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Enhancing Motor Learning in Cycling Tasks: The Role of Model Predictive Control and Training Sequence

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Abstract— **We evaluated the impact of Model Predictive Control (MPC) robotic-assisted versus unassisted training on motor learning of a complex bicycle steering task. Ten participants were divided into two groups, alternating between MPC-assisted and unassisted training to ride a steer-by-wire bicycle on a treadmill to collect virtual stars.**

At Baseline, Mid-Training, and Post-Training, motor skills were assessed by the average and standard deviation (SD) of distance to stars, while performance was measured by the mean absolute and SD of the steering rate. We found significant improvements in task skill and steering performance, with notable benefits observed in the performance of the group initially trained unassisted.

Our findings suggest that starting the training unassisted could stimulate an internal focus (concentrating on one's own body movements) and intrinsic skill perception. This foundation may then form a basis for later integration of MPC assistance to refine further the gained motor skills. Such a sequential training approach may benefit motor skill acquisition of complex dynamics tasks. Further research is necessary to validate and apply these findings to enhance training methods.

I. INTRODUCTION

Learning to ride a bicycle is a complex daily-life skill that involves mastering balance and advanced techniques like cornering and steering [1]. In countries like the Netherlands, where bicycles are a primary mode of transportation, this skill is especially crucial [2]. Importantly, the emergence of electric bicycles (E-bikes) has added new dimensions to this task, offering higher speeds but also increased risks, especially for less skilled or elderly riders [3], [4].

Traditional bicycling training methods, such as the use of training wheels, while popular, come with limitations. Training wheels can mask the real dynamics of bicycle riding, potentially hindering the development of essential balancing skills [5], [6]. More advanced training approaches, like those proposed by Klein et al. [7] that replaced the bicycle wheels with rollers of varying radii, offer improvements but require continuous mechanical adjustments in the training setup. In contrast, robotic assistance, particularly Model Predictive Control (MPC), presents a promising alternative. MPC is an optimal control strategy that dynamically adjusts assisting forces based on the learner's performance, offering a tailored learning experience. This method is particularly advantageous as it potentially reduces the risk of learners becoming passively reliant on assistance and potentially preserving the perception of the task's dynamics [8], [9], [10].

Recent advancements in robotic motor learning have demonstrated the efficacy of MPC in learning dynamic tasks such as swinging a virtual pendulum [11], suggesting its potential applicability in more complex dynamic scenarios like bicycle steering. MPC could be particularly suitable for the task of steering & balancing a 2-wheeler since this task's generally unstable non-minimum phase dynamics requires an advanced control strategy. This could not be achieved by simply nudging the steer towards the on-road target, as in [12], but requires an initial countersteering, followed by steering towards the target while stabilizing. However, MPC, while offering a potentially tailored learning experience of the dynamic task, must be carefully managed, e.g., it is unclear if it should be provided at the early phases of learning or in more advanced phases to avoid over-reliance on the assistance.

Our research investigates the effectiveness of MPC in training for complex bicycling tasks. We hypothesized that MPC-assisted training will significantly improve motor skill acquisition and performance compared to unassisted training in a steering and navigating bicycling task. Furthermore, we explored the impact of training sequence on skill acquisition and performance, evaluating the effectiveness of starting training with MPC assistance versus without it. This aspect of our study aims to provide insights into how the order of training modalities influences learning outcomes and performance in complex bicycling tasks, addressing a gap in current research and offering potential advancements in training methodologies for bicycling.

II. METHODS

A. Experimental setup

The task was performed on a treadmill (Fig. 1), providing a controlled environment with complimentary visual information (Fig. 2) while retaining realistic steering and balancing dynamics. Participants wore a safety harness connected to a fixed point on the ceiling, just above the center of the treadmill, to reduce the risk of injury. Note that due to the harness, participants did not need to pedal and thus could mainly focus on the steering and balancing task. We used a custom steer-by-wire bicycle, previously developed at Delft University of Technology in the Netherlands, to provide steering assistance during bicycle riding [13]. This bicycle allows the provision of guiding torques to the handlebar using a motor and encoder attached to the handlebar stem.

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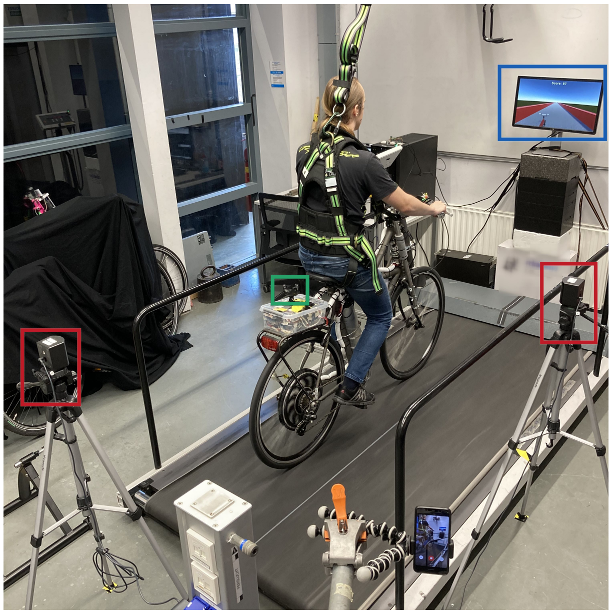

Fig. 1. Experimental setup with a participant riding the steer-by-wire bicycle on a treadmill. The participants wore a harness securely attached to the ceiling for safety. The width of the treadmill's usable space is 1.1 m. The display showing the virtual star-shaped targets from a first-person perspective is highlighted with a blue box. The locations of the SteamVR Base Stations 2.0 are shown within red rectangles. The location of the HTC Vive Tracker 3.0 is shown in green.

The lateral position, yaw angle, and roll angle of the steer-by-wire bicycle were measured using an HTC Vive Tracker 3.0 (HTC, Taiwan) installed right above the rear wheel center (Fig. 1). The steering angle, from which the steering rate was derived, was measured using an encoder at the handlebars of the bicycle. Two SteamVR Base Stations 2.0 (HTC, Taiwan) were located on the back and side of the treadmill to enable this tracking. Tracker data was sent to the supplied USB dongle, which was connected to a Raspberry Pi 4 Model B 4 GB (Raspberry Pi Foundation, UK). This computer runs a 32-bit Raspberry Pi OS Lite version in headless mode. `Libsurvive`'s [14] Simple Application Programming Interface (API) was used to read the data from the tracker, calculate the position and orientation of the tracker, and send the data using User Datagram Protocol (UDP) at 220 Hz to a Windows 10 desktop computer, which runs the MPC and virtual reality game. The desktop computer was equipped with Intel i7-7700K 4.2 GHz processor (Intel, US), running Simulink Desktop Real-Time (MathWorks, US). The desktop computer and the bicycle communicated wirelessly using Bluetooth at 200 Hz for the bicycle-to-computer communication, and 75 Hz for the computer-to-bicycle communication. Although we did not explicitly measure latency between the Unity scene and the bicycle interface, participants reported no perceptible lag or mismatch, suggesting minimal impact on the user experience.

A 24-inch computer monitor was placed around 2 m in front of the participant (Fig. 1) to show the location of the virtual targets (see subsection B). The game was implemented using Unity (Unity Technologies, US) on the desktop computer.

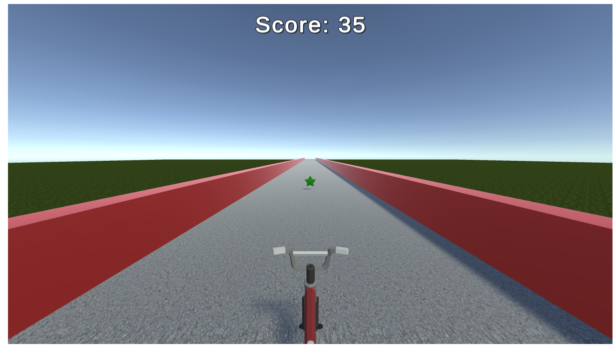

Fig. 2. The virtual environment shown to the participants. The participants controlled the lateral position of the virtual bicycle by steering the real bicycle on the treadmill. The task consisted of collecting stars that appeared on the horizon and approaching at 15 km/h (same speed as the treadmill). After passing through a star, a score appeared on the top of the screen that depended on the distance between the virtual bicycle and the center of the star. The red walls correspond to the edges of the treadmill.

B. Steering and Navigation Task: Collecting Virtual Stars

The steering task consisted of collecting virtual star-shaped targets approaching the rider at a constant velocity of 15 km/h (the same speed as the treadmill) resembling an 'endless runner' game [15]. A first-person perspective of the virtual bicycle was shown on a road of the same width as the width of the treadmill (Fig. 2). The real bicycle acted as a Human Interface Device for the game, i.e., the virtual bicycle moved in the lateral direction, mapping to the measured lateral position of the real bicycle on the treadmill measured with the HTC tracker placed at the back of the bicycle. This tracker location was chosen to ensure model consistency and realistic cycling behavior, aligning with the Whipple-Carvallo model's coordinate system.

To collect a star, the rider had to steer and navigate the real bicycle which in turn steered the virtual bicycle (shown on a screen in front of them) to place it in front of the star and pass through it. The interval between the appearance of two consecutive stars was 6 s. A score was displayed each time a star was passed to provide feedback to the participants about their navigational steering in the star collection task. The score was calculated based on the distance between the lateral position of the bicycle's rear wheel contact point on the treadmill (y_P) and the lateral position of the star's center y_S, both in meters. Scores were assigned using three conditions: 100 for distance ≤ 0.02 m, 0 for distance > 0.22 m. For distances between 0.02 and 0.22 m, the score ranged linearly from 100 to 0, calculated as $500 \cdot (0.22 - \text{distance})$.

C. The MPC Robotic Assistance

Our MPC used a mathematical model of the bicycle lateral dynamics [16] to predict the system's behavior throughout a specified time horizon. We choose a control signal such that the predicted system state follows a given reference state. A cost function (and its weights) is specified —e.g., minimizing the assistance and minimizing the distance to the stars— which is then used by the controller to determine the control action at each time step t, through real-time optimization.

Several constraints can be put on the system to guarantee, e.g., safety.

The linear MPC problem employed in our study is stated in Equation 1, where k represents the discrete time index that iterates over the time steps, J is the cost function to be minimized, t is the current time, N is the number of steps in the time horizon, x is the bicycle state, r is the reference state, u is the control input, and Q and R are designer-defined weighing matrices. The input varies stepwise across the N steps, resulting in N input values to be optimized by the MPC. Only the first (next) input is applied and the following inputs are reoptimized at the next time step based on the updated system state. The subscripts lb and ub stand for *lower bound* and *upper bound*, respectively, and are used to enforce constraints on the controller, i.e., maximum and minimum values of lateral position ($\pm 0.5\,\mathrm{m}$), steering angle ($\pm 40\,deg$), roll angle ($\pm 20\,deg$), and assisting torque ($\pm 10\,\mathrm{Nm}$). The matrices A and B are linear time-invariant state-space matrices.

$$
\begin{aligned}
J = \sum_{k=t}^{t+N} (x_k - r_k)^T Q_k (x_k - r_k) + \sum_{k=t}^{t+N-1} u_k^T R_k u_k \\
\text{subject to } x_{k+1} = A x_k + B u_k \\
x_{lb,k} \leq x_k \leq x_{ub,k} \\
u_{lb,k} \leq u_k \leq u_{ub,k}
\end{aligned}
\tag{1}
$$

In our study, N was set to 150, which is equal to a time horizon of 2 s with a sample rate of 75 Hz. The control input u is the steering torque applied by the handlebar motor. The bicycle and reference states, x and r, consist of the lateral position of the rear wheel of the bicycle y_P, the yaw angle ψ, the roll angle ϕ, the steering angle δ, the roll rate $\dot{\phi}$ and the steering rate $\dot{\delta}$. Thus, the cost function stabilizes the bicycle in steer and roll while minimizing deviation from the target and motor steer effort. The target tracking task is represented by the lateral position relative to the target at the time needed to reach the target. Thus, the MPC derives an optimal steering sequence to reach the target. The state-space matrices A and B were obtained using the `HumanControl` software [17], which can convert the equations of motion of a linear Whipple-Carvallo bicycle model to a state-space representation. Bicycle parameters of the *Davis Instrumented Bicycle* (specified under *Rigid* on pages 91-92 of [18]) were used due to their physical similarity to the bicycle used in this study. A forward speed of $15\,\mathrm{km/h}$, equal to the treadmill's speed, was chosen.

D. Study Protocol

Ten healthy adult participants were divided into two groups (9 between 25-39 years old and one between 60-64 years old; 3 female). All gave written consent to participate in the experiment. The study was approved by the TU Delft Human Research Ethics Committee (HREC).

The study protocol is depicted in Fig. 3. The experiment consisted of six blocks: Familiarization (*Free riding*), Baseline (*BL*), Training 1 (*T1*), Mid-Training evaluation (*MT*), Training 2 (*T2*), and Post-Training evaluation (*PT*). The experimental design followed a between-subject format, where participants were randomly assigned to one of two groups. The five participants allocated to Group 1 (MPC first) trained with MPC assistance during T1 and without assistance during T2, while the order was reversed for Group 2 (MPC second).

In the Free riding (Familiarization) session, participants spent 5 minutes bicycling on the treadmill without any assistance and were verbally encouraged to carry out lane change maneuvers of varying amplitudes.

Baseline, Mid-Training, and Post-Training blocks were designed to evaluate the participants' skill acquisition and steering performance before, after the first, and after the second training block, respectively. During these evaluation blocks, no MPC assistance was provided, and riders cycled for 2 x 1-min trials trying to collect the stars appearing on the screen by steering the bike. Each (1-min) trial contained 10 stars to be collected. The location of the 10 stars was pseudo-randomized but similar for all participants with varied placements on the virtual road.

The training blocks T1 and T2 were started right after the Baseline and Mid-Training blocks, respectively. Participants were informed that they may be assisted during the training. Two-minute breaks were enforced between T1 and Mid-Training blocks, and between T2 and Post-Training blocks.

E. Data Analyses

We investigated the motor skill (development and acquisition of skill) and motor performance (actual execution of developed skill).

1) Skill Acquisition and Performance Measures: To evaluate the skill acquisition in the stars collecting task, the average and standard deviation (SD) of the distance (in meters) from the bike position to targeted stars averaged over 20 stars per evaluation time point (BL, MT, and PT) was obtained. This measure aims to indicate changes in the **accuracy (average distance)** and **consistency (standard deviation of distance)** in the steering and navigation task compared to the baseline measurement. A decreased average and standard deviation indicate higher precision (accuracy) and repeatability (consistency) in task execution, respectively, associated with an improved skill acquisition [19].

For evaluating the participants' navigation and steering performance, the **average steering rate (rad/s)** quantified by the mean absolute value of the steering rate [20] and the standard deviation of steering rate (**SD of steering rate (rad/s)**) in a 6-second time frame from appearing until hitting the stars were calculated. These values provide insights into how smoothly the riders maneuver the bicycle within each 6-second interval between star appearances. For statistical analysis, the average and standard deviation of the steering rate across 20 stars (2 x 10 stars) for each evaluation time point (BL, MT, and PT) were calculated, reflecting the participants' average performance over a total of 120 seconds (2 x 1-min trial). The standard deviation of the steering rate serves as an indicator of consistency or variability in the steering rate, where a decreased SD of the steering

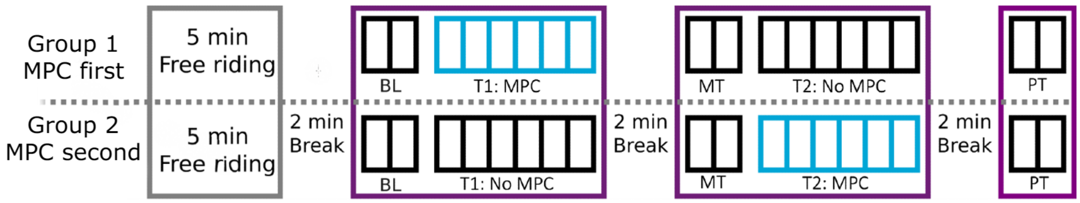

Fig. 3. Study protocol. Participants were randomly assigned to one of two groups. Each trial was 1 minute long and contained 10 stars. *BL*: Baseline evaluation, *MT*: Mid-training evaluation, *PT*: Post-Training evaluation, *MPC*: training with MPC, *No MPC*: training without MPC

rate implies a more consistent and refined motor control in steering behavior.

2) Statistical Analyses: We applied a repeated measures ANOVA on the average and SD of the distance to stars, and on the average and SD of the steering rate. The analysis specifically focused on two factors and their interaction that might influence participants' skill acquisition and performance: evaluation Time Points (Baseline [BL], Mid-Training [MT], and Post-Training [PT]), and Group, denoting the different participant groups subjected to varying training sequences, enabling a detailed evaluation of how the sequence of training interventions influenced participants' task skill acquisition and steering performance. The statistical analyses were performed in Jasp (version 0.16). The significance level was determined at p-values < 0.05.

III. Results

All participants completed the experiment without falling or reporting motion sickness, as assessed by the experimenter's observation and self-reports. The analysis focused on changes in accuracy and consistency of collecting stars by evaluating the average and standard deviation of the distance to virtual stars, respectively, together with the average and standard deviation of steering rate (Fig. 4). Results from the statistical analyses are summarized in Table I.

A significant improvement in skill was evidenced by a decrease in the standard deviation of the distance to stars (improved consistency), with no effects of Group or interaction of Time Point x Group (Table I, Fig. 4). However, we did not find a significant effect of evaluation Time Point or Group on the average distance to the stars (Table I, Fig. 4).

We found a significant effect of the evaluation Time Points on average steering rate and a significant interaction between Time Points and Group, as shown in Table I and Fig. 4. Posthoc analysis for Group 1 (MPC first) revealed no significant improvement in average steering rate between the Baseline (BL) and Mid-Training (MT) or BL and Post-Training (PT) evaluation time points ($t = 2.535$, $p = 0.171$, Mean Difference $= 0.015$ (rad/s) and $t = 1.251$, $p = 0.806$, Mean Difference $= 0.007$ (rad/s), respectively). In contrast, significant differences in average steering rate were observed within Group 2 (MPC second). Specifically, a significant improvement was noted between BL and MT ($t = 3.914$, $p = 0.013$, Mean Difference $= 0.022$ (rad/s)), indicating enhanced steering performance (decreased steering rate) during this training period. Furthermore, a significant improvement from BL to PT was also observed ($t = 5.165$, $p = 0.001$, Mean Difference $= 0.030$ (rad/s)) in Group 2.

Similarly, we found a significant effect of the evaluation Time Points on the standard deviation of steering rate and a significant interaction between Time Points and Group as shown in Table I and Fig. 4. Posthoc analysis for Group 1 (MPC first) revealed no significant improvement in SD of steering rate between the Baseline (BL) and Mid-Training (MT) or BL and Post-Training (PT) evaluation time points ($t = 2.463$, $p = 0.193$, Mean Difference $= 0.018$ (rad/s) and $t = 1.171$, $p = 0.844$, Mean Difference $= 0.008$ (rad/s), respectively). However, posthoc analysis revealed a significant difference in SD of steering rate within Group 2 (MPC second) between the Baseline (BL) and Mid-Training (MT) evaluation time points ($t = 4.113$, $p = 0.009$, Mean Difference $= 0.030$ (rad/s)), indicating a significant improvement in steering performance (decreased variation of steering rate) during this training period. Furthermore, a significant improvement was also noted from the Baseline (BL) to Post-Training (PT) time points in Group 2 (MPC second) ($t = 5.1005$, $p = 0.001$, Mean Difference $= 0.037$ (rad/s)). These results suggest that Group 2 (MPC second), which started training without MPC assistance, experienced substantial improvements in steering performance over the course of the training, something that was not observed in Group 1 (MPC first).

TABLE I

Results from the Repeated Measures ANOVA

Variable	**F-value**	**p-value**	η_p^2
Average of Distance to Stars			
Time Points (Level)	2.775	0.109	0.258
Group (MPC Order)	1.785	0.218	0.182
Level*Group Interaction	0.061	0.903	0.008
SD of Distance to Stars			
Time Points (Level)	**5.083**	**0.048**	**0.389**
Group (MPC Order)	0.213	0.657	0.026
Level*Group Interaction	0.195	0.697	0.024
Average of Steering Rate			
Time Points (Level)	**13.791**	**<.001**	**0.633**
Group (MPC Order)	0.359	0.566	0.043
Level*Group Interaction	**3.942**	**0.041**	**0.330**
SD of Steering Rate			
Time Points (Level)	**13.876**	**<.001**	**0.634**
Group (MPC Order)	0.365	0.563	0.044
Level*Group Interaction	**3.998**	**0.039**	**0.333**

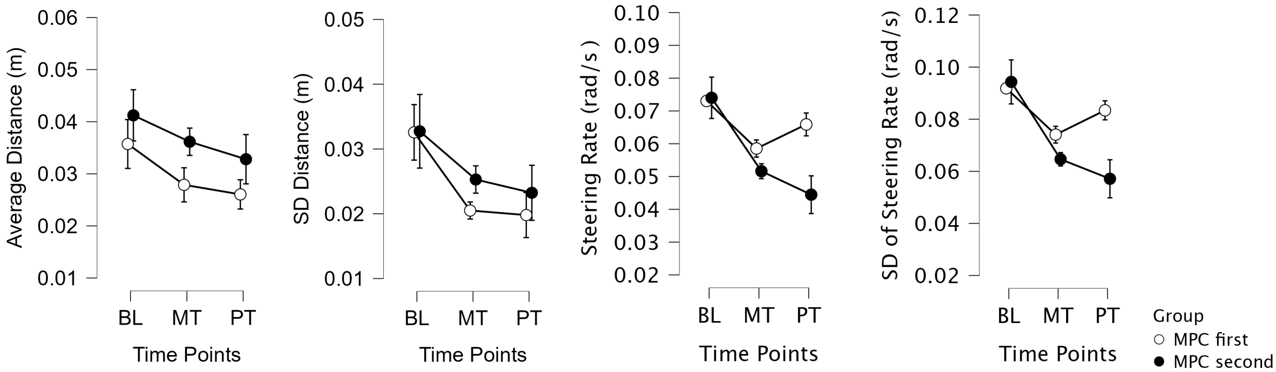

Fig. 4. The average and the standard deviation of the lateral distance to stars (m), the average of steering rate (rad/s), and the standard deviation of steering rate (rad/s) at Baseline (BL), Mid-Training (MT) and Post-Training (PT) time points. Error bars indicate the standard errors. The results at each time point represent the average group behavior.

IV. Discussion

We investigated the impact of MPC assistance on motor skill acquisition and motor performance in a complex bicycling task (steering and navigation), with a particular focus on the timing of MPC introduction during training. Contrary to our initial hypothesis that training with MPC assistance would be inherently superior, the skill acquisition results revealed that both training methods led to improvements in motor skill, yet the improved steering performance results proved that the sequence of training without MPC followed by training with MPC is more effective for refined motor learning and retention of acquired skill.

Group 1, which received MPC assistance initially, did not show significant changes in the average and variation of steering actions. In contrast, Group 2, which started training without MPC assistance, experienced significant improvements in the steering actions average and variation over the course of the training. This result highlights the potential benefits of gradually introducing MPC assistance to enhance learning. This finding is particularly intriguing as it suggests the importance of mastering fundamental skills before introducing technological assistance in this particular bicycling task. This is aligned with the principles of motor learning, particularly the Guidance Hypothesis, which states that too much augmented feedback during training, i.e., additional to the natural feedback mechanisms inherent in performing a task, guides learners but can cause dependency (slacking) if used too frequently [5]. MPC provided additional information to the participants, augmenting their natural sensory feedback with predictive data about future states of the system. Thus, in line with the Guidance Hypothesis, our results suggest that MPC use might disrupt the development of intrinsic motor skills, especially during the early stages of learning, necessitating a balanced approach with unassisted training in its application to prevent over-reliance. The observed worsening of post-training steering rate and its standard deviation when participants trained first with MPC assistance indicates potential dependency on the assistance, suggesting that reliance on MPC could impair the retention of motor skills in its absence.

A potential problem of providing robotic assistance while learning to interact with environments with complex dynamics is that the assistance could inadvertently mask the perception of the dynamics of the environment, just as adding training wheels disturbs the perception of the bicycle dynamics. The study by Wähnert and Müller-Plath (2021) states the functionality hypothesis in motor learning of a balancing task, indicating that an internal focus, emphasizing body-internal senses, is more beneficial in tasks where external feedback could add cognitive load [21], or in our study, hinder the perception of the task dynamics through body-internal senses. Our findings support the functionality hypothesis in motor learning suggesting that training initially without MPC likely fostered an internal focus, enabling participants to develop a deeper intrinsic understanding of the navigating and steering through their body-internal senses in this bicycling task. This phase of self-reliance in learning appears to be crucial for establishing a solid foundation upon which technological assistance can build.

Furthermore, the study on audio-motor coordination in learning piano performance skills provides relevant insights into our findings [22]. Their research demonstrates that predictive motor control mechanisms, essential for determining the sequence and timing of actions, play a crucial role even in the early stages of learning complex motor skills. In our study, the initial training phase without MPC might have similarly encouraged the development of internal predictive motor control skills, allowing participants to independently navigate the task and refine their ability to anticipate and respond to the bicycling dynamics. The subsequent introduction of MPC then provided targeted feedback and assistance, leading to further refined motor control and enhancing and retention of the skills developed during the initial phase.

Our preliminary results on a confirmatory post-experiment test on one rider showed that with minimal rider steering input, MPC assistance significantly outperformed the non-MPC approach. This finding may suggest that in cases where riders rely on MPC assistance due to inaccuracies in sensory processing, balance disorders, or age-related impairments, the application of MPC could be more effective.

This potential enhancement of MPC's efficacy is particularly relevant when riders, aware of their limitations, rely on the technology, minimizing reliance on their compromised internal models [5]. These observations offer insights for future research and practical applications.

We studied steering actions in a bicycling task without the effect of pedaling. While this allowed us to focus on steering performance and ensure cognitive effort was concentrated on steering, future work should investigate the combined task to provide a more comprehensive understanding of motor learning in realistic cycling scenarios.

The small sample size (n = 10) raises questions about the generalizability of our findings. Further research is necessary to validate these preliminary findings comprehensively, particularly in aiding those with diminished skill perception and balance impairments. Future studies could benefit from a larger, more diverse participant group and the addition of two focused groups, one training exclusively with MPC and the other solely without it, to strengthen our conclusion.

Moreover, the MPC model could be enhanced to adjust to individual rider characteristics. This includes calibrating the weights in the MPC cost function to align with each rider's responsiveness and control preferences, modifying constraints to match their specific steering abilities, and fine-tuning the feedback mechanism to offer customized guidance based on the rider's skill level. These targeted modifications aim to optimize the MPC system for each individual rider, potentially increasing the training effectiveness. Furthermore, future research should investigate the long-term impacts of various training sequences and the optimal, tailored integration of technological aids like MPC in enhancing motor performance.

V. Conclusion

Our study highlights the feasibility and effectiveness of Model Predictive Control in complex steering and bicycling tasks, with a focus on the training sequence. We found that unassisted learning strategies beginning with the development of intrinsic predictive motor control, followed by the integration of MPC-assisted learning, led to more refined motor control. This highlights the importance of mastering fundamental skills before introducing robotic assistance and the need for well-structured training sequences.

While the study provides valuable findings, its small sample size and focus on a bicycle steering task limit generalizability. Future research should involve larger participant groups and diverse tasks to validate and expand these insights.

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