Individualized three-dimensional gait pattern generator for lower limbs rehabilitation robots *

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***Abstract*— In the field of robotic gait rehabilitation, controlling robotic devices to follow specific human-like trajectories is often required. In recent years, various gait generator models have been proposed, providing customized gait patterns adjustable to a range of heights and gait speeds. However, these models were developed with a focus on gait rehabilitation devices designed to control the angular trajectories of the subject's joints, e.g. exoskeletons. Similar devices, e.g. end-effector robots, control the orientation and also the 3D position of the subject's joints and cannot easily implement these models. In this study, it is proposed a new individualized three-dimensional gait pattern generator for gait rehabilitation robots. The generator employs multi-variable regression models to predict the joint angular trajectories of the pelvis, hip, and ankle along the gait cycle. The 3D joints positions are then reconstructed by applying the predicted angular trajectories over a human model inspired on the inverted pendulum analogy using inverse kinematics. The generator's performance was statistically evaluated against real gait patterns from 42 participants walking at 8 different velocities. The predicted trajectories matched the measured ones with an average Root Mean Squared Error of 25.73 mm for all joints at all Cartesian axes, with better results between 3.3 - 5.4 km/h. Suggesting to be a good solution to be applied in end-effector gait robotic rehabilitation devices.**

I. Introduction

Over the past decade, the field of gait rehabilitation robotics has experienced considerable progress, marked by the development of multiple robotic platforms [1]. These platforms are generally designed to assist the users affected limbs to follow human-like position/angular trajectories inducing motor learning [1]. Traditional methods for acquiring these trajectories typically involve either the use of clinically pre-determined gait patterns or gait reconstruction derived from devices kinematic measurements [3]–[5].

While these methods have been widely applied, they present certain constraints. Firstly, they tend to overlook gait variability arising from physical factors, such as subject dimensions and gait speed [4], as they rely on clinical pre-determined trajectories. Secondly, gait reconstruction derived from devices kinematic measurements can result in unnatural walking trajectories due to the inertias of the devices and the complexities of human-robot interaction.

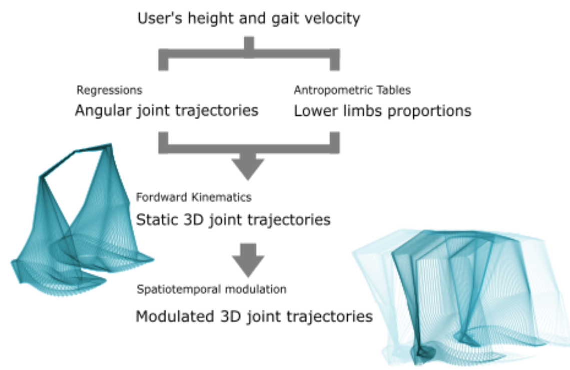

Figure 1.Gait generator algorithm for lower limb three-dimensional gait control.

Recent approaches worked around this issue by proposing gait pattern generators based on multivariable regressions models applied in overground and treadmill walking gait datasets [2]–[4]. The obtained predicted trajectories successfully estimated gait angular variability improving the user-machine coupling during exoskeleton gait rehabilitations and rehabilitation outcomes [4].

Although these recent gait generators have been successfully implemented in some gait rehabilitation robotic platforms, [5], they are mainly focused on angle trajectory estimations in specific anatomical planes sagittal (front-to-back) or transversal (side-to-side) [2]. However, this approach has limitations when it comes to some end-effector robots.

These robots control the cartesian (three-dimensional) position and orientations of the user's joints during gait. The current approach cannot be directly applied to these robots because the target patients may have different body proportions, and the system needs to know the exact position of the joints in space [6].

In this article, we present a three-dimensional gait pattern generator adaptable to the users' height and walking speed to

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control the 3D lower limbs' motion, see Figure 1. The generator uses multi-variable regressions models inspired by Koopman [2] to predict pelvis, hip and ankle angular key-events for a range of gait speeds and heights. This predicted key-events are then used to reconstruct the angular joints gait profiles by applying piece-wise quantic spline fitting. The reconstructed angular trajectories are combined with the anthropometric users' dimensions applying forward kinematics, resulting in 3D joints trajectories. By estimating the spatiotemporal information (step length and step period) of the gait and analyzing the relative joints displacement over the gait cycle the final 3D gait trajectory is estimated.

In this article the proposed generator has been particularly implemented in the Discover2Walk robotic platform [6]. An end-effector gait rehabilitation robot for toddlers with Cerebral Palsy (CP)[6], composed by two modules: a suspended cable-driven system that performs bodyweight support while controlling the pelvic position and rotations (rotation and obliquity). And an parallel cable-driven module to control the ankles positions.

II. ALGORITHM

A. Speed-dependent joint angular trajectories estimation

To estimate the angular trajectories of the lower joints, first a multi-variable regression model is applied over statistically significant points (key-events) of the angular joint trajectories subtracted from a public gait dataset [7]. Then, the angular trajectories are reconstructed by applying piece-wise quantic spline fitting over the estimated key-events.

Our approach is considered an extension of Koopman's regression model [8],[2] which applied multi-variable regressions and spline fitting to obtain the ankle, knee and hip angular trajectories along the sagittal plane and the hip's transversal plane.

In our approach, since we aim to reconstruct a 3D gait pattern, we also include pelvic trajectories estimations over the sagittal and frontal plane (rotation and obliquity).

- *Dataset:*

The used gait dataset [7] contains information about 42 healthy adults walking at 8 different self-selected gait velocities (from 40%-145% of the self-preferred gait speed) over a instrumented treadmill during 90 seconds. The joints positions were measured with a photogrammetric system with 28 body markers (motion-capture system 12 cameras Raptor 4 ; Motion Analysis Corporation, Santa Rosa, CA, USA) and the dynamic information recorded with the treadmill pressure platforms (dual-belt instrumented treadmill FIT; Bertec, Columbus, OH, USA). The subjects involved in the experiments had an average height of $\hat{h} = 167.3\ cm$ and their average gait speed was $\hat{v} = 4.4\ km/h$, see Table 1.

TABLE 1 GAIT DATASET INFORMATION

Variable	**Median**	P_{25}	P_{75}	**Max**	**Min**
Height (cm)	168.2	157.5	174.2	192	147
Velocity (km/h)	4.5	3.3	5.4	6.3	1.2
Mass (kg)	67.5	61.2	75.8	95.4	44.9

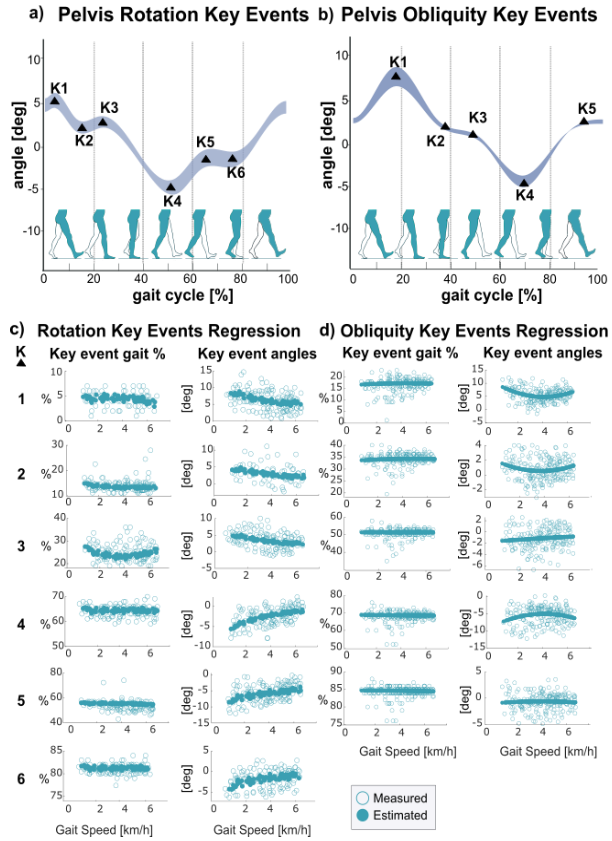

Figure 2. Key events gait positions (%) and angular values (deg) predictions for the pelvis rotation and abduction. Subplots a) and b) represent the average angular gait trajectories for the pelvis rotation and obliquity of the hole dataset and the corresponding key events positions along the gait cycle. Subplots c) and d) represent the measured key events values (deg) and positions (%) and the estimated ones based on the multivariable regression output for all the dataset.

- *Gait analysis*

Based on the raw data of the joints markers data, using MATLAB2022b the joint angles of each subject and trial were subtracted and segmented in gait cycles. Segmentation was archive based on the treadmill's reaction force plates data: when the subjects land a foot over the ground surpassing a minimum force threshold a new step was counted. This is event is called heel strike and defines the starting point of the gait cycle, see Figure 2 a), b). During segmentation to avoid errors or wrong measurements of the equipment, any step size larger than the 25 and 75 percentile of all segmented steps was excluded.

- *Key-events:*

To reduce the complexity of the angular gait trajectories we down sample the data into meaningful points: joints angles values and its corresponding gait %. These meaningful points were identified by undertaking a statistically significant analysis over the maximum angular, speed and acceleration values for all patients at all gait velocities. Those points dependent on the gait velocity or height (p-values smaller than the typically threshold 0.01) were determined as meaningful since they were statistically significant for gait speed and height modifications. In Figure 2 a) are showed the pelvis angular trajectories (obliquity and rotation) during a gait cycle and its corresponding key-events positions and values. In this case, six key-events were obtained for the pelvis rotation and five for the pelvis obliquity (without counting the start and end of the joint trajectory corresponding to the heel-strike).

- *Regression model:*

Once the angular trajectories are down sampled into key-events, they are used as independent variables in a multivariable regression model to obtain its correlation with the gait speed and patient height (dependent variables). Robust regression with ‘bisquare’ weighting function Y was used for this approach:

$$Y = \beta_0 + \beta_1\, v + \beta_2\, v^2 + \beta_3\, l \tag{1}$$

where v represents the gait velocity, l the subject’s height and Y the predicted value.

With the aforementioned method we were able to get a regression that fits the identified key-values as showed in Figure 2 c) and d).

- *Angle trajectory reconstruction:*

From the estimated key-events, the continuous angular trajectory is reconstructed by applying quintic spline fitting over the obtained key-values gait cycle positions and angular values.

B. *Kinematic model of the lower limbs*

To model the 3D human walking we applied a kinematic approximation based on a simple mechanical mode, see Figure 3 a). Our approach generates the 3D gait kinematics by applying the estimated angular gait trajectories over the kinematic human model. At each instant k of the gait cycle, the general rotation matrix $\mathbf{R}(k)$ is computed at each joint (j) (see Eq. 2). The cartesian positions of the joints are obtained by applying forward kinematics over a kinematic model using the users’ limbs anthropometric dimensions, provided by D.A. Winter [8], and $\mathbf{R}(k)$, (see Eq. 3 and 4 and Figure 3 b)).

$$\mathbf{R}_{\mathrm{j}}(k) = \boldsymbol{R}_{roll}(k)\boldsymbol{R}_{pitch}(k)\boldsymbol{R}_{yaw}(k) =$$

$$= \begin{bmatrix} \cos\alpha(k) & -\sin\alpha(k) & 0 \\ \sin\alpha(k) & \cos\alpha(k) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\beta(k) & 0 & \sin\beta(k) \\ 0 & 1 & 0 \\ -\sin\beta(k) & 0 & \cos\beta(k) \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma(k) & -\sin\gamma(k) \\ 0 & \sin\gamma(k) & \cos\gamma(k) \end{bmatrix} \tag{2}$$

$$\boldsymbol{q}^{r}{}_{\mathrm{j}}(k) = \mathbf{R}_{j-1}(k) \times \boldsymbol{d}_j \tag{3}$$

$$\boldsymbol{q}^{p}{}_{\mathrm{j}}(k) = \boldsymbol{q}^{p}{}_{\mathrm{j-1}}(k) + \boldsymbol{q}^{r}{}_{\mathrm{j}}(k) \tag{4}$$

where α, β and γ are the estimated joint angles for each anatomical plane, $\boldsymbol{q}^{r}{}_{\mathrm{j}}(k) \in \mathbb{R}^3$ is the 3D position of the joint j at instant k relative to the upper join $j-1$, $\boldsymbol{d}_j$ is the anthropometric dimension of the body segment, $\mathbf{R}_{\mathrm{j-1}}(k) \in \mathbb{R}^{(3x3)}$ is the general rotation matrix of the joint $j-1$ at instant k, $\boldsymbol{q}^{p}{}_{\mathrm{j-1}}(k) \in \mathbb{R}^3$ and $\boldsymbol{q}^{p}{}_{\mathrm{j}}(k) \in \mathbb{R}^3$ are the 3D positions at the instant k of the joint j and j-1 respect the pelvis origin reference system $\boldsymbol{q}^{0}{}_{\mathrm{pelvis}}(k)$.

The computed 3D trajectories are “static trajectories” since they do not consider the inherent translation in human gait. The angular data is relative to the body so the point of origin is the pelvis joint, a static point in space, defined by the user leg length $\boldsymbol{q}^{0}{}_{\mathrm{pelvis}} = [0\ 0\ d_{\mathrm{leg}}]'$.

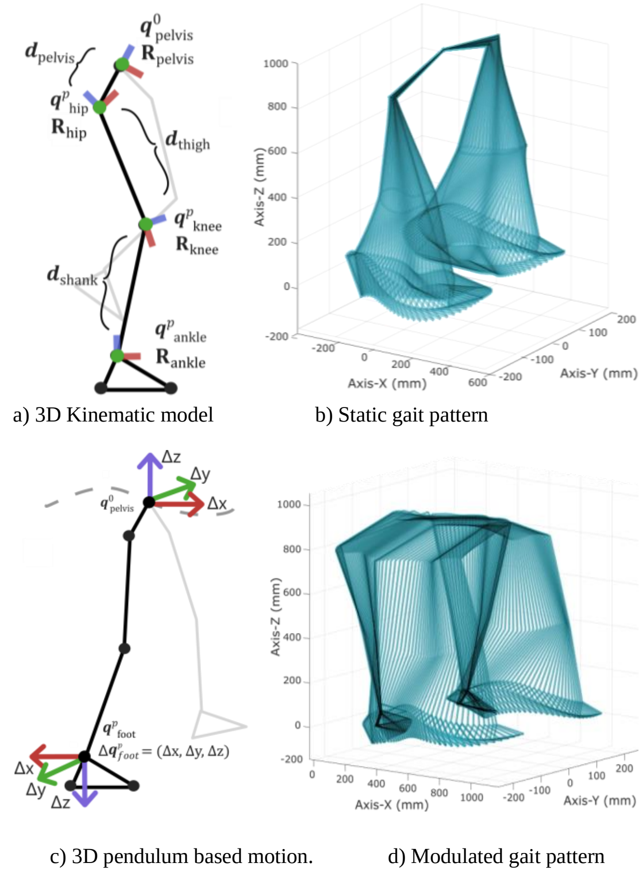

Figure 3. Kinematic model of the gait generator. a) 3D human model used to reconstruct the static gait pattern based on the subject segments dimensions ($\boldsymbol{d}_j$) and the joint rotations ($\mathbf{R}_{\mathrm{j}}$); b) reconstructed static 3D gait pattern along a full gait cycle; c) gait translation model based on the relative foot displacement in the x, y and z axis respect the pelvis reference point, d) reconstructed 3D gait pattern including translation displacement.

C. *Spatiotemporal gait modulation*

- *Spatial translation*

The translational motion derived from the computed static gait pattern is obtained by applying an inverted pendulum analogy [9]. The joints positions during the gait cycle are obtained by studying the feet displacement with respect to the pelvis during its contact with the ground and considering enough the floor friction force to avoid slippage, see Figure 3 c).

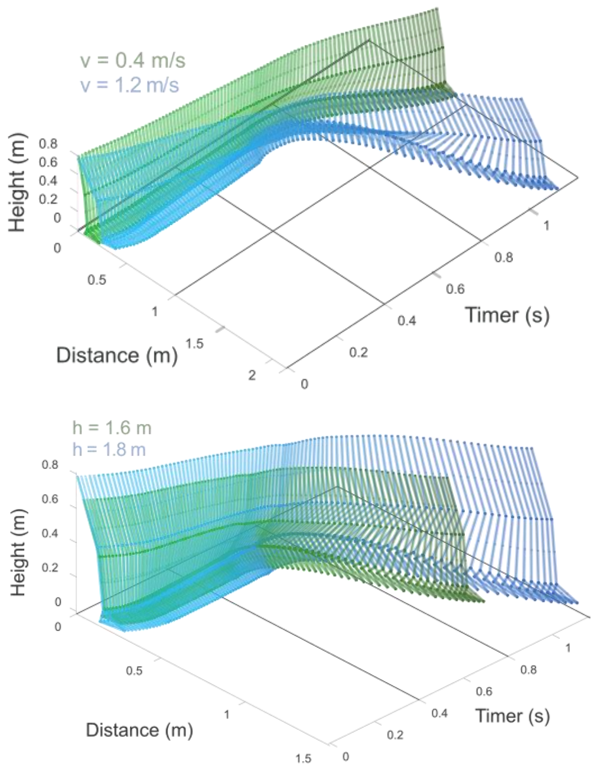

Figure 4. Spatiotemporal modulation of the gait trajectories due to speed and subject height variation. a) 3D gait trajectories of two gait speeds (0.4 m/s green and 1.2m/s blue) and same height (1.8m). b) 3D gait trajectories for two heights (1.8 m and 1.6 m) and same velocity (0.7 m/s).

The motion is transmitted from the foot's initial contact with the floor till the foots lifts-off the ground, phase known as "stance", typically from the 0% to the 60%-65% of the gait cycle. By adding the relative motion of the foot ($\Delta \boldsymbol{q}^{p}{}_{\text{foot}}$) respect the pelvis ($\boldsymbol{q}^{0}{}_{\text{pelvis}}$) during stance, the gait translation of the pelvis during the gait cycle is obtained, see Figure 3 c), d).

These 3D estimated trajectories present small artifacts due to angular trajectory and/or segment length errors. A fixed length window moving average was applied for smoothing the signals, eliminating artifacts and ensuring gait trajectories continuity.

- *Temporal modulation*

To modulate the computed 3D trajectories, it is needed to add its temporal information. The sampling frequency of the generator is computed based on the gait cycle period ($T_{gait\ cycle}$) and the desired number of generated samples per second. Based on the stride length (L_{stride}) defined as the foot motion over the x axis during stance and the subjects gait speed (v_{gait}), the gait period is computed as:

$$L_{stride} = 2 \cdot \sum_{k\,=\,0\%}^{\sim 65\%} \Delta \boldsymbol{q}^{\boldsymbol{p}}{}_{foot_x}(k) \tag{5}$$

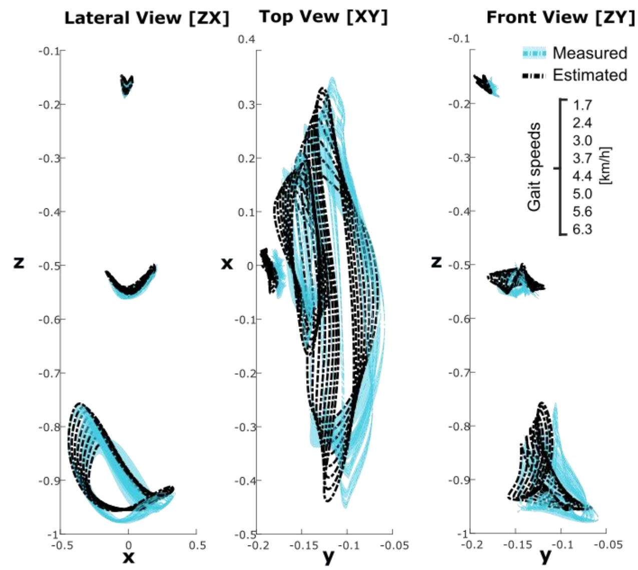

Figure 5. Representation in the cartesian space of the gait comparison between the static gait generated trajectories (black dashed lines) and the dataset measured ones (semitransparent blue lines) for the hip-knee-ankle joint of the subject 19. Subject 19 walked at 8 gait velocities ranging from 1.7 to 6.3 km/h and measured 175 cm.

$$T_{gait\ cycle} = \frac{v_{\text{gait}}}{\text{L}_{\text{stride}}} \tag{6}$$

Based on $T_{gait\ cycle}$ the obtained 3D trajectories are modulated. So variations of gait speed and subjects height affects both stride length and gait duration (see Figure 4 a) and b)).

III. VALIDATION AND RESULTS

The presented gait generator outputs estimations of the lower joints 3D gait trajectories dependent on the specified subject height and gait velocity.

To evaluate the precision of the generated trajectories we compare them against the data provided by the aforementioned public gait dataset [7]. For each subject's session, at each gait velocity, we computed the average 3D joints trajectories based on the body-markers positions data.

The obtained trajectories were then compared with the generated ones for the specific subject's height and gait velocity (see Figure 5).

This comparison was used to obtain the quality of the model by computing the Root-Mean-Square error (RMSE) for all subjects heights and gait velocities and the RMSE average for each joint (see Figure 6 and Figure 7).

The results suggest the generated trajectories matched the measured ones well. The average RMSE for all joints was of 25.73 mm, were the smallest error was found on the hip's Y trajectory (14.87 mm) and the greatest in the ankle's

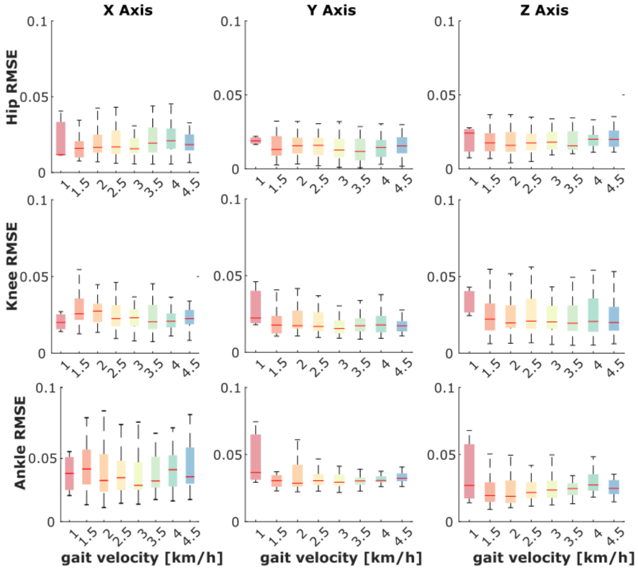

Figure 6. Statistical analysis evaluating the performance of the gait generator model in comparison to the measured data. The plots depict the median, 25th percentile, 75th percentile, as well as the maximum and minimum RMSE values that compared the three-dimensional measured and generated gait profiles for all 42 subjects in the dataset. It was observed that slightly higher errors and deviations occurred at lower gait velocities.

X trajectory (43.59mm); mainly because distal joints (knee and ankle) have higher ranges of motion.

While observing the RMSE results over all gait velocities we found similar errors for all velocities except for velocities slower than 1.5 km/h. Higher errors and deviations were observed for them. This can be directly related with the dataset gait speed distribution shown in TABLE 1 and suggests that our model performance is better suited form gait velocities between the $P_{25} - P_{75}$ of the database (3.3 -5.4 km/h).

IV. Conclusion

In this article we presented an individualized three-dimensional gait pattern generator dependent on the gait speed and subject height. By applying multi-variable regression models to reconstruct angular gait trajectories we obtained estimate joint angular trajectories. When applied over human kinematic models we derive the spatiotemporal gait trajectories specifically tailored to each patient's anthropometric data and gait velocity.

Our gait generator was benchmarked against real gait patterns, captured using photogrammetric systems and demonstrating compelling efficacy. The model was evaluated across a variety of heights and walking speeds resulting in an average three dimensional RMSE for all the joints at all cartesian axis of 25.73 mm.

Further scrutiny of the results suggest that our model's RMSE values are smaller and present less deviations when

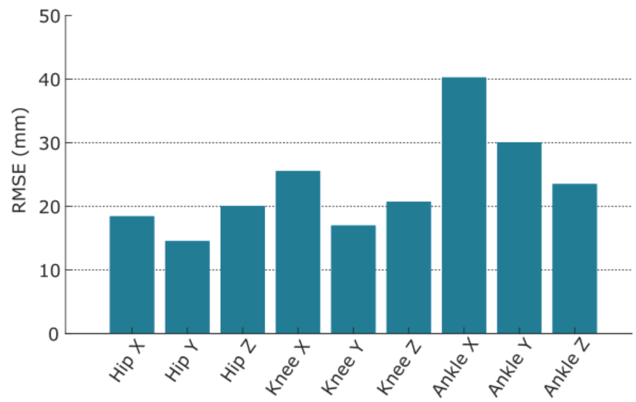

Figure 7. Averaged RMSE values for all joints at all measured velocities.

applied over gait speeds between the $P_{25} - P_{75}$ of the evaluated dataset as displayed in the statistical analysis in Figure . Suggesting that it would offer better-fitted trajectories when applied over 3.3 - 5.4 km/h.

For future improvements, the intent is to expand the gait dataset should include a more diverse range of data, enabling a more accurate estimation of slower gait velocities, thus improving the model's overall precision and reliability.

As a conclusion, this work creates a tool for three-dimensional gait control. Contributing to any gait rehabilitation robotic platform that intends to control speed-height sensible gait trajectories over the cartesian space. Its successful integration into a novel end-effector platform (Discover2Walk) underlines its potential for real-world applications in rehabilitative contexts.

Acknowledgment

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References

[1] H. Vallery, E. H. F. Van Asseldonk, M. Buss, and H. Van Der Kooij, "Reference trajectory generation for rehabilitation robots: Complementary limb motion estimation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 17, no. 1, pp. 23–30, Feb. 2009, doi: 10.1109/TNSRE.2008.2008278.

[2] B. Koopman, E. H. F. van Asseldonk, and H. Van der Kooij, "Speed-dependent reference joint trajectory generation for robotic gait support," *J Biomech*, vol. 47, no. 6, pp. 1447–1458, Apr. 2014, doi: 10.1016/J.JBIOMECH.2014.01.037.

[3] X. Wu, D. X. Liu, M. Liu, C. Chen, and H. Guo, "Individualized Gait Pattern Generation for Sharing

Lower Limb Exoskeleton Robot," *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 4, pp. 1459–1470, Oct. 2018, doi: 10.1109/TASE.2018.2841358.

[4] X. Hu, F. Shen, Z. Zhao, X. Qu, and J. Ye, "An individualized gait pattern prediction model based on the least absolute shrinkage and selection operator regression," *J Biomech*, vol. 112, Nov. 2020, doi: 10.1016/J.JBIOMECH.2020.110052.

[5] J. S. Lora-Millan, F. J. Sanchez-Cuesta, J. P. Romero, J. C. Moreno, and E. Rocon, "A unilateral robotic knee exoskeleton to assess the role of natural gait assistance in hemiparetic patients," *J Neuroeng Rehabil*, vol. 19, no. 1, pp. 1–24, Dec. 2022, doi: 10.1186/S12984-022-01088-2/FIGURES/16.

[6] C. M. Verónica Palomino-Díaz, Pablo Romero-Sorozábal, Gabriel Delgado-Oleas, "Diseño conceptual de una plataforma robótica para ayudar a que los niños con parálisis cerebral descubran cómo caminar," in *XII Simposio CEA de Bioingeniería*, 2021, pp. 83–88.

[7] C. A. Fukuchi, R. K. Fukuchi, and M. Duarte, "A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals," *PeerJ*, vol. 6, no. 4, 2018, doi: 10.7717/PEERJ.4640.

[8] D. A. Winter, *Biomechanics and motor control of human movement*. John Wiley & Sons, 2009.

[9] J. Doke, J. M. Donelan, and A. D. Kuo, "Mechanics and energetics of swinging the human leg," *Journal of Experimental Biology*, vol. 208, no. 3, pp. 439–445, Feb. 2005, doi: 10.1242/JEB.01408.