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Virtual Reality for Evaluating Prosthetic Hand Control Strategies: A Preliminary Report

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Abstract— **Improving prosthetic hand functionality is critical in reducing abandonment rates and improving the amputee's quality of life. Techniques such as joint force estimation and gesture recognition using myoelectric signals could enable more realistic control of the prosthetic hand. To accelerate the translation of these advanced control strategies from lab to clinic, We created a virtual prosthetic control environment that enables rich user interactions and dexterity evaluation. The virtual environment is made of two parts, namely the Unity scene for rendering and user interaction, and a Python back-end to support accurate physics simulation and communication with control algorithms. By utilizing the built-in tracking capabilities of a virtual reality headset, the user can visualize and manipulate a virtual hand without additional motion tracking setups. In the virtual environment, we demonstrate actuation of the prosthetic hand through decoded EMG signal streaming, hand tracking, and the use of a VR controller. By providing a flexible platform to investigate different control modalities, we believe that our virtual environment will allow for faster experimentation and further progress in clinical translation.**

I. INTRODUCTION

For decades, the public and the scientific community have been greatly inspired by the possibility of controlling a prosthetic hand naturally as if it is one's own. Currently, there are around 2 million Americans living with limb loss , and approximately 20% of them have had an upper limb amputation [1]. Losing any limb would be a severe detriment to quality-of-life for the amputee, and the loss of hand function would especially reduce self-independence and the ability to conduct everyday tasks. Therefore, restoring hand functionality through prosthetic devices would drastically improve amputee outcomes. However, there are numerous challenges in upper-limb prostheses that limit patient satisfaction and usage rates. A survey conducted on veteran upper-limb amputees indicated that around 50% of prosthetic wearers use their devices for less than 8 hours per day. Additionally, the survey found that a majority of respondents had abandoned their prosthesis at some point, citing poor functionality, unintuitive operation, and low reliability [2]. Thus, problems and limitations surrounding current prosthetic hands must be addressed to increase patient satisfaction.

Current research in myoelectric prosthetic control could ameliorate current shortcomings in prosthetic hands by providing more realistic control strategies, such as joint force and angle estimation through decoding high density electromyography signals [3][4]. These methods could potentially improve prosthetic hand dexterity and functionality by allowing more degrees of freedom to be controlled by the amputee. While these high degree-of-freedom control strategies demonstrate promising results in the laboratory for intact subjects, they have yet to be tested in realistic situations for amputees. Therefore, there is a need to translate novel prosthetic control methods from the laboratory to use in clinical settings. On the other hand, implementing high degree-of-freedom control for amputees in a physical setting would require significant efforts to fit amputees with a novel prosthetic hand that supports high density electromyography array recordings. It may be risky and costly to deploy laboratory results directly to the clinic without validating its potentials. Alternatively, virtual reality environments can be effective tools in testing prosthetic systems in highly repeatable, controlled, and realistic settings. For instance, Kluger et al. used the Mujoco HAPTIX application and found that trans-radial amputees were able to successfully perform closed loop tasks such as texture identification and pick-and-place within the environment [5]. Nissler et al. described the VITA system that enables rehabilitation and prosthetic training in a variety of simulated environments [6]. In this paper, we build upon the promising capabilities of simulated prosthetic hands by describing our implementation of a fully immersive virtual reality prosthetic hand testing environment based on Unity and Mujoco physics. We believe that our virtual reality environment would further enable low-cost testing of prosthetic hand control strategies, or facilitate training of new prosthetic utility by prosthetic users.

II. METHODS

A. Virtual Environment Overview

The overall workflow of the virtual environment is summarized in Figure 1. During operation, the user can visualize the virtual environment through a virtual reality headset. Meanwhile, the Oculus Unity SDK provides motion tracking data that helps transport the base of the simulated hand. The virtual reality environment is built using Unity 2019.4.18f1 (Unity Technologies, San Francisco, CA). The Oculus Integration Package was used to enable visualization and interaction on an Oculus Quest 2 headset (Facebook Technologies LLC, Menlo Park, CA). We disabled Unity's built-in physics engine in favor of the Mujoco Engine (Mujoco Pro 150) [7]. Compared to other physics engines, Mujoco is superior in modeling accurate contact dynamics, making it desirable for prosthetic hand control simulations. We utilize Mujoco in a Python back-end through the mujoco-py library. The Mujoco Unity plug-in was used to facilitate communication between Unity and the Python back-end. By having a high-quality

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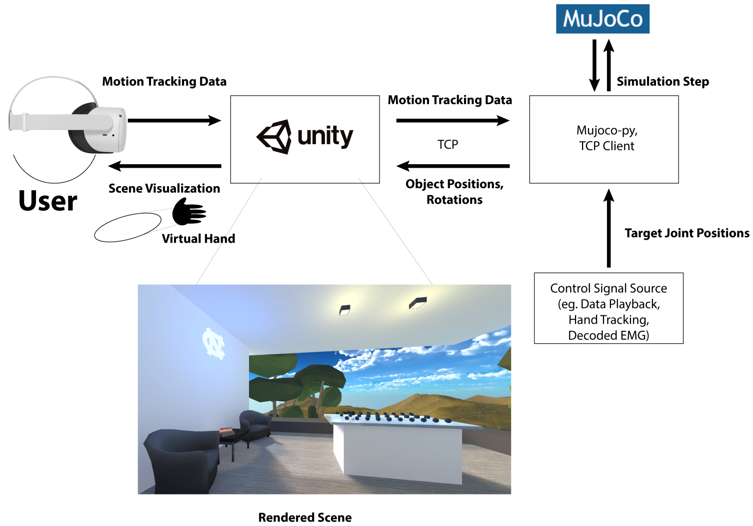

Fig. 1. Overview of the methodology. During a simulation session, the user visualizes a rendered scene in a VR headset. User input is sent to the Mujoco physics simulation to actuate the simulated hand. After a simulation step, the transformations of all physics objects are sent back to Unity for rendering.

rendering and physics engine, we can create immersive environment visuals without compromising realism during operation.

The simulation models in the virtual environment are derived from the pre-built XML files that were included with the Mujoco HAPTIX application [8]. We use the Modular Prosthetic Limb (MPL) as virtual prosthetic hand. The MPL is a highly dexterous prosthetic hand with 22 hinge joints and 13 motors. It also contains joint position and velocity sensors, motor position, velocity and force sensors, and IMUs in each fingertip [9]. The MPL's advanced capabilities make it ideal for testing new control strategies where many degrees-of-freedoms may be controlled.

B. Hand Control Modes

We sought to demonstrate the use of the environment by actuating the prosthetic hand using various input methods. First, a set of 9 index and 9 middle finger angle data derived from electromyography measurements of three intact subjects was streamed to the simulation to emulate EMG real-time interaction and determine control error. Each of the 18 angle data contains 482 samples sampled at 100Hz. Because the user does not provide real-time input during playback, no task was performed during the trials. We combine the index and middle finger trials and only use the data to actuate the index metacarpophalangeal joint.

Hand tracking was one method used to interact with the simulation in real-time. By providing a digital copy of the hand, Hand tracking can serve as a proxy for a high degree-of-freedom control method. Hand tracking data was provided by the Oculus Integration Package as an iterable of finger bone transformations. Since the MPL expects joint angle inputs, we mapped bone transformations into finger joint angles. Let p be the unit quaternion representing the rotation of the wrist and q be the unit quaternion representing the rotation of a proximal phalange. Let $r = pq^{-1}$ be the rotation from q to p. Then the mapping is given by:

$$\theta = -2sgn(r)\arccos(swingtwist(r, qz)),$$

Where $swingtwist$ is a function that returns the real part of the twist quaternion from the swing twist decomposition [10] The swing twist decomposition is used to decompose a given rotation (r) into orthogonal rotation components: twist and swing. The twist rotation's imaginary part is the input axis, (qz), where z is the z unit vector corresponding to the local axis of rotation for the joint motor. A two-sample rolling average was used on the input bone quaternions to reduce finger jitter. During use, the tracked hand remained in view of the headset's tracking cameras under bright lighting conditions. By mapping finger bone transformations to joint angles, we were able to actuate all ten controllable finger joints of the MPL.

Another input modality we used was the virtual reality controller trigger. This method emulates a body-powered gripper with single degree-of-freedom actuation. The user controls how much the virtual hand is open or closed by modulating the index finger trigger on the VR controller. The Oculus Integration Package was again used to track the controller and to read the controller state.

C. Performing Object Interaction Tasks

By comparing hand tracking and trigger control, we show that the virtual environment is capable of measuring prosthetic hand performance. Three environments derived from the HAPTIX application were used as benchmarks. The three environments included object interaction tasks found in the Southampton Hand Assessment Procedure (SHAP), namely 1: picking up three coins and dropping them into a jar, 2: picking and placing a spherical object, and 3: Picking and placing small box-shaped objects (Box Block test). For the coin and the sphere task, we measure the total time elapsed between initiating the task and completing the task through

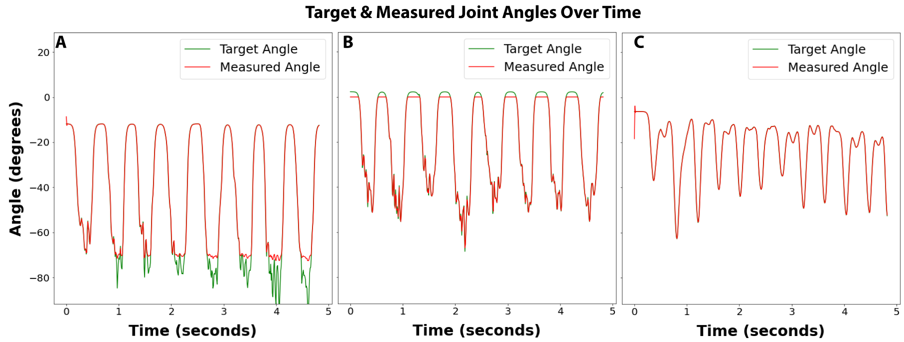

Fig. 2. Playback results for three exemplar joint data. In plots A and B, the full range of motion was not achieved due to the physical limitations of the MPL. Positive angles denote finger extension, while negative angles denote finger flexion.

a button built into the virtual environment. For the box task, we set up a one-minute timer in the virtual environment and measured how many boxes were successfully relocated in the one-minute interval. Ten trials were performed by one able-bodied subject for each environment and for each control mode. The two-tailed, paired T-test was used to determine the statistical difference between the two control modes.

III. RESULTS

A. Decoded EMG Signal Playback

We streamed 18 sessions of pre-recorded finger joint angle data to the simulated prosthetic hand. As Figure 2 shows, the hand achieves good position accuracy using the built-in PD controller. The average RMSE for all trials was 2.56 degrees. Some target angles could not be attained due to limited range of motion in the MPL $(0° - 73°)$. Grouping RMSE across the three participants shows that the errors were 3.47, 1.64, and 2.55 degrees, respectively.

B. Comparing Task Performance in Different Control Modalities

Using hand tracking to mimic high degree-of-freedom prosthetic hand control and using a VR controller trigger to mimic a single degree-of-freedom, body-powered gripper, we compared the performance of these two control modalities in three simple tests derived from SHAP. Figure 3 shows that the single degree-of-freedom gripper performed significantly better than hand tracking in all three tasks $(p < 0.05)$.

IV. DISCUSSION

In this paper, we demonstrated an implementation of a virtual reality environment to test prosthetic control strategies. We were able to show that the virtual environment can control a prosthetic hand through multiple means, including data playback, hand tracking, and trigger control. A comparison between hand tracking and trigger control was made through three benchmarks derived from SHAP. Performance results showed that trigger control performed significantly better than hand tracking in performing the benchmarks despite only controlling one degree-of-freedom. Some reasons for the result are discussed. Firstly, the proximal and distal interphalangeal joint angles of the MPL digits are coupled to the metacarpophalangeal joint angles. Thus, hand tracking data for the PIP and DIP joints were discarded during use. This led to a mismatch between the real-world finger angles and virtual finger angles of the user, making position control unpredictable. In contrast, trigger control only requires the user to press the controller trigger for hand actuation. This means that the user will know exactly where the fingers will be when the trigger is pressed a certain amount. Another factor influencing hand tracking control performance was noise and latency. Although tracking noise was controlled for by averaging and having sufficiently bright lighting, jitters in the controlled joints and tracking latency made it difficult to place fingers with accuracy and precision. On the other hand, trigger control using controllers is essentially noise-free with minimal delay. Finally, the absence of sensory feedback in hand tracking meant that the user could only rely on visual cues to complete tasks. In trigger control, the user could still ”feel” the object indirectly through the resistance of the controller trigger, allowing for finer tuning of finger positions.

Some implications of our results towards future prosthetic control are discussed. By comparing the performance of trigger control and hand tracking control, we have shown that virtual environments could hold promise for testing new control strategies. Further, the performance advantage of trigger control compared to hand tracking suggests that using high-dimensional inputs alone is not sufficient for robust and intuitive control of prosthetic hands. Rather, any future method for controlling a high degree-of-freedom prosthetic hand should also consider the effects of noise, latency, predictability, and sensory feedback during implementation.

A. Future Work

In the future, we would like to integrate the environment with real-time EMG control. The process is straightforward, since a stream of playback data can be simply replaced by a stream of real-time data, but current world circumstances prevented its realization. While we specifically addressed testing electromyography control in the environment, it is conceivable that a diverse set of methods can be used

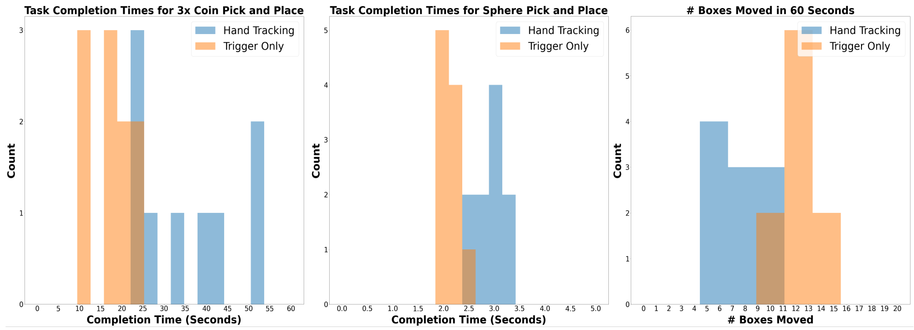

Fig. 3. Pick and place task performance results for coins, sphere, and box-block. One degree-of-freedom trigger control was able to outperform hand-tracking in the measured metric for all tasks (Coins: $p = 0.0033$, Sphere: $p = 3.87 \times 10^{-5}$, Box-Block: $p = 4.16 \times 10^{-5}$).

to control the virtual prosthetic hand, as long as motor inputs are given to the system. Similarly, different prosthetic hand designs may be used in the environment, allowing for increased hardware flexibility without the need to physically acquire costly hardware. In this report, we tested the virtual environment using simple tasks taken from SHAP. However, virtual environments are capable of supporting a diverse set of assessments that will better reflect the needs of a prosthetic hand user. For example, the user could be tasked with handling fragile items in a kitchen space. A potential benefit of using the virtual environment in this scenario would be increased safety and reduced overhead associated with setup.

Some limitations of the VR environment regarding generalization to the physical environment should be considered when designing future studies. While the Mujoco simulator is able to produce realistic interactions, there may be discrepancies between the results produced in the physical and the virtual world due to un-modeled effects or mismatched physics parameters. Therefore, the performance of a prosthetic hand in VR may not accurately reflect its performance in real-life. A more comprehensive comparison between VR and physical world performance could help address this question. Due to uncertainties in how reliably simulators reflect their physical counterpart, it may be also necessary to sample physics parameters from a distribution during VR evaluation to better improve generalization of the environment.

A potential future candidate for prosthetic hand control would be deep reinforcement learning. Recently, deep reinforcement learning has shown to be capable of learning highly dexterous robotic hand manipulations to solve various RL tasks[11] [12]. It is yet to be seen whether RL can be successfully integrated into high DOF prosthetic hands for human use. This integration can potentially enable shared control of prostheses by a computer and a human user, which can improve the robustness and functionality of prosthetic hand control [13]. Virtual environments could accelerate research in the area of RL prosthetic control by providing a realistic and flexible platform for human-in-the-loop robotic simulations.

References

[1] K. Ziegler-Graham, E. J. MacKenzie, P. L. Ephraim, T. G. Travison, and R. Brookmeyer, "Estimating the prevalence of limb loss in the united states: 2005 to 2050," *Archives of Physical Medicine and Rehabilitation*, vol. 89, no. 3, pp. 422–429, 2008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0003999307017480

[2] L. Resnik, S. Ekerholm, M. Borgia, and M. A. Clark, "A national study of veterans with major upper limb amputation: Survey methods, participants, and summary findings," *PLOS ONE*, vol. 14, no. 3, pp. 1–24, 03 2019. [Online]. Available: https://doi.org/10.1371/journal.pone.0213578

[3] F. Xu, Y. Zheng, and X. Hu, "Real-time finger force prediction via parallel convolutional neural networks: a preliminary study," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*, 2020, pp. 3126–3129.

[4] C. Dai and X. Hu, "Finger joint angle estimation based on motoneuron discharge activities," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 3, pp. 760–767, 2020.

[5] D. T. Kluger, J. S. Joyner, S. M. Wendelken, T. S. Davis, J. A. George, D. M. Page, D. T. Hutchinson, H. L. Benz, and G. A. Clark, "Virtual reality provides an effective platform for functional evaluations of closed-loop neuromyoelectric control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 5, pp. 876–886, 2019.

[6] C. Nissler, M. Nowak, M. Connan, S. Büttner, J. Vogel, I. Kossyk, Z.-C. Márton, and C. Castellini, "Vita-an everyday virtual reality setup for prosthetics and upper-limb rehabilitation." *Journal of neural engineering*, vol. 16 2, p. 026039, 2019.

[7] E. Todorov, T. Erez, and Y. Tassa, "Mujoco: A physics engine for model-based control," in *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2012, pp. 5026–5033.

[8] V. Kumar and E. Todorov, "Mujoco haptix: A virtual reality system for hand manipulation," in *2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, 2015, pp. 657–663.

[9] B. Perry, C. Moran, R. Armiger, P. Pasquina, J. Vandersea, and J. Tsao, "Initial clinical evaluation of the modular prosthetic limb," *Frontiers in Neurology*, vol. 9, 2018.

[10] P. Dobrowolski, "Swing-twist decomposition in clifford algebra," *ArXiv*, vol. abs/1506.05481, 2015.

[11] O. M. Andrychowicz, B. Baker, M. Chociej, R. Józefowicz, B. McGrew, J. Pachocki, A. Petron, M. Plappert, G. Powell, A. Ray, J. Schneider, S. Sidor, J. Tobin, P. Welinder, L. Weng, and W. Zaremba, "Learning dexterous in-hand manipulation," *The International Journal of Robotics Research*, vol. 39, no. 1, pp. 3–20, 2020. [Online]. Available: https://doi.org/10.1177/0278364919887447

[12] A. Rajeswaran, V. Kumar, A. Gupta, G. Vezzani, J. Schulman, E. Todorov, and S. Levine, "Learning complex dexterous manipulation with deep reinforcement learning and demonstrations," in *Proceedings of Robotics: Science and Systems*, Pittsburgh, Pennsylvania, June 2018.

[13] K. Z. Zhuang, N. Sommer, V. Mendez, S. Aryan, E. Formento, E. D'Anna, F. Artoni, F. Petrini, G. Granata, G. Cannaviello, W. Raffoul, A. Billard, and S. Micera, "Shared human–robot proportional control of a dexterous myoelectric prosthesis," *Nature Machine Intelligence*, vol. 1, no. 9, pp. 400–411, Sep 2019. [Online]. Available: https://doi.org/10.1038/s42256-019-0093-5