Friday, May 21st			
Start Time (UTC)	**Finish Time (UTC)**	**Event**	**Presenter**
2:00pm	**2:50pm**	**GPB Podium Session (concurrent)**	
2:00pm		DIFFERENTIATING FALLER AND NON-FALLER OSTEOPOROSIS PATIENTS USING DYNAMIC STABILITY	Seong Hyun Moon
2:10pm		HEAD MOVEMENT VARIABILITY IN CHILDREN WITH CEREBRAL PALSY	Elena Najdenovska
2:20pm		MODELING SPATIAL ASYMMETRY IN VISUOMOTOR COORDINATION	Kolby Brink
2:30pm		A MULTISCALE APPROACH TO HUMAN MOVEMENT VARIABILITY	Corey Magaldino
2:40pm		IS HIGHER GAIT KINEMATIC VARIABILITY INDICATIVE OF LOWER GAIT STABILITY?	Sina Mehdizadeh

DIFFERENTIATING FALLER AND NON-FALLER OSTEOPOROSIS PATIENTS USING DYNAMIC STABILITY

Seong Hyun Moon[1], Rahul Soangra[2], Chris Frames[1], Krupa Doshi[3], Thurmon Lockhart[1*]
[1]School of Biological and Health Systems Engineering, Arizona State University, Tempe, AZ 85287, USA
email: smoon13@asu.edu
[2] Crean College of Health and Behavioral Sciences, Chapman University, Orange, CA, 92866
[3] Division of Endocrinology, Mayo Clinic, Scottsdale, AZ, 85259

Presentation Preference: **Poster**

INTRODUCTION

Osteoporosis is a multifactorial skeletal disease that continuously reduces bone mass and tissue deterioration of microarchitectural structure [1]–[3]. Numerous patients who were diagnosed with this illness have a higher rate of experiencing bone fracture compared to the healthy group. Within the United States, 55% of people who are 50 years and older are expected to have osteoporosis disease [4]. The basic aspects that increase osteoporotic patients to fall are associated with aging, and physical degradation, and cognitive functionality [5]. The dynamic stability is quantified with the Maximum Lyapunov Exponent, which quantifies the local divergence of nearby trajectories and is approximated measurement of microscopic perturbation from its real-time responses [6]. The purpose of this research was to quantify dynamic stability while walking from osteoporosis patients and investigate if it can differentiate the Faller and Non-Faller group.

METHODS

For this study, a total of 16 osteoporosis patients participated, eight Faller and eight Non-Faller, and their anthropometry data is indicated in Table 1. Any subjects with current surgical treatment or hospitalization with any severe mental, respiratory, cardiovascular, and musculoskeletal diseases were excluded from the study. The participants signed the written consent authorized from Arizona State University and MAYO IRB before conducting the experiment. The Dynaport MM+ (Motion Monitor+, McRoberts BV, The Hague, Netherlands) IMU sensor was used to collect the continuous walking data from the subjects with a sampling frequency of 100Hz. While collecting the data, this device was located at the posterior lumbar region of the spine area. To collect the continuous gait data, 3minute walking was performed with each subject's normal walking speed without stopping on the clear pathway setting in a Mayo clinic.

Table1: The anthropometry information of Osteoporosis Faller and Non-Faller subject

	Osteoporosis			
	Faller (n = 8)		Non-Faller (n = 8)	
	M	**SD**	**M**	**SD**
Age	78.13	8.49	67.50	10.41
Height (cm)	162.19	9.48	164.39	9.03
Weight (kg)	66.73	15.19	70.73	21.45
Body Max Index (BMI)	25.86	6.53	25.89	6.58

RESULTS AND DISCUSSION

The result indicated that the Maximum Lyapunov Exponent for the Osteoporosis Fallers were 1.71 and Non-Fallers were 1.31, shown in Figure 1. Since the Maximum Lyapunov Exponent indicates the average logarithmic rate of divergence, the higher value represents instability of the larger divergence between the nearest neighbors and the lower value implies more stable kinematic stability [7]. This determines that the Faller group had immense instability when they are walking continuously compared to the Non-Fallers.

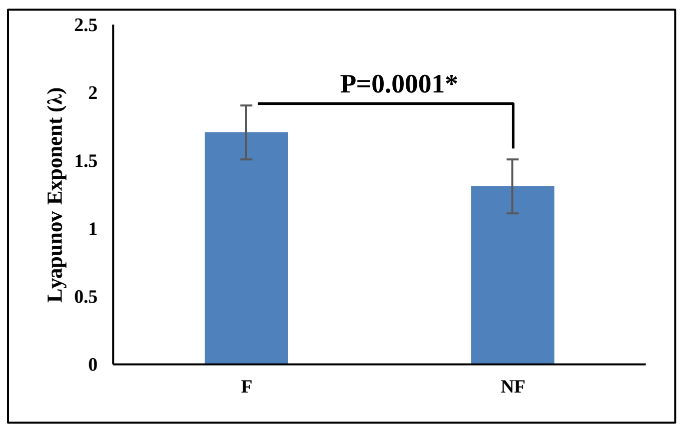

Figure 1: This graph represents the Lyapunov Exponent difference between the Faller and Non-Faller Osteoporosis patients

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Head movement variability in children with cerebral palsy

Ante Rosandic[1], Elena Najdenovska[1], Anne Tabard-Fougère[2], Stéphane Armand[2], Laura Elena Raileanu[1] and Jennifer Wegrzyk[3]
[1]University of Applied Sciences and Arts of Western Switzerland (HES-SO), La Haute École d'Ingénierie et de Gestion du Canton de Vaud (HEIG-VD), Yverdon-les-Bains, Switzerland; [2]Willy Taillard Laboratory of Kinesiology, Geneva University Hospitals and Geneva University, Geneva, Switzerland; [3]School of Health Sciences (HESAV), University of Applied Sciences and Arts Western Switzerland (HES-SO), Lausanne, Switzerland
Email: jennifer.masset@hesav.ch

Presentation Preference: **Podium**

INTRODUCTION

Motor deficits in children suffering from cerebral palsy (CP) result in gait deviations and vary depending on pathology severity. Head stabilization allows for visual-vestibular control of gait and posture and is likely to be perturbed in children with CP [1]. Head variability can be assessed between repetitive gait cycles using clinical gait analysis and might represent an indicator of overall walking function.

This exploratory study focuses on quantifying and comparing head variability between young individuals with CP and control subjects.

METHODS

249 subjects comprising 211 individuals with CP (hemiplegia, n=122; diplegia, n=76, quadriplegia, n=13) and 38 control subjects were included in this study. The analyzed trajectory was the average of all four head markers. For each subject, five gait cycles were randomly selected. Each cycle was further represented using 100 points (0%-100%) obtained by applying a linear interpolation. For each individual, the modeling included a projection of all points into the frontal plane. All points were then wrapped in one polygon concave hull. Based on least squares method, an ellipse that best encompasses the given points in a polygon was then fitted [2], and the ratio between the two axes of the ellipse was calculated. Finally, the standard deviation (SD) of the ratio for all five gait cycles represented the variability measure of each subject.

To compare the dispersion between groups, one-way ANOVA was used, with Tukey's HSD correction for multiple comparisons on post hoc, Cohen's d for effect size and significance level $p \leq 0.05$*.

RESULTS AND DISCUSSION

ANOVA results show that the SD ratio's mean values are significantly different for all three groups ($p < 0.0001$). Table 1 gives a more detailed comparison between the mean of the groups (post hoc comparison), which shows highest significant difference for control versus patients with severe motor deficits. Overall, the dispersion of cycle points is wider in patients than controls (Figure 1), reflecting increased head roll as a compensatory strategy for movement deficits [1].

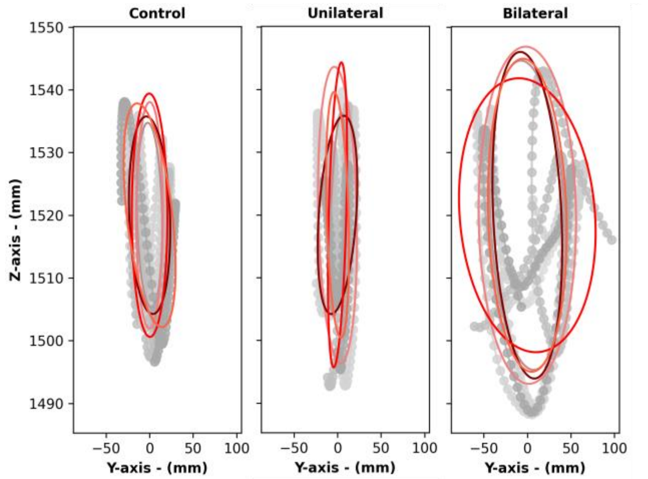

Figure 1: Frontal-plane movement dispersion/fitted ellipses on five cycles represented for one control subject, one patient with unilateral CP, and one patient with bilateral CP.

CONCLUSIONS

Head movement variability was increased for patients with severe motor deficits. The presented findings should be confirmed after correction for age and walking speed. Further studies are needed to explore variability metrics of different segments, as well as machine learning methods for an automatic classification of these groups.

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ACKNOWLEDGEMENTS

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Group A	Group B	Measures					
		mean(A)	mean(B)	diff	se	p-value	cohen
Control	**Bilateral CP**	0.20167	0.27153	-0.06987	0.01605	0.00100*	-0.84382
Control	**Unilateral CP**	0.20167	0.24018	-0.03852	0.01538	0.03316*	-0.46520
Bilateral CP	**Unilateral CP**	0.27153	0.24018	0.03135	0.01154	0.01834*	0.37862

Table 1: Tukey HSD post hoc comparison of the mean variability values (based on the SD of the ratio of all five cycles) between groups with correction for multiple comparisons.

Modeling Spatial Asymmetry in Visuomotor Coordination

Kolby Brink, Aaron Likens, and Nicholas Stergiou
[1]Department of Biomechanics, University of Nebraska at Omaha, Omaha, NE USA
email: kolbybrink@unomaha.edu

Presentation Preference: **Podium**

INTRODUCTION

Coordination is foundational to human movement[1]. One prominent model of coordination is the Haken-Kelso-Bunz (HKB) which predicts change in relative phase between two oscillators according to the following equation:

$$\dot{\phi} = \Delta\omega - a\sin(\phi) - 2b\sin(2\phi) - \sqrt{Q}\zeta_t,$$

where Δω quantifies differences in natural periods between the oscillators. The ratio, *b/a*, models the collective frequency of coordinated oscillation. $\sqrt{Q}\zeta_t$ is a noise term with strength Q. $\Delta\omega$ is an 'imperfection parameter' that predicts deviations in relative phase, ϕ, due to timing differences in oscillators. Another possibility is that deviations of ϕ might result from asymmetries in spatial alignment of oscillators, such as in visual motor coordination. We propose two possible mechanisms for modeling asymmetry based on a modified HKB model:

$$\dot{\phi} = \Delta\omega + \Delta s - a\sin(\phi - \eta) - 2b\sin(2\phi) - \sqrt{Q}\zeta_t$$

Two potential terms, Δs and η, can model the effects of spatial asymmetries of oscillators. Both predict shifts in mean relative phase, $\bar{\phi}$, away from stable fixed points. Only the Δs parameter predicts a shift in $SD_{\bar{\phi}}$, a decrease in the stability of coordination. This study was designed to distinguish which, if either, of those parameters best models spatial asymmetry.

METHODS

10 healthy adults (26.4 ± 6.87 years, 7 males, 3 females) participated in this study. A 6-camera system (Optotrak, NDI) measured upper body movement at 100 Hz. The aim was to investigate the effects of reference frame alignment on the form and stability of visuomotor coordination. Participants coordinated their arm movements with a visually displayed sinusoidally oscillating stimulus (S_{Sine}). Forearm movements pivoted about the elbow which rested on a rotating platform. A user controlled visual stimulus (S_{RA}) was displayed on the screen that oscillated due to elbow rotation. Figure 1A shows a display in which the horizontal centers of oscillation of S_{Sine} and S_{RA} are manipulated. Given horizontal screen coordinates (x) an amplitude of oscillation (A) of S_{Sine}, we scaled this offset parameter as $\rho = x_{shift}/A$ (Figure 1C). Figure 1B depicts the relative positions of S_{Sine} and S_{RA} for ρ = -2.0 over several cycles. We hypothesized that particular spatial offsets will be preferred. To test this hypothesis, we studied preferences for particular spatial arrangements of S_{Sine} and S_{RA} that arise from initial arrangements of ρ = -3, -2, -1, 0, 1, 2 or 3. Participants were free to move the location of S_{RA} as long as they could comfortably perform anti-phase and in-phase coordination. Subjects performed 3 trials for each phase (in-phase, anti-phase) × ρ pair, each lasting 60 seconds. 3 practice trials were given at ρ = 0 to familiarize subjects with the task.

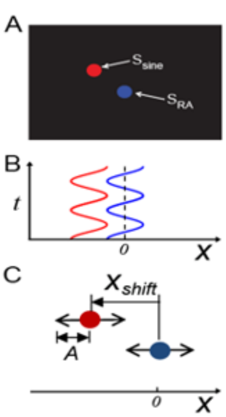

Figure 1. See Text

Analysis Strategy. We computed instantaneous relative phase between S_{Sine} and S_{RA} for all trials, along with circular means and standard deviations.[2] We then modeled $\bar{\phi}$ and $SD_{\bar{\phi}}$ as a function of ρ and phase (inphase/antiphase) in separate Bayesian multilevel models developed specifically for circular/directional dependent variables.[3]

RESULTS AND DISCUSSION

Estimates in Table 1 replicate well known differences between required phases because the 95% credible intervals defined by LB and UB do not overlap. Modeling results in Table 2 show that most slope estimates indicate that a one unit change in ρ predicts a negative change in $\bar{\phi}$ because credible intervals do not contain 0. Models relating ρ and $SD_{\bar{\phi}}$ (not reported to due to space) found no evidence of such a relationship, implying that Δs may not be useful in modeling asymmetry effects.

Table 1. Estimated circular descriptive statistics for $\bar{\phi}$ as a function of required phase. Estimates are in radians.

	Mean	Mode	SD	LB	UB
Anti-phase	-2.82	-2.87	0.13	-2.98	-2.59
In-phase	0.14	0.12	0.03	0.08	0.21

Table 2. Slope estimates for ρ predicting $\bar{\phi}$

Slopes	Mean	SD	Mode	LB	UB
β_c	-0.18	-0.22	0.23	-0.31	0.14
AS	-0.08	-0.08	0.15	-0.22	-0.02
SAM	-0.08	-0.09	0.06	-0.20	-0.02

Note: β_c = Slope at inflection point, AS = Average Slope, SAM = Slope at Grand Mean, LB/UB = Upper and lower bounds of 95 % credible interval from Bayesian estimates.

CONCLUSIONS

Results suggest that, in the current context, spatial asymmetries may best be modeled via the η parameter in the modified HKB model. Future work will investigate the extent to which this modification transfers to other conditions of asymmetry.

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A MULTISCALE APPROACH TO HUMAN MOVEMENT VARIABILITY

Corey M. Magaldino[1], Aaron D. Likens[2], Polemnia G. Amazeen[1], & Stephen G. West[1]
[1]Department of Psychology, Arizona State University, Tempe, AZ USA
email: cmagaldi@asu.edu
[2]Department of Biomechanics, University of Nebraska at Omaha, Omaha, NE USA

Presentation Preference: **Podium**

INTRODUCTION

Foundational studies in the field of motor coordination suggest that coordination is multiscale in nature. Von Holst [1] demonstrated that two oscillators coordinating at different frequencies influence each other. The participant whose data are depicted in Figure 1 moved the forearms up and down to establish a 2:1 pattern, with one arm moving twice as fast as the other. Superposition is evident in the trace of each arm: spectral decomposition would reveal the presence of both fast and slow frequencies in each signal.

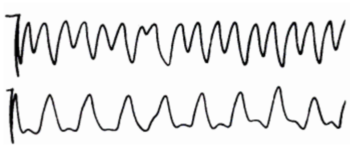

Figure 1: Von Holst (1937) observed bidirectional influence across the arms during performance of 2:1 coordination. The slow arm (bottom) shows influence of the faster arm (top) and vice versa.

A general characteristic of polyrhythmic coordination is that behaviors are performed at different tempos (frequencies) and are integrated into an overall, system-level, pattern. Since many group activities – e.g., teamwork in business, sport, etc. – result from integration of differently-timed behaviors, the primary goal of this research is to use multiscale analyses to understand coordination of polyrhythms within people at different scales.

METHODS

Data were from a pilot study on the polyrhythm performance in humans. Participants were seated in front of an iPad that displayed an image of the pattern to be performed (Figure 2).

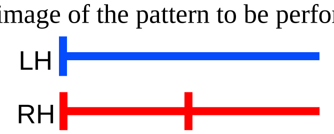

Figure 2: Performance templates identify required relations across processes. Vertical hash marks indicate the timing of finger flexion for both the left and right hands.

Participants read the image from left to right like a score of music and attempted to make a finger tap for each vertical mark they encountered. Participants continually tapped the given polyrhythm for 3 minutes. The motion of the fingers of the participants was recorded. Movement measurements were recorded using Northern Digital Optotrak 3-D Investigator motion tracking system. The motion tracking camera, which was positioned facing the participant, recorded the three-dimensional positions of two infrared-light-emitting diodes (IREDS) that were attached to the end of the participant's index fingers. Data were sampled at 100 Hz (see raw data, Figure 3A) and analyzed using wavelet coherence analysis (WCA) [2]. WCA characterizes multiscale relationships in between two time series in time-frequency space (Figure 3B) and provides insight into the time scales of coordination.

RESULTS AND DISCUSSION

Illustrative results from one participant are shown in Figure 3B. Frequency bands show that the movements of the left and right index fingers are coordinated across multiple frequencies. The strongest coherence is evident just above 1 Hz.

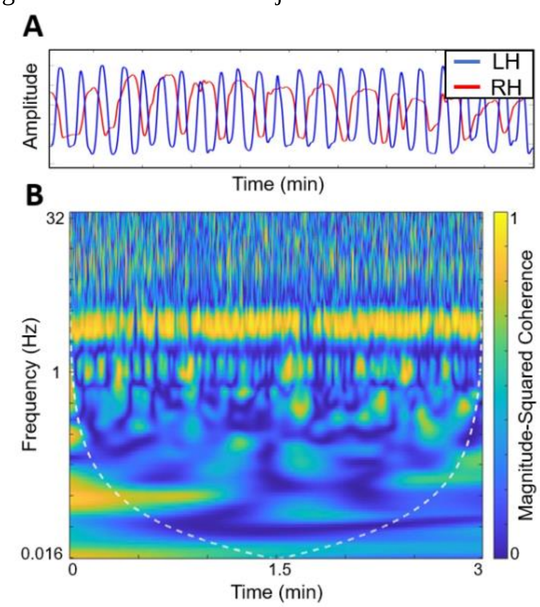

Figure 3: (A) Raw position data from a participant performing a 2:1 ratio. (B) Wavelet coherence measuring correlation between the two signals at varying frequencies.

CONCLUSIONS

Multiscale analysis revealed that polyrhythmic performance entails simultaneous coordination at multiple frequencies. That proves preliminary support for foundational observations made nearly eighty years ago (Figure 1). Ongoing research explores the multiscale structure of polyrhythms using a variety of multiscale methods.

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IS HIGHER GAIT KINEMATIC VARIABILITY INDICATIVE OF LOWER GAIT STABILITY?

Sina Mehdizadeh[1] & Paul S. Glazier[2]
[1]KITE-Toronto Rehabilitation Institute, University Health Network, Toronto, ON, Canada
[2]National Sports Institute, Kuala Lumpur, Malaysia
email: sina.mehdizadeh@uhnresearch.ca

Presentation Preference: [**Podium**]

INTRODUCTION

A persistent belief of the gait research community is that higher kinematic variability is indicative of lower stability. This viewpoint has emerged mainly because early studies on gait variability reported higher kinematic variability in older adults' walking compared to young individuals [1]. Since older adults have lower gait stability and thus a higher risk of falling, higher variability has typically been equated to lower stability.

However, higher kinematic variability may not be the result of lower stability only. Indeed, two factors can contribute to gait kinematic variability, namely external perturbations (mechanical and non-mechanical), which can cause instability, and sensorimotor noise [2]. As increased gait kinematic variability could be the result of increased sensorimotor noise, kinematic variability may not cause gait instability. However, the effect of sensorimotor noise on gait kinematic variability and stability has not been studied.

The aim of this study was, therefore, to investigate the effect of simulated sensorimotor noise on gait kinematic variability and stability using a biped walking model.

METHODS

The simplest passive dynamic walking model [3] was used to investigate the effect of simulated sensorimotor noise on gait kinematic variability and stability. Gaussian white noise of different amplitudes (0.001,0.002,0.003) was added to the differential equations of the biped model resulting in a stochastic differential equation (SDE). The SDE was solved using the Euler-Maruyama method [4]. The inter-step standard deviation (SD) of step time and swing angle trajectory were calculated as the measures of kinematic variability. The local divergence exponent (LDE) was calculated as the measure of gait stability. Poisson regression analysis was performed to determine the effect of noise level on the kinematic variability and stability measure. The significance level was set at 0.05.

RESULTS AND DISCUSSION

The regression coefficients were statistically significant ($p<0.05$) for step time SD, swing angle SD, and LDE. In addition, step time SD and swing angle SD had greater regression coefficients and coefficient determination (R^2) compared to LDE (Table 1). Moreover, step time SD ($p=0.007$) and swing angle SD ($p=0.009$) had lower p-values compared to LDE ($p=0.04$). These findings indicate that sensorimotor noise mainly resulted in higher levels of kinematic variability but its influence on gait stability is minimal.

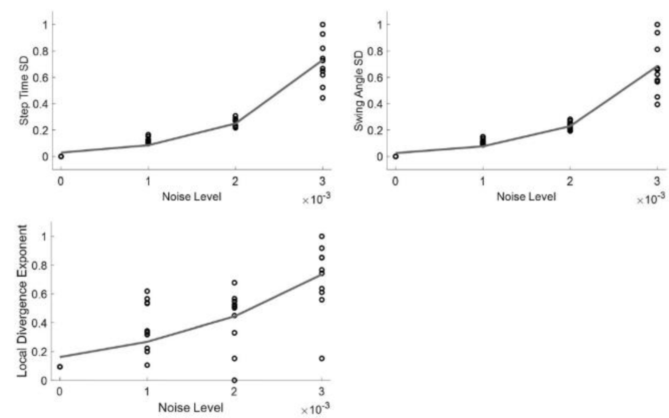

Figure 1: Kinematic variability (step time SD and swing angle SD) and gait stability (LDE) at three noise amplitudes.

CONCLUSIONS

The findings of this preliminary study imply that kinematic variability observed in older adults' gaits might be the result of internal sensorimotor noise but this noise may not result in gait instability.

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Table 1: Kinematic variability and gait stability regression analyses.

	Regression Coefficient	**Standard Error**	R^2	***p*-value**
Step time SD	1076.60	403.08	0.90	0.007
Swing angle SD	1095.90	423.40	0.87	0.009
LDE	504.60	247.23	0.55	0.040