Identifying gait quality metrics sensitive to changes in lower limb constraint

Kinsey Herrin (kinsey.herrin@gatech.edu)
Georgia Institute of Technology https://orcid.org/0000-0002-4292-8611

Samuel Kwak
Georgia Institute of Technology

Young-Hui Chang
Georgia Institute of Technology

Research

Keywords: Gait, wearable, robotics, sensors, prosthetics, outcome measures

Posted Date: May 26th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-544297/v1

Abstract

Background

Manual tuning of robotic lower limb prostheses can be time consuming for both the patient and the clinician and requires in-person visits to a clinic. An automated process for the tuning parameters of a robotic lower limb prosthesis could result in a substantial savings in healthcare resources. A critical challenge to an automated parameter tuning algorithm is the quantification of a person's gait quality. There is not good agreement in the literature of an objective outcome measure that can rapidly assess gait quality in lower limb amputees. As a first step, we investigated the ability of four common gait quality metrics to detect differences in gait quality: Prosthetic Observational Gait Score (POGS), Gait Deviation Index (GDI), Lateral Sway, and Impulse Asymmetry.

Methods

We systematically applied four unilateral lower limb joint constraint conditions (baseline/no constraint, ankle constraint, knee constraint, and knee + ankle constraint) to nine able-bodied participants walking at three different speeds (0.7, 0.85 and 1.0 m/s). We calculated and compared the resulting GDI, POGS, Lateral Sway and Impulse Asymmetry scores across all conditions. We performed a 2-way ANOVA statistical analysis to compare sensitivity of the metrics to the various conditions with significance defined by an alpha-level = 0.05.

Results

The Lateral Sway metric distinguished three joint constraint conditions and two of the speed conditions. Both GDI and POGS were able to distinguish four out of six possible constraint-speed conditions, while Impulse Asymmetry was only able to detect differences between three of the six constraint-speed conditions.

Conclusions

No single gait quality metric could distinguish every condition. Accordingly, a single metric of gait quality may be inadequate for tuning a prosthesis and therefore multiple metrics and sensors may provide the best results for tuning a prosthesis to the most natural gait pattern for an individual. Compared to the more complex gait measures, Lateral Sway performed well as a simple metric that might easily be operationalized into a real-time parameter tuning controller.

Background

The tuning of robotic lower limb prostheses can be a time consuming and complex process for clinicians and patients with lower limb amputation. Current clinical methods for tuning of robotic lower limb prostheses involve one-on-one sessions between a clinician and the patient, and are done through visual observation and patient-reported feedback. A single patient may require multiple tuning sessions as they acclimate to a device over time. Efforts to reduce this burden through the use of an automated tuning process have the potential to expedite the process for clinicians and patients alike and make the technology more accessible to those who need it most. However, prior to developing an algorithm for automatic prosthesis parameter tuning, an investigation into which gait metrics are most sensitive to changes in gait quality is needed.

A primary challenge in developing an automated prosthesis tuning algorithm is deciding upon an objective and quantifiable definition of what constitutes a 'good gait'. In typical clinical settings, gait quality is assessed through observation and patient reported feedback due to its simplistic and cost-effective nature(1). Although observational gait analysis can be done quickly, it can be highly subjective (1) and is difficult to translate into a quantitative algorithm. Advanced gait analysis systems can provide objective and quantitative kinematics and kinetics data. Typically, these more involved gait analyses involve comparison to some gold standard, either a set of control data that represents good gait(2), or there is an assumption made that bilateral symmetry represents good gait(3–5). Currently, there is not good agreement in the literature about how to best assess gait quality.

Multiple metrics have been utilized in the evaluation of gait of individuals with lower limb amputation, including observational scores(6), spatiotemporal parameters(7), kinematic and kinetic analyses(8, 9), balance metrics(10, 11), overall gait scores(12, 13), functional clinical outcome measures(9, 14) and patient reported measures(9, 15). In our study, we selected the Prosthetic Observational Gait Score (POGS) (6), the Gait Deviation Index (GDI) (2), Impulse Asymmetry (IA) (8) and truncal Lateral Sway (LS) as our gait metrics under investigation. These metrics were selected as they represent a range of commonly used clinical and biomechanical approaches with the potential for use with wearable sensors capable of providing input into a robotic prosthesis. The POGS is an observational and visual clinical metric which can be used by clinicians to quantify changes in the gait of an individual using a prosthesis or orthosis over time through the systematic analysis of 16 different aspects of an individual's gait at the anatomical levels of the trunk, hip, knee, ankle and foot; the maximum score is a 32 with lower scores indicating less pathology of gait.(6) Duffy, et al. used POGS to compare differences in gait for individuals with a transfemoral amputation using both a microprocessor knee and a mechanical prosthetic knee joint. (16) While POGS can be performed immediately on-site in a clinical setting, it is preferable to utilize video recordings for improved accuracy.(1)

While observational gait analysis is heavily relied upon in clinical settings, instrumented gait analysis is widely recognized as the preferred method for gait assessment in pathological populations. (1) Accordingly, the GDI is one metric of gait quality which requires the use of an instrumented gait platform and has been reported as an appropriate measure for individuals with lower limb amputation. (12, 13) The GDI utilizes 3-dimensional kinematic data from the pelvis and hip, sagittal plane data from the knee

and ankle joints as well as foot progression data in the transverse plane at each 2% increment throughout the gait cycle for a total of 51 points for each gait cycle with scores equal to or greater than 100 indicative of a more normal gait pattern.(2) The GDI has been used to understand levels of disability and impacts of medical interventions in children with cerebral palsy (12) as well as varying suspension types in users of transtibial prostheses, showing significant differences from a healthy control population.(13) GDI has also been shown to be correlated with more simple outcome measures such as step length, self-selected walking speed and the distance traversed during the 6 minute walk test in individuals with amputation.(9)

While kinematics represents one important aspect of evaluation for gait pathology, the use of kinetic information also bolsters the assessment capabilities associated with instrumented gait analysis. Individuals with amputation are noted to spend more time and exert higher loads on their intact side. (5) These temporal and loading asymmetries are important given their associations with higher risks for falls, osteoarthritis and back pain.(5) Because there is a high incidence of low back pain(17, 18) and osteoarthritis (19, 20) seen in prosthesis users, efforts to normalize their gait will make important gains toward improving their overall quality of life. Cutti, et al. showed differences in impulse symmetry between individuals with transfemoral and transtibial amputations; this work further showed that more advanced prosthetic technology improved loading symmetry.(5) The work of Zmitrewicz, et al. also showed a similar trend with Impulse Asymmetry improving with more advanced prosthetic componentry.(8) Specifically, Impulse Asymmetry was utilized in individuals with transtibial amputation to distinguish differences in the response to varying prosthetic feet and improved symmetry was noted during use of an energy storage and return (ESAR) foot compared to a non-ESAR foot.(8)

Trunk sway angular movements have been used as a measure of balance capability in individuals with amputation(21) and in aging populations (22) as well as a marker of disease progression in multiple sclerosis (23) and Parkinson's disease(24). Balance is a critical metric for clinical populations with functional limitations such as prosthesis users given the high probability for falls and their subsequent detrimental impacts.(10) Trunk position variability has been correlated with step width, which has also been used as a metric of balance during walking(25).

With this motivation, we studied the sensitivity of four representative metrics of gait quality toward various constraints of lower limb joints in an able-bodied population. Our purpose in this study was to define the best gait metric for tuning a robotic lower limb prosthesis with a future goal of combining one (or more) of these metrics with a wearable sensor which may be used to automatically tune a prosthesis. We hypothesized that our selected biomechanically-based metrics, Gait Deviation Index, Lateral Sway and Impulse Asymmetry would outperform the clinical metric, POGS, as these metrics are measured objectively and defined on a continuous scale, compared to the POGS, which is a visual, subjective measure on an ordinal scale.

Methods

Nine able-bodied (AB) individuals (age 39.3 ± 16.7 years, 82 ± 30.8 kg, height 1.7 ± 0.08 m) provided informed, written consent prior to participating in this study according to the Georgia Institute of Technology Institutional Review Board protocol. Subjects walked on a dual-belt treadmill at three speeds (0.7 m/s, 0.85 m/s and 1.0 m/s) and four joint constraint conditions imposed on the left lower extremity for a total of 12 different conditions. We collected three trials for each of the different conditions. The four joint constraint conditions consisted of a baseline, ankle constraint, knee constraint and a knee + ankle constraint combined (Fig. 1). In the baseline condition, the subject walked normally without any lower limb constraints. With ankle constraint, the subject wore an orthopedic ankle boot (SideKICK Walker, DJO) locked in a 90-degree ankle alignment with a proximal trimline just distal to the knee joint. The knee constraint consisted of a knee orthosis (Formfit Post-op Knee, Ossur) which was locked in 180 degrees of extension with the addition of a 4-buckle knee pad to prevent flexion of the knee through deflection of the knee orthosis uprights. The knee + ankle constraint was a combination of both the knee constraint and ankle constraint together. All devices were fit to each subject by a certified orthotist to ensure proper fit for inhibiting motion as well as maximum comfort during the experiment. All subjects wore their normal walking footwear for the entirety of the experiment except in conditions when they wore the ankle boot in which they could not wear their regular shoe on this limb. Additionally, while in conditions wearing the ankle boot, subjects were fit by a certified orthotist with an adjustable external lift (Evenup, OPED Medical) attached to the outside of their contralateral shoe to ensure equal leg lengths were maintained. Order of speed conditions was randomized for each subject, but the order of joint constraint at each speed always occurred in the following order: baseline, ankle, knee, knee + ankle. Three trials lasting 15 seconds each were collected for each of the 12 conditions.

We collected lower body and trunk kinematics using an 8-camera motion capture system (Vicon, Centennial, CO; Visual 3D, C-Motion, Germantown, MD). Ground reaction forces were recorded from under each foot using force plates (AMTI, Watertown, MA) embedded within a custom dual-belt treadmill. (26, 27) Reflective markers were placed on anatomical landmarks using a modified Helen Hayes marker set. (28) Subjects acclimated to walking in each constraint-speed condition for three minutes before data were recorded for three consecutive 15 second trials. Synchronized, optical video data were also recorded in both the sagittal and frontal planes (Vicon Bonita cameras) for scoring the POGS outcome measure. Visual 3D software (C-Motion, Germantown, MD) was used to filter data (fourth-order Butterworth with cut-off frequencies at 6 Hz for force and marker data), as well as to calculate joint angles and force impulses.

Data were exported to R Studio and MATLAB (R2017a, Mathworks, Inc.) for additional processing. The Prosthetic Observational Gait Score (POGS) was calculated by summing the total of 16 separate aspects of an individual's gait observed on the limb affected by the constraint condition.(6) All trials were viewed using the recorded video data and scored by the same clinician (certified prosthetist/orthotist). Impulse Asymmetry was calculated as the absolute value of the difference between the right and left steps of the vertical ground reaction force impulse for each complete gait cycle and then averaging the difference across all steps. In trials in which the limbs did not have an equal number of gait cycles, one gait cycle was left out to prevent biasing of the calculation. Lateral Sway was calculated for each stride by taking

the difference in the maximum and minimum values of the mediolateral trajectory of a sternal chest marker in the coronal plane. The Gait Deviation Index (GDI) was calculated using the method of Schwartz and Rozumalski (2) through custom code in Matlab (see appendix in (2)).

Two-way repeated measures ANOVAs were conducted in SPSS (IBM Corp., v22, Armonk, NY) to determine significant differences between the sensitivity of the different gait metrics to the various constraint conditions. A Greenhouse-Geisser correction was used if Mauchly's test of sphericity was not met and epsilon was less than 0.75. In cases where epsilon was greater than 0.75, we used a Huynh-Feldt correction. Since the GDI metric is based on a z-score, statistical significance for comparisons to the baseline condition were defined as a GDI score lower than 80.4/100, which represents a difference greater than 1.96 standard deviations. For comparisons between the remaining constraint conditions for the GDI metric, we used the same repeated measures ANOVA statistical analysis described above. We defined significance at an alpha-level = 0.05 throughout our analysis.

Results

Lateral Sway (Fig. 2) showed trends of increasing with more severe joint constraint across the three speeds. Statistical differences were detected between baseline and knee constraint ($p = 0.017$), between baseline and knee + ankle condition ($p = 0.008$), and between ankle condition and knee + ankle condition ($p = 0.004$). Differences were also seen when comparing the 0.7 m/s trials to 0.85 m/s ($p = 0.006$) and 1.0 m/s ($p = 0.002$) trials, but no difference in Lateral Sway was observed between 0.85m/s and 1.0 m/s. Lateral Sway could not distinguish differences between baseline and ankle conditions, ankle and knee conditions or knee and knee-ankle conditions. Thus, the Lateral Sway metric could distinguish differences between three of six possible joint constraint comparisons and two of the three gait speed conditions (Table 1).

The GDI metric (Fig. 3) showed trends of decreasing (indicative of poorer gait quality) with more severe joint constraint. We found statistically significant differences between the baseline condition and every other joint constraint condition (ankle, knee, knee + ankle, $p < 0.05$). GDI was also significantly different between the ankle and knee + ankle conditions ($p = 0.029$). GDI was unable to distinguish differences between the ankle and knee conditions and the knee and knee + ankle conditions. GDI also did not indicate any differences across gait speed. In total, the GDI metric could distinguish four of the six different joint constraint comparisons.

The POGS outcome measure (Fig. 4) showed trends of increasing (indicative of poorer gait quality) with increased joint constraint but we did not observe an effect of gait speed with POGS. Statistical differences were detected between the baseline condition compared to both the knee condition ($p < 0.001$) and knee + ankle condition ($p = 0.001$) conditions. Also, differences in POGS were observed in the ankle condition compared to the knee ($p = 0.002$) and knee + ankle ($p = 0.002$) conditions. POGS could not, however, differentiate the knee and knee + ankle conditions from one another; nor could POGS detect

differences due to gait speed. In total, POGS could detect differences in four of the six different joint constraint comparisons.

Impulse asymmetry (Fig. 5) tended to increase (indicative of poorer gait quality) with increasing joint constraint, but no trends were observed with speed. We found statistical differences between the baseline condition compared to the knee + ankle condition ($p = 0.02$). Differences were also observed between the knee + ankle condition compared to both the ankle ($p = 0.014$) and knee conditions ($p = 0.019$). Impulse Asymmetry could not detect differences due to speed nor between baseline and either the ankle nor knee conditions, respectively. It also did not detect differences between the ankle and knee conditions. In total, Impulse Asymmetry was able to detect differences between three of the six different joint constraint comparisons.

To compare the sensitivity of each gait metric to distinguish across different walking conditions, we computed a general gait deficit sensitivity score as the sum of significant comparisons tallied across all nine possible comparisons (Table 1). In terms of detecting the most significant differences between the various joint constraint conditions, the GDI and POGS performed better than Lateral Sway and Impulse Asymmetry. GDI and POGS could each distinguish differences in four of six joint constraint comparisons that were made. By comparison, Lateral Sway and Impulse Asymmetry could only distinguish 3/6 and 2/6, respectively. When we also consider the ability to detect changes due to walking speed, Lateral Sway was able to distinguish 5/9 possible comparisons. GDI and POGS performed similarly with a score of 4/9 each, and Impulse Asymmetry could only distinguish 3/9 conditions

Table 1. Gait metric comparison table.

	Conditions Compared									
	Joint Constraint Comparisons						Speed Comparisons			
Gait Metrics	Baseline vs. Ankle	Baseline vs. Knee	Baseline vs. Knee+ Ankle	Ankle vs. Knee	Ankle vs. Knee+ Ankle	Knee vs. Knee+ Ankle	0.7 m/s vs. 0.85 m/s	0.7 m/s vs. 1.0 m/s	0.85 m/s vs 1.0 m/s	General Gait Deficit Sensitivity Score
Lateral Sway	0.186	**0.017***	**0.008***	0.053	**0.004***	1	**0.006***	**0.002***	0.126	5
GDI	**p<0.05***	**p<0.05***	**p<0.05***	0.351	**0.022***	1	0.207	0.207	0.207	4
POGS	0.075	**p<0.001***	**0.001***	**0.002***	**0.002***	1	0.234	0.234	0.234	4
Impulse Asymmetry	0.565	0.23	**0.002***	0.466	**0.014***	**0.019***	0.427	0.427	0.427	3

** indicates significant difference ($p \leq 0.05$).*

Discussion

GDI outperformed all the other metrics in terms of its ability in distinguishing different joint constraints from baseline walking, which is particularly compelling for an automated system intended for optimizing gait quality to the most natural kinematic state. A metric that can distinguish a baseline healthy gait from

a pathological gait may provide for a faster tuning process than metrics that can only distinguish between severities of pathological gait. Both POGS and GDI consider multiple joint angles in the calculation of their score, which perhaps explains their superior performance over the other two metrics. However, both are kinematics-based in nature and therefore may miss deviations or alterations that are kinetic in nature, such as walking at a faster pace. While the POGS metric considers all anatomical segments of the subject (6), GDI focuses strictly on the lower limbs(2). However, POGS is limited in terms of its scope for an automated sensor as it represents a clinical measure that must be done visually by a trained observer. Given its high sensitivity and relatively easy scoring system, it may be worth further exploring whether the more sensitive aspects of the POGS measure could be automated to quantify and assess gait. Finally, a limitation of the POGS in the scope of this study is that it could not be done in a blinded fashion; the evaluator knew which condition was being evaluated due to the observational nature of the metric.

Only Lateral Sway was able to distinguish differences in 2 out of the three speeds comparisons. No other gait quality metric that we analyzed was able to distinguish differences in speed categories. While we did not measure self-selected walking speed, all of our subjects were able-bodied, healthy community ambulators and it is likely that the 0.7 m/s speed condition represented a significant deviation from their typical preferred walking speed. This gait speed also carries an important clinical meaning. A walking speed of 0.7 m/s is reported to be in the range of ‘limited community ambulation’, while speeds greater than 0.8 m/s are defined as ‘community ambulation’. (29) So it is of particular interest that a relatively simple measure such as Lateral Sway could potentially be used to automatically identify those in the population that have limited community ambulation. The 0.85 m/s and 1.0 m/s trials fit into the community ambulation category and no differences in lateral sway were seen between these conditions. Because community ambulation often requires an individual to change speeds, we believe the sensitivity of Lateral Sway to speed could be a useful metric when designing a sensor to automatically detect gait quality for the purposes of tuning a prosthesis for an individual who is a community ambulator.

Lateral Sway and Impulse Asymmetry performed equally in ability to distinguish between different joint constraints in that both detected differences in three of six comparisons. It is notable that Lateral Sway could distinguish conditions which could not be distinguished by Impulse Asymmetry, and vice-versa. It is easy to imagine small, independent wearable sensors that can non-invasively and relatively non-intrusively quantify each of these gait metrics. For example, detailed motions of the trunk have been measured in other studies through the use of the SwayStar System, Balance Int. Innovations (GmbH, Switzerland) which consists of two gyroscopes mounted inside a case worn around the lower trunk. (24, 30, 31) Miniaturized load cells within the shoes or prosthesis could be used to detect Impulse Asymmetry. (32) Together, these two different sensor inputs could be fused to automatically tune robotic prosthesis parameters to improve force symmetry during ambulation across different walking speeds.

Given the varying sensitivity of these four metrics to changes in gait quality, it is logical to conclude that a single sensor and single metric may not be a robust enough solution for the requirements in tuning a prosthesis to an optimum quality for an individual user. There is precedent in the literature showing

improved performance of intent recognition in a powered knee and ankle prosthesis with the fusion of inputs from multiple sensors as opposed to a single sensor.(32) With all four metrics combined, we were able to detect differences between every single condition compared. Our selected gait quality metrics are kinematic and kinetic based, but we have left out another frequently cited metric in regards to evaluating gait quality and efficiency, which is metabolic cost of transport(33). Particularly in individuals with lower limb amputation, metabolic energy associated with walking is known to be much higher than the able-bodied population and powered prostheses are designed to reduce this burden on their users. (34, 35) However, the current gold standard for measuring energy consumption is open-circuit spirometry which is a time-consuming process and requires a user to be tethered to a machine(36). While metabolic cost does play an important role in a person's gait quality, studies have shown that individuals may optimize their gait for a combination of metabolic cost and other factors(37), which could include stability, speed, comfort, or esthetics. Because metabolic cost requires the use of bulky equipment, it is currently not well suited for the goals set in this study. Our goal is to elucidate metrics that would allow for an individual to walk freely in community environments and yet still contribute to an optimizing process for gait quality.

In this study, we assessed the ability of four commonly used gait metrics to detect changes in gait quality when an able-bodied individual is challenged with systematically varied lower limb joint constraint. Our long-term goal is to assess which of these gait metrics may be leveraged for use in tuning a robotic lower limb prosthesis. We recognized that the joint constraints we apply to an able-bodied individual may not precisely represent the deficits of a lower limb prosthesis user. However, we were able to draw general conclusions about how sensitive each of these gait metrics might be when applied to someone with lower limb amputation. These findings can guide further testing on prostheses users to refine our understanding of the capabilities of these gait metrics for use in this population.

Conclusion

Improving our ability to objectively quantify and automatically detect gait quality may significantly improve a clinician's ability to efficiently tune an individual's prosthesis. Moreover, it could provide a more effective means to re-establish a more natural gait pattern. Improved understanding of the sensitivity of gait metrics for identifying changes in gait quality may extend beyond the population of individuals with amputation to those with other movement disorders, such as cerebral palsy and multiple sclerosis. If operationalized with real-time wearable sensors, these gait metrics can be used in combination with clinical professional judgement to augment an individual's performance through the use of exoskeleton technology or simply to monitor real-time progress with therapeutic intervention.

Abbreviations

AB- Able Bodied

BC- Baseline Condition

ESAR- Energy Storage and Return

GDI- Gait Deviation Index

IA- Absolute value of Impulse Asymmetry

LS- Lateral Sway

POGS- Prosthetic Observational Gait Score

Declarations

Ethics approval and consent to participate: This study was approved by the Georgia Institute of Technology Investigational Review Board and all subjects gave informed consent to participate.

Consent for publication: Not applicable.

Availability of data and materials: The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests: The authors declare that they have no competing interests

Funding: This work was supported by a grant from the National Science Foundation, NSF-NRI 1734416.

Authors' contributions: KRH performed the POGS, LS, IA analyses and was the major contributor for writing the manuscript. STK wrote the code to analyze GDI, LS and IA and conducted the GDI analysis. Both KH and STK contributed toward collecting all data. YHC conceptualized the idea for the study and provided oversight for the entirety of the project. All authors contributed to and approved the final version of the manuscript.

Acknowledgements: The authors acknowledge the efforts of Margaret Berry and Navya Katragadda in processing the Vicon data.

References

1. Rathinam C, Bateman A, Peirson J, Skinner J. Observational gait assessment tools in paediatrics–a systematic review. Gait & posture. 2014;40(2):279-85.
2. Schwartz MH, Rozumalski A. The Gait Deviation Index: a new comprehensive index of gait pathology. Gait & posture. 2008;28(3):351-7.
3. Isakov E, Burger H, Krajnik J, Gregoric M, Marincek C. Influence of speed on gait parameters and on symmetry in transtibial amputees. Prosthetics and Orthotics International. 1996;20(3):153-8.
4. Riveras M, Ravera E, Shaheen A, Ewins D, Formento PC, editors. Spatio temporal parameters and symmetry index in transtibial amputees wearing prosthetic feet with and without adaptive ankles.

2019 Global Medical Engineering Physics Exchanges/Pan American Health Care Exchanges (GMEPE/PAHCE); 2019: IEEE.

5. Cutti AG, Verni G, Migliore GL, Amoresano A, Raggi M. Reference values for gait temporal and loading symmetry of lower-limb amputees can help in refocusing rehabilitation targets. Journal of neuroengineering and rehabilitation. 2018;15(1):1-12.
6. Hillman SJ, Donald SC, Herman J, McCurrach E, McGarry A, Richardson AM, et al. Repeatability of a new observational gait score for unilateral lower limb amputees. Gait & posture. 2010;32(1):39-45.
7. Highsmith MJ, Schulz BW, Hart-Hughes S, Latlief GA, Phillips SL. Differences in the spatiotemporal parameters of transtibial and transfemoral amputee gait. JPO: Journal of Prosthetics and Orthotics. 2010;22(1):26-30.
8. Zmitrewicz RJ, Neptune RR, Walden JG, Rogers WE, Bosker GW. The effect of foot and ankle prosthetic components on braking and propulsive impulses during transtibial amputee gait. Archives of physical medicine and rehabilitation. 2006;87(10):1334-9.
9. Kark L, Odell R, McIntosh AS, Simmons A. Quantifying prosthetic gait deviation using simple outcome measures. World journal of orthopedics. 2016;7(6):383.
10. Wong CK, Chen CC, Blackwell WM, Rahal RT. Balance ability measured with the Berg balance scale: a determinant of fall history in community-dwelling adults with leg amputation. Journal of rehabilitation medicine. 2015;47(1):80-6.
11. Hof AL, van Bockel RM, Schoppen T, Postema K. Control of lateral balance in walking: experimental findings in normal subjects and above-knee amputees. Gait & posture. 2007;25(2):250-8.
12. Kark L, Vickers D, McIntosh A, Simmons A. Use of gait summary measures with lower limb amputees. Gait & Posture. 2012;35(2):238-43.
13. Eshraghi A, Osman NAA, Karimi M, Gholizadeh H, Soodmand E, Abas WABW. Gait biomechanics of individuals with transtibial amputation: effect of suspension system. PloS one. 2014;9(5):e96988.
14. Lythgo N, Marmaras B, Connor H. Physical function, gait, and dynamic balance of transfemoral amputees using two mechanical passive prosthetic knee devices. Archives of physical medicine and rehabilitation. 2010;91(10):1565-70.
15. Kark L, Simmons A. Patient satisfaction following lower-limb amputation: the role of gait deviation. Prosthetics and Orthotics International. 2011;35(2):225-33.
16. Duffy C, Dolan M, Buis A, editors. Comparison of function and mobility pre and post prescription of a microprocessor-controlled knee joint. British Association of Prosthetists and Orthotists Conference; 2019.
17. Kulkarni J, Gaine W, Buckley J, Rankine J, Adams J. Chronic low back pain in traumatic lower limb amputees. Clinical rehabilitation. 2005;19(1):81-6.
18. Morgenroth DC, Orendurff MS, Shakir A, Segal A, Shofer J, Czerniecki JM. The relationship between lumbar spine kinematics during gait and low-back pain in transfemoral amputees. American journal of physical medicine & rehabilitation. 2010;89(8):635-43.

19. Struyf PA, van Heugten CM, Hitters MW, Smeets RJ. The Prevalence of Osteoarthritis of the Intact Hip and Knee Among Traumatic Leg Amputees. Archives of Physical Medicine and Rehabilitation. 2009;90(3):440-6.
20. Norvell DC, Czerniecki JM, Reiber GE, Maynard C, Pecoraro JA, Weiss NS. The prevalence of knee pain and symptomatic knee osteoarthritis among veteran traumatic amputees and nonamputees. Archives of Physical Medicine and Rehabilitation. 2005;86(3):487-93.
21. Lamoth CJ, Ainsworth E, Polomski W, Houdijk H. Variability and stability analysis of walking of transfemoral amputees. Medical engineering & physics. 2010;32(9):1009-14.
22. Gill J, Allum J, Carpenter M, Held-Ziolkowska M, Adkin A, Honegger F, et al. Trunk sway measures of postural stability during clinical balance tests: effects of age. The Journals of Gerontology Series A: Biological Sciences and Medical Sciences. 2001;56(7):M438-M47.
23. Corporaal SH, Gensicke H, Kuhle J, Kappos L, Allum JH, Yaldizli Ö. Balance control in multiple sclerosis: correlations of trunk sway during stance and gait tests with disease severity. Gait & posture. 2013;37(1):55-60.
24. Adkin A, Bloem B, Allum J. Trunk sway measurements during stance and gait tasks in Parkinson's disease. Gait & posture. 2005;22(3):240-9.
25. Perry JA, Srinivasan M. Walking with wider steps changes foot placement control, increases kinematic variability and does not improve linear stability. Royal Society open science. 2017;4(9):160627.
26. Toney ME, Chang Y-H. Humans robustly adhere to dynamic walking principles by harnessing motor abundance to control forces. Experimental brain research. 2013;231(4):433-43.
27. Kram R, Griffin TM, Donelan JM, Chang YH. Force treadmill for measuring vertical and horizontal ground reaction forces. Journal of applied physiology. 1998;85(2):764-9.
28. Collins TD, Ghoussayni SN, Ewins DJ, Kent JA. A six degrees-of-freedom marker set for gait analysis: repeatability and comparison with a modified Helen Hayes set. Gait & posture. 2009;30(2):173-80.
29. Perry J, Garrett M, Gronley JK, Mulroy SJ. Classification of walking handicap in the stroke population. Stroke. 1995;26(6):982-9.
30. Van de Warrenburg BP, Bakker M, Kremer BP, Bloem BR, Allum JH. Trunk sway in patients with spinocerebellar ataxia. Movement disorders: official journal of the Movement Disorder Society. 2005;20(8):1006-13.
31. Verhoeff LL, Horlings CG, Janssen LJ, Bridenbaugh SA, Allum JH. Effects of biofeedback on trunk sway during dual tasking in the healthy young and elderly. Gait & posture. 2009;30(1):76-81.
32. Bhakta K, Camargo J, Donovan L, Herrin K, Young A, Valdastri P, et al. Machine Learning Model Comparisons of User Independent & Dependent Intent Recognition Systems for Powered Prostheses. IEEE Robotics and Automation Letters. 2020.
33. Au SK, Weber J, Herr H. Powered ankle–foot prosthesis improves walking metabolic economy. IEEE Transactions on Robotics. 2009;25(1):51-66.

34. Ingraham KA, Choi H, Gardinier ES, Remy CD, Gates DH. Choosing appropriate prosthetic ankle work to reduce the metabolic cost of individuals with transtibial amputation. Scientific reports. 2018;8(1):1-12.
35. Zelik KE, Collins SH, Adamczyk PG, Segal AD, Klute GK, Morgenroth DC, et al. Systematic variation of prosthetic foot spring affects center-of-mass mechanics and metabolic cost during walking. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2011;19(4):411-9.
36. Herndon SK, Bennett BC, Wolovick A, Filachek A, Gaesser GA, Weltman A, et al. Center of mass motion and the effects of ankle bracing on metabolic cost during submaximal walking trials. Journal of orthopaedic research. 2006;24(12):2170-5.
37. Summerside EM, Kram R, Ahmed AA. Contributions of metabolic and temporal costs to human gait selection. Journal of The Royal Society Interface. 2018;15(143):20180197.

Figures

Figure 1

Four systematic constraints applied during experiment. A. baseline condition with no constraints. B. ankle constraint C. knee constraint D. knee+ankle constraint

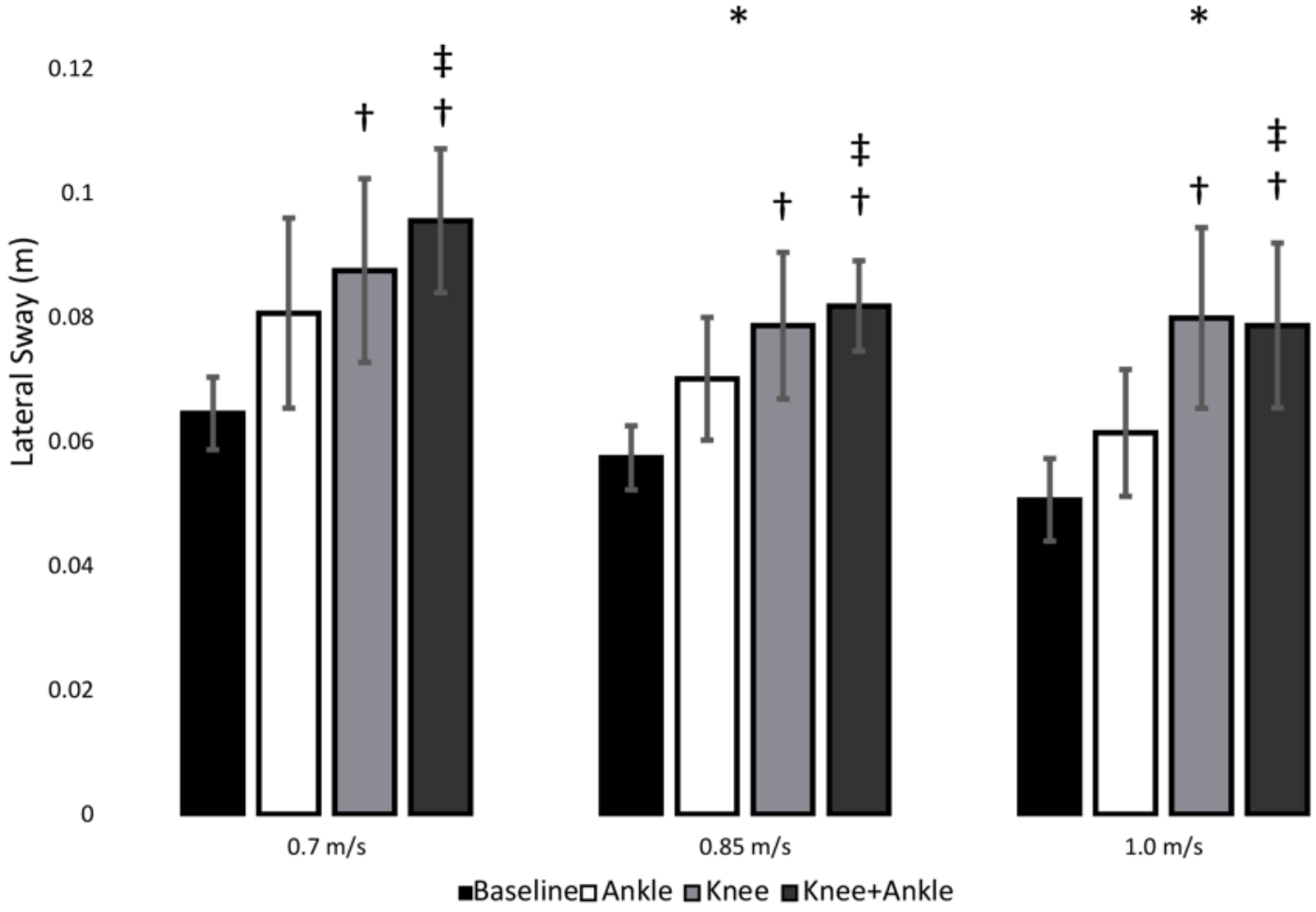

Figure 2

Results of Lateral Sway metric indicating differences seen in speed and joint constraint comparisons between the baseline and ankle constraint and knee+ankle conditions as well as between the ankle constraint and knee+ankle conditions. *indicates significant difference compared to 0.7 m/s speed, † indicates significant difference compared to baseline condition, ‡ indicates significant difference compared to ankle condition, ◊ indicates significant difference from knee condition

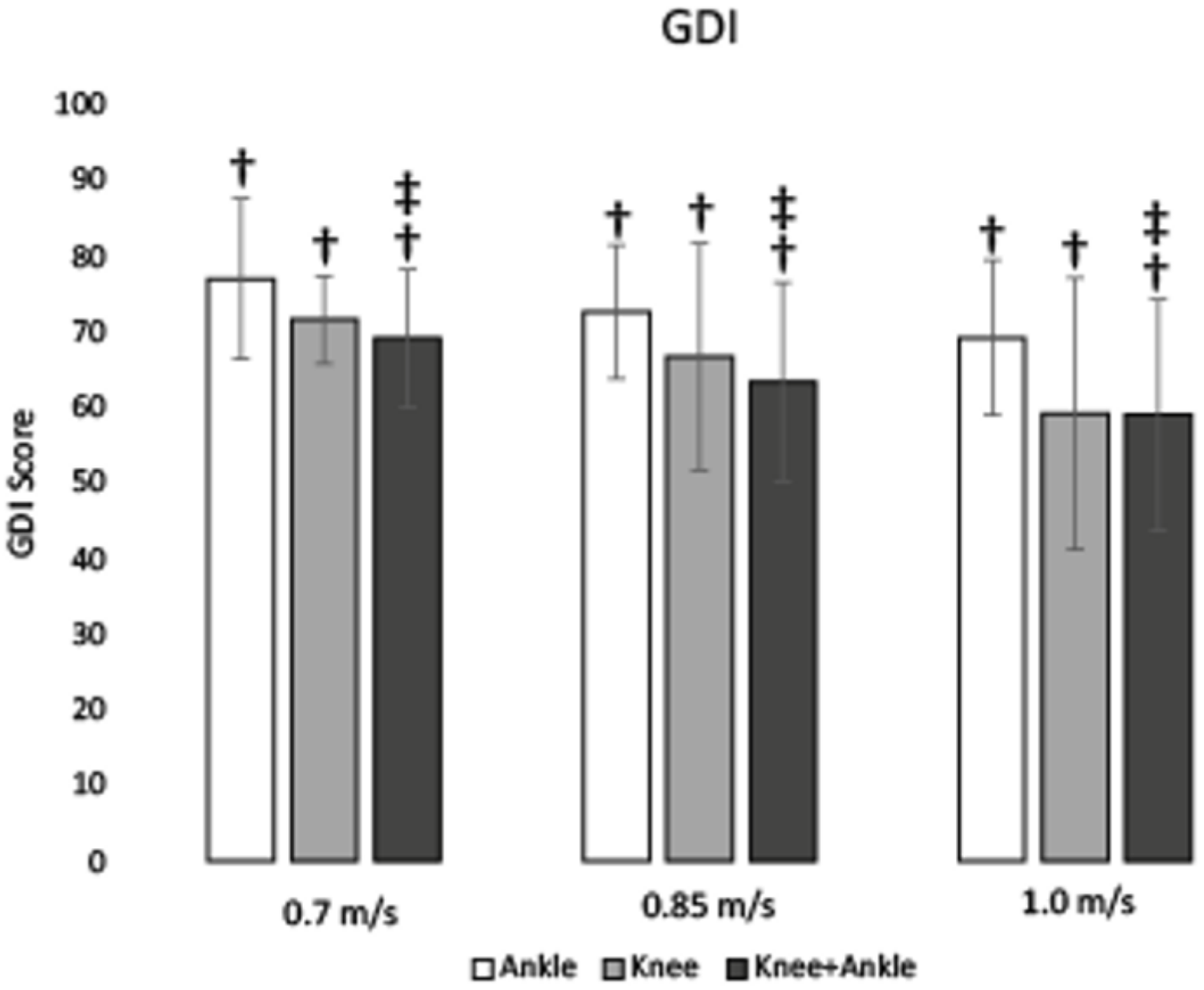

Figure 3

Results of Gait Deviation Index indicating significant differences between the baseline and every other constraint condition as well as differences between the ankle constraint and knee+ankle conditions. *indicates significant difference compared to 0.7 m/s speed, † indicates significant difference compared to baseline condition, ‡ indicates significant difference compared to ankle condition, ◊ indicates significant difference from knee condition

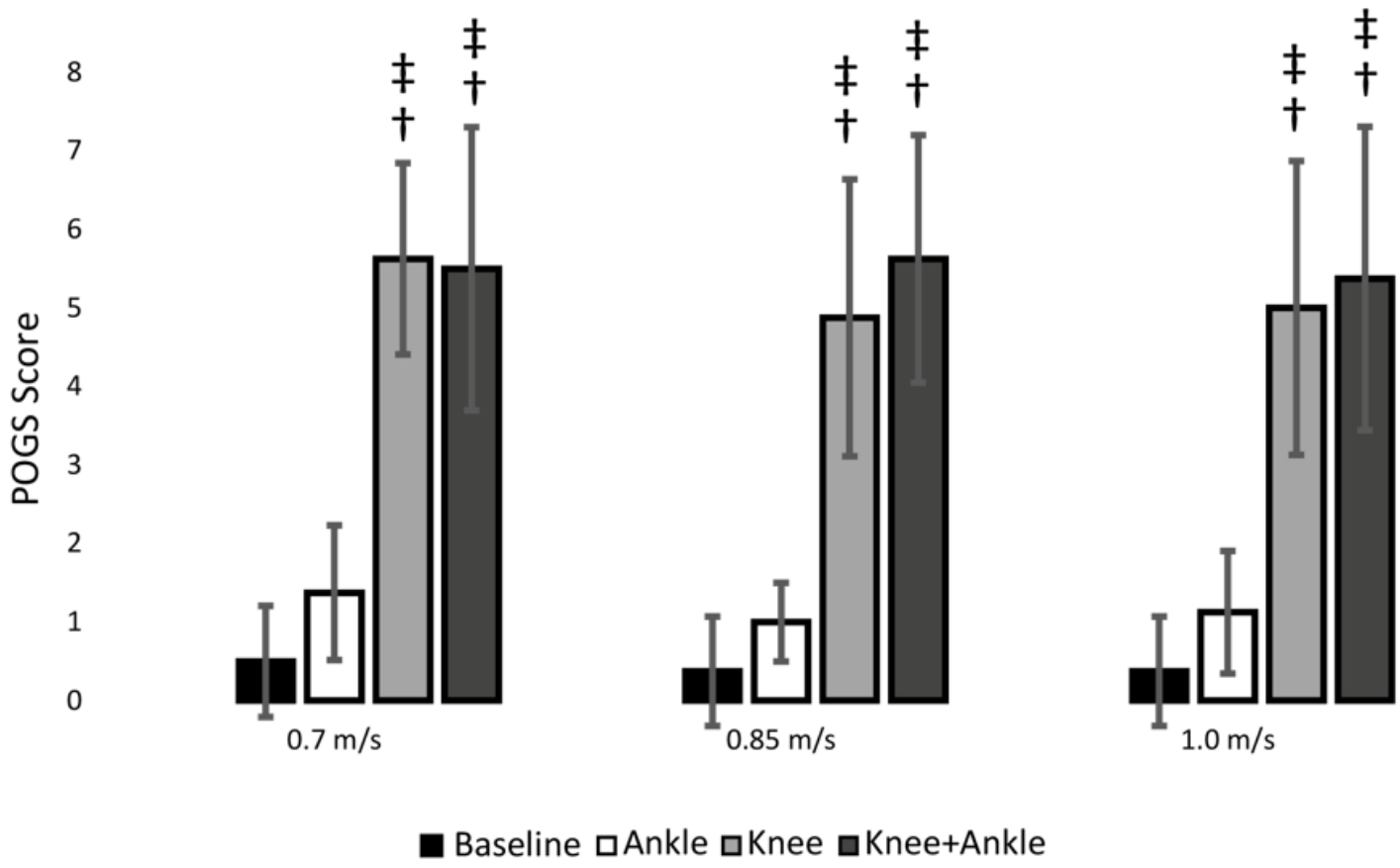

Figure 4

Results of Prosthetic Observational Gait Score indicating differences between baseline and knee and knee+ankle as well as between ankle and knee+ankle and knee+ankle. *indicates significant difference compared to 0.7 m/s speed, † indicates significant difference compared to baseline condition, ‡ indicates significant difference compared to ankle condition, ◊ indicates significant difference from knee condition

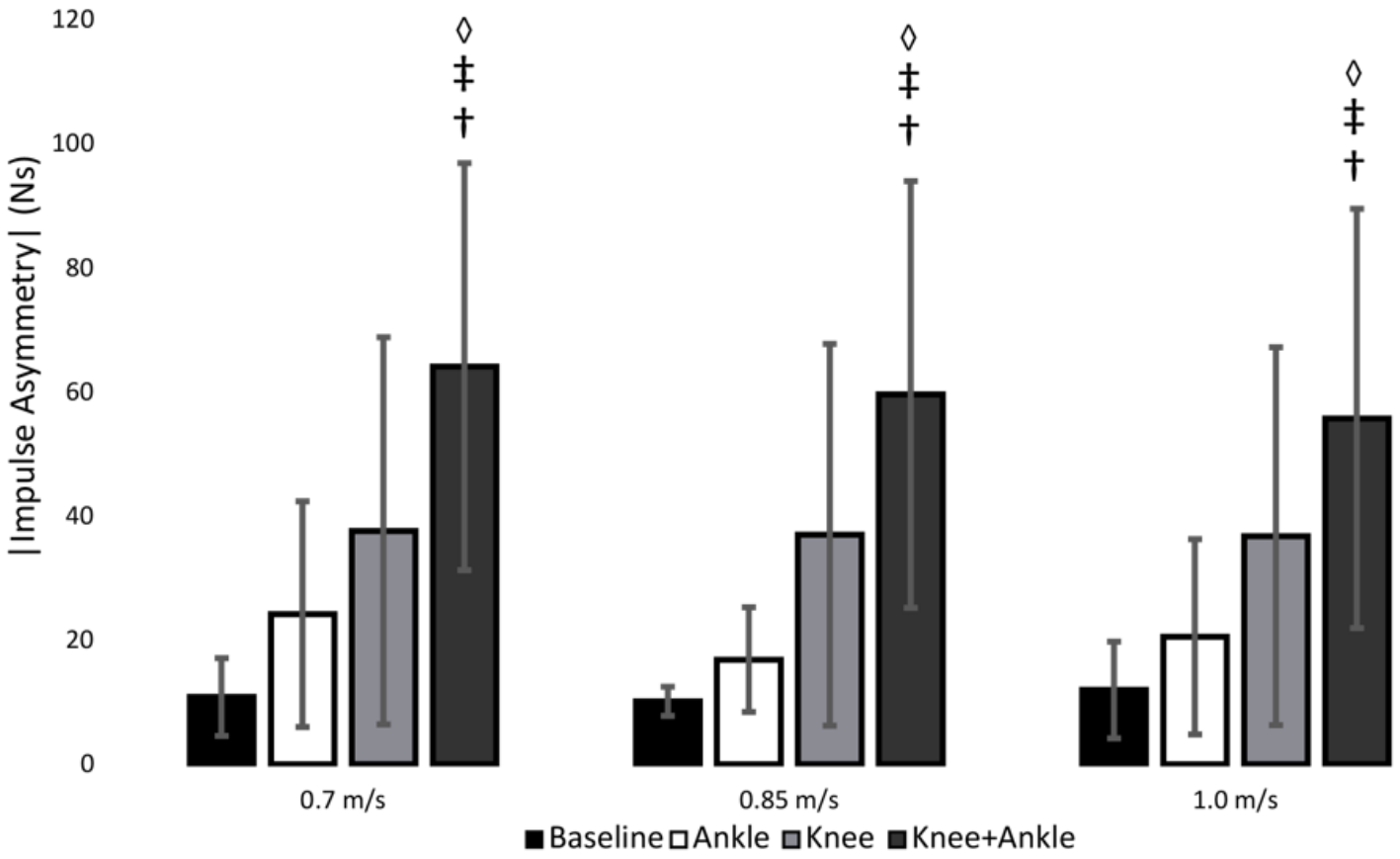

Figure 5

Results of Impulse Asymmetry indicating significant differences seen between knee+ankle and every other constraint condition. *indicates significant difference compared to 0.7 m/s speed, † indicates significant difference compared to baseline condition, ‡ indicates significant difference compared to ankle condition, ◊ indicates significant difference from knee condition