The Dynamics of Centre of Mass Changes During Whole Body Motor Sequence Learning

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Bachelor Thesis

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Artificial Intelligence Disclaimer: In the development of the software prototype and statistical analysis, OpenAI's
ChatGPT (GPT-4) was instrumental, translating pseudocode into executable MatLab, Python and R code for the prototype and statistical analysis, thereby facilitating a more efficient familiarization and a faster prototyping process. The use of ChatGPT for drafting textual content was deliberately minimal, serving primarily to refine paragraph structure and organize thoughts without influencing the thesis's intellectual direction. Grammatical accuracy and textual clarity were enhanced through Grammarly and Overleaf's autocorrect feature. This approach underscores a judicious application of AI tools to augment the research process, maintaining the integrity and originality of the work.

Abstract

Motor sequence learning (MSL) is the basis for actions we perform every day such as tying our shoe laces or typing a message. The Discrete Sequence Production (DSP) task is a common paradigm that investigates MSL via keypress tasks. This pilot of the Dance-Step Discrete Sequence Production (DS-DSP) task adapted the DSP task to investigate MSL for whole body movements. Participants (n=12) completed four training blocks each consisting of 48 sequences which were all made up of six steps. Response Time (RT) and triaxial centre of mass (COM) acceleration were recorded as behavioural and kinematic measurements to examine chunking and concatenation. Results generally showed improvements in RT and COM acceleration through all blocks. Step number and block were significant for improvements of both RT and acceleration. RT and y-acceleration both shared the lowest and highest value at the fourth step respectively, indicating chunks longer than 3-4 stimuli because the next chunk only seems to get prepared after that. All three axes of acceleration were significant in predicting RT, suggesting an inverse relationship. Y-axis acceleration provided the best fit as a predictor for RT indicating that participants optimise their left to right movement the most to be faster. Further studies should examine this for longer sequences and while accounting for step position.

1. Introduction

You probably spent some time today tying your shoe laces or typing up a message on your smartphone or keyboard. These are seemingly simple tasks we perform on a daily basis. Motor learning is the process that allows us to do these tasks so effortlessly and enables us to complete even more complex movements, such as playing a musical instrument or dancing to our favourite song. Motor learning refers to the process of acquiring and perfecting motor skills and movements (American Psychological Association, n.d.).

More specifically, motor sequence learning (MSL) focuses exclusively on the process by which an individual acquires, refines, and automates sequences of movement. Over the course of time and practice, through chunking, performance of sequences becomes more automated, which makes them more efficient and therefore often times faster as well as less error-prone (Abrahamse et al., 2013). Previous studies on MSL have mostly looked at movements such as keypresses to analyse and understand the underlying processes (Rhodes, 2004). However, this also bares some limitations of their translation into more naturalistic tasks (Thompson et al., 2019). More naturalistic tasks involving whole body movements imply cognitive and motor functions which are not required for chunking in keypress versions. Moreover, the kinematics may play a key role in further understanding concatenation in chunking and deliver insights to key mechanisms of action and learning.

1.1 Discrete Sequence Production Task

The Discrete Sequence Production (DSP) task (Verwey, 1999, 2001) is a widely established experimental paradigm in motor sequence learning. During the DSP task, participants typically sit in front of a computer with four to eight fingers on the assigned keys of the keyboard. Depictions which correspond to each of the keys light up on the screen to imply that the participant has to press the (spatially) matching key (Abrahamse et al., 2013). The dance-step-DSP presents an adaptation by Chan et al. (2022) of the DSP that allows for investigation of whole body dynamics.

1.2 Chunking of Motor Sequences

Based on the results of research with the DSP task, Verwey (2001) developed the Dual Processor Model (DPM). The DPM distinguishes between a cognitive (later ‘central’, see Verwey et al., 2015) and a motor processor. Both processors work together to identify the response that matches the presented stimuli (cognitive) and execute the selected response (motor). The interplay of these two processors depends on the stage of learning.

Verwey and Abrahamse (2012) classified the three modes reaction, associating, and chunking for executing movement sequences which categorise the process of learning sequences. At first, in the reaction mode participants rely heavily on external stimuli to replicate sequences. Through extensive practice, participants go through the associative mode where the processing of stimuli primes them to replicate sequences faster (Abrahamse et al., 2013) and ultimately they utilise the chunking mode. In the chunking mode, no external guidance is required to execute a sequence (Verwey & Abrahamse, 2012).

Motor chunking refers to information processing that allows short movement series (sub-sequences) to be selected, prepared, and executed as if they were a single response (Verwey, 1999). Motor chunks are developed through the three phases called initiation, execution, and concatenation. A motor chunk is usually identified by a longer response time (RT) which marks the beginning of the chunk (initiation) and that is followed by a group of shorter RTs (execution)(Verwey, 2010). Toward the end of a motor chunk which is usually made up of 3-4 stimuli, a slowing down of the responses can be observed (concatenation) which is believed to indicate a concatenation point where the succeeding motor chunk is prepared by the cognitive system (Sakai et al., 2004; Verwey, 2010; Abrahamse et al., 2013).

1.3 Centre of Mass (COM)

The COM is a commonly used measurement in kinematics. COM refers to the point where the total body mass can be assumed to be concentrated (Mapelli et al., 2014). It has been widely used as an indicator for stability, balance, and performance during physical activities such as walking, football, volleyball, cricket and dancing (Tesio & Rota, 2019; Manolopoulos et al., 2005; Wagner et al., 2009; Ferdinands et al., 2010; Quadrado et al., 2022) respectively. Just like any other movement, COM movement can be measured in three directions along the y-, x-, and z-axis. The y-axis tracks horizontal (also referred to as medio-lateral) movement, the x-axis tracks depth (also referred to as anterior-posterior) of movement, and the z-axis tracks vertical movement. These translate into side to side (lateral), forward and back (longitudinal), and up and down movement of the COM. Vertical displacement of the COM during gait and running has been identified as indicator for gait efficiency (Saini et al., 1998; Gutierrez-Farewik et al., 2006). Horizontal movement of the COM has been linked to balance and stability in gait (Halvorsen et al., 2009). Better performing athletes have been shown to direct their COM more efficiently which allows them to yield better results (Delaney et al., 2019; Bedo et al., 2023).

In line with that, the study of Lin et al. (2014) on ultramarathon runners found that the group of better performing runners had significantly better control on their COM acceleration along the x- and y-axis. In particular, their control along the y-axis had the largest impact on their running performance (average running speed they were able to maintain). This implies that the variation in COM kinematics is related to the motor skill an individual possesses. Especially the COM acceleration along the y-axis seems to be related to the motor skill and learning process of movements. As pointed out by Smith et al. (2018), while in daily activities the large majority of variance could be explained by the vertical axis, the main direction of movements in a sport considerably affects the percentage of variance for which the vertical axis accounts. These findings imply that the influence of each acceleration-axis heavily depends on the general direction of the performed movement. For the DS-DSP, this suggests that throughout the learning process changes in acceleration for each axis that are similar to the ones in movements related to the dance-step can be expected.

1.4 Present study

In our pilot study of the DS-DSP task, we aim to investigate how previously established paradigms like the DSP task translate into whole body movement. This could deliver data to understand the dynamics of motor sequence learning in a more realistic setting which could be used for application in various areas such as protocols for learning new movements, interventions to help injured or elderly in recovery, and high-performance athletes to maximise their output.

As a pilot study it combines behavioural, kinematic and neurological measurements to test their practical application and the usability of the data when collected in a single study. However, in this bachelor thesis, I will only be investigating the former two. The study consists of six blocks, including four training blocks and two test blocks. In my analysis, I looked at the reaction times and the acceleration of the COM during the four training blocks. The primary interest is to investigate the concatenation of acceleration in the task and provide additional insights to the behavioural data. More specifically, to understand concatenation in whole body MSL, how the body represented by COM acceleration changes along with learning and concatenation, and to what extent COM acceleration can predict RT.

In line with previous research and inferences made from it, it is expected that:

1. The speed for the RTs shows a similar pattern to DSP tasks where the participant gets faster with practice throughout the blocks with the largest changes occurring through blocks one and two. RT is expected to be slow for the first step (initiation), get faster until the fourth step (execution) and start to slow down after the fourth step (concatenation).
2. While the translation of previous findings into whole body MSL is not entirely clear, the COM acceleration is thought to be closely related to RT as acceleration is made

up from sensors measuring the movement of the lower body. Therefore, faster movement should relate to higher acceleration. Hence, COM acceleration is expected to show a curve opposing the one of RT where participants' acceleration increases the most in the first two sessions. The acceleration for the first step is expected to be lower, while the acceleration for the latter steps is expected to get higher as the participant automates the performance of the sequences and displays patterns of chunking. A concatenation point is expected to show up for the fourth step where acceleration decreases.

3. All three dimensions of acceleration are expected to be significant in (negatively) predicting RT. In line with previous research, acceleration is expected to be closely linked to reaction time as a high acceleration suggests a better performance. The y-dimension is expected to predict the RT the best, as it has been the best predictor in previous literature for similar movements and also seems applicable to the side to side movement of the DS-DSP task.

2. Methods

2.1 Participants

The 12 participants for this pilot-study were collected through convenience sampling. 50% of the participants were male and the other 50% were female. The majority of the participants were second year psychology students and other Bachelor or Master students who were already familiar to the researchers. The participants age ranged from 20 to 27 (mean = 23.25) with a mean height of 171.9 cm. The majority of participants considered their right leg to be their dominant/preferred one in physical activity (75% right-legged, 16.6% left-legged, 8.3 % no preference). An additional participant was excluded due to measurement issues with the EEG and to keep the counter-balancing of sequences effective. The study was approved by the ethics committee of the University of Twente, Faculty of Behavioural, Management, and Social Sciences (BMS) and all participants gave written informed consent prior to participation.

2.2 Material

2.2.1 Dance Step Task in E-Prime®, Dance Mat, JoyToKey

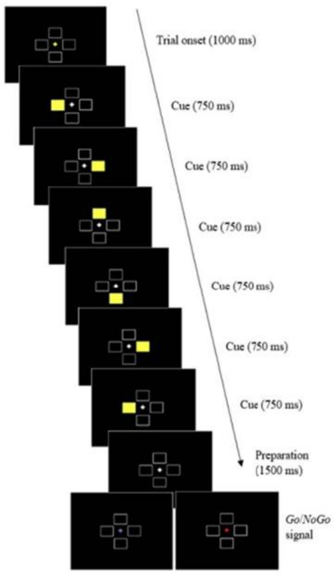
The experiment was conducted in the EEG-lab which is part of the BMS lab structures in the Cubicus building. As stimulus presentation and behavioural data collection software, E-Prime®3 was used because of its ease in programming and its consistency in collecting behavioural data (RT and accuracy). The stimulus layout of the dance mat spatially corresponds to four areas (↑, ↓, → and ←) with a neutral position in the centre (Figure 1). Additionally, the mat has a space labelled X and O which each were mapped to correspond to space and enter on a keyboard. The X pad was also used to initiate the task by the participant. The dance mat used is a commercially available dance mat (Nonslip Dance Pad Version 5 from D-Force, see Figure 1). JoyToKey was used to convert the spaces on the map (↑, ↓, → and ←) into the matching key presses of W, S, D, and A, respectively. The pads X and O were at the top left and right of the mat, respectively.

Figure 1

Dance Mat used in the Experiment

Figure 2

Example of Trial from Onset to Go/NoGo Signal



2.2.2 Motion Capture: Xsens MTw Awinda and MVN Analyze

To capture the movement of participants, the Xsens MTw Awinda system was used. Sensors capture a participant’s motion and transmit the data wirelessly through a local Wi-Fi network to the MTw Awinda station which is linked to a desktop. The 7 sensors for the lower body are placed symmetrically at the feet, lower legs, upper legs, and the final one around the pelvis (Figure 3). The computer that was running the recording and saving the data at a rate of 100hz is running the accompanying software MVN Analyze. This software depicts a 3D representation of the lower body movement from the participant which allowed for visual tracking and enabled the recording of the data. Throughout the task, participants had to be recentered in MVN Analyze to counteract a drift that can affect the sensors over time.

Figure 3

Xsens Sensor Placement

Note. Circles mark the placement of the seven sensors. The pelvis sensor was placed on the backside, the upper leg sensors were placed on the outer side of the upper legs, and the lower leg sensors were placed on the inner side of the lower legs. Feet sensors were placed on top of the feet.

2.3 Procedure

2.3.1 Preparation of Participants with Xsens and EEG

Prior to the experiment, participants were asked to wash their hair and to wear preferably tightly fitting clothes to avoid issues with the Xsens sensors. At the beginning of the experiment, participants were welcomed into the lab. The researchers were all introduced and the name of the supervisor was given to the participants. Upon entering the lab, the participants stored away their belongings, aside from a bottle to drink during the breaks of the experiment. Participants were also reminded to go to the bathroom before the experiment if necessary as this would be difficult once all the equipment was set up. Once participants were ready to proceed, they were asked to sit down on a chair and begin reading the informed consent form. After they finished reading and signed the form, they were explained the task. This was followed by setting up the EEG caps with the software. To finalise the setup, the tablet and amplifier were placed in a backpack which the participants then put on for the remainder of the experiment. Upon completion, participants underwent the Xsens setup. Weight, height, and foot length were recorded into MVN Analyze. Before placing the straps with the sensors, the participants were again informed where on their body these straps would go and asked for consent to place them. After this procedure, participants were presented with a questionnaire to measure their initial stress- and workload at the time. Once the questionnaire was filled out, the Xsens sensors were calibrated through the calibration function of MVN Analyze. During the calibration, participants have to follow the auditive instructions which was output through speakers and supported by the researchers to ease understanding for the participants. The calibration required the participants to calmly stand still, walk for a few seconds, turn around and keep walking for a few more seconds, until the signal was given for them to return to their original stance. Starting and turning point were indicated on the floor via duct tape. After positive evaluation by the software and manual verification of the calibration results, the experiment continued. Before the participants started with the task, any questions they had were clarified and the task was confirmed with them again. The entire preparation took 20-60 minutes, being considerably quicker once the process was familiar to the researchers after a few participants.

2.3.2 Dance-Step Discrete Sequence Production Task

The task required the participants to stand in the middle of the dance pad and look at a large screen in front of them. Participants had to memorise the sequence shown on the screen and copy it on the matching tiles of the dance pad when a blue cross was shown, or not do the sequence at all when a red cross was shown after a sequence. Further, participants were free to choose their own strategy. The only instruction they received was to be as quick and accurate as possible when reproducing the sequences. Before the participants started, it was ensured that all the required recordings were running and that they were good to go. The entire task was split into six blocks, each of which consisted of 48 sequences. The two sequences that made up a block were presented in random order to make up a total of 24 appearances per block. Each block was estimated to take around 10 minutes per participant. The first four blocks comprised training blocks, while the last two were test blocks. The same two sequences were randomly presented to the participants throughout the first five blocks. The sixth block consisted of two new sequences which were unfamiliar to the participant. The selection of familiar and unfamiliar sequences was counterbalanced across the participants by rotating the sequences. In between each block was a very short break and participants were free to take a longer break of around 10 minutes after three blocks. If participants required a longer break between the blocks before or after that, they were also granted to do so. The questionnaire they filled out in the beginning was also handed to them at the end of every two blocks and at the end of the task (each participant filled it out four times) to keep track of how the task affected them. Filling out the questionnaire also lengthened the break a few minutes between the applicable blocks. In total, the task took around 1-2 hours with considerable variance between participants, depending on how fast they were during the trials.

2.4 Data Preprocessing

The behavioural data from E-Prime was processed using RStudio version 4.4.0. Since I only analysed the sequences from the training blocks which were entirely accurate, data from the test blocks and sequences with one or more mistakes were removed (391 inaccurate sequences removed). Outliers were also removed via interquartile range, 1.5 * below the first quartile and 1.5 * above the third quartile, which exempted another 580 trials (96.7 sequences) from the training data. Outliers needed to be removed to avoid skewing of the data where participants may have missed the go-signal or got distracted when performing the sequences. This left me with 143.5 sequences per participant from the original 151.6 sequences per participant for all four training blocks.

2.5 Data analysis

First, raw behavioural data was visualised to examine learning (see Appendix A). A linear model to analyse the change of response time throughout the sessions (used interchangeably with blocks) with session as independent and reaction time as dependent variable was run. To examine concatenation of chunks from reaction time, a linear mixed model with session and step number as fixed effects and participant as random effect was run. To examine the concatenation in chunking of acceleration, a linear mixed model with session and step number as fixed effects and participants as random effect were run. Lastly, to examine the relation between response time and acceleration, a linear mixed model with acceleration as fixed effect and participant as random effect was performed. The acceleration models were computed three times to account for the x, y and z dimensions of acceleration output from Xsens. Post hoc tests were done accordingly.

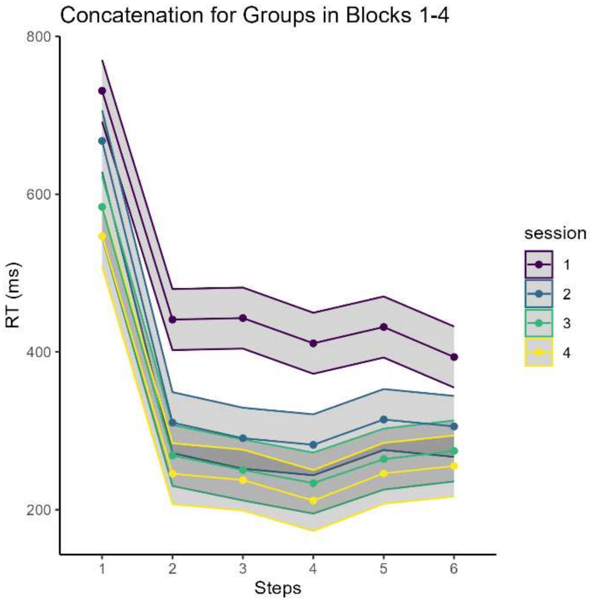
3. Results

3.1 Behavioural Analysis

A mixed effects model to analyse RT with the step number as fixed effect and subject as random effect was run. Another mixed effects model with the fixed effects session and step number as well as subject as random effect was run (Figure 4). The first step was always the slowest, while the quickest RT in every block was marked by the fourth step. Aside from block 1, RT slightly increased after that. The ANOVA performed on the model revealed session $\chi2 = 2790.8$ ($F = 885.61$) and step number $\chi2 = 7312.72$ ($F = 1379.57$) as significant effects ($p < 0.01$) on response time and session as significant interaction effect $\chi2 = 92.58$ ($F = 6.16$, $p < 0.01$). Steps 2 through 6 also significantly reduce the response time ($p < 0.01$) compared to the baseline of step 1. Post-hoc analysis also revealed session 1 to consistently have the highest response time for all steps (394-731 ms) while session 4 consistently has the lowest response time for all steps (212-547 ms). Also, within each step number, the mean response time decreases throughout all four sessions. Changes in RT from session 1 to session 2 were found to be significant for steps 2-5, while no other sessions revealed significant effects for this.

Figure 4

Reaction Times per Step over Block by Group



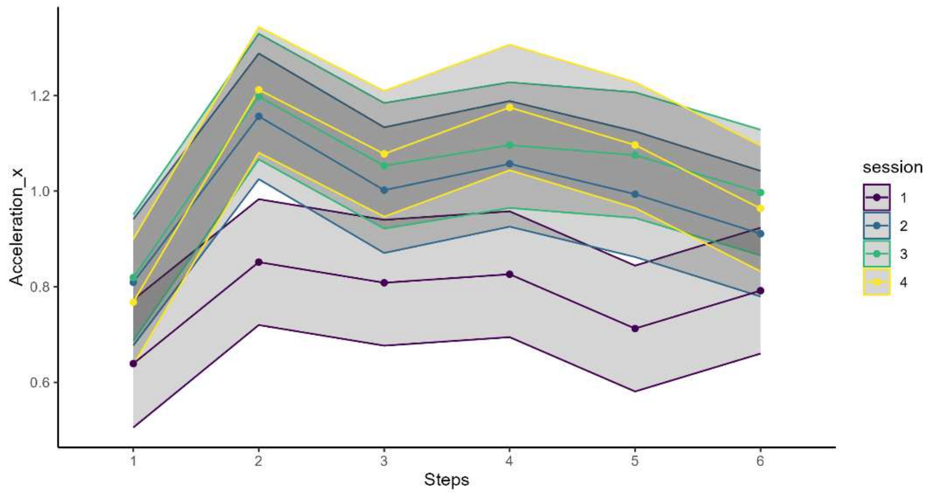
Note. Linear mixed effects model of RT per step across sessions with subject as random effect. A decrease in RT implies participants completing the step and the sequence more quickly. RTs in every session drop after the first and overall decrease per session. Note the continued concatenation at the fifth step.

3.2 Acceleration Analysis

Mixed effects models were also run for the acceleration in x- (Figure 5), y- (Figure 6), and z-axis (Figure 7) with the fixed effects of session and step number and subject as random effect. For x-axis acceleration, session $\chi 2$ (3, N=12) = 517.98, step number $\chi 2$ (5, N= 12) = 474.41 and their interaction $\chi 2$ (15, N= 12) = 55.36 were significant ($p < 0.01$). Post-hoc tests with asymptotic degrees of freedom showed higher estimated marginal means (EMMs) across all step numbers for session 2-4 than for session 1. For y-axis acceleration session $\chi 2$ (3, N=12) = 688.25 and step number $\chi 2$ (5, N= 12) = 778.32 as well as their interaction effect ($\chi 2$ = 151.56) were significant ($p < 0.01$). Post-hoc tests with asymptotic degrees of freedom showed increasing EMMs across all sessions and within all sessions along with the step number. Significant interaction between session and step number was confirmed. For z-axis acceleration, session $\chi 2$ (3, N=12) = 682.0, step number $\chi 2$ (5, N= 12) = 692.34, and their interaction $\chi 2$ (15, N= 12) 102.17 were significant ($p < 0.01$). Post-hoc tests with asymptotic degrees of freedom showed increasing EMMs across all sessions and within all sessions along with the step number until step number 3 or 4, after which the increase slows down or slightly decreases. Interaction effect between session and step number was confirmed.

Figure 5

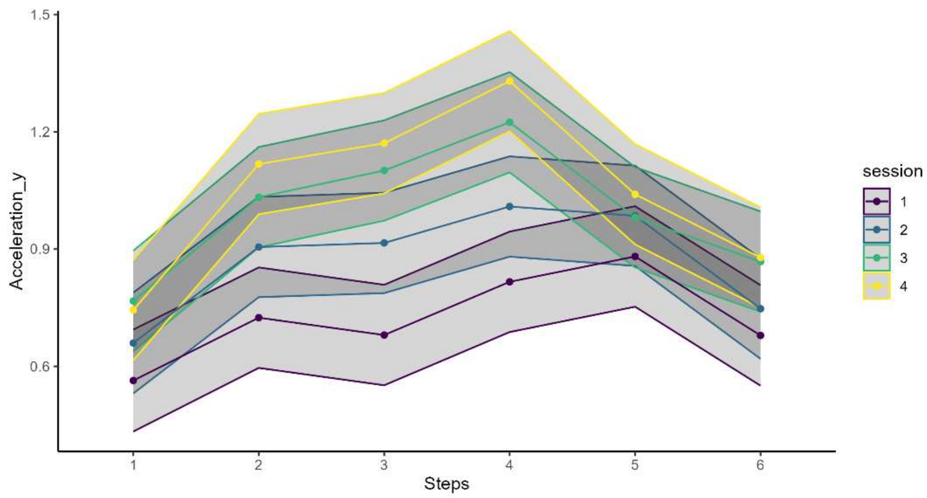
X-axis Acceleration per Step per Block by Group



Note. Linear mixed effects model of x-acceleration per step over sessions with participant as random effect. Note the continued peak at the second step.

Figure 6

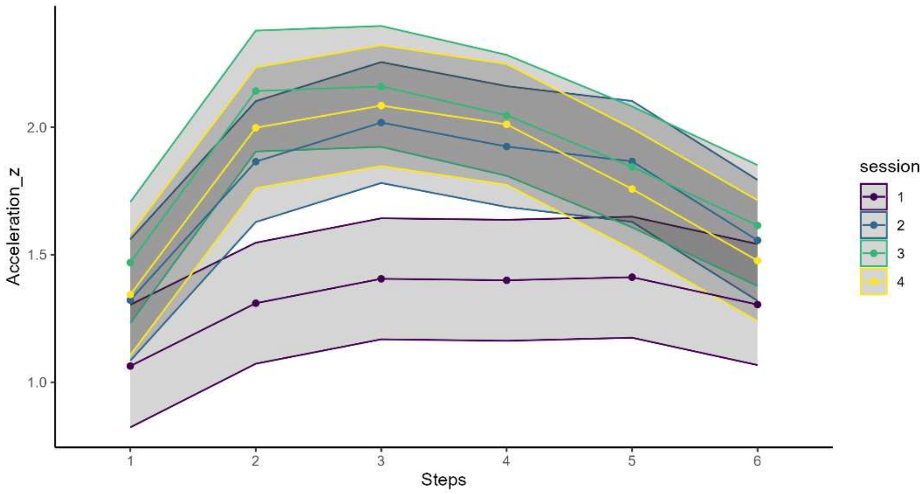
Y-Axis Acceleration per Step per Block by Group



Note. Linear mixed effects model of y-acceleration per step over sessions with participant as random effect. Note the continued peak at the fourth step.

Figure 7

Z-Axis Acceleration per Step per Block by Group



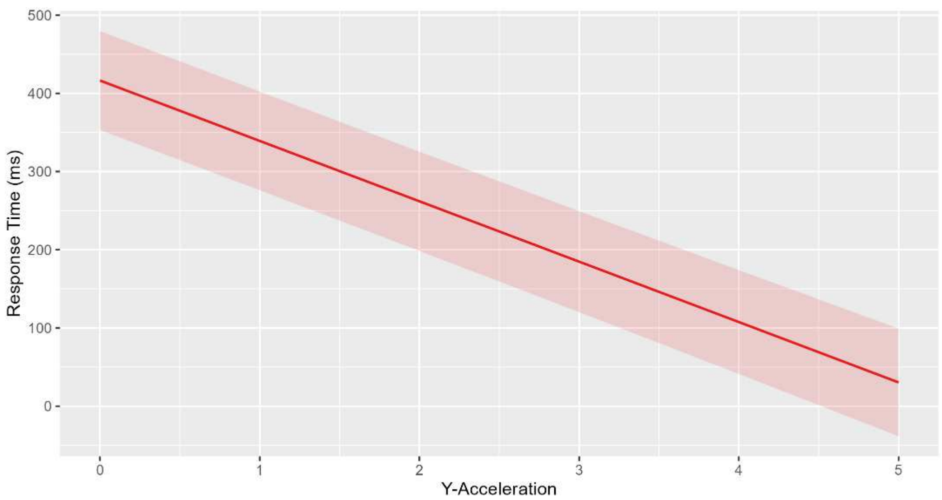
Note. Linear mixed effects model of z-acceleration per step over sessions with participant as random effect. Note the shape going from more linear to more curved over the sessions.

3.3 Response Time and Acceleration

To examine the relationship between RT and acceleration, mixed effects models with acceleration (x,y,z) as a predictor of RT were run. Post-hoc tests with Satterthwaite degrees of freedom with Akaike's information criterion and the Bayesian information criterion to compare the fit of the models were run (Table 1). All three axis show a significant p-value of <0.01. The lowest AIC and BIC resulted from the y-axis with 136814 and 136842,9 respectively. A linear regression of RT and y-acceleration was run to visualise their relationship.

Figure 8

Linear Regression of Response Time and Y-Acceleration



Note. Linear Regression of Response Time and y-Acceleration. Figure shows a strong inverse relationship between both variables. In other words, y-Acceleration has a strong predictive ability for RT where high values of y-Acceleration indicate low values of RT.

4. Discussion

This pilot-study examined behavioural and kinematic facets from the DS-DSP task to investigate the concatenation of acceleration data and it's relation to behavioural data.

Reaction Time

As expected, reaction times decreased throughout the sessions which indicates a learning process. Participants are considerably slower during the first session which suggests them getting used to the stimuli and responding (reaction mode). Results of significant reduction in RT from session one to session two suggest that the participants performs most of the learning during the first to second blocks. This is also in line with previous findings from the DSP task (Abrahamse et al., 2013). The reaction time overall being the lowest in the fourth block also confirms this. The pattern of RT with the first step being the slowest, a decrease of RT for the following steps until the fourth step where RT increases again indicates chunking as described by Verwey (2010). Therefore, the first hypothesis can fully be confirmed by the findings that support most of the learning to take place in the first to second block and indications of chunking throughout all sessions.

Acceleration

Acceleration of all three axis generally shows an increase across all sessions. The only exception is posed by the z-acceleration shift from session 3 to session 4 where the acceleration for every step decreases (Figure 7). Whether this stems from a shift in strategy from the participants or other reasons is unclear as this is not a phenomena that has appeared in previous literature. While the acceleration for steps overall increases within each session, a dip in acceleration is visible for the sixth and final step of each session which coincides with the data from RTs. Interestingly, x-acceleration does not show this dip for the first session and instead acceleration peaks in the second and fourth step. The changes observed in x-acceleration could be an indication of chunking taking place where participants begin to form motor chunks through the practice of the first and second block. The slowing down of acceleration in the third and sixth step could therefore suggest concatenation where the next motor chunk is being prepared. This would make sense with previous findings that indicate this pattern of chunking and the length of chunks being 3-4 stimuli (Abrahamse et al., 2013).

Reaction Time & Acceleration

As hypothesised, the results showed all three axes of acceleration to have a significant effect on reaction time ($p < .001$). This indicates that changes of acceleration in any direction are closely related to changes in reaction time. Participants seem to utilise all three directions of acceleration to achieve the fastest RTs. The x-axis showed the lowest chi-squared value which imply it being closest to what would be expected. However, when considering the fit of the models via AIC and BIC, the y-axis acceleration scores the lowest on both which indicates y-acceleration to be the best fitting one, although it has the highest values for chi-squared. The latter may also suggest higher fluctuations which could be interpreted as containing more information as participants move side to side more. Figure 8 illustrates that y-acceleration and RT have a strong inverse relationship where high acceleration values predict a low RT. Results also showed a coinciding peak/drop off in RT and y-acceleration for the fourth step which signifies how closely related the two measurements are and points to motor chunks likely being longer than 3-4 steps. RT increasing and y-acceleration dropping off towards the sixth step, indicating a concatenation point, also confirms this. Thus, the third hypothesis can be confirmed as well.

Limitations and Future Research

The nature of this study being a pilot and therefore having a small sample which was acquired through convenience sampling implies less reliable results. Future research needs to investigate the findings in a larger scale to account for variability and allow for generalizability. A minor practical limitations may be that taller participants seemed to struggle with the last step of a sequence being registered by the dance pad a few times. They therefore had to repeat the last step to complete the sequence which may have lead to some longer RTs and potentially inaccurate acceleration for the sixth step. Future research should account for this by filtering participants on their height and potentially including a second dance pad for taller participants where each space of the map is larger and thereby not as close to the center. Additionally, the positions of the steps from the participants have not been taken into consideration. Participants had total freedom in terms of the strategy they used to complete the sequence. The models used for analysis are able to determine a relationship, however, they disregard step and sequential position which makes the question of whether this still falls under the umbrella of sequence learning disputable. Future research could consider this by constraining the strategy to have more interaction with the sequence by e.g. limiting the foot they can use for each position. This would allow for analysis of the effects of different step positions and sequences on RT and acceleration. In particular, the consequences for the predictive abilities of the different acceleration axes for RT.

In line with that, future research could investigate whether the same patterns apply to the test blocks. Inquiring whether the same applies for unfamiliar sequences which show up during the test blocks would solidify the findings and allow for much better generalizability. Further, testing sequences consisting of more than six steps is recommended to understand how concatenation functions in longer sequences and to confirm or deny the suggestion of longer motor chunks. To what extent the length of sequences in whole body tasks affects the peaks in RT and acceleration and how it affects chunking still needs to be understood.

Conclusion

To conclude, this pilot-study investigated behavioural aspects of the DS-DSP task. Response times during the DS-DSP task show similar patterns from previous research on the DSP task which suggests chunking. The kinematic data also points to motor chunking translating into whole body movement. Y-acceleration was most predictive for RT which implies that participants optimise their left to right movements the most to improve their performance. Accordingly, all three hypothesis can be confirmed. (1) RT was slow for the first step (initiation), got faster until the fourth step (execution) slowed down after the fourth step (concatenation). (2) COM acceleration showed a curve opposite to RT where the values were low at first and increased throughout sessions as participants automated the performance of sequences and displayed patterns of chunking. (3) All three dimensions off acceleration significantly (negatively) predicted RT. As expected, y-acceleration (horizontal) was the best predictor of RT. However, the late peaks of RT and y-acceleration possibly indicate motor chunks longer than 3-4 steps. The pattern of variation in the acceleration data needs to be investigated further, especially with longer sequences. Further, future research should account for step position beyond the directions that determine response times to have more interaction with the sequence.

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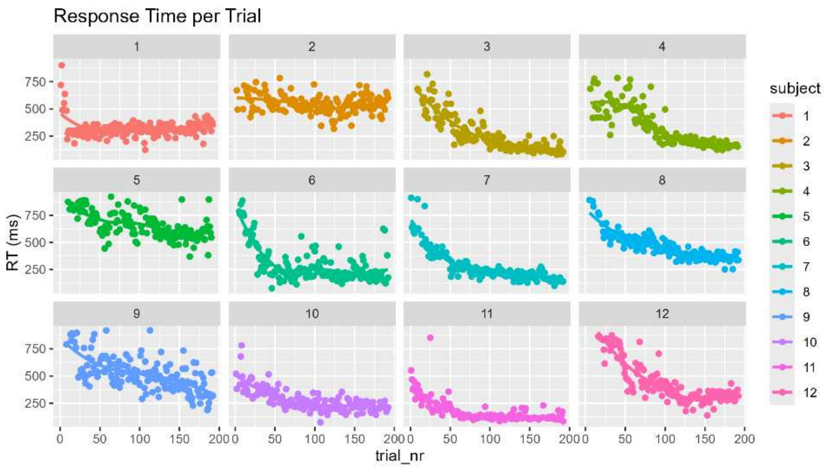
Appendix A

Figure 9

Visualization of Response Time Learning Curves for Trials



Note. Response time learning curves for each participant via trials. Outliers 1.5 * below the first quartile and 1.5 * above the third quartile have been removed. A decrease in reaction time indicates learning.

Appendix B

Table 1

Predictive Functions of Acceleration-axis for Response Time

	AIC	**BIC**	**$\chi 2$**	**P-value**
X-Acceleration	136**957**.0	136**986**.0	349.78	<.001
Y-Acceleration	136**814**.0	136**842**.9	498.67	<.001
Z-Acceleration	136**846**.0	136**847**.9	465.16	<.001