1-D Manual Tracing Based on a High Density Haptic Stimulation Grid - a Pilot Effort

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***Abstract*—Lower limb amputees lack the neurological pathways needed for perception of how their prosthetic limbs are interacting with the environment, leading to a lack of confidence in their devices and reduced balancing capabilities. Sensory substitution methods, such as vibrotactile and electrotactile feedback applied to unaffected body segments offer a potential way to restore some of the lost information pathways. While high resolution haptic stimulation grids have become commercially available, few studies have tried to make use of these devices to provide more intuitive sensory substitution methods. This study developed an encoding approach, which is based on the illusory "phantom actuator" phenomenon, to convert 1-D position information to a wearer through a bHaptics Tactsuit. By evaluating performance of 1-D manual tracking task among 14 participants under the proposed approach and a traditional amplitude modulation approach, we demonstrated an improvement of velocity tracing accuracy (p=0.0375) with the proposed approach, although the proposed approach did not lead to significant improvement in the position tracing accuracy.**

***Index Terms*—haptics, sensory substitution, phantom actuator**

I. Introduction

Capacity to accurately sense the interaction between lower limbs and their surrounding environments is critical for human beings to effectively maintain balance, coordinate body motion, and handle external disturbance during locomotion. However, lower limb amputees lose major neural pathways needed for such perception when they go through amputation. While amputees still receive some sensory feedback based on loading distribution on the interface between the residual limbs and their prosthetic sockets, studies have shown this feedback is unreliable and that amputees often have to rely on other senses. such as vision for compensation [1]. This loss of sensation on the lower limb has significant negative impacts on their gait efficiency, confidence of maintaining balance, and contributes to their high rate of fall [2] [3]. Things can be even more challenging for patients with neuropathy, which is often related to diabetes, the number one reason for lower limb amputations [4].

To regain intuitive sensory feedback for lower limb amputees, major efforts are usually in one of the two solutions: direct neural stimulation and sensory substitution. Although direct neural stimulation aims to reconnect the broken neural pathways and are expected to generate natural sensations, the existing approaches have limited control on what type of sensations can be generated and relies on intensive trial and error to locate the point of sensation on the missing limb [5]. Despite its popularity in the research field, direct neural stimulation has not been adopted clinically, due to 1) majority of them rely on invasive approaches to mount the electrodes next to the targeted nerves [6], 2) scar tissues are often built up close to the invasive electrodes and reduces their long term effectiveness [7], and 3) noninvasive approaches, such as L. Pan's work on evoking sensations in the phantom limbs of amputees, suffer additional reliability challenges [8].

One interesting alternative approach for direct neural stimulation is Herr's group, which constructed an agonist-antagonist myoneural interface (AMI) to regain the natural agonist-antagonist interaction [9]. Although the AMI is able to serve both prosthesis control and biofeedback interfaces, it requires new surgical operations and provides information related to body segment orientation only.

Sensory substitution replaces the haptic sensation on the missing limb with signals from other neural pathways, including auditory [10], visual [11], and haptic feedback [12]. Because visual and audio sensations also play key roles in everyday life, transferring continuous information through them can be distracting. So, haptic sensation applied to other body segments is a popular approach for sensory substitution. The substituted sensation is often through stimulators, such as electrotactile stimulation [13] [14], inflatable balloons for pressure feedback [15] [16], or vibrotactile motors [17] [18]. Vibrotactile motors are very popular due to their small size and low cost [19].

Several studies have investigated vibrotactile feedback as a means of restoring sensory information back to lower limb amputees. The most common application is to convey the center of pressure on the prosthetic foot, which is critical knowledge to help them maintain balance [20] [21] [22]. Currently, amplitude modulation (AM) is the standard approach, which can be realized using only two motors. However, there is not clear way to integrate the existing binary AM approach into a high resolution stimulation grid.

Recent developments in virtual and augmented reality, especially in the gaming industry, have led to the commercialization of high resolution stimulation grids. With these developments, numerous studies have demonstrated the existence of haptic illusions, such as the “phantom actuator” (PA) [23]. The PA phenomenon is based on the observation that a single PA appears when multiple adjacent stimulators are activated together, and the location of the PA can be modulated by the amplitudes of the adjacent stimulators. However, there has been little effort to utilize this interesting illusion to improve sensory substitution.

In this paper, we transformed the bHaptics Tactsuit x40 (bHaptics Inc., Daejeon, South Korea), a high definition haptic feedback vest, into a sensory substitution evaluation tool. We compared the performance of human subjects in 1-D tracing tasks with two types of information encoding approaches, the AM and PA approaches. Our results demonstrated that implementing PA significantly improves velocity tracing performance when compared to the AM approach although no significant difference in position tracing performance was noticed.

II. Methods

To deliver vibrotactile stimulation, a bHaptics Tactsuit x40 was used. The Tactsuit provides two high definition haptic feedback grids using vibrotactile motors on the front and back of the vest respectively. Each grid is 4x5 with five rows of motors. The distance between each motor is 7 cm along the vertical direction and 8 cm along the horizontal direction. Each motor has a fixed vibration frequency at approximately 90 hz with vibration amplitude independently adjustable. Low level control of the the Tactsuit is realized by using bHaptic’s open source C# library available on github [24] and through the Unity Asset Store [25].

The tracing task is conducted on a touchscreen laptop (Lenovo Yoga, Lenovo, China) using a touch pen (Lenovo Digital Pen, Lenovo, China). A user interface was made in Unity which presented the participants with a graph containing a 4x5 grid of red circles representing each of the motors on the back of the vest. The rows of the interface were numbered -2 to 2, and the columns numbered 1-4. Users were prompted to draw the path of the trajectory over this grid, the location of the tip of the touch pen was recorded at 50 Hz and synchronized with the bHaptic suit. A block diagram illustrating this process can be seen in Fig. 1.

A. Encoding approaches

In this study we compared 2 haptic encoding approaches to convey 1-D vertical movement of a target point to participants. In order to avoid the influence of body shape on the perception accuracy, we only consider the back grid of the vest, which faces the back of the torso, a relatively flat surface.

The first encoding method was the PA approach. We manipulated the location of the PA to follow the movement of the target point. The amplitude of the adjacent motors were calculated using the tactile brush approach [26] shown in equations 1 and 2:

$$A_N = \sqrt{1-\beta} \times P \tag{1}$$

$$A_{N+1} = \sqrt{\beta} \times P \tag{2}$$

Where A_N and A_{N+1} represent the amplitudes of two adjacent actuators, which the PA is between. P is a constant, which defines the maximum permitted amplitude of the motors, and β is the distance between the targeted point and actuator N normalized by the distance between adjacent actuators. Fig 2a shows the amplitude of the different motors as the target point moves along the Y axis.

The second method was the AM approach in which the distance from the center of the grid were linearly modulated by the amplitude of the motors on the top and bottom of the grid. As shown in Fig. 2b, only the motors close to the targeted position were actuated. Because all motors were disabled when the targeted point is at the center of the grid, the AM approach led a very reliable reference at the center of the grid.

B. Experimental Procedures

14 participants were recruited for this study and provided informed consent with ethical approval by the North Carolina State University Institutional Review Board. Exclusion criteria ensured participants had no cognitive impairments, serious morbidities such as stroke or heart disease, and had no history of epilepsy. Of the 14 recruited, 13 were able to perform well in an evaluation segment and move on to the experimental tracing task.

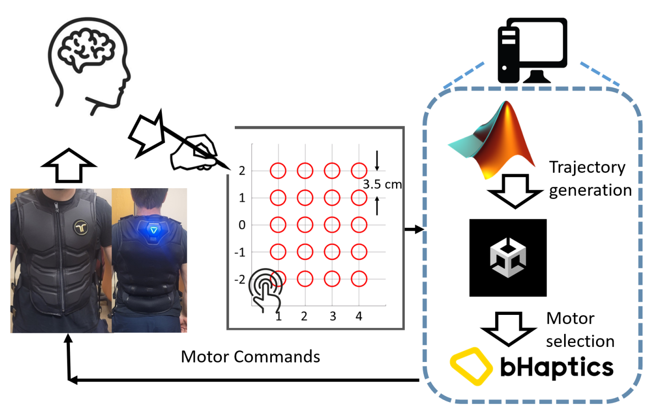

Fig. 1. Block diagram illustrating flow of information during 1-D tracing task. Predefined tracking trajectories are managed by Matlab and sent to Unity, which then sends commands to the bHaptics interface to control the motors on the vest. The user responds to haptic sensations by tracing their perceived location of the moving point, the trajectory of their input is saved by the touch screen for later post-processing.

A cross-over design is adopted to compare the two encoding approaches over two separate sessions. All participants were tested with each of the two encoding approaches in different sessions at least 48 hours apart. To compensate for the carryover effects, we randomized the sequence of whether AM or PA was tested first among participants.

For each session, the procedure included two training segments and a testing segment. An evaluation segment is also included when the PA approach was tested. First, participants completed a training segment designed to get them used to the location of the motors. The participant sat comfortably in front of the user interface shown on the touch screen computer. The system automatically activates all the motors on the back grid one by one following the sequence from the right to the left then from the top to the bottom. Each motor was activated to its maximum vibration amplitude for 250 ms with 1 second in between and a green circle was displayed on the interface on the top of the corresponding motor to provide additional visual feedback. The scanning was repeated three times and could be requested anytime during the experimental procedure to help participants re-calibrate their sensation.

Next, the evaluation segment was done to decide whether the participant was able to reliably differentiate between the different motors of the grid for the PA approach. The motors were activated in a predefined random sequence at its maximum amplitude for 250 ms and the participants were required to identify the location of the activated motor by clicking the touch screen interface. If the location was identified correctly, a green cycle would show around the identified motor. If the location was incorrect, a red cross would be shown on the identified motor and a green cycle would be shown at the correct location. There was a 1 second delay between the user clicking on the screen and the activation of the next motor. A 1 minute break was given after 20 activations.

If a participant was not able to reach the 70% accuracy threshold in the previous 20 activations, we would repeat this identification task 20 times and do the evaluation again. If the participant met the threshold, we would move to the next training session. If the participant failed in 10 evaluations, we excluded the participant.

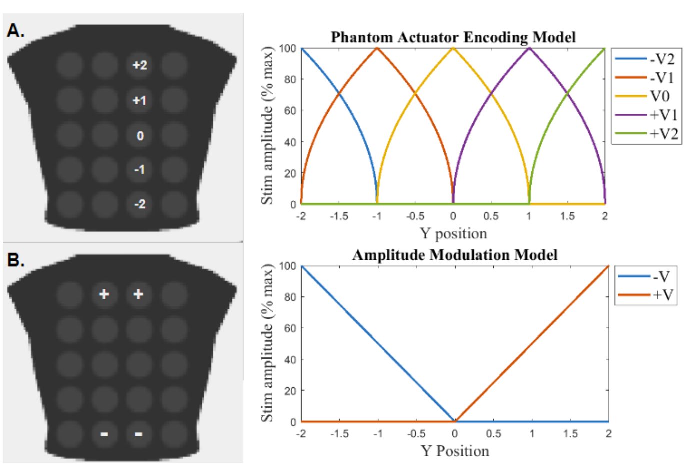

Fig. 2. Encoding methods used in study. A. shows the amplitudes of the 5 motors used in the PA method. B. shows the amplitudes of the 4 motors used in the AM method.

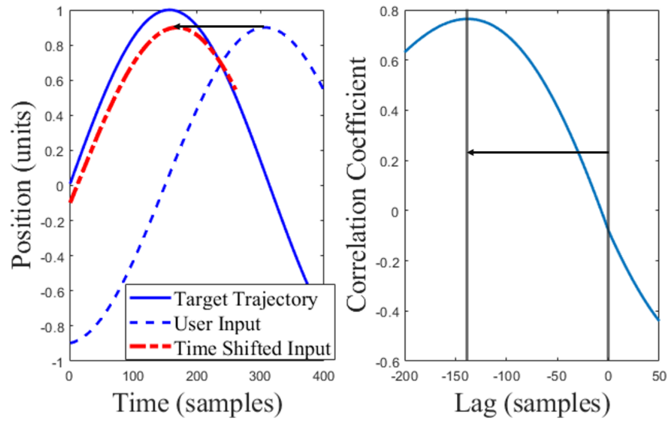

Fig. 3. Illustration of how user input was time shifted to account for input delay. The number of samples the input needed to be shifted was found using a cross correlation function, in which the lag with the highest correlation coefficient was used to determine the input delay.

A second training segment was then completed to help the participants to get familiar with the tracing task. The trajectories were constructed based on the work of A. Foulkes, where tracks were randomly generated though the summation of randomly phase shifted non-harmonic sinesoids with frequencies .06 Hz, .11 Hz, .13 Hz, .25 Hz, and .33 Hz [27]. After generating the trajectories, the amplitude was normalized to range of ±2 to ensure each path used the full range of motion provided by the vest. In total 33 of these paths were generated and stored in a database for this study. 3 of the tracks were picked for the training segment. Using the corresponding encoding method, a track was projected to the bHaptics. At the same time, the track was shown on the touch screen as a moving green dot. The participants were instructed to follow the track using the touch pen continuously based on their haptic sensation. The track generated by the user was displayed as blue curves on the touch screen. Each of the tracks lasted about 20 seconds.

The final tests included the remaining 30 tracing tasks. The procedure was identical to what the participants went through in the training segment with the exception that no visual reference was provided. The tasks were organized into six sets with 5 tracks in each and a 2 minute break in between to prevent participants from adapting and tuning out the feedback [28]. The sequence of the tracks was also randomized for each participant.

C. Data Analysis

The collected data were saved and the tracing performance was quantified based on accuracy of position tracing and velocity tracing.

Because the starting points of the tracks were randomized, it was expected that the participants would need some time to align the touch pen with the track. So the data collected from the first second of the tracing task was ignored to avoid participants' initial transient responses. Then the collected 1-D tracing data were filtered using the MATLAB signal processing toolbox's lowpass filter with cut-off frequency set at 5 Hz to remove high frequency noise.

Two factors contributed to the delay between the reference tracks and the tracing results, the time needed for data to transfer from Unity to the bHaptics vest and the time for the participants to trace the haptic feeling using their forearms. As a pilot work, we did not have enough data to quantify either of them accurately. To avoid the impact of delay, we estimated the delay using cross correlation and calculated the tracing errors after the delay was corrected. The procedure was shown in Fig. 3.

We calculated their mean absolute tracing error for position and velocity across each tracing task and averaged across all the tracing tasks for a given participants for the two approaches. The maximum cross correlation between tracing records and the reference was also used for evaluation. The jerk of the tracing trajectory was also calculated to quantify the smoothness of the tracing. Because all position measurements were done through the GUI, all data were recorded simply in "units" where 1 unit represents the distance between each motor on the screen, which is approximately 3.5 cm.

A two-tail *paired-t* test was adopted to compare the performance under the two encoding approaches. The significant level was set at 0.05 to reject the null hypothesis that selected participants achieved similar performance under two encoding approaches.

Since the study was counter balanced with different participants starting with different encoding methods, we analyzed whether the starting method had any impact on performance. Participants were divided into 2 groups, group A and group B, based on whether the PA approach of the AM approach was used first respectively. We compared the mean absolute position error for a given encoding approach between groups, as well as the mean absolute velocity error. A two-tail t test was adopted and the null hypothesis, being that the performance of group A and group B was identical, was rejected with a significant level 0.05.

III. Results

Of the 13 participants that passed the evaluation segment, two participants seemed to be using a quite different tracing strategy in the experimental procedure and generated very jerky results and were treated as outliers (more details are shown in the discussion section).

Fig. 4a shows the mean absolute positional errors for each participant. For the PA and AM approaches, the mean absolute errors were 0.6988 ± 0.1052 units (mean±standard deviation) and 0.6991 ± 0.1120 units respectively. No statistical significance was observed between the two approaches (p=0.9919).

TABLE I

Between Day Analysis			
	A (AM 1st)	B (PA 1st)	p-val
Pos Err AM	0.7453±0.0624	0.6436±0.0684	1.2659e-07*
Pos. Err. PA	0.6629±0.0529	0.7418±0.0760	1.8875e-05*
Vel. Err. AM	0.7804±0.0602	0.7131±0.0683	1.5494e-04*
Vel. Err. PA	0.7052±0.0460	0.6943±0.0651	0.4566

*Statistical significance

The PA approach permitted the participants to trace the velocity more accurately (p=0.0375). As shown in Fig 4b, the mean absolute velocity errors were 0.7003±0.0788 units/s and 0.7498±0.1109 units/s for PA and AM respectively.

No significant differences were noticed from the maximum value of cross correlation between the tracing trajectories and the reference for the PA and AM approaches. As shown in Fig 5, the PA approach reached a maximum cross correlation, 0.9460±0.0114 and 0.6953±0.0617 across participants for position and velocity respectively; AM approaches reached a maximum cross correlation, 0.9459±0.0118 and 0.6946±0.0532 for position and velocity respectively.

The final parameter investigated was lag. The AM method saw significantly less lag on average than the PA method, with the average PA lag being 961.2727±196.1033 ms, while the AM lag averaged at 790.7879±115.6915 ms. This was a significant difference at p = 0.0130.

Table 1 shows the results of the between session analysis, in which group A (N=6) consists of participants that started with the AM method and group B (N=5) shows participants that started with the PA method. For both groups there was a general trend where whichever method was used first saw worse positional accuracy then the method used on the second

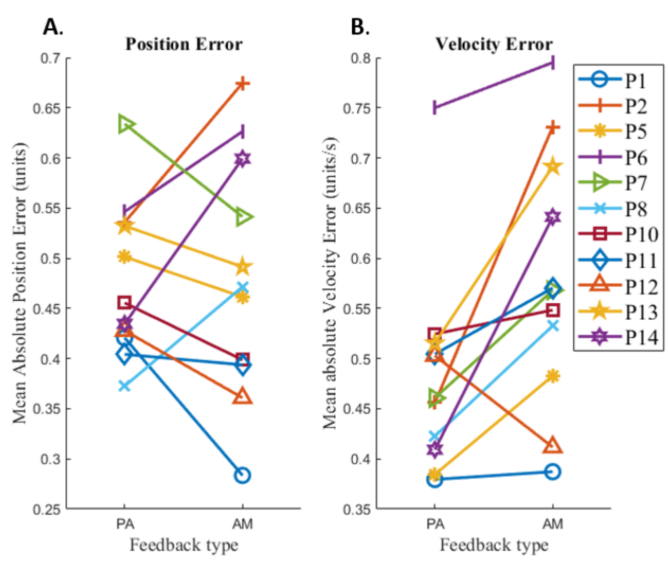

Fig. 4. A. Mean absolute position error and B. mean absolute velocity error averaged across each subject after time shifting data to account for input delay.

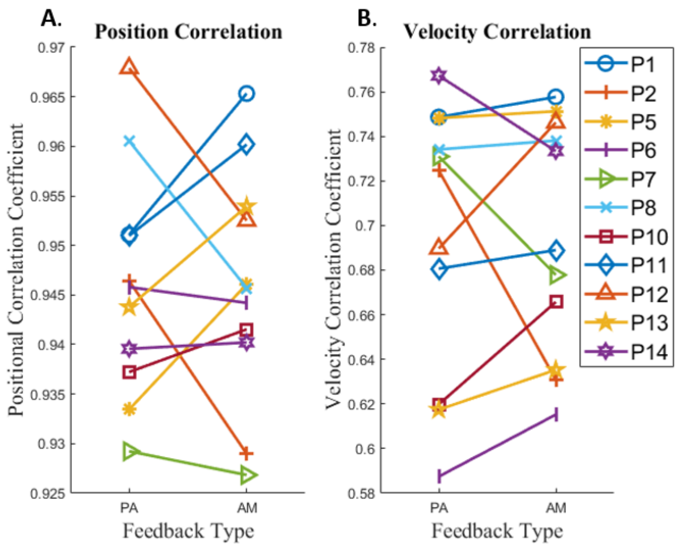

Fig. 5. Average correlation coefficients of each participant for A. position and B. velocity tracking of user input compared to target trajectory.

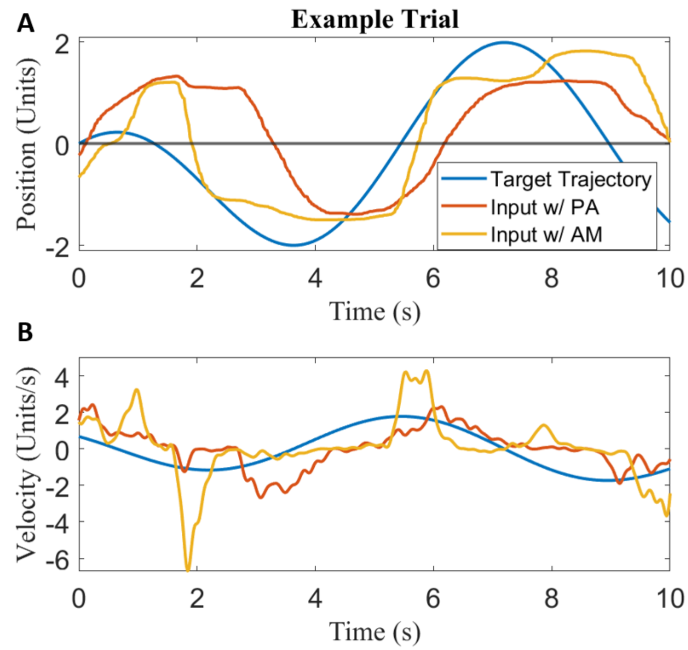

Fig. 6. 10 second sample of an example trial showing performance of PA and AM methods for A. position and B. velocity.

day of testing. For velocity tracking there was a trend in which those who started with the PA method performed better with the AM method than those who started with AM, however for the PA method there was no significant velocity tracking differences brought about by starting method.

IV. Discussion

A. Tracing performance

Although the PA approach permitted participants to trace velocity of the targeted point more accurately, it did not improve the performance of position tracing. This phenomenon may be explained by the different strategies used by the participants with the different encoding approaches. When the AM approach was used, all participants noticed the clear reference point at the center of the grid, so participants usually adopt a "catch then guess" strategy. When the target point passes the center, the participants quickly re-calibrates themselves, then moves along the targeted point (often with an overshoot). As shown in Fig. 6b, the "catch then guess" strategy often leads to huge velocity peaks when the target point passes the center.

When the PA is adopted, a "wait then evaluate" strategy was noticed. Because it is always easier to locate the target point when it is near the boundary of the grid, the participants tended to use the -V2 and +V2 (as shown in Fig. 6a) as the reference points and re-calibrate themselves after the point was close to them However, these reference points were not as clear as the center one with the AM approach; and participants often need time to make sure that the targeted points are closer to these reference points.

These different strategies affect the performance of the participants. Although the AM approach did not lead to very accurate tracing, the participants experienced better and more frequent reference points than the ones they experienced with the PA approach. The repeated calibration helped to reach a reasonable tracing performance. Because the starting location of the targeted point was also decided randomly, the participants might wait until the point moves close to a reference, then they were more confident about their perception and tracing. The fact that the reference was given more often when the AM was adopted may also reduce tracing delay.

B. Outliers

Of the 14 participants recruited for this study, one participant was excluded for being unable to achieve the motor identification evaluation criteria. This was an indicator that the participant struggled to perceive the feedback provided by the vest and so they were excluded from the study.

In addition to this, 2 other participants were excluded from the final results as outliers. Their outlier status was determined by investigating the mean jerk of each participant. Jerk is the 3rd derivative of position and an indicator of rapid acceleration and high frequency vibration [29]. Because the target trajectory is the summation of low frequency sinusoids with very low jerk, observed jerky motion can be attributed to sudden and rapid movements coming as a result of uncertainty of the target position or quick corrections to the user's input. The mean jerk for the 13 participants was 0.0351 ±0.0154 units/s^3 for the PA method and 0.0397 ±0.0236 units/s^3 for the AM method.

Using the 1.5 IQR rule [30] we declared any jerk greater than 0.0511 units/s^3 in the PA method or .0553 units/s^3 in the AM method as an outlier. Participant P4 was defined as an outlier with 0.0556 and 0.1146 units/s^3 jerk for the PA and AM methods respectively, and S9 was also excluded with 0.0781 and 0.0504 units/s^3 in PA and AM respectively. While

S9 was not an outlier with the AM method, their high jerk with the PA method showed they were not able to properly use that method and so their data was excluded from the final results. When we take a closer look of their tracing performance, it seemed that both of them used the "catch then guess" strategy with both encoding approaches extensively.

C. Limitations

As a pilot effort to explore the feasibility to apply PA in sensory substitution, there are a quite few limitations in the experimental design besides the limited number of participants. The results analyzing performance differences between different study sessions show that there are some significant carry-over effects between sessions, which can be addressed in future work by either increasing the time between sessions or providing more training at the start to reduce learning effects during data collection. The threshold for the evaluation segment is very low to validate that reliable feedback has been established. The evaluation segment could be treated as additional training for the PA approach and biased the results. Starting the tracks at a given reference point might help participants to avoid the initial uncertainty, which is often reported by the participants, and reduce observed lags. We only explore linear AM, and there are other types of AM encoding approaches.

V. Conclusion

In this study we compared the 1-D manual tracing performance of the "phantom actuator" based encoding approach using a high-resolution stimulation grid with a traditional AM approach. Our results showed that while there was no significant change in position tracking accuracy, the participants could take advantage of the high spatial resolution of the simulation grid and demonstrate better velocity tracing capability. Future work will investigate whether the improved sense of motion given by this feedback method can be used to improve control for lower limb amputees. This can be done by encoding biomechanical parameters, such as the center of pressure on the prosthetic foot, into a PA-based haptic feedback system for amputees.

While the vest used in this study consists of a 4x5 grid allowing for an exploration of 2D haptic feedback, this study focused on a 1D tracing task. Future work will move towards making better use of the 2D nature of the device however for this initial study it was necessary to understand how participants interpreted the haptic sensation in a simple 1D task.

Despite limitations in the experimental design, these encouraging results will guide us to further explore the feasibility of 2-D tracing, a much more challenging task, and integrate the encoding approach to help participants conduct real-time control.

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