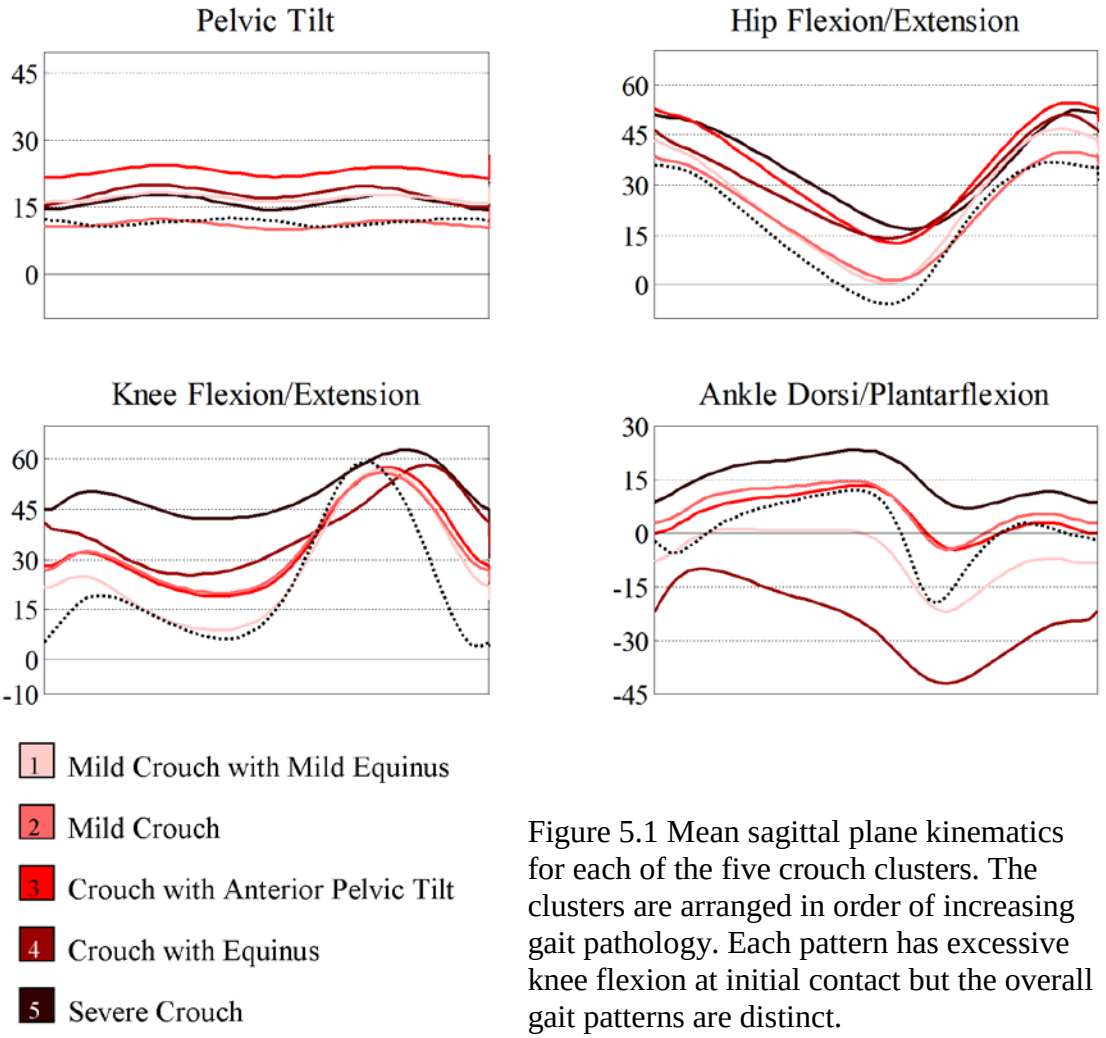

Figure 5.1 Mean sagittal plane kinematics for each of the five crouch clusters. The clusters are arranged in order of increasing gait pathology. Each pattern has excessive knee flexion at initial contact but the overall gait patterns are distinct.

Age

When comparing the ages of the subjects, cluster membership was a significant factor. Mean age for each cluster was 8.2, 10.7, 12.0, 6.8, and 12.3 respectively. Cluster 4 (crouch with equinus) was the youngest then clusters 1, 2, 3, and 5 increased in age respectively. The only two clusters that were not significantly different were 3 and 5.

Contracture

When comparing the number of subjects with joint contractures in each of the different clusters, the chi-square statistic was significant for the hip flexors, knee flexors and plantarflexors ($p<.001$). The percentage of subjects who had hip flexion contracture increased steadily from cluster 1 to cluster 5 (**Figure 5.2**). The rate of contracture for knee flexors did not show the same consistent trend. Clusters 4 and 5 had a noticeably higher percentage of contracted subjects. All of the subjects had excessive knee flexion at initial contact, but less than 20% of the subjects in clusters 1, 2, and 3 had a knee flexion contracture. The cluster with the largest percentage of subjects exhibiting plantarflexor contractures was cluster 4 (crouch with equinus) (**Figure 5.2**).

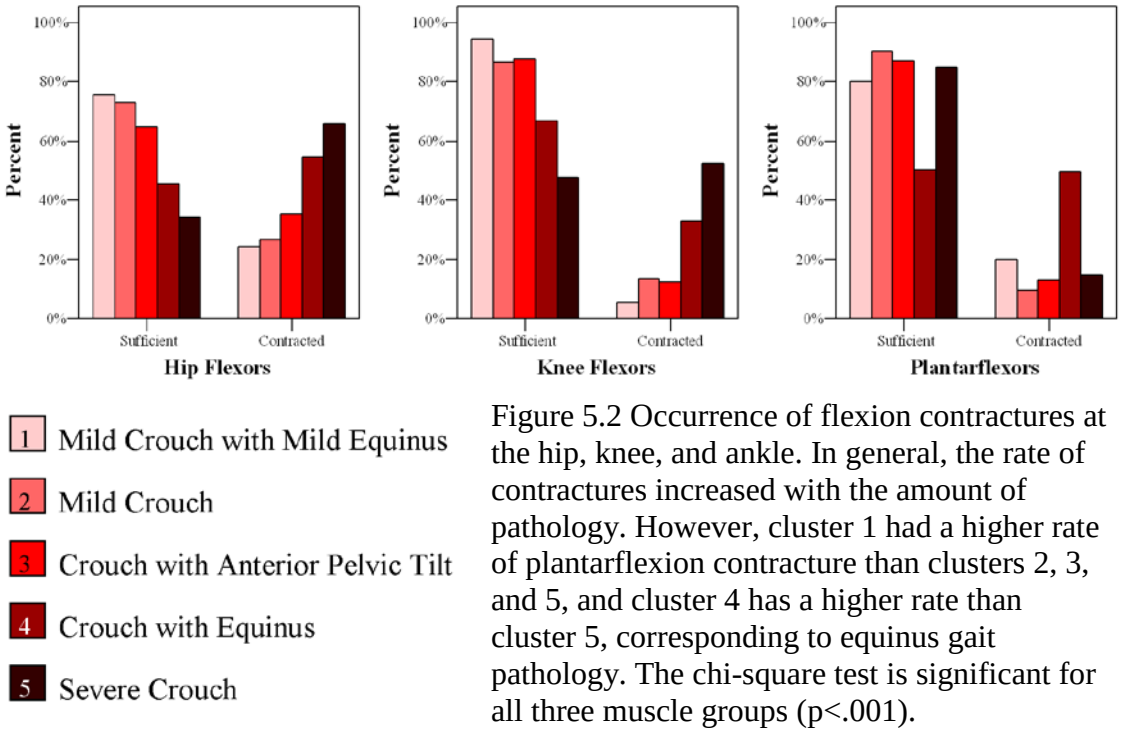

Figure 5.2 Occurrence of flexion contractures at the hip, knee, and ankle. In general, the rate of contractures increased with the amount of pathology. However, cluster 1 had a higher rate of plantarflexion contracture than clusters 2, 3, and 5, and cluster 4 has a higher rate than cluster 5, corresponding to equinus gait pathology. The chi-square test is significant for all three muscle groups ($p<.001$).

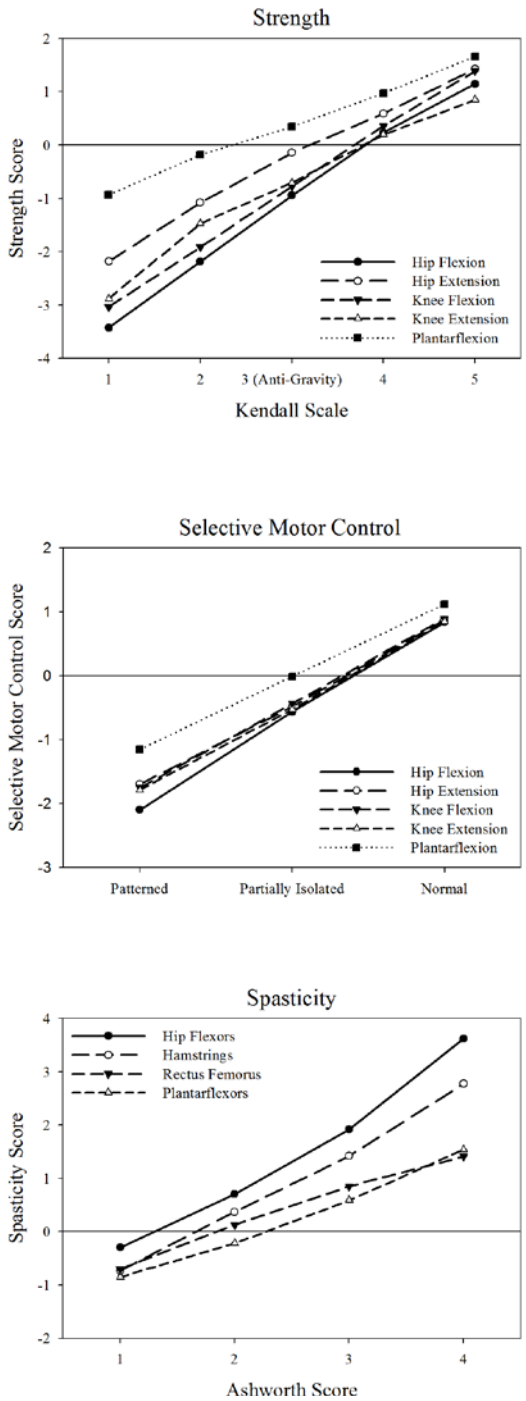

Figure 5.3 Principal component analysis of strength, selective motor control, and spasticity reveals strong linear relationships between the first principal components (scores) and the original measures. This implies that strength, selective motor control, and spasticity can each be described with a single score.

Principal Component Analysis

Strength was highly correlated ($p<.001$) between the hip, knee and ankle, as were selective motor control and spasticity ($p<.001$). When the principal component analysis was performed, the first principal component of strength, selective motor control, and spasticity accounted for 64%, 58%, and 52% variance respectively (**Figure 5.3**). The first principal components were then used as overall measures of strength, selective motor control, and spasticity.

Strength and Selective Motor Control

The strength score and selective motor control score varied similarly across clusters (**Figure 5.4**). Cluster membership was a significant factor for both scores ($p<0.001$). The mean of the scores monotonically decreased (impairment increased) from cluster 2 to cluster 5. Clusters 1 and 2 were not significantly different from each other but all other

comparisons between clusters averages were significant ($p<.001$).

Spasticity

The distribution of the spasticity scores was not as simple as those for strength and selective motor control (**Figure 5.4**). Although cluster membership was a significant factor ($p<.001$), subjects in clusters 1, 2, and 3 did not have significantly different spasticity scores. Subjects in cluster 4 (crouch with equinus) clearly had the most spasticity, followed by subjects in cluster 5 (severe crouch). Subjects in cluster 1, 2, and 3 had significantly less spasticity than subjects the other two clusters ($p<.001$).

Discussion

Classifying crouch gait patterns in children with CP using *gait features* and k-means cluster analysis results in five unique clusters. By definition, all of the clusters have excessive knee flexion at initial contact. However, each cluster has a distinct sagittal plane gait pattern. From cluster 1 to cluster 5 there is an increase in mid-stance hip and knee flexion

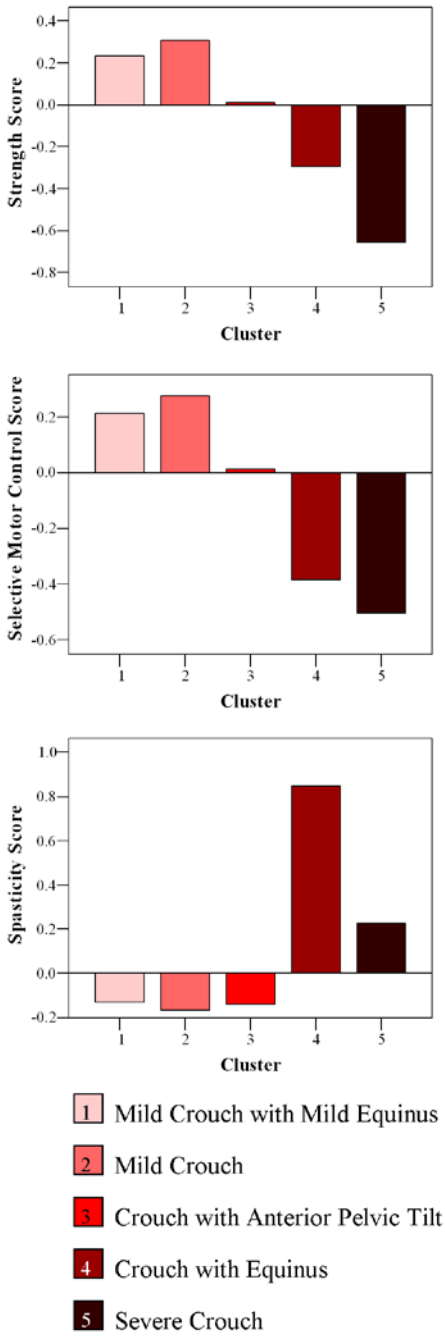

Figure 5.4 Mean clinical domain scores for each cluster. In general, clinical pathology increases with gait pathology. The scores for every cluster in each domain are significantly different from one another ($p<.001$) except for: clusters 1 and 2 for strength, clusters 1 and 2 for selective motor control, and clusters 1, 2, and 3 for spasticity.

corresponding to an increase in severity of crouch gait. At the ankle, clusters 1 and 4 exhibited persistent plantarflexion while clusters 2, 3, and 5 exhibited persistent dorsiflexion further separating the clusters into those with equinus and those without. Cluster 3 (mild crouch with anterior pelvic tilt) demonstrated the most anterior pelvic tilt which distinguishes it from cluster 2 (mild crouch). The clusters were also shown to be related to underlying clinical pathology. Clinical domains such as age, joint range of motion, strength, selective motor control, and spasticity all showed significant differences between clusters.

Spasticity across multiple muscle groups was found to be well represented by a single principal component. This suggests that although joint-to-joint variations in spasticity exist, there is a single dominant spasticity "signal". Strength and selective motor control displayed this same property. For this reason, spasticity, strength, and selective motor control all had their own overall score. Each clinical domain score showed significant differences between clusters which are also based on kinematic measurements taken at several joints. This implies that overall severity of spasticity, strength, and selective motor control are related to overall severity of grouch gait.

It is common to infer that weakness and poor selective motor control contribute to crouch gait [1]. The results of the current study show that as strength and selective motor control decrease, the severity of crouch worsens, conforming to general clinical impressions. This type of face validity is generally considered a key issue for the acceptance of any new gait classification scheme [27].

Spasticity is also thought to be a contributor to gait pathology [1]. However, the distribution

of the spasticity scores suggests that more spasticity does not necessarily mean more crouch. When looking at the mean of the spasticity score for subjects in each cluster, it is clear that subjects in cluster 4 (crouch with equinus) have the most spasticity. However, subjects in this cluster do not have the most crouch gait pathology. The mean of the spasticity score is significantly lower for subjects in the severe crouch cluster. Subjects in the three clusters with the least pathology also had the least amount of spasticity. This study did not examine prior treatments, including those aimed at reducing spasticity. The relationship between prior/future treatment and cluster membership is currently being examined.

Joint flexion contractures are known to be associated with crouch gait [1]. This is evident in the distribution of joint contractures among the clusters. As the amount of gait pathology increases, so too does the rate of joint contracture. The notable exception to this is the plantarflexors, where subjects in cluster 1 (mild crouch with mild equinus) had higher rates of contracture than subjects in cluster 2, 3, and 5 (mild crouch, crouch with anterior pelvic tilt, and severe crouch), and subjects in cluster 4 (crouch with equinus) had higher rates than subjects in cluster 5 (severe crouch). This exception reflects the fact that equinus is strongly associated with plantarflexion contractures, and that the k-means cluster analysis automatically distinguishes these subjects from those with neutral or excessively dorsiflexed ankles.

Many clinicians believe that there is a progression of sagittal plane kinematic pathology in CP [61,65]. This chronology was generally well reflected in the clusters derived here. The youngest cluster (cluster 4 – crouch with equinus) had the most persistent plantarflexion.

The remaining clusters 1, 2, 3, and 5 demonstrated an increasing age, accompanied by an increase in dorsiflexion, knee flexion and hip flexion throughout the gait cycle.

Using k-means cluster analysis, five distinct crouch clusters are defined. However, the Dunn index was less than 1.0 for all of the tested cluster configurations (2-20 clusters). This implies that the clusters are not "compact and well separated". There is a continuum of gait patterns between the cluster centers; and this is reflected in the actual data. Categorization of a subject in a single cluster is somewhat of an oversimplification. Any one subject will display traits from multiple crouch clusters. The closer the subject is to a cluster center, the more stereotypical she will be of that cluster, while a subject near a cluster boundary will display elements of the neighboring clusters. One of the strengths of this analysis is that the distance of any subject to any one crouch cluster center (or inter-cluster boundary) can be quantified.

The identification of five clusters was based on the Dunn index and v-fold cross validation. However, choosing three clusters performs only slightly less well. In the three cluster solution, clusters 1 and 2 are combined as are clusters 3 and 5. Most of the important trends would be maintained in this scenario but some of the subtle differences would be overlooked, such as subjects in cluster 1 walking with mild equinus and having a higher rate of plantarflexor contractures than clusters 2. Similarly, the three cluster solution fails to show the difference in spasticity, strength, or selective motor control between subjects in clusters 3 and 5. The study by Kienast *et al.*, performing cluster analysis on kinematic variables from children with diplegic CP, found three clusters as well [66]. However, one of the clusters in that study was made up of subjects with normal

kinematics.

Using *gait features* to simplify sagittal plane gait kinematics provides a framework for classifying gait. The five distinct crouch clusters identified by purely objective means differentiate themselves by more than just the kinematics on which they are based. There are clear differences in age, contracture, and generalized scores for strength, selective motor control, and spasticity. This new classification scheme can be used to describe crouch gait, help guide treatment decisions, and improve outcome assessment.

Chapter 6

6. Crouch gait clusters are related to treatment decisions

Adapted from:

Crouch Gait Patterns Derived from Cluster Analysis are Related to Clinical Parameters and Surgical Interventions

Adam Rozumalski and Michael H. Schwartz

Podium presentation at the 2009 Annual Meeting of the Gait and Clinical Motion Analysis Society, Denver, CO

Gait & Posture 30 (2009) S99-S100

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Introduction

Classification schemes have been used to describe walking patterns of children with cerebral palsy (CP), and to help guide treatment decisions [27]. One such pattern is crouch gait, which is characterized primarily by increased knee flexion in stance. A method has been developed to automatically identify homogeneous groups within the overall pattern of crouch gait [67]. The method uses a reduced order approximation of gait based on a limited number of *gait features* – elements of an optimal basis for describing kinematics. A subject's gait can be well described by just a few gait feature scores. When the gait feature scores of subjects in crouch are organized using a k-means cluster analysis, homogeneous groups that relate to underlying pathology emerge [67].

Classification schemes, when used correctly, are able to help guide treatment decisions and lead to more consistent outcomes. These classification schemes work best when they present a clear relationship between the treatment decision and the multitude of input streams that influence the treatment decision. The present study explores the relationship between objectively determined cluster group membership and subsequent, subjective, treatment decisions. Delineating meaningful groups within the overall gait pattern known as crouch will allow clinicians to better focus their treatment plans.

Methods

Using singular value decomposition, gait features of sagittal plane kinematics were derived from a subsequent analysis of the large database of strides described in the previous study [67]. The first four gait feature scores were calculated for children with Cerebral Palsy who walked with >20º knee flexion at initial contact. K-means cluster analysis was performed on the gait feature scores and the resulting clusters were

numbered by increasing pathology (1-mildest, 5-most severe, **Figure 5.1**) as measured by their proximity to normal gait [67].

The database was also queried to find patients who underwent surgical treatment after their gait analysis. The surgeries were classified into 10 meta-categories describing the general surgical goal (**Figure 6.1**). The number of limbs that underwent a specific surgery was counted for each cluster. The 95% confidence interval of the odds ratio was used to test for statistically significant differences in surgical decisions between clusters.

Results

K-means cluster analysis resulted in five clusters with robust centers identical to the previous study. Based on the observed gait patterns the clusters were named, in order of increasing severity, 1) mild crouch + mild equinus, 2) crouch, 3) crouch + anterior pelvic tilt, 4) crouch + equinus, and 5) severe crouch.

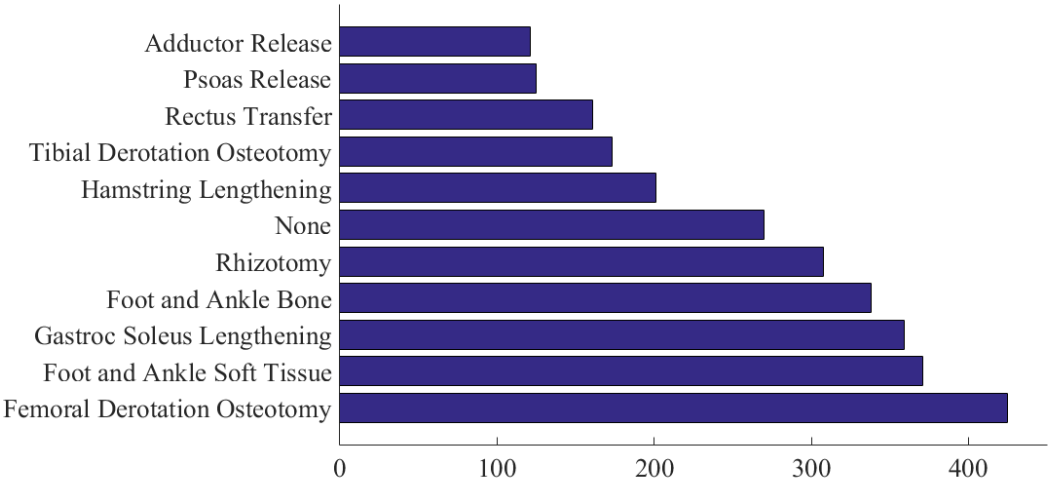

Figure 6.1 Histogram of treatment meta-categories. These categories account for 88% of the treatments done on this group. Note that "None", or no surgical intervention, is the 6th most common procedure.

There were 1281 subjects in this population who underwent a surgery after gait analysis. There were another 185 subjects included that did not have a subsequent surgery.

The most common 10 surgeries, as well as no intervening surgery, account for 88% of the treatments performed for this population (**Figure 6.1**). Therefore, it is appropriate to assume that this subset of all possible surgeries represents the bulk of treatments performed for this population.

Based on the 95% CI for the odds ratios, the surgeries that are significantly more or less likely are shown in **Figure 6.2**. From the figure it can be seen that the strides in all of the clusters are equally likely to receive no treatment. There is also an even distribution of the likelihood of receiving a gastroc/soleus lengthening. Cluster 1 is the mildest group

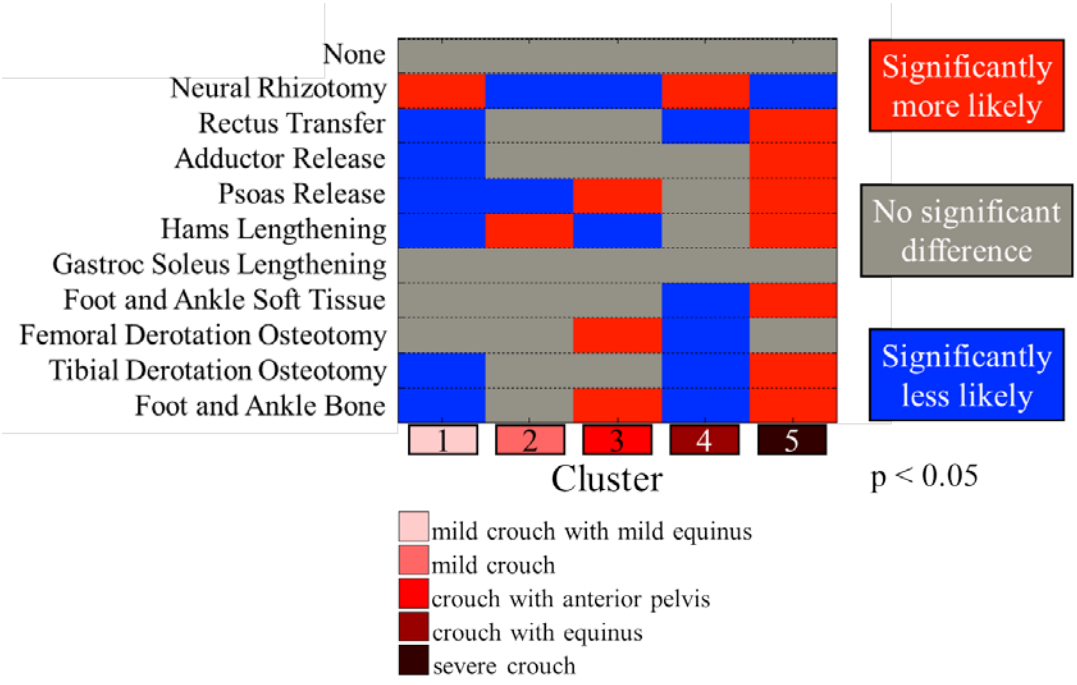

Figure 6.2 Summary of the odds ratios for each treatment. Blue cells indicate a surgery is less than half as likely to have performed on that Cluster. Red cells indicate a surgery that is at least twice as likely to have been performed. Grey cells indicate no significant difference (the 95% confidence interval of the odds ratio contains 1.0).

and is the least likely to undergo more than half (6 of the 11) of the treatments but cluster 4 is also less likely to undergo many treatments (5 of the 11). Cluster 5, the severe cluster, is more likely to undergo more than half of the treatments (7 of 11). It is also interesting that the two equinus clusters are the most likely to get a rhizotomy. These two clusters were observed to have more spasticity than the other groups in the previous analysis (**Figure 5.4**).

Discussion

The previous study showed that five distinct crouch clusters identified by purely objective means differentiate themselves by more than just the kinematics on which they are based. There were clear differences in age, contracture, and generalized scores for strength, selective motor control, and spasticity [67]. The results of this current study show that the crouch clusters also have distinctive treatment patterns.

Cluster 4 (crouch + equinus) has been shown to have a much higher level of overall spasticity than any of the other 4 clusters (**Figure 5.4**). Related to this is the finding that Cluster 4 patients are much more likely to undergo a selective dorsal rhizotomy (**Figure 6.2**). Cluster 5, however, is the only other cluster with elevated levels of overall spasticity (**Figure 5.4**), but it is significantly less likely to undergo a rhizotomy (**Figure 6.2**). Cluster 5 is also the oldest cluster. It is likely that this treatment pattern represents a center-specific treatment bias. At Gillette Children's Specialty Healthcare, the current treatment paradigm is to treat the patient's spasticity before treating orthopedic deformities. Cluster 4 is significantly less likely to undergo many of the orthopedic

procedures. It is possible that these two clusters represent the natural progression of CP treatment at this center.

The analysis done in this study is useful for highlighting when the clinical impression (described by the spasticity, strength and selective motor control scores, and by the incidence of contracture), the kinematics and the treatment plan all agree. The two clusters with the most anterior pelvic tilt (Clusters 3 and 5, **Figure 5.1**) are also the two clusters which are significantly more likely to have a psoas lengthening (**Figure 6.2**). These two clusters are also two of the three clusters with the highest rates of hip flexor contractures (**Figure 5.2**).

This analysis can also be useful in pointing out discrepancies that exist in the data streams. For example, Clusters 1 and 4 have the highest rates of plantar flexor contracture (**Figure 5.2**) and are the clusters with the most plantarflexion during gait (**Figure 5.1**). However, these clusters are no more likely to undergo a lengthening of the gastroc/soleus (**Figure 6.2**). Given that this treatment is one of the top three performed (**Figure 6.1**), this could point to an over-prescription of this treatment. However, further analysis will need to be done to test this hypothesis.

One of the limitations of this study is the fact that all interventions prior to the gait analysis were ignored. It would be interesting to see if these prior interventions have as strong a relationship with the Clusters as the subsequent interventions. The prior interventions are also likely to influence current treatment decisions.

The crouch clusters defined using the gait features and k-means cluster analysis arise from purely mathematical considerations. However, the strong relationship of these

clusters to underlying pathology and surgical intervention suggest that they may represent a valuable scheme for categorizing subjects who walk in crouch. Further value may be added to this analysis by examining the outcomes of treatments for each cluster.

Chapter 7

7. Assessment of Surgical Criteria

Presented as:

The Clinical Impact of Applying a Criterion for Predicting Rectus Femoris Transfer Surgery Outcomes: Evaluation via Retrospective Case-Control Design

Adam Rozumalski, Dinesh Thawrani, Tom F. Novacheck, and Michael H. Schwartz

Poster presentation at the 2011 Annual Meeting of the Gait and Clinical Motion Analysis Society, Washington, DC

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Introduction

Distal rectus femoris transfer (RFT) is widely considered an effective treatment for stiff knee gait (SKG) in ambulatory individuals with cerebral palsy (CP) [30]. However, controversy exists regarding the expected outcomes [31,32]. Reinbolt *et al.* hypothesized that the inconsistency of outcomes was due to a lack of an optimal patient selection criterion. To address this, supervised learning was used to derive a score capable of correctly predicting outcomes after RFT 80% of the time [33]. No control group was tested in Reinbolt's study, thus it is unclear whether the score was specific to the RFT, or merely predicted subjects likely to benefit from single event multi-level surgery (SEMLS). The current study re-evaluates Reinbolt's criterion on both a group of subjects who underwent RFT as part of a SEMLS and a matched control group that also underwent SEMLS without RFT.

Methods

This retrospective, case-control study examined 145 individual limbs from 112 children with CP and SKG who underwent SEMLS that either included or did not include an RFT (± RFT). For this study, SEMLS was defined as two or more major orthopedic procedures on any one limb, and individual limbs were considered separately. Each subject had a pre-operative gait analysis no more than 18 months prior to the SEMLS, and a post-operative gait analysis between 9 and 24 months after the SEMLS. All of the subjects were able to walk without the use of an assistive device. Following Reinbolt, SKG was defined as a limb meeting 3 or 4 of the following parameters: 1) peak swing-phase knee flexion less than 48.1°, 2) timing of peak swing-phase knee flexion later than 80.6% of the gait cycle, 3) early swing-phase (foot-off to maximum flexion) knee flexion

range of motion less than 18.0°, and

4) overall knee flexion range of

motion less than 45.9°. These values represent a decrease or delay of at least 2 standard deviations when compared to a control group.

The criterion developed by Reinbolt was used to retrospectively predict which limbs would benefit from including RFT as part of the SEMLS. The value of the criterion, *c*, was calculated using the following equation:

$$\boldsymbol{c = 0.63 - 0.28 \times KFVEL_{FO} - 0.49 \times KPWR_{40} + 0.50 \times HPWR_4.} \quad \text{Eq 7.1}$$

where $KFVEL_{FO}$ is the knee flexion velocity at foot-off, $KPWR_{40}$ is the knee power at 40.7% of the gait cycle and $HPWR_4$ is hip power at 4.4% of the gait cycle. A value c < 0.5 indicates that the limb is predicted to benefit from an RFT. The outcome of the intervention was considered good if the limb was not classified as walking in SKG after surgery (recall that all limbs were classified as SKG prior to surgery). The benefit (percentage of good outcomes) that could be expected when following the criterion was calculated as

$$\boldsymbol{b = (\%crit^{+} \times \%good\ \mathbf{SEMLS + RFT}) + (\%crit^{-} \times \%good\ \mathbf{SEMLS - RFT})} \quad \text{Eq 7.2}$$

Where $\%crit^{+}$ and $\%crit^{-}$ are the percentage of limbs that did or did not meet the criterion respectively and %good SEMLS+RFT and %good SEMLS-RFT are the percentage of limbs that had a good outcome with or without an RFT respectively. To analyze the benefit of following the current practice, all of the limbs that had SEMLS+RFT are considered in the $crit^{+}$ group and all of the limbs that had SEMLS-RFT are considered in the $crit^{-}$ group.

Results

Table 7.1 Chi-square tables for all subjects and for only subject who meet the criterion

		All Subjects		All Subjects who met criterion	
		+RFT	-RFT	+RFT	-RFT
Outcome	Good	52	21	33	17
	Bad	37	35	14	19
Odds ratio		2.34		2.63	
Chi-square test		p = 0.014		p = 0.034	

The odds ratio was 2.34 for SEMLS±RFT regardless of the criterion. This increased slightly to 2.63 when only the group that met the criterion was analyzed (Table 7.1). The results of the benefit analysis show that 49% of the limbs with SKG are expected to have good outcomes when following the recommendations of the criterion while 50% of the limbs are expected to have good outcomes when following the current clinical practice (Table 7.2).

Discussion

Table 7.2 Percentage of good outcomes expected using the criterion vs current clinical practice

	Reinbolt Criterion	Current practice
% met criterion (%$crit^{+}$)	57%	61%
	×	×
% good outcomes SEMLS+RFT	70%	58%
	+	+
% did not meet criterion (%$crit^{-}$)	43%	39%
	×	×
% good outcomes SEMLS-RFT	20%	38%
% good outcomes total	**49%**	**50%**

This study shows that the criterion proposed by Reinbolt does no better at predicting the outcome of RFT surgery than the current clinical practice at our center. This is likely due to the fact that the criterion was derived using only subjects who had undergone an RFT and therefore may have lacked specificity in terms of RFT

mediated vs. SEMLS mediated improvements. The current study adds a control group: limbs that had SKG and underwent a SEMLS but *did not* receive an RFT. The group that met Reinbolt's criterion did better overall (60% corrected SKG after SEMLS±RFT) and did better with an RFT (70% corrected SKG after SEMLS+RFT). However, the benefit is limited due to the fact that only 57% of the limbs with SKG met the criterion. The limited value of the criterion can only be seen when a control group is identified and analyzed. In this study, the criterion did not perform as well on the +RFT group (63% correct prediction) as in the Reinbolt study (80% correct). This may be due to the fact that in the original study, "*nineteen [of 81] subjects were classified as borderline cases postoperatively and excluded from further analysis*." [33] The current study shows that, when taking a control group into account, the criterion developed by Reinbolt is no better than the current clinical practice at predicting who will do well with RFT surgery. Further study needs to be done to develop decision support tools that help predict good and bad outcomes, and thereby optimize clinical benefit.

Chapter 8

8. Assessment of muscle synergies during treadmill gait

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Muscle Synergies Do Not Change in Typically Developing Children Walking on a Treadmill at Multiple Slopes and Speeds

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Introduction

Recent research suggests that the central nervous system (CNS) uses a modular approach to controlling movement [35–37]. These modules reduce the number of degrees of freedom the CNS needs to control by allowing groups of muscles to be recruited together as one unit. These groups of muscles are commonly referred to as synergies or modes. It has been shown that similar synergies are recruited during many different physical activities (*e.g.*, walking, running, cycling, etc.)[38,39]. However, it is still unclear whether these synergies are neurological in origin (*i.e.*, the neurological pathways exist specifically to recruit muscles together) or mechanical in origin (*i.e.*, mechanical constraints dictate certain patterns of muscle coordination)[40,41].

Individuals with neurological deficits (*e.g.*, stroke or cerebral palsy) use fewer synergies in order to complete a movement task [42–45]. If synergies truly have a neural origin, this could be an adaptation to the injury that further simplifies control. However, this simplification comes at a cost. The movement patterns of individuals with neurological deficits are significantly different from, and less efficient than, the movement patterns of intact individuals [1]. If synergies are mechanical in origin, the reduction in the number of synergies could be explained by the fact that the simplified movement pattern favors a certain muscle activation pattern independent of neural control [40]. Understanding the etiology of synergies is important for interpreting the impact that altered synergies may have in cerebral palsy and other neurological disorders. These factors may help guide treatment decisions in these patient populations.

Synergies are identified from electromyography (EMG) data using algorithms such as non-negative matrix factorization. A small number of synergies can be used to describe

the activity of a larger number of muscles. In one study of normal walking, only 6 synergies were required to describe over 90% of the variance in 38 muscles [68]. Synergies with similar structures have been found in several independent studies [36,69,70]. These synergies also describe large amounts of the variance in the EMG data. Furthermore, the same synergies can be used for several different activities. One recent study of adults found that synergies remained constant when the participants were asked to voluntarily change their stepping pattern on a treadmill [71]. This would suggest that synergies do have a neural origin. However, other studies have explored the biomechanical constraints of the task performed in order to assess the range of possible control strategies. They found that some activities, like controlling the fingers, have only a small set of possible activation patterns, regardless of neurological input [41]. Clearly synergies cannot describe all of the muscle activity across all possible tasks. Still, studying how individuals adapt their motor control can provide valuable insight into how movement is directed by the CNS.

The aim of this study was to investigate if synergies change when unimpaired individuals walk on a treadmill at different speeds and slopes. In this study, children with normal motor control walked at several different speeds and slopes on an instrumented treadmill to test their ability to actively adapt their muscle activations in response to the changing conditions on the treadmill (biomechanical task constraints). Changes in speed and slope have been shown to elicit significant changes in lower limb kinematics and kinetics [72,73]. This requires adaptations of both the position of the joints, and the force produced by the various muscle groups. The changes in force generation and joint position were measured

along with corresponding synergies that were used to generate the new muscle forces. If there were no measureable changes in synergies, this would imply that there was an underlying tendency, independent of the biomechanical task constraints, for certain muscle groups to be activated together. Our hypothesis was that the significant changes in movement pattern associated with the slopes and speeds would not be accompanied by significant changes in synergies. By examining this question, we can gain insight into the neural and mechanical origins of synergies which may be important in the clinical recommendations and rehabilitation strategies for individuals with neurologic al deficits.

Methods

Sixteen typically developing children (10 male) were recruited for this study with an age range of 6 to 18 years old. There was a wide variety of experience with using a treadmill; with many of the younger participants having no prior treadmill experience.

Each participant completed a full over-ground gait analysis [74]. They were then asked to walk on an instrumented tandem belt treadmill (AMTI, Watertown, MA) starting at a speed matched to their self-selected over-ground speed. They were given 6 minutes to acclimate to the treadmill while it was level with the ground. The biomechanical task constraints of the walking task were then incrementally changed every thirty seconds for a total of nine different “stages.” Data was collected for each of the nine stages, each with a unique combination of speed and slope; 1) free speed, 0° slope, 2) 110% of free speed, 0° slope, 3) 120% of free speed, 0° slope, 4) free speed, 6° slope, 5) 110% of free speed, 6° slope, 6) 120% of free speed, 6° slope, 7) free speed, 12° slope, 8) 110% of free speed, 12° slope, and 9) 120% of free speed, 12° slope.

Lower extremity kinematic and kinetic data were collected using a 12 camera motion capture system (Vicon, Oxford, UK). Ground reaction forces were collected on the instrumented treadmill with custom software (Matlab, Natick, MA). Surface EMG data from 5 muscles on each leg (gastrocnemius, anterior tibialis, rectus femoris, vastus lateralis, medial hamstrings) was simultaneously collected (MLS, Baton Rouge, LA). EMG was sampled at 1080 Hz, band-pass filtered between 20 and 400 Hz, rectified, and then low-pass filtered at 10 Hz. To facilitate comparisons between participants, EMG from each muscle was normalized to its peak value for the stride.

The muscle synergies and synergy activations were calculated for each stride using non-negative matrix factorization [37]. Detailed descriptions of the algorithm can be found elsewhere [75]. Briefly, this algorithm calculates synergies (W) and the relative activation of those synergies (C) that satisfy the following equation:

$$\boldsymbol{X} = \boldsymbol{W} \times \boldsymbol{C} + \boldsymbol{\epsilon} \qquad \text{Eq 8.1}$$

Where X is an $m \times t$ matrix of muscle activations represented by the filtered, rectified and normalized EMG data, W is an $m \times n$ matrix of synergy weights, C is an $n \times t$ matrix of synergy activations, and ϵ is an error term. In this case, m is the number of muscles (five in this study), n is the specified number of synergies (from one to four in this study), and t is the number of time points (101 across the normalized gait cycle in this study). Therefore, the relative weighting of muscles in each synergy is the columns of W and the activation level of each synergy over the gait cycle is the rows of C. In order to avoid potential local minima, repetition of the non-negative matrix factorization was carried out with an iterative optimization that tested random initial estimates of W and C. The matrices that minimized ϵ, in a least squares sense, were chosen as the best estimate.

The total variance accounted for (VAF) by n synergies was calculated by comparing $W \times C$ and the EMG data. The analysis was repeated with the number of synergies, n, increasing from 1 to 4. A three synergy solution was able to account for 90% of the variance in the EMG data for 99% of the strides collected [Fig 1]. Therefore, the results from the three synergy solution were used for further analyses.

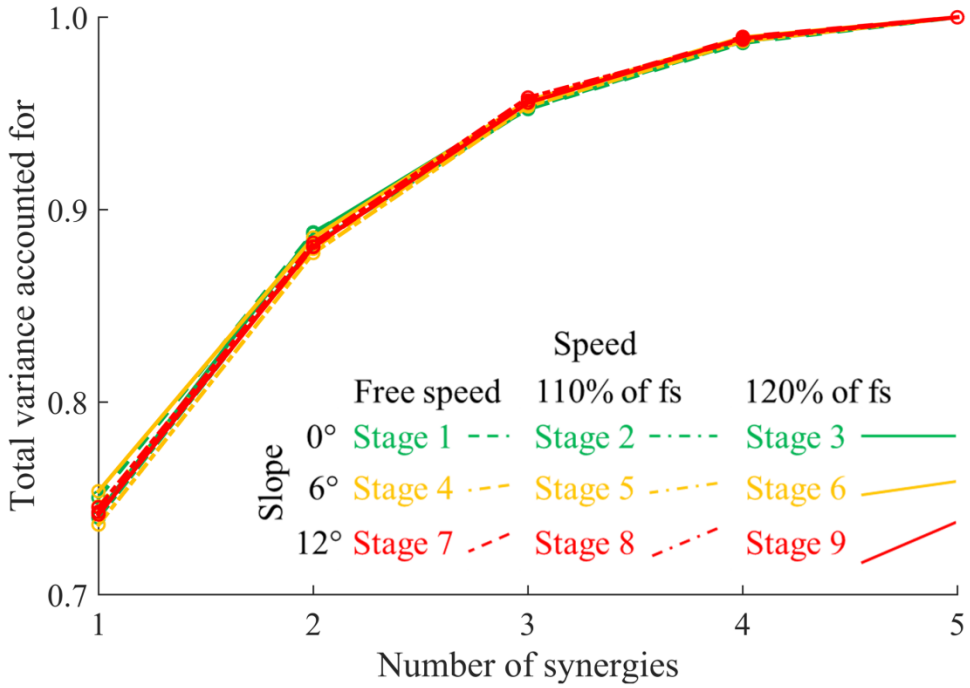

Figure 8.1 The mean total variance accounted for by 1 to 5 synergies was nearly identical for each stage.

It is possible that two different strides may have a synergy that relates to hamstrings activation, but this is the first column of W in the first stride and the second column of W for the second stride. In order to ensure that the synergies were organized consistently between strides, a K-means clustering algorithm was used [42]. Each column of W was taken as a point in m-dimensional space. Three clusters (one for each synergy) were then identified, such that the sum of the squares of the Euclidean distance of each synergy to

the cluster centers was minimized. Each stride then had a consistent and distinct label for each synergy.

The Pearson correlation coefficient was used to measure the consistency of synergies between stages [37]. The correlation coefficient was calculated for each stride in one stage compared to each stride in another stage. The two strides with the highest correlation coefficient were matched. The process was then repeated for the remaining strides until all the strides were matched for those stages. Each stage was then compared to each other stage in this way. A composite correlation coefficient was calculated as the mean of the matched correlations of one stage to all the other stages. A high composite correlation coefficient would indicate that the synergies were consistent between stages. These results were compared to the correlations that would be expected by chance. The same technique to make between-stage comparisons was used to compare each stage to randomly generated synergies (synergies comprised of random numbers between 0 and 1 for the weights). This is similar to the technique used by Tresch et al. [37]

The kinematics and kinetics for each stride were calculated using the Plug-in-Gait model with functional model calibration (Vicon, Oxford, UK) and compared between stages (*i.e.,* altered biomechanical task constraints). Changes in speed and slope have been shown to elicit significant changes in lower limb kinematics and kinetics [72,73]. These responses require adaptations of both the position of the joints, and the force produced by various muscle groups. The changes in force generation and joint position were measured along with corresponding changes in synergies. Since synergies represent activation from multiple muscles as they occur throughout the entire gait cycle, the kinematics and

kinetics were also summarized across the gait cycle. For the kinematics this was done using a modified version of the Gait Deviation Index (GDI) that only includes the sagittal plane angles of the pelvis, hip, knee, and ankle (GDIsag). The GDIsag measures the deviations in the kinematics from free-speed, level, over-ground walking in unimpaired children. Similarly, the kinetics for each stride were summarized by the GDIsag-kinetic which includes sagittal plane moments at the hip, knee and ankle as well as power from each of those joints. The GDIsag-kinetic measures the deviations in the kinetics from free speed, level, over-ground walking in unimpaired children. For both of these measures, a score of ≥100 in either index indicates normal kinematics or kinetics and each 10 points below 100 is 1 standard deviation from normal [55,76]. The choice to use only sagittal plane kinematics and kinetics stems from the fact that the muscle groups examined in this study function mostly in this plane. Furthermore, biomechanical changes induced by the treadmill occur predominantly in the sagittal plane. Therefore, related changes in the kinematics and kinetics are expected to be more prominent in the sagittal plane.

There was no regulation of the number of strides collected for each participant at each stage on the treadmill. However, at least four strides of data were collected for each participant at each stage. If more than four strides were collected, four strides were selected at random from all available strides. Data was pooled across subjects for each stage and t-tests were performed between each stage mean for the GDIsag and GDIsag-kinetic. If there were significant changes in GDIsag and GDIsag-kinetic at the same time that there were no measureable changes in the synergies, this would imply that there was

an underlying tendency, independent of the biomechanical task constraints, for certain muscle groups to be activated together across treadmill walking conditions.

Results

Synergies

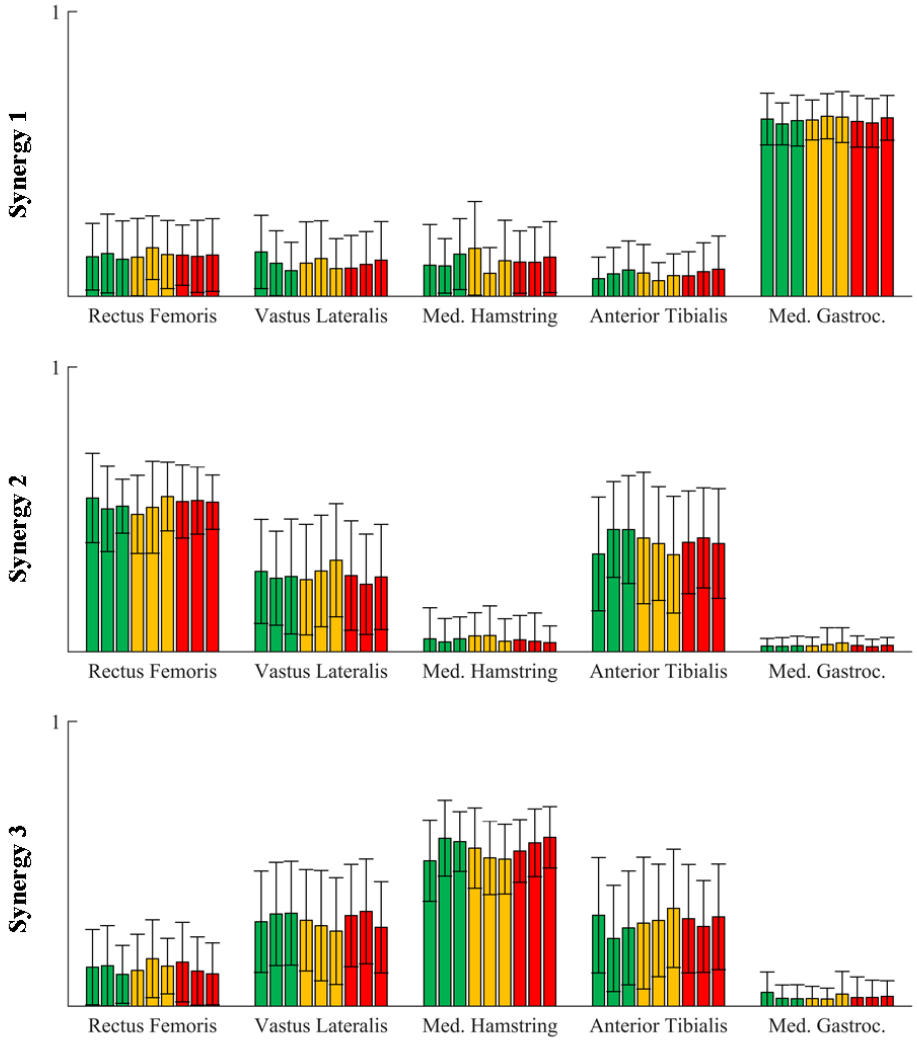

Figure 8.2 Synergy structures during treadmill walking were similar across the different stages. Stages are organized 1 through 9 from left to right for each muscle.

The structure of the synergies at each stage was nearly identical [Fig 2]. The correlations of the synergies between the stages were high [Fig 3a] with an average correlation

coefficient ranging from 0.867 to 0.983. These correlations were also significantly higher than what would be expected from a random group of synergies ($p<.001$) [Fig 3a]. This indicates that the synergy structure did not change across the multiple speeds and slopes on the treadmill.

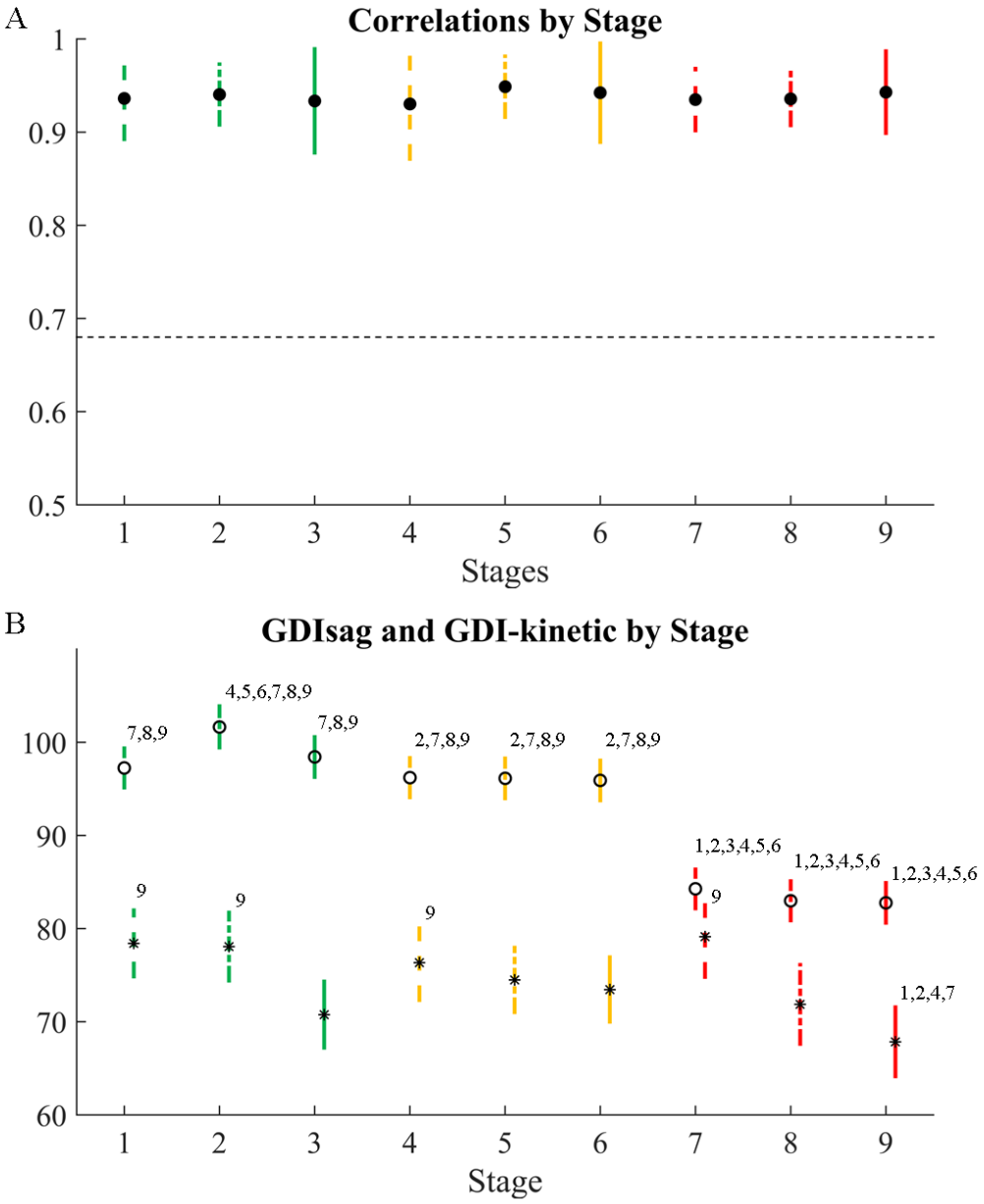

Figure 8.3 Summaries across the stages A) Correlations Average correlation coefficients comparing synergy weights of the synergies for each stage. There were no significant differences between stages and each stages was more highly correlated to each other stage than it was to a randomly generated set of synergies (dashed horizontal line). B) Average GDIsag and GDIsag-kinetic show significant differences between stages. The numbers indicate the stage for which there is a significant difference ($p<.001$ for kinematics and $p < .05$ for kinetics).

Kinematics

The kinematics showed significant and meaningful differences between stages. In general, increases in slope caused larger changes than increases in speed. Figure 4 shows

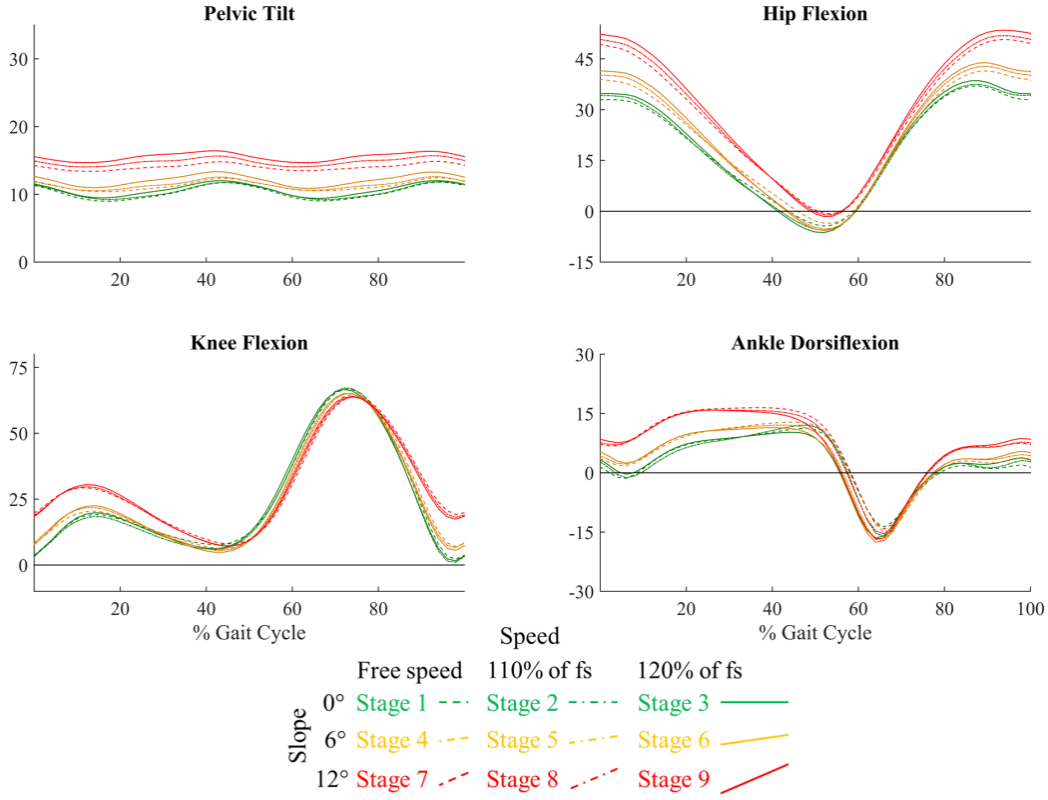

Figure 8.4 Average sagittal plane kinematics for each stage. The color scheme is identical to figure 1. In general flexion increases at each joint as the slope increases.

an increase in pelvic tilt throughout the gait cycle and an increase in hip flexion, knee flexion and ankle dorsiflexion in the early stance and late swing phases with increasing slope. Statistical analysis of the GDIsag shows that, on average, the kinematics at the highest slope were significantly different from those at the lower slope and at level walking ($p<.001$) [Fig 3A].

Kinetics

The kinetics also showed subtle, but significant differences between stages. Some of these differences appeared to be slope related, like a decrease in the knee moment in early stance and an increase in ankle power in late stance with increasing slope [Fig 5]. While changes in hip moment and power in early stance appeared to be more speed related. As

indicated by GDIsag-kinetic, the differences in the kinetics at the highest speed and slope were significantly different from those at the lower speeds (stage 9 was significantly different from stages 1, 2, 4 and 7, $p<.05$) [Fig 3b].

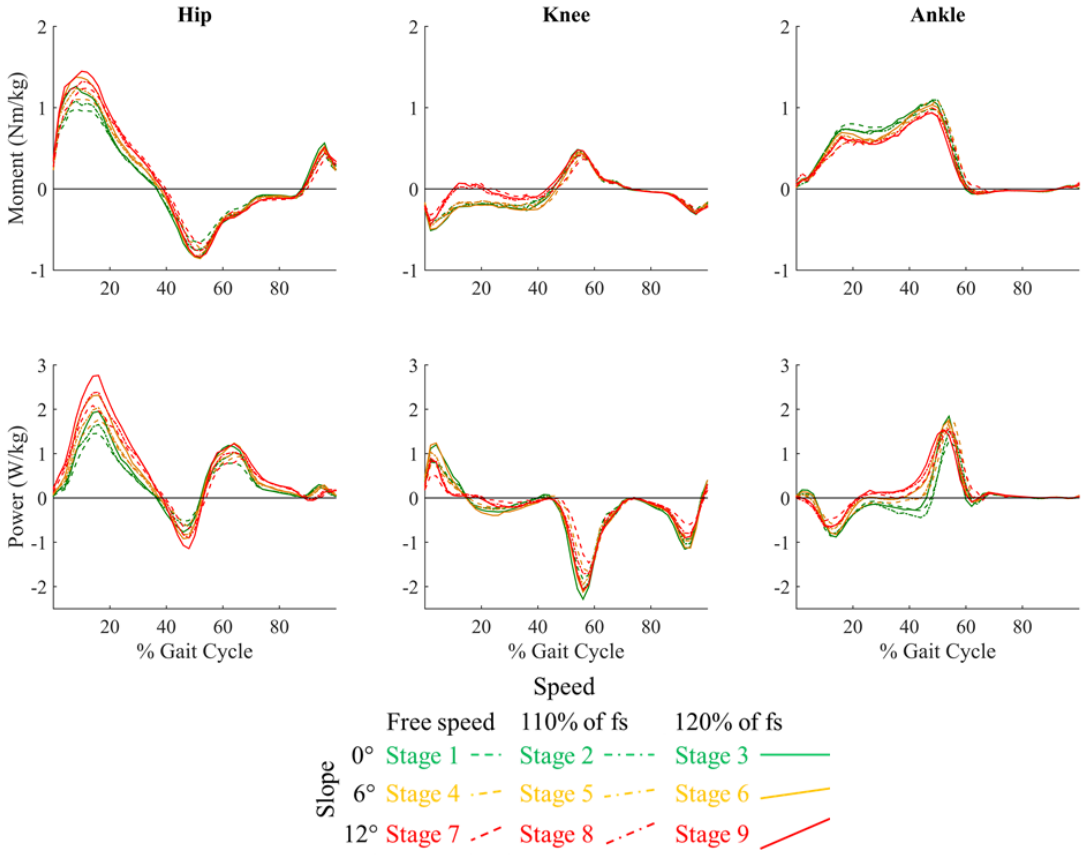

Figure 8.5 Average sagittal plane kinetics for each stage. The color scheme is identical to figures 1 and 4. In general moments and powers increase with both speed and slope.

Discussion

The lack of differences in muscle synergies between stages indicates that the participants in this study consistently activated similar synergies, even as speed and slope were increased while walking on a treadmill. However, despite the fact that synergies did not change, the participants were able to significantly change their kinematics and kinetics. The results of this study are similar to other studies in adults that show that similar muscle synergies are used across different activities such as walking, running, and cycling [38,39].

The current study provides further evidence for the theory that synergies are neurological in origin. The participants were able to actively adapt their muscle activations in response to the changing conditions on the treadmill (biomechanical task constraints). Changes in speed and slope have been shown to elicit significant changes in lower limb kinematics and kinetics [72,73]. This required an adaptation of both the position of the joints, and the force produced by the various muscle groups. However, the changes in force generation and joint position were not accompanied by a corresponding change in synergies. This implies that there is an underlying tendency, independent of the biomechanical task constraints, for certain muscle groups to be activated together.

The question then arises: if the synergies are not changing as the biomechanical task constraints change, what is causing the changes in movement pattern? One explanation is that the synergies are only part of the equation. To reconstruct the muscle activation patterns requires multiplying the synergies by their activations across the duration of the task. It is possible that the same synergies are being activated at different points in the task, creating the different movement patterns seen in this study. Another possible

explanation is that the differences in movement pattern are due to something other than synergistic muscle activation. In this study, the three synergy solution (synergies multiplied by their activations) accounted for over 90% of the variance in the EMG patterns across all of the stages. However, it is possible that the changes in movement pattern are due to the variance not accounted for by the synergies.

There are several limitations to this study. Only 5 muscles in the lower extremity were used to calculate synergies. These muscles, though, are routinely collected during gait analysis and are thought to be the main contributors to gait [50]. If there were alterations in the activations of the muscles in response to changes in gait, it is assumed that these muscles would be affected. Furthermore, the synergies identified in this study were similar to those identified in previous studies with larger sets of muscles [43]. It is therefore reasonable to assume that these results will be generalizable to larger sets of muscles. There was also a large range in the amount of prior treadmill experience between the participants. Several of the younger children in the group had never been on a treadmill before. This could potentially affect how they respond to the novel environment as they may adopt a gait pattern that makes them feel more stable. However, these adaptations would be expected to be small relative to the changes between stages [77]. Furthermore, each child was given several minutes to acclimate to the treadmill which has been shown to be enough time for habituation [78,79].

This study shows that for typically developing children walking at several different speeds and slopes on a treadmill, their muscle synergies do not change in response to changing biomechanical task constraints. It has been shown that children with

neurological deficits and simplified motor control, as in cerebral palsy, have fewer synergies that they are able to recruit. This has major implications for orthopedic surgery in this population. One hypothesis is that externally inducing a change in the biomechanical task constraints in these children (via surgery to the musculoskeletal system) would not be likely to change their synergies. Therefore, the expected outcome after orthopedic surgery for the child with large neurological deficits would be different than those for the child with only mild neurological impairment. Further study is needed to clarify the extent to which muscle synergies can be used to guide clinical expectations after orthopedic surgery.

Chapter 9

9. Concluding Remarks

Clinical gait analysis, as commonly prescribed for children with CP, is a complex set of procedures which includes examining data from several sources. Patient history, physical examination, electromyography, energy consumption, and three-dimensional motion analysis all supply data related to the patient's gait impairments. Distinguishing patterns and tendencies within this large set of data can be difficult. However, subjective pattern recognition is the most common way that clinicians interpret the results of a clinical gait analysis, and make treatment decisions [1]. For this reason, the tools developed in this project will be particularly useful. These tools are able to identify groups of patients with common underlying clinical problems and/or solutions.

In today's healthcare environment, the objective analysis of clinical data is more important than ever. The tools developed with this project are able to provide robust, repeatable, evidence-based guidance to highlight the most effective treatments for children with CP. These tools will also supply objective measures that can be included in the analysis of the outcome of the treatments.

The key to this research project has been the ability to take advantage of the vast amount of historical data present in the Center for Gait and Motion Analysis at Gillette Children's Specialty Healthcare. This was used to uncover underlying patterns that occur in the gait data of the patients seen in the motion analysis lab, in the clinical decisions that have been made based on that data, and in the outcomes of those decisions.

This project has highlighted the importance of a well-organized, robust patient database in medical research. The tools developed for data extraction have now also been used in subsequent projects that have provided a wide variety of translatable information. These

diverse follow-on projects include applications of data mining techniques to predict surgical outcome [80,81] and determining how neurological muscle control can influence expected surgical outcome [34].

The tools developed in this project have already made an impact in the field of gait analysis. The paper defining the GDI has been cited more than 200 times according to Google Scholar and is now more widely used in research and clinical settings than the Gillette Gait Index it was designed to replace. The crouch cluster paper, showing the mathematical relationship between gait data and clinical interpretation, and the GDI-kinetic paper have each been cited more than 20 times (Table 9.1).

Table 9.1 Number of citations for each of the included papers according to Google Scholar

Title	Citations	Reference
The Gait Deviation Index: a new comprehensive index of gait pathology	208	52
Crouch gait patterns defined using k-means cluster analysis are related to underlying clinical pathology	25	67
The GDI-Kinetic: a new index for quantifying kinetic deviations from normal gait	21	76

It is clear that the hypothesis from Specific Aim 1 is correct. The development of an objective, robust and intuitive measure of gait pathology has made a large impact on outcome assessment in gait analysis.

The patterns in crouch gait that were found using k-means cluster analysis showed that the first hypothesis of Specific Aim 2 was correct. The patterns in the kinematics were robust and related to clinical impression and treatment. These types of analyses could prove to be very useful in treatment guidance or in the training of new clinical staff in the field of gait analysis.

The second hypothesis of Specific Aim 2, however, was shown to be incorrect. Strict adherence to the clinical algorithms for determining appropriateness of psoas lengthening surgery or rectus transfer surgery did not results in meaningful improvements in outcome. These algorithms were largely based on accepted clinical wisdom, but only a thorough retrospective analysis that included a control group could show that these clinical impressions were incomplete. Further analysis is needed that does not rely on the historical clinical decision making process.

In the third Specific Aim I was able to show that muscle synergies are robust to biomechanical task constraints set by a treadmill. This implies that the synergies rely more on neurological input than responses to external mechanical constraints. This has the potential to make a large impact in the clinical decision making process. Patients with poor motor control (as measure via synergy analysis) may not be able to take full advantage of their realigned musculoskeletal system after orthopedic surgery.

As I move forward from this project, it is my goal to implement, and measure the impact of, these tools in the clinical setting at Gillette Children's Specialty Healthcare. If it can be shown that these tools have a direct clinical benefit, they can be used as a roadmap for designing and implementing further decision support tools in medicine.

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