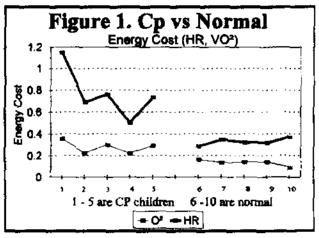
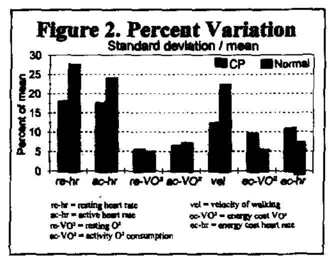
in children with cerebral palsy needs to be documented. The purpose of this study was to investigate the between day variability of energy consumption measurements for children with CP.

Methodolgy: Ten children, five with CP, and five non-disabled, age-matched peers volunteered for this study. Age of subjects ranged from six to sixteen years, with a mean age of ten years. Energy consumption was measured for each subject on five seperate days. A portable telemetric testing system was used to collect heart rate and oxygen consumption (VO^2). Expired air was continuously sampled, mixed in a dynamic chamber, and analyzed for % O^2. The portable unit transmitted data to a receiver, where it was later downloaded to a PC. Velocity was measured in meters/ minute. Heart rate and VO^2 were recorded in three phases: resting, self-paced walking, and post-walk resting. Equipment was calibrated prior to each test. At the beginning of each session, HR monitor and Rudolph mask were applied and the child was asked to sit quietly for three minutes. The child then walked through an extended hallway while a minimum of four minutes of steady state walking were recorded. Mean VO^2 and HR (at rest and during walk) and mean walking velocity were calculated for each subject.

Results: Figure 1 displays mean values for energy cost (energy consumption/ velocity) as a factor of either HR or VO^2, for all ten subjects. Figure 2 reports the percent variation in the measurements of resting HR and VO^2, walking HR and VO^2, walking velocity, and energy cost. These percentages were calculated by converting the mean and standard deviation for each variable, per subject, to a normalized score (SD/mean), and comparing scores within groups. Findings indicate that the variation in energy consumption measures for children with CP is similar to that in normal children. Despite relatively large variations in velocity for all subjects, the variability of VO^2 was minimal, and demonstrated less fluctuation than measures of energy cost. Intraclass correlation coefficeint (ICC) were calculated for the children with CP and normal using the 5 tests per child. The ICC for normal children's oxygen based energy cost was .778 and for the children with CP it was .877. The ICC for heart rate based energy cost for normal children was .718 and for children with CP it was .948.





Discussion: The clinical assesment of energy cost of walking has proved difficult in the past due to sophisticated testing equipment needs, and a poverty of pediatric normative data. This study examined a practical clinical method to collect energy consumption measurements. Findings for children with CP are comparable to other reports on the variability of these measures in normal children. Athough not significantly different, based on the ICC calculations there is a trend towards less variability in children with CP compared to non-disabled children of the same age. This indicates that methods for testing established for the normal population can be applied to children with cerebral palsy as a functional outcome assesment. The relationship of velocity to VO^2 needs further investigation. Although the data here do not provide a clear indication of which measures will be most useful in outcome assesment, we are encouraged with its potential for clinical testing.

References:

Bell, K. J., et al; Gait and Posture; 3(2); 87; 1995.
Rose, J., et al; DMCN; 32(4); 333-340; 1990.
Bandini, L.G., et al; Pediatric Research; 29(1); 70-77; 1991.

Quality Assurance/Reliability Studies: Theoretical Analyses

BOOTSTRAP SIMULTANEOUS PREDICTION AND CONFIDENCE INTERVALS FOR GAIT DATA

MW Lenhoff BS, TJ Santner PhD*, JC Otis PhD, MGE Peterson PhD, L Daly
The Hospital for Special Surgery, New York, NY, *Ohio State University, Columbus OH

Introduction

Traditional statistical methods used to analyze gait data calculate either prediction or confidence intervals at a set of time points across the gait cycle. A computationally intensive statistical method which calculates simultaneous intervals for gait data has significant advantages over the traditional methods. In addition to producing simultaneous intervals, the method we advocate is non-parametric in that it does not suppose a parametric form for the underlying curves being analyzed. The technique used to calculate the intervals is called a "bootstrap", and has been used previously. [1, 2] We have developed an easy to use software package to provide this type of analysis.

Methodology

A computer program written in the C language for the SunOS platform was designed to determine prediction and confidence intervals for joint angle and joint moment data across the gait cycle or any portion of the gait cycle.

The program calculates a Fourier series representation of the form

$$f(t) = \alpha_0 + \sum_{k=1}^{k=24} [\alpha_k \cos(\frac{2\pi k t}{t_{max}}) + \beta_k \sin(\frac{2\pi k t}{t_{max}})]$$

for each curve in the group of N curves to be analyzed. The mean value of the group was calculated by averaging each individual α and β coefficient across all files in the data set, and summing the Fourier series based on the averaged coefficients.

At each point t_j, $1 \le j \le t_{max}$, for the mean curve, the half length of the prediction interval was calculated, having the form $L = M * \sigma(t_j)$, where $\sigma(t_j)$ is the standard deviation calculated at point t_j, and M is a multiplier value calculated through the following iterative bootstrapping process:

For each iteration b, N "pseudo" curves were selected at random, where N is equal to the number of curves to be analyzed. After the pseudo data were selected, a set of values $M[1,b]...M[n,b]$ for the multiplier M was calculated for that iteration by the following formula:

$$M[i,b] = \max_{0 \le t_j \le t_{max}} \frac{|f_i(t_j) - \bar{f}(t_j)_{b_i}|}{\sigma(t_j)_{b_i}}$$

where $f_i(t_j)$ represents the value of the i th curve at the t_j point of the gait cycle, $\bar{f}(t_j)_{b_i}$ represents the average of the files selected in the current bootstrap iteration, and $\sigma(t_j)_{b_i}$ represents the standard deviation of the files selected in the bootstrap iteration.

After the final bootstrap iteration, the $M[i,b]$ values were placed into a list and sorted from the largest value to the smallest. The M value used to calculate the prediction interval was determined by selecting a value from the list such that a percentage P of the $M[i,b]$ values were less than the value of the multiplier. For example, if a 90% prediction interval was calculated, M was greater than 90% of the $M[i,b]$ values calculated through the iterative process. Confidence intervals are calculated through a similar iterative process.

A comparison was performed between the traditional point by point method and the bootstrap method for both confidence and prediction intervals. The effect of the number of iterations, number of Fourier coefficients used in the underlying model, the spread of the data, and the number of curves to be analyzed on the length and stability of the intervals was evaluated. This evaluation was performed with the intention of establishing a set of guidelines for proper use of the bootstrap intervals.

Discussion

The bootstrapping method provides a way to determine simultaneous prediction and confidence intervals. It has significant advantages over traditional methods of calculating these intervals on a point by point method. Simultaneous prediction bands cover the entire curve for a new subject drawn from the same population as the sample data, and are thus consistent with the visual interpretation that clinicians make from the plots of such curves. If the curve for a new subject is not covered by the simultaneous band, then that subject is considered to be significantly different than the sample population. In addition the approach also has the benefit of being a non-parametric analysis.

The stability of the confidence and prediction intervals generated through the bootstrap method increases as the number of curves to be analyzed increases. The stability also increased with an increasing number of bootstrap iterations. Further investigation is necessary to determine the minimum number of bootstrap iterations needed to provide a stable interval for a given number of curves.

It is our intention to make the code available to investigators for improvement and further beta testing. We believe that this method can provide the basis for a standard method of evaluating gait data.

References

1. Sutherland, D., Olshen, R., Biden E., Wyatt, M.: The Development of Mature Walking, Mac Keith Press, London, 1988.
2. Efron, B., Tibshirani, R.: An introduction to the bootstrap, Monographs on statistics and applied probability, Chapman & Hall, 1993.

FACTOR ANALYSIS OF CEREBRAL PALSY KINEMATICS: A PILOT STUDY

Robert D. McAnelly, M.D., J. Gail Walden, B.S., Nicolas E. Walsh, M.D.
Dept. of Rehabilitation Medicine, Univ. of Texas Health Science Center at San Antonio,
South Texas Veterans Health Care System, Audie Murphy Division, San Antonio, TX 78284

Introduction

Gait patterns vary in cerebral palsy (Gage, 1991). This study attempts to classify cerebral palsy objectively by factor analysis (Morrison, 1990 & Timm, 1975). Factor analysis identifies common patterns in a population, and we have looked at the factors of cerebral palsy joint plane kinematics to better understand the kinesiology of cerebral palsy gait.

Methodology

We reviewed the gait analysis data of 30 cerebral palsy patients who had undergone preoperative analysis using a 6-camera Vicon system with Helen Hayes marker sets. Twenty-two were previously diagnosed diplegic or quadriplegic, 7 were hemiplegic and 1 was athetoid. The 30 patients included 14 females and 16 males, ages 4 to 15 years old, weighing 13 to 57 kg, and measuring 0.93 to 1.68 meters in height. We averaged 3 gait cycles of overground gait, and produced joint plane kinematics every 6% of gait cycle for 60 patient sides. We used the statistical package SAS to generate common factors of each joint plane angle. We then calculated correlation coefficients to compare how the factor scores for each individual patient side correlated to the diagnosis of diplegia/quadriplegia, ipsilateral hemiplegic weakness and contralateral hemiplegic weakness, considering a correlation of > 0.4 or < -0.4 or more to be significant for this pilot study.

Results

The factors of Pelvic Tilt, Pelvic Rotation and Knee Flexion/Extension correlated significantly with the diplegic or hemiplegic diagnoses.