1 Paper Review | M. C. Rosenberg, J. L. Proctor, and K. M. Steele, 2024

Rosenberg et al. [1] applies data-driven machine learning to investigate how the use of an ankle exoskeleton (Exo) affects gait mechanics in both unimpaired and stroke populations, with a focus on alterations in an individual's center-of-mass (CoM) during locomotion. The CoM undergoes changes during walking to optimize balance and energetics, making it crucial to understand how CoM dynamics are affected using an Exo for proper control of these devices. To analyze these nonlinear changes in dynamics, the authors employed Hybrid-SINDy to develop "individual-specific" models illustrating how the use of an Exo impacts each phase of the gait cycle, including stance and swing.

1.1| Summary

As noted by Rosenberg et al. [1], Exo can improve locomotion, but their effects vary widely among individuals, particularly those with neurological injuries. Due to these varying effects, this paper suggests that personalization of Exo mechanical parameters, such as stiffness, are crucial for optimizing their benefits. Center-of-mass (CoM) dynamics during walking are shown to contribute significantly to energetics and balance for locomotion, but changes in CoM dynamics resulting from an Exo are not well understood. Additionally, since an individual's response to an Exo is difficult to generalize to population-based models [2], this study uses a data-driven modeling technique to identify individual-specific patterns in response to Exo usage.

Simplified models of CoM dynamics, such as variations of the inverted pendulum model, have been proposed to describe walking. These models, deemed "template" models, offer a simplified framework for studying CoM dynamics, but pose challenges when investigating the impact of an Exo on an individual's walking function. To emphasize and understand the diverse impacts of Exo usage on walking function, the authors the use of data-driven modeling to identify individual-specific template-signatures from walking data. A hybrid sparse identification of nonlinear dynamics (Hybrid-SINDy) algorithm was implemented to identify template-signatures in human locomotion with and without an Exo. Briefly, Hybrid-SINDy identifies and characterizes the underlying dynamics of complex non-linear systems. SINDy is utilized to find the governing equations of a dynamical system from observed data and works by finding a concise set of equations that can describe the system's behavior with minimal complexity. For human walking, the authors identify the 3D CoM accelerations, $\ddot{\boldsymbol{q}}(t) \in \mathbb{R}^{m*n}$, where m denotes the number of samples and n denotes the output variables, as a function of nonlinear dynamics:

$$\frac{d^2}{dt^2}\boldsymbol{q}(t) = \ddot{\boldsymbol{q}}(t) = f\big(\boldsymbol{q}(t), \dot{\boldsymbol{q}}(t)\big), \tag{1}$$

where $\boldsymbol{q}(t)$ and $\dot{\boldsymbol{q}}(t)$ are the CoM positions and velocities over time relative to the feet in three principal directions. This dynamical equation can be simplified using SINDy, leading to:

$$\ddot{\boldsymbol{q}} = \boldsymbol{\Theta}(\boldsymbol{q}, \dot{\boldsymbol{q}})\boldsymbol{\Xi}, \tag{2}$$

where $\boldsymbol{\Xi} \in \mathbb{R}^{p*n}$, is a linear map to assist in interpreting CoM dynamics, $\boldsymbol{\Theta}(\boldsymbol{q}, \dot{\boldsymbol{q}}) \in \mathbb{R}^{m*p}$, in relation to the CoM accelerations. This SINDy algorithm generates a sparse model with $p = 14$ (7 per leg) based on a threshold met by sequential least-squares regression. Hybrid-SINDy pairs this approach with clustering and automatic selection of system dynamics. The authors use Hybrid-SINDy to cluster unique dynamics in different phases of the gait cycle (deemed "template-phases") and automatically chose and define system dynamics that best describe the collected data.

Using Hybrid-SINDy, Rosenburg and colleagues analyzed walking data collected using a 3D motion capture system from twelve unimpaired adults and one stroke survivor. Participants walked at a self-selected pace in three conditions: 1) no-Exo, 2) Exo with no applied stiffness (zero stiffness), and 3) Exo with applied stiffness (high stiffness). Hybrid-SINDy clustering was used to reduce noise and identify frequently occurring dynamics within specific gait phases, and model estimation was accomplished by using SINDy to estimate sparse coefficients for multiple template-signatures based on gait phase. Multi-model inference was used to construct a template signature for each gait phase, which were then normalized to participant parameters. The impact of an Exo on CoM dynamics was assessed by comparing template-signature coefficients between the three different walking conditions.

Following this framework, the authors demonstrated that template-signatures derived from the no-Exo walking revealed common representations of CoM dynamics among the individual unimpaired participants. Unimpaired adults were shown to have unaffected CoM dynamics that remained robust for passive Exo walking compared to the no-Exo condition. During single-limb support in the gait cycle, an Exo had minimal effects on template-signatures compared to no-Exo walking. During double-limb support, however, the deviation from the no-Exo template varied. In particular, the single stroke participant had template-signatures that revealed asymmetry in CoM dynamics, particularly in double-limb support. Despite variations between participants, however, the identified template-signatures explained 67-94% of the CoM variance with the given algorithm constraints. These identified template-signatures showed consistent selection of near spring-loaded inverted pendulum models used to represent a simplified model of walking with a stiffness-varying Exo. The applied Hybrid-SINDy algorithm was crucial in discerning individual-specific changes resulting from the Exo and provided interpretable insights into how the CoM dynamics vary for individuals. These insights hold significant implications for the development of control algorithms for assistive and rehabilitative devices like an Exo, as understanding individual-specific patterns in CoM dynamics and gait can inform the design of personalized control strategies tailored to optimize locomotion for each user.

1.2 | Limitations and Societal Considerations

Rosenberg et al. [1] identifies several limitations in their study, noting that while Hybrid-SINDy effectively captured the CoM dynamics while walking with an Exo, the derived template-signatures showed similar accuracy to prior work with predefined 2D template-structures, suggesting limited improvement over pre-existing models of simplified dynamics. Additionally, it is acknowledged that only lower-limb dynamics are evaluated, leading to potential inaccuracies that may arise from lack of upper-limb or torso dynamics during locomotion. This work also acknowledges the inability to generalize findings to different populations or tasks, such as individuals with neurological injuries, due to their limited sample size and task-specific data. While Hybrid-SINDy offers advantages in identifying changes in CoM dynamics, it may not fully capture phase-varying dynamics. This assumption of the time invariance in CoM dynamics ignores potential adaptation to Exo usage while walking.

Inaccurate representation of whole-body dynamics, lack of generalizability to populations, and assumptions of time invariant responses to an Exo can impact control applications. Incomplete mechanism libraries for modeling CoM dynamics with an Exo, along with the impact of noise in collected data and non-generalizable findings, may lead to inaccuracies in models used for control algorithms. This may potentially compromise the control algorithm effectiveness, particularly in neurologically impaired populations with gait deviations. Use of an Exo for improving locomotion, especially among individuals with neurological injuries, is a crucial societal consideration for both rehabilitative and assistive purposes. Understanding the effects of an Exo on gait is crucial for optimizing Exo benefits and ensuring safe and effective use, as improper use can lead to detrimental effects.

In the broader context of control and machine learning, the challenges highlighted by the limitations of the study demonstrate the importance of robust modeling techniques for informing control algorithms, particularly in complex systems such as exoskeleton-assisted locomotion. Additionally, the use of Hybrid-SINDy shows the adaptability of data-driven modeling applications to provide targeted control algorithms that allow personalized assistance/rehabilitation, such as only providing Exo stiffness as certain points in the gait cycle as identified by Hybrid-SINDy models. This study contributes to building a foundation for control applications in rehabilitation and assistive technologies through use of data-driven modeling, such as SINDy, outside of simulations and synthetic datasets and in more noise-prone environments.

1.3 | Data Availability and Replication

The paper provides detailed information about the methodology used, including the Hybrid-SINDy algorithm and its implementation for analyzing CoM dynamics with and without an Exo. The data used for this study is publicly available and included in the publication, as well as the analysis and model code. For replication of this work, adherence to the published methods and instructions in the available code can be used, although slight deviations in results may occur due to the cutoff points of the algorithms implemented.

2 Related Literature

2.1 | Ankle Exoskeletons

Ankle exoskeletons, such as those analyzed by Rosenberg et al. [1], are wearable devices that may assist or resist the user during a specific task to improve energetics, gait mechanics, or rehabilitation outcomes [1], [3]–[8]. These wearable devices may be powered or unpowered but operate under the same strategy of supplying additional torque or stiffness at key points in the gait cycle to achieve desired walking mechanics [3], [5], [6], [9]. This torque or stiffness is achieved through spring-damper interactions as described in Rosenberg et al. [1]. An example of their use is improving toe-clearance during walking by providing additional torque [3] or by restricting ankle rotation to provide stability during locomotion [1]. Their effectiveness for rehabilitative or assistive purposes is often contested due to the individual-specific response, leading to potential deficits in walking function if device parameters are not controlled properly [5], [8]. Thus, there is a need to develop individual-specific models for ankle exoskeletons to maximize the benefits and optimally control the various parameters that contribute to changes in gait mechanics.

2.2 | Individual Specific Modeling

Individual specific models are often used in biological systems due to the individualized responses elicited from various interventions or interference [1], [10]–[14]. As demonstrated by Rosenberg et al. [1], there exists unique characteristics and behaviors of individual subjects within a population when analyzing gait mechanics [1], [14]. These differences are more noticeable and prevalent in populations with neurological impairments, such as stroke, leading to a lack of generalizability for many control algorithms for wearable robotic devices [1], [13]–[15]. Consequently, individual-specific models may be employed to account for individual differences, thus improving the accuracy and applicability of control algorithms and developing a more accurate understanding of the underlying dynamics driving the investigated responses [1], [15], [16].

Individual specific modeling can be achieved by using observed experimental or simulated data to develop models that do not rely on a generalized algorithm or inaccurate assumptions that do not account for variety within a population. While use of a simplified or generalized model may assist in interpretation, such as the spring-loaded inverted pendulum model for walking as described by Rosenberg et al. [1], these models do not account for variability in individuals with deviations when compared to the nominal response expected. Thus, it is suggested that implementation of fundamental underlying physics can be used and individualized when building models for interpretation of response to interventions, control applications, and more [1], [5], [15], [16].

2.3 | Sparse Identification of Nonlinear Dynamics (SINDy)

Sparse identification of nonlinear dynamics (SINDy) is a data-driven method that uses sparse regression and compressed sensing within high-dimensional data to discover the underlying dynamical equations governing a system [17], [18]. Traditional modeling approaches may be challenging to implement due to limited knowledge of the underlying physics, presence of noise in data, or extreme non-linearity, and thus SINDy is an alternative method for developing lower-dimensional models that account for dynamical responses in a system[1], [17], [18]. SINDy leverages the existence of sparse dynamics that most physical systems demonstrate, such as those analyzed by non-negative matrix factorization and principal component analysis in walking [17], [18].

Briefly, application of SINDy begins with the collection of observational or simulated time-series measurements of a system [17], [18], such as walking kinematics and CoM as analyzed in Rosenberg et al. [1]. Following this, the SINDy algorithm constructs a library of possible functions based on the chosen state variables to discover appropriate models based upon the input data. SINDy uses sparse regression techniques to identify most relevant terms in the system's dynamics that account for most of the system's variance. Using these techniques, SINDy identifies and constructs a model using a lower-dimensional sparse set of coefficients representative of the system dynamics and the found dynamical equations derived from the library of functions [17], [18].

Since the techniques used by SINDy are data-driven, SINDy can build individual-specific models that do not rely on generalized equations or assumptions as demonstrated by Rosenberg et al. [1]. Additionally, the use of SINDy allows for the discovery of unknown dynamical equations that may govern a system, such as those that occur when walking with an ankle exoskeleton of various applied torque and stiffness[1], [17], [18]. Consequently, using SINDy and SINDy based applications to analyze human locomotion when walking with wearable devices, such as ankle exoskeletons, is particularly useful to determine accurate dynamical models of the non-linear behavior demonstrated [1].

2.4 | Potential Applications and Future Work

Utilizing a Hybrid-SINDy approach to analyze impact from ankle exoskeleton usage in human locomotion demonstrated the need for discovering the underlying dynamics governing responses to determine the appropriate exoskeleton parameters to achieve desired gait mechanics [1]. Rosenberg et al. [1] found that unimpaired individuals may generalize to certain gait-phase specific responses depending on the applied exoskeleton stiffness. It is suggested that responses in individuals with neurological injury, such as the case study analyzed in Rosenberg et al. [1] may be better understood when the dynamics are discovered through data-driven approaches to mitigate assumptions made in simplified locomotion models [5], [6], [8], [10]. Thus, future work should explore employing the use of SINDy in neurologically impaired populations to aid in developing appropriate parameters for rehabilitative and assistive usage of ankle exoskeletons and avoid potential negative effects of these devices arising from improper usage and personalization.

While CoM dynamics and variation in response to ankle exoskeleton usage has highlighted the importance of individual-specific personalization for these devices in order to optimize energetics and balance, there remains an uncertainty as to how these devices impact other factors of human walking, such as muscle activity and pattern recruitment [19]-[21]. Understanding how ankle exoskeletons impact muscle activity is crucial to evaluating their effectiveness for assistive and rehabilitative purposes to prevent fatigue and optimize usage of the device on walking mechanics. Additionally, many ankle exoskeletons have investigated using muscle activity to independently control the response and behavior of the exoskeleton, however, the control algorithms implemented are often insufficient to control non-linear behavior outside of single-task environments, such as walking on a treadmill [4], [6], [22].

As outlined by Rosenberg et al. [1], SINDy and related variations offer promising alternatives to traditional individual specific modeling approaches. It has been shown that muscle activity may describe individual specific gait patterns, allowing for use of muscle activity in building models for control purposes [16], [23]. Incorporating SINDy-based approaches into the analysis of muscle activity dynamics could provide valuable insights into the interplay between exoskeleton effects and muscular responses, enabling more nuanced control strategies. Using SINDy to interpret the responding dynamics of muscle activity to inform control algorithms, such as those that occur from a gait-phase specific ankle exoskeleton torque or stiffness, may achieve higher control accuracy than traditional generalized methods, particularly for individuals with neurological injury that may have gait deviations that cannot be described by simple linear models.

3 | References

[1] M. C. Rosenberg, J. L. Proctor, and K. M. Steele, "Quantifying changes in individual-specific template-based representations of center-of-mass dynamics during walking with ankle exoskeletons using Hybrid-SINDy," *Sci Rep*, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-023-50999-0.

[2] S. W. Lipfert, M. Günther, D. Renjewski, S. Grimmer, and A. Seyfarth, "A model-experiment comparison of system dynamics for human walking and running," *J Theor Biol*, vol. 292, pp. 11–17, Jan. 2012, doi: 10.1016/j.jtbi.2011.09.021.

[3] Z. F. Lerner *et al.*, "An untethered ankle exoskeleton improves walking economy in a pilot study of individuals with cerebral palsy," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 10, pp. 1985–1993, Oct. 2018, doi: 10.1109/TNSRE.2018.2870756.

[4] D. P. Ferris and C. L. Lewis, "Robotic lower limb exoskeletons using proportional myoelectric control," *Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009*, pp. 2119–2124, 2009, doi: 10.1109/IEMBS.2009.5333984.

[5] J. de Miguel-Fernández, J. Lobo-Prat, E. Prinsen, J. M. Font-Llagunes, and L. Marchal-Crespo, "Control strategies used in lower limb exoskeletons for gait rehabilitation after brain injury: a systematic review and analysis of clinical effectiveness," *Journal of NeuroEngineering and Rehabilitation*, vol. 20, no. 1. BioMed Central Ltd, Dec. 01, 2023. doi: 10.1186/s12984-023-01144-5.

[6] A. Nasr, B. Laschowski, and J. McPhee, "Myoelectric control of robotic leg prostheses and exoskeletons: A review," in *Proceedings of the ASME Design Engineering Technical Conference*, American Society of Mechanical Engineers (ASME), 2021. doi: 10.1115/DETC2021-69203.

[7] K. M. Steele, R. W. Jackson, B. R. Shuman, and S. H. Collins, "Muscle recruitment and coordination with an ankle exoskeleton," *J Biomech*, vol. 59, pp. 50–58, Jul. 2017, doi: 10.1016/j.jbiomech.2017.05.010.

[8] P. Slade, M. J. Kochenderfer, S. L. Delp, and S. H. Collins, "Personalizing exoskeleton assistance while walking in the real world," *Nature*, vol. 610, no. 7931, pp. 277–282, Oct. 2022, doi: 10.1038/s41586-022-05191-1.

[9] A. J. Young and D. P. Ferris, "State of the art and future directions for lower limb robotic exoskeletons," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 2, pp. 171–182, Feb. 2017, doi: 10.1109/TNSRE.2016.2521160.

[10] M. C. Rosenberg, B. S. Banjanin, S. A. Burden, and K. M. Steele, "Predicting walking response to ankle exoskeletons using data-driven models," *J R Soc Interface*, vol. 17, no. 171, Oct. 2020, doi: 10.1098/RSIF.2020.0487.

[11] A. J. Meyer, I. Eskinazi, J. N. Jackson, A. V. Rao, C. Patten, and B. J. Fregly, "Muscle synergies facilitate computational prediction of subject-specific walking motions," *Front Bioeng Biotechnol*, vol. 4, no. OCT, p. 211855, Oct. 2016, doi: 10.3389/FBIOE.2016.00077/BIBTEX.

[12] V. Grimm *et al.*, "A standard protocol for describing individual-based and agent-based models," *Ecol Modell*, vol. 198, no. 1–2, pp. 115–126, Sep. 2006, doi: 10.1016/J.ECOLMODEL.2006.04.023.

[13] D. Bonetti and M. Johnston, "Perceived control predicting the recovery of individual-specific walking behaviours following stroke: Testing psychological models and constructs," *Br J Health Psychol*, vol. 13, no. 3, pp. 463–478, Sep. 2008, doi: 10.1348/135910707X216648.

[14] L. Bianchi, D. Angelini, and F. Lacquaniti, "Individual characteristics of human walking mechanics," *Pflugers Arch*, vol. 436, no. 3, pp. 343–356, 1998, doi: 10.1007/S004240050642/METRICS.

[15] M. R. Ebers, M. C. Rosenberg, J. N. Kutz, and K. M. Steele, "A machine learning approach to quantify individual gait responses to ankle exoskeletons," *J Biomech*, vol. 157, Aug. 2023, doi: 10.1016/j.jbiomech.2023.111695.

[16] T. S. Winner, M. C. Rosenberg, K. Jain, T. M. Kesar, L. H. Ting, and G. J. Berman, "Discovering individual-specific gait signatures from data-driven models of neuromechanical dynamics," *BioRxiv*, 2022, doi: 10.1101/2022.12.22.521665.

[17] S. L. Brunton, J. L. Proctor, and J. N. Kutz, "Discovering governing equations from data by sparse identification of nonlinear dynamical systems," *Proc Natl Acad Sci U S A*, vol. 113, no. 15, pp. 3932–3937, 2016, doi: 10.1073/pnas.1517384113.

[18] S. L. Brunton and J. N. Kutz, "Data-Driven Science and Engineering Machine Learning, Dynamical Systems, and Control," 2021.

[19] B. C. Conner, J. Luque, and Z. F. Lerner, "Adaptive Ankle Resistance from a Wearable Robotic Device to Improve Muscle Recruitment in Cerebral Palsy," *Ann Biomed Eng*, vol. 48, no. 4, pp. 1309–1321, Apr. 2020, doi: 10.1007/s10439-020-02454-8.

[20] B. C. Conner, M. H. Schwartz, and Z. F. Lerner, "Pilot evaluation of changes in motor control after wearable robotic resistance training in children with cerebral palsy," *J Biomech*, vol. 126, Sep. 2021, doi: 10.1016/j.jbiomech.2021.110601.

[21] A. M. Spomer, B. C. Conner, M. H. Schwartz, Z. F. Lerner, and K. M. Steele, "Audiovisual biofeedback amplifies plantarflexor adaptation during walking among children with cerebral palsy," *J Neuroeng Rehabil*, vol. 20, no. 1, Dec. 2023, doi: 10.1186/s12984-023-01279-5.

[22] I. S. Dhindsa, R. Agarwal, and H. S. Ryait, "Principal component analysis-based muscle identification for myoelectric-controlled exoskeleton knee," *J Appl Stat*, vol. 44, no. 10, pp. 1707–1720, Jul. 2017, doi: 10.1080/02664763.2016.1221907.

[23] A. M. Spomer, R. Z. Yan, M. H. Schwartz, and K. M. Steele, "Motor control complexity can be dynamically simplified during gait pattern exploration using motor control-based biofeedback," *J Neurophysiol*, vol. 129, no. 5, pp. 984–998, May 2023, doi: 10.1152/jn.00323.2022.