Kinematic Analysis of Postural Anticipation and Recovery in Young and Older Adults

Elnaz Torabinejad

A Thesis

In the Department

Of

Electrical and Computer Engineering

Presented in Partial Fulfilment of the Requirements

for the Degree of

Master of Applied Science (Electrical and Computer Engineering) at

Concordia University

Montreal, Quebec, Canada

May 2021

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis prepared

By: Elnaz Torabinejad

Entitled: Kinematic Analysis of Postural Anticipation and Recovery in Young and Older Adults

and submitted in partial fulfillment of the requirements for the degree of

Master of Applied Science (Electrical and Computer Engineering)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final Examining Committee:

Dr. Hassan Rivaz	______________________	Chair, Examiner
Dr. Nizar Bouguila	______________________	Examiner
Dr. Christopher Steele	______________________	Examiner
Dr. Habib Benali	______________________	Supervisor
Dr. Karen Li	______________________	Co-Superviser

Approved by ____

Dr. Yousef R. Shayan Chair of Department

____ Dr. Mourad Debbabi Dean of Faculty

Abstract

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Elnaz Torabinejad

The maintenance of balance is one of the most important capabilities of humans. This ability is more crucial for older adults considering that over one in four elderly adults experience at least one fall (Bergen et al., 2016a) Empirical evidence showed that working memory plays role in maintaining balance. Working memory degrades by increased age. In the present study, the Dual Mechanisms of Control framework (Braver, 2012), was utilized to evaluate the role of working memory in maintaining balance in older and younger adults. Participants were presented with visual cues indicating if the platform beneath them was likely (A) or unlikely (B) to move. On 70% of trials, cue A was followed by a forward horizontal translation of the platform. On 10% of trials, the B cue was followed by a platform movement (invalid trials). The remaining non-movement trials were either valid (B cue, 10%) or invalid (A cue, 10%) and not analyzed. Retention of goal-relevant cue information in working memory is thought to decline with aging. Kinematic signals (hip, knee, ankle joint angles) were captured by a Vicon system and characterized as (i) peak amplitude, (ii) peak latency and (iii) recovery deviation, were analyzed as a function of age group (young, older), cue type (A: likely platform movement; B: unlikely movement), and testing stage (early Block 1; late Block 6). To address the anticipated age differences in proactive control, an additional factor was considered using a neuropsychological test of working memory capacity.

Together, these four factors were included in a series of MANOVAs, using the three kinematic parameters for each of the three joint angle data. The results of multivariate ANOVAs suggested that the there was a significant effect of age and level of working memory in different age groups in some joint angles.

Furthermore, using methods of machine learning, the prediction of age group based on the kinematic characteristics was applied. Each measurement was considered as a feature and due to the excess number of features, feature selection methods (PLS, PCA, Correspondence Analysis) were applied on the dataset. The selected features by each method, composed new datasets. Three different method of Machine Learning (Decision Tree, Random Forest and Naïve Bayes) were applied to the datasets with 10-fold cross-validation. The best accuracy (0.83) was achieved by applying the Decision Tree method on a dataset selected with Partial Least Square (PLS) method. Together these results supports the Dual Mechanism of Control framework and suggests that working memory is used to maintain balance, and older adults utilized cues differently than younger adults.

Acknowledgements

I would like to extend my heartfelt thanks to my supervisors, Dr. Habib Benali and Dr. Karen Li, for their invaluable advice and ongoing support through my master's degree. This thesis would not be possible without their continuous guidance and insightful comments.

I would like to express my gratitude to Dr. Nizar Bouguila and Dr. Nancy St-Onge for their unconditional support and guidance. Also, I would like to thank the Faculty of Engineering and Computer Science of Concordia University,PERFORM Center and NSERC for their financial supports. I deeply appreciate the support of my friends and lab fellows at Concordia University.

I would like to appreciate my beloved parents, Afsaneh and Shahram, and my dear sister, Sahar for their unconditional love. I would like to thank my best friend, my love and my husband, Behrad Bezyan, for always being there for me. None of these was possible without your love, support and understanding.

At last, I would like to thank me for not giving up on me even in darkest moments of my life.

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List of Abbreviation

EF	Executive Function
DMC	Dual Mechanism of Control
APA	Anticipatory Postural Adjustments
CPA	Compensatory Postural Adjustment
ML	Machine Learning
RD	Recovery Deviation
MANOVA	multivariate ANOVA analysis
PLS	Partial Least Square
PCA	Principle Component Analysis
CA	Correspondence Analysis

Chapter 1. Introduction

Balance is one of inherent capabilities of the human. Loss of balance leads to risk of falling (Panjan & Sarabon, 2010). Decline of the ability to maintain balance decreases a person's independence and can lead to increases in isolation. The risk of falling increases with increased age (Sammy & Robertson, 2018). Over one in four seniors falls every year in United States. Every fifth fall results in a serious injury, such as a broken bone or a head injury. Over 95% of hip fractures caused by falling sideways (Bergen et al., 2016b). Therefore, in order to prevent or decrease falling, evaluating the process of maintaining balance is essential to improving the lives of older adults.

1.1 Background and Motivation

Problems in maintaining balance are common among elderly adults. However, deteriorated muscle is not the only reason. There are different reasons for the high rate of falling among elderly adults, such as degradation of working memory. Working memory capacity decreases as a function of age (Pliatsikas et al., 2018).

Executive Functions (EF) encompass various cognitive skills including working memory, flexible thinking and self-control. EFs are involved in important activities such as attention, organization and prioritizing, self-monitoring, and emotions. EFs are strongly connected to gross motor skills (Frederiksen et al., 2015). Robust evidence shows the engagement of EF in postural control (Al-Yahya et al., 2011). Additionally, structural changes in the brain are related to the postural instability in elderly (Sullivan et al., 2009). For example, gray and white matter volumes of anterior brain regions are associated with EFs and motor regions (Li et al., 2018).

A more direct research strategy to examine the role of EFs in older adults' motor performance is to add a simultaneous cognitive load to the primary balancing or walking task, termed dual tasking (Woollacott & Shumway-Cook, 2002). Evidence points to the role of EFs in gait and balance reduction while dual-tasking (Iersel et al., 2008). Functional neuro-imaging evidence shows older adults use brain regions that are associated with attentional control and working memory (e.g., frontal-lateral and temporal-parietal areas) during balance and walking performance (Lin et al., 2017). Further, studies involving dual-task walking lead to higher activity in prefrontal brain regions than during single-task conditions, however older adults shower underactivations compared to younger adults (Holtzer et al., 2011). Kearney et al. (2013) showed that impairment of the EFs is strongly related to falling risk in older adults.

1.2 Aging and Executive Function

Decline in EFs is related to typical healthy aging (Murman, 2015). Evidence showed that age-related decline appears in at least three domains of EF: (1) attention, utilized in focusing on goal-related events (Aschenbrenner & Balota, 2015); (2) inhibition, utilized to suppress the unrelated events to the goals (Bloemendaal et al., 2016); and (3) working memory, utilized to preserve events related to goals (Klencklen et al., 2017). The Dual Mechanism of Control (DMC) framework combines these three domains of EF by incorporating them into two mechanisms: Proactive Control (PC) and Reactive Control (RC). Proactive control is a cognitive mechanism that facilitates goal-related behavior by employing working memory, attention, and concentration to prepare for an upcoming event. Reactive control, on the other hand, describes processes that take place in response to the onset of goal-related stimuli (Braver, 2012).

There are some advantages and disadvantages for using each cognitive mode. In proactive control (PC), a cue prompts the participant to attend to goal-relevant information in advance therefore, the advantage is that behaviors can be modified constantly to achieve the goal more quickly and efficiently; however, there is a higher demand for cognitive resources due to the anticipation process involving working memory. For reactive control (RC), the goal trigger and goal activation take place simultaneously and hence, RC is less resource-consuming and more free resources are available between cues; however, as there is no use of memory or sign of anticipation, this cognitive mode has the disadvantage of being highly dependent on the goal-triggers. If the triggers are not salient enough, there will not be any re-activation (Braver, 2012).

Deficits in prefrontal cortex (PFC) functionality increase with age (Paxton et al., 2008). Normative aging is associated with declines in executive functions such as working memory, inhibition, and attention (Braver et al., 2001). Considering that RC requires fewer available working memory resources, older adults tend to utilize RC more. Early temporal activation is related to PC, which is seen more often in younger adults, however, late temporal activation corresponding to RC is more often seen in older adults (Paxton et al., 2008). In PC, higher capacity of working memory and anticipation leads to faster responses.

The AX-CPT (Braver, 2012) is a method for quantifying PC and RC processes. In this method different cues are used as goal-relevant triggers. Therefore, participants should keep goal-related events in mind to respond faster to the stimuli and inhibit false alarms. The AX-CPT procedure consists of four different conditions (Cue A evokes an expectation and Cue B does not evoke an expectation of the target stimulus, X). Participants are instructed to respond “yes” if they see an A cue followed by an X stimulus. Any other cue-stimulus pairing should result in a “no” key press response. In the majority of trials there is congruency between cue (A) and the expected stimulus (X). Because they occur most frequently, participants build up this AX association along with their expectation. In a second trial type (BY), the cue (B) does not evoke the expectation of stimulus X, and instead, should be followed by a non-target (Y). A third trial type (BX) signals that a non-target Y will follow but instead, X follows. Participants with weakened PC processing or poor working memory may not retain the cue, and may incorrectly respond because the target stimulus X has been shown. The fourth and final trial type involves mis-cued pairs (AY), which start with a cue that evokes the expectation of an X target to follow, but it does not. Individuals who are strong in PC might incorrectly respond “yes”due to strong preparation / anticipation of X.

1.3 Dual Mechanism of Control in Postural Responses

The effect of aging on DMC processes has not been clearly examined in the context of postural control to date. However, there is empirical evidence to demonstrate that the cortical activity is different depending on the predictability of a platform movement during tests of quiet standing (Jacobs et al., 2008). Anticipation of change in position based on goal-trigger cues can be conceptualized as proactive control. Anticipatory Postural Adjustments (APA), refer to the process of postural preparation when expecting a perturbation (Kanekar & Aruin, 2014). APA tend to slow with age. Compensatory Postural Adjustment (CPA) refers to the activity of muscles in reaction to the perturbation after it happened. The APA and CPA were compared in different studies. Santos et al.(2010) designed an experiment for finding out the relationship between APA and CPA in maintaining balance. They designed two conditions of predictable and unpredictable platform movements to compare the APA and CPA for maintaining the equilibrium of body while predictable and unpredictable perturbations were applied to the shoulders of participants. There were two types of trials, the trials with open eyes which they considered “predictable perturbations”, and trials with closed eyes and headphones to prevent participants from seeing or hearing any warning of the perturbations. They found larger changes in the angular position of ankle, knee and hip joints in unpredictable trials compared with predictable trials. In predictable trials, participants utilized APA to manage their postural control. However, no invalid trials (i.e., AY or BX analogues) were utilized in their experiment, and aging effects were not considered.

The postural system utilizes different strategies in order to maintain balance during tests of postural recovery. These strategies are “ankle strategy”, and “hip strategy” or even “mixed strategies” (Blenkinsop et al., 2017). While there are multiple definitions of the aforementioned strategies, the most commonly used definitions are those proposed by Horak and Nashner (1986). In their framework, an ankle strategy is defined as using mostly ankle joint rotation and small amount of hip rotation, however if the majority of movement (extension or flexion) is observed at the hip, it is a hip strategy (Horak & Nashner, 1986). This topic is fully explained in Section 3.2.

1.4 Machine Learning Approach

In 1956, John McCarthy, father of Artificial Intelligence, coined the term “Artificial Intelligence” for the first time for the “the science and engineering of making intelligent machines”(Hayes & Morgenstern, 2007).There are several methods to define Artificial Intelligence however, we can define artificial intelligence systems as “systems which can behave like human” (Kok et al., 2010).

Machine learning (ML) is a term which encompasses all the beneficial technics in statistics, probability, algorithms widely used in different fields worldwide. Samuel (1959) defined ML as the “field of study that gives computers the ability to learn without being explicitly programmed”. ML provides the ability of learning from dataset for computers. The ability of classification, regression or prediction based on a provided dataset, makes ML a powerful and popular method in different fields.

The use of ML in psychology is on the rise. Kosinski et al. (2013) used machine learning algorithms in order to find out the personality of Facebook users based on their social media behaviors (Kosinski et al., 2013). The use of machine learning in generating generalized predictions based on a multidimensional dataset is one of the powerful functions of ML in psychology (Dwyer et al., 2018).

The utilization of the ML method for human motion detection, gait and balance patterns is very practical. Begg and Kamruzzaman, (2005) used Support Vector Machine (SVM) for recognition of changes in gait due to the subject's age. Mundt et al. (2020), used the Neural Network method in order to estimate the gait pattern based on motion signals captured by wearable sensors. Gholami et al. (2018), used Neural Network and Random Forest methods for estimation of knee joint angles based on the motion signals of wearable sensors. Costa et al. (2016) used ML methods such as SVM, for diagnosis of Alzheimer's disease based on motion signals of older adults captured by wearable sensors.

1.5 Purpose of Current Research

In the current study for the first time, the DMC framework was utilized in evaluating the role of working memory in maintaining balance in older and younger adults. Considering empirical evidence demonstrating that working memory is diminished in normative ageing, we created a novel experiment in which participants' use of visual cues (A versus B), could be examined as a function of working memory. Kinematic analyses allowed the characterization of anticipatory postural responses in relation to the A and B cue types, as well as the efficiency of recovery from platform perturbations. Furthermore, utilizing machine learning techniques, age group was predicted by the pattern of lower body joint displacements. This second phase of analysis allows for simultaneous consideration of all movement parameters and joints and thus provides a more holistic prediction of age differences in postural control.

Based on the assumption that there is good working memory capacity in young adults, it was hypothesized that younger adults would show greater anticipatory postural responses on AX trials than on BX trials. However, if older adults have reduced working memory capacity, then according to DMC theory, the representation of the A or B cue is not as well maintained over the time interval in older adults compared to younger adults. Therefore, it was predicted that anticipatory postural responses would not differ between cue types for the older group. Finally, because multiple blocks of balance trials were given and participants may have learned over time, we also asked if PC was an effective strategy at the beginning and then diminished in strength over time.

Chapter 2 Methodology

2.1 Participants

20 healthy older adults (between 60 and 80 years old) and 20 healthy young adults (between 18 and 35 years old) participated in this experiment however, due to the difficulties during data acquisition, only the data of 15 older adult (*M* = 72 , *SD* = 4.22, 9 female) and 13 younger adults (*M* = 26.5, *SD* = 4.77, 10 female) were applicable for the following analysis. Participants were excluded if they reported any physical or cognitive issue which affected their the level of attention or caused problems in their vision or balance. In order to check for potential mild cognitive impairment, all participants were evaluated with the Montreal Cognitive Assessment (Nasreddine et al., 2005) and were excluded if they scored below 26/30. The experiment was approved by the Human Research Ethics Committee of Concordia University located in Montreal and all participants gave informed written consent.

2.2 Measures

Session 1

A telephone session was conducted as the first step of checking eligibility of participants using a questionnaire. The participants who met eligibility criteria were invited for Session 1 of the experiment. Session 1 consisted of a neuropsychological assessment battery to assess global cognition, processing speed, working memory, and inhibition (see below for tests). Each session lasted about 1.5 hours and cognitive fatigue was reduced by offering breaks as needed.

Additionally, the participant’s confidence in balance was assessed through the self-assessment report using Activities-specific Balance Confidence Scale (Powell & Myers, 1995).

Neuropsychological assessments. The MoCA (Nasreddine et al., 2005) is a global cognitive screener for Mild Cognitive Impairment and involves subscales to assess orientation, short term memory, attention, and visual construction. The Trail Making Test, is a method for assessment of executive functions such as attention and switching (Delis et al., 2001). The Stroop task is an evaluation of response inhibition. In this task, the dominant response should be inhibited while the task-relevant and task-irrelevant information are incongruent (Banich et al., 2000). The Letter-Number Sequencing (LNS) (Wechsler et al., 2008) test includes a series of letters and numbers which are shown to participants randomly and participants should first repeat the numbers in ascending order and then the letters in alphabetic order (Vaughan et al., 2008). The maximum score of LNS is 30. In this dataset, the LNS scores are categorized in two groups of participants with higher level of LNS "(19-22]" as group 1 and participants with lower level of LNS "(14-19]" as group 2. The Digit-Symbol Coding is a test for evaluation of processing speed. The test is paper-based and the participant should assign as many as correct symbols as possible to the 135 corresponding digits in 120 seconds (Wechsler et al., 2008)

Session 2

Session 2 concerned the experimental balance protocol that was adapted from the commonly used computerized test of proactive and reactive control (Braver et al., 2001), termed the AX-CPT protocol. In the original cognitive AX-CPT protocol, the target is defined as cue A, followed by an X. Therefore, participants are instructed to keypress "yes" whenever they see the AX combination (Braver et al., 2001). The frequency of AX targets is 70% of all trials. For all other cue-target combinations, participants are instructed to respond "no" (AY, BX, BY). Each of these trial types appear with 10% frequency and the four trial types are randomized. The high frequency of targets leads to two type of bias in participant. First, it creates a tendency to prepare a "yes" response when an A cue is presented in anticipation of the X following. However, in 10% of trials, the A cue is followed by another letter (e.g., AY), thus requiring a “no” keypress response. Over-anticipation might lead to a false alarm for such AY trials. Failure to remember the cue identity, as in the case of individuals with lower working memory capacity, may also lead to false alarms, for example, when cue B is followed by an X (Braver et al., 2001). The design of the postural version of the AX-CPT was adapted from the computerized version (below).

2.2.2.1 Experiment Design

During the present postural control analogue of the AX-CPT protocol, participants stood on a moving platform and the goal was maintaining their balance during sudden transitional movements of platform. The platform movements were forward horizontal translations and the participants were protected by a harness attached to a rail on the ceiling, that allowed for the participants to move freely but avoid falls.

The experiment consisted of 6 blocks and each block consisted of 19 trials. Each trial started by one second of showing the Cue (‘A’ or ‘B’) on a computer monitor placed at eye level 125 cm away from the participant. Participants were previously informed that when the A cue was presented, a platform movement was likely to follow, whereas a B cue would not likely be followed by a platform movement. Similar to the original AX-CPT procedure, the A and B cues were used to signal the occurrence of a platform movement (‘X’) or no movement of the platform (‘Y’). This led to four trial types: AX, BX, AY, BY. Overall, 70% of trials in each block were AX, then BX, AY, BY, which each occurred in 10% of trials per block (Table 1).

Participants were familiarized with format of experiment by a practice block prior the original experiment. Practice block consists of 10 trials distributed in AX-CPT method. The balance AX-CPT was performed on Inquisit4 software which also moves the perturbation platform. (H2W Technologies, Santa Clara, CA, USA).

Table 1

NAME	CUE	MOVEMENT
AX (70%)	+	+
AY (10%)	+	-
BX (10%)	-	+
BY (10%)	-	-

Within one trial**,** after presentation of the cue, following three seconds of rest, ten seconds was designated as the 'perturbation window' for movement of the platform. There were four possible temporal patterns for the delivery of the platform perturbation: six, nine or 12 seconds after the start of the trial, or no perturbation at all. Then, there were five seconds for the platform to move forward to the initial position (Figure 1). Every platform movement involved a backward horizontal translation for 6 s, and peak acceleration of 1.2 $\frac{m}{s^2}$,following this, for 100 ms maintain the constant velocity of 0.36 m/s, then negative acceleration of -1.2$\frac{m}{s^2}$ for 200 ms.

The next trial immediately started after previous trial (Figure 1). However, there were 2 minutes of rest after each block in order to reduce fatigue.

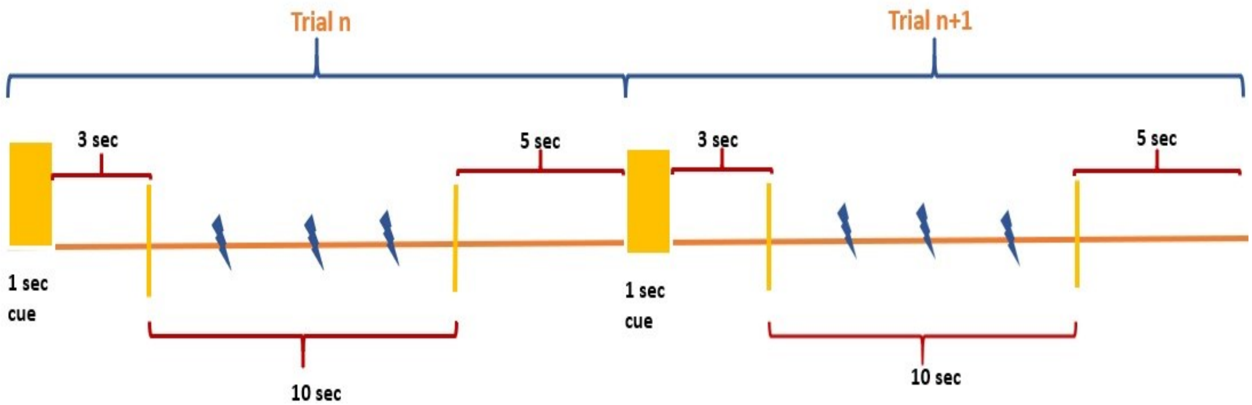


Figure 1. Trial Content

Apparatus

Motion capture,Vicon MX is a set of connected Vicon cameras, devices, units and software for providing the real time or offline digital-optical motion capture data. The main elements of Vicon MX architecture are MX cameras, MX units, MX software, Host PC, MX cables, MX peripherals. Third party devices such as force plates, EMG equipment and audio devices can be added to the network if applicable (Forest, 2005).

There are different architecture models for installing the Vicon MX equipment in the lab. the current experiment was run in the PML lab at PERFORM center of Concordia University by Basic Vicon MX architecture model. the Basic architecture model consist of 8 Vicon camera, one MX net and a host PC (Figure 2).

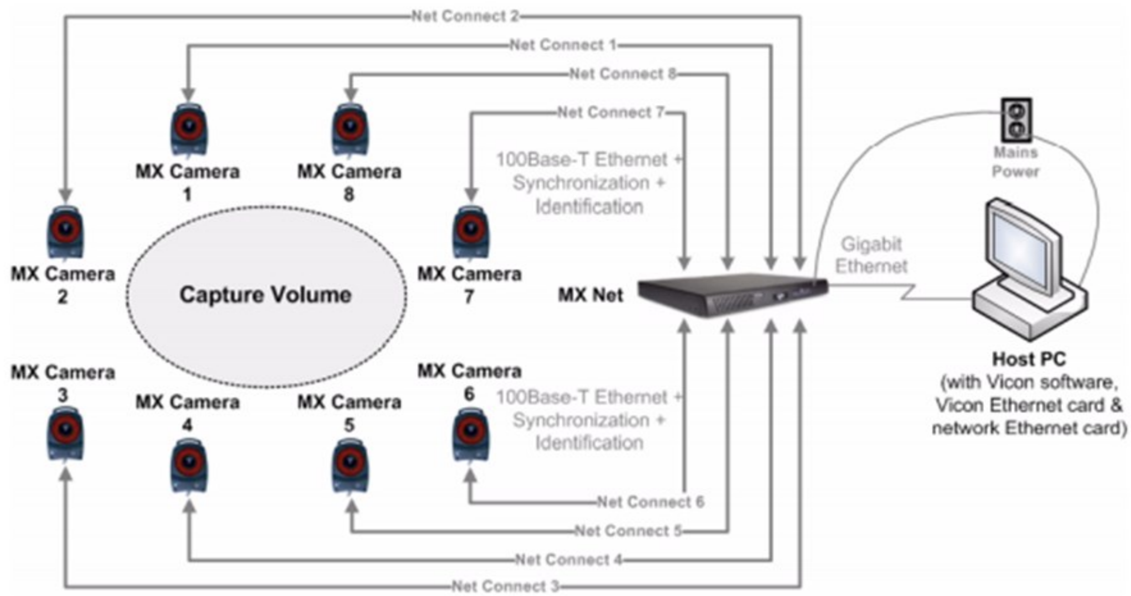


Figure 2. Basic architecture of Motion Capture system(Forest, 2005)

There are different methods of motion capture however, in this experiment the "Optical passive" method was used, however, there will be a quick review on different methods of motion capture in the following (Forest, 2005):

- *Optical passive*: In this method retroreflective markers are utilized. Retroreflective markers are the markers which reflect the light to the source with the minimum amount of scattering.
- *Optical active*: In this method LED markers are used and tracked by cameras. As LED markers emit light, they need battery or chargers.
- *Video/Marker-less*: In this method no marker is utilized and the movement of subject is tracked by software. There's some advantages with this method, such as reduction in preparation time, however, there are still some controversies about the precision of this method (Ceseracciu et al., 2014).

- *Inertial*: Inertial sensor (also called IMUs) are wearable sensors and signals are transmitted to the PC wirelessly so there's no need to camera.

Positioning System of Vicon

Positioning system functions as a three-dimensional Cartesian system. The origin and three mutually perpendicular axes which called x-, y- and z- axis are set during the calibration procedure by Vicon software. Therefore, In order to indicate position of a point such as "M" under the cameras, Vicon software prepares a point coordinate as M (x, y, z).

Vicon software, moreover, provide a Cartesian coordinate system for the angle of each point in the space under the cameras. This system utilizes the same x-, y- and z- axis of location coordinate system however it's rotational. If the thumb of left hand located in the direction of positive x- axis, the direction of rotation of other fingers presents the positive direction of x- axis of angle. the same procedure by y-axis and z-axis leads to find the positive angle direction of y- and z- angle axis.

Three main joint angles of the lower body were analyzed in this report: Hip, Knee and Ankle. the following report covers the analysis of angles of these joints.

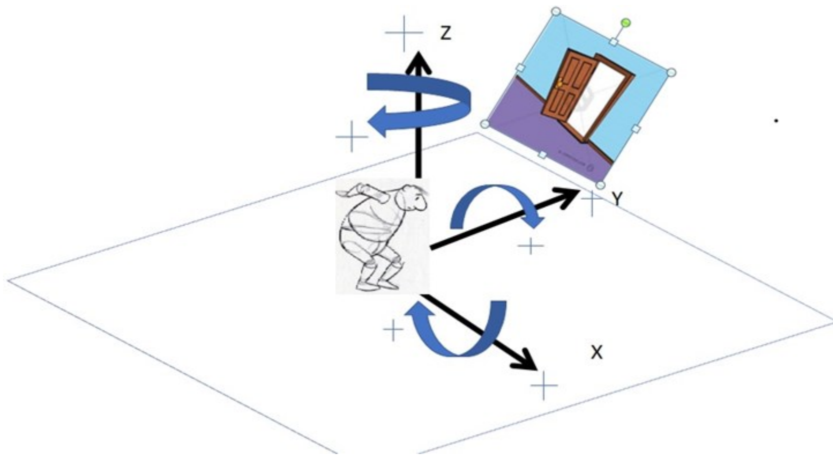


Figure 3. The coordinate system of Vicon software in lab and the position of participant

T20 cameras, Infrared cameras are utilized in this system (Forest, 2005).

MX Giganet Unit, This unit converts the analog signals to digital. The input of this unit is analog signal of cameras and the output is the digital signals and they will be transferred to the host PC by cables (Forest, 2005).

Vicon Nexus v1.8.5, The biomedical signals capturing by cameras cab be labeled, modeled and integrated by this software.

Pearl Hard Markers, In order to capture the optical movement, the pearl hard markers are utilized. These markers are covered by very high reflective materials. They were stuck to the body by marker fixing tapes. Marker fixing tapes are double-sided tapes.

Perturbation platform, XY Theta Gantry

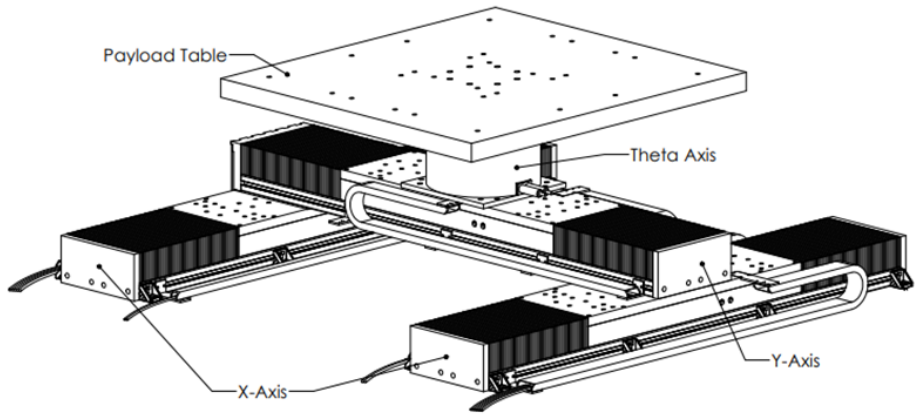


Figure 4. Perturbation platform

Perturbation Platform Software, GalilTools v1.5.0 (Galil Motion Control, Rocklin CA, USA).

Force Plates, They are mechanical systems for measuring the ground reaction forces and moments in biomedical researches (Methods, n.d.). Force cells are used in the force plates to measure the ground reaction. The technology of piezoelectric elements, strain gauges, or beam load cells are utilized in the force cells. Applying any force on the force plates will cause a sensor distortion which leads to change in the voltage. Any change in the voltage can be measured (Lamkin-Kennard & Popovic, 2019)

EMG

Noraxon Telemyo DTS (Noraxon, Scottsdale, AZ, USA) Electromyography (EMG) was used to record the muscle activity. Any physiological changes in the muscle fiber membrane produce myoelectric signals. Myoelectric signals can be sensed by bipolar electrodes and measured (Konrad, 2005). The myoelectric signals of the Tibialis Anterior muscle were recorded during the experiment. The Root Mean Square values of the EMG signal were calculated before and after perturbation in the two trial types that involved a platform movement (AX and BX) as power of the signal. The EMG data are reported elsewhere, and are not discussed in this thesis.

Chapter 3 Data preprocessing

3.1 Data Analysis

The data was analyzed by MATLAB (MATLAB 2017b) and PYTHON (python 3.7, Jupyter notebook) using custom scripts. The data of angle and location of markers both have the sampling rate of 1/100s (100 Hz) and signals with frequency lower than 6 Hz were filtered (2nd order Butterworth low pass filter FIR, zero phase shift). An Inquisit file, which conveys the signal of presentation of cues, has a sampling rate of 1/1500s (Frequency 1500 Hz) that did not need to be filtered as it was designated with a constant signal previously.

Each block consisted of 19 trials and as each had to be analyzed separately, a related script was prepared and applied to the platform marker excel file related to blocks and they were checked visually by plotting the graphs to make sure all of them were 19 seconds in duration. During this procedure, a lag in the movement of platform was detected. In order to minimize the effect of lags on the trials the delay of each block was calculated and divided by 19 and result was added to the length of each trial, therefore, each real trial length is 210-263 ms more than 19 seconds.

The cue onset times (Inquisit) were integrated with the platform onsets times to determine the temporal landmarks of each trial.

The current report focuses on the analysis of joint angles in the sagittal changes in joint angles (X) (Tokuno et al., 2010). Three different parameters were calculated for each joint: peak amplitude, peak latency, and Recovery Deviation (RD).

3.2 Joint Movement

In the analysis of changes in the angles of hip (Figure 5 and Figure 6) and knee (Figure 7 and Figure 8), flexion is indicated by positive values and extension of hip joint is represented by negative values.

Figure 5. Flexion and extension in hip join in hip strategy, The blue figure shows an extension, and white one shows a flextion (http://ironbutterflypilates.com/can-we-improve-balance-2/)

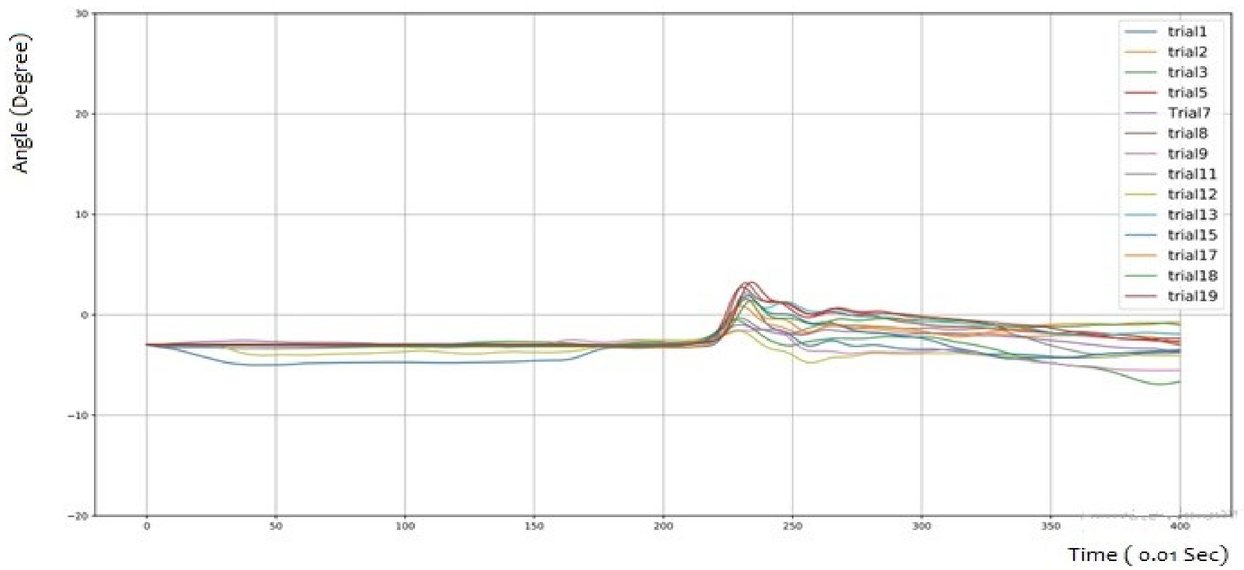


Figure 6. Graph of the hip joint sagittal angle for all the AX trials in Block 1. It indicates that after a perturbation of the platform, hip flexion was observed for some trials, followed by hip extension

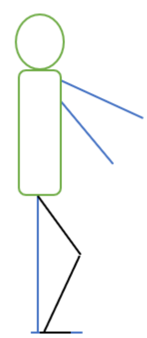


Figure 7. Flexion and Extension in the knee joint angle, The blue leg represent knee extension and the black leg shows knee flexion.

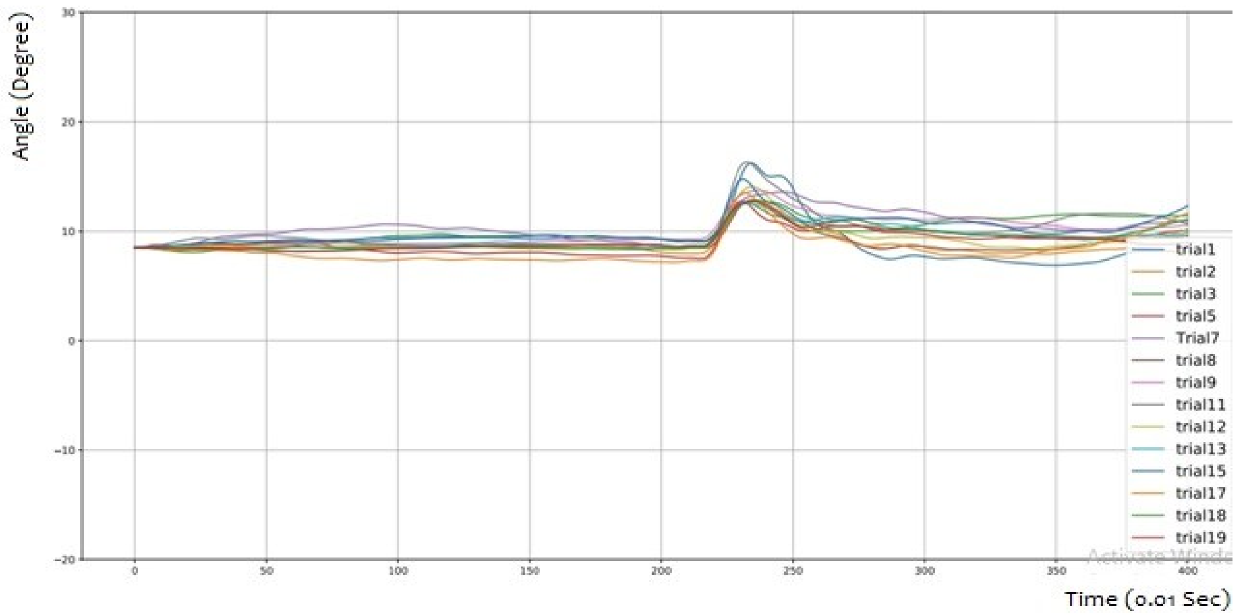


Figure 8. Graph of the sagittal knee joint angle for all the AX trials in Block 1. Graph indicates that after perturbation of platform, a knee extension happened

For the ankle joint, dorsiflexion is shown with more positive values and negative values present plantarflexion (Figure 9and Figure 10).

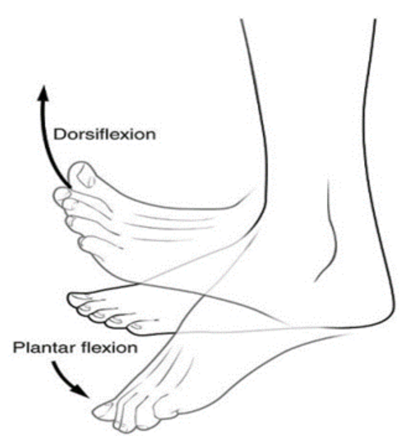


Figure 9.plantar flexion and dorsiflexion in ankle joint

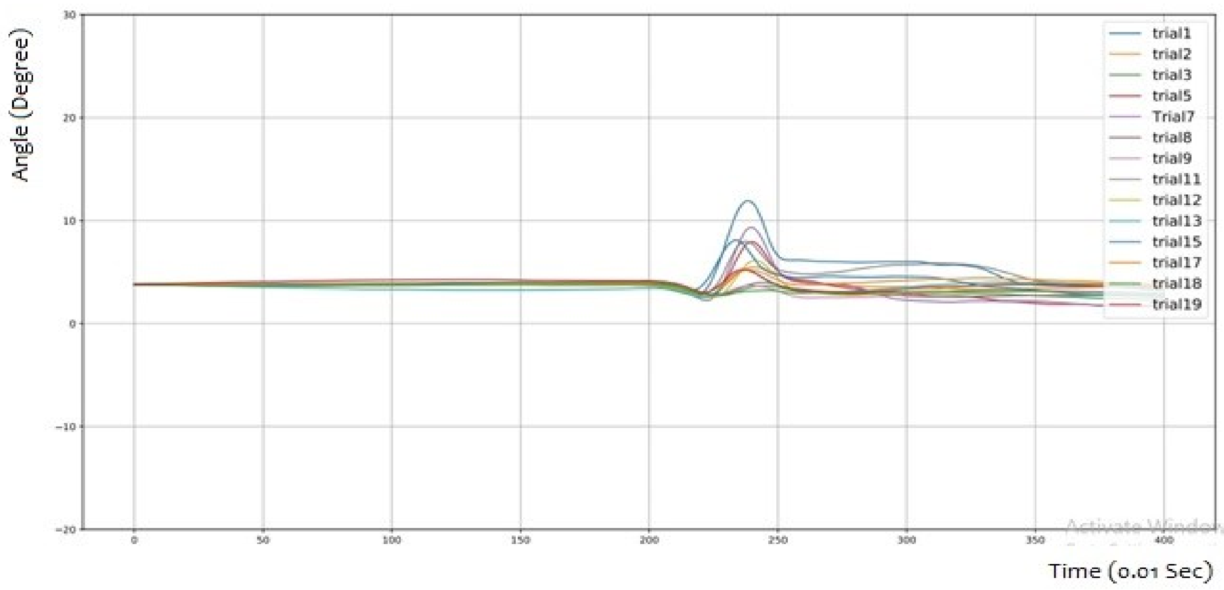


Figure 10. Graph of the sagittal ankle joint angle for all the AX trials in block 1, Graph indicates that after perturbation of the platform, a first small plantarflex is followed by dorsiflexion

3.3 Data Integrity

For peak amplitudes, peak latency and RD, by utilizing z-score transformation, the outlier data (>2SD), were substituted by maximum and minimum values for each participant. However, the dataset remained non-normal. Therefore, log-transformations were used to reduce the skewness of dataset.

Missing Data

Some parts of the recording signal were lost during the experiment due to problems such as occlusion of the lower body markers by the random movement of the hands. Missing data are generally classified in three major groups based on the reason: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR) (Sterne et al., 2009). As mentioned before, the missing data is related to the random movement of upper body, it can be considered as MCAR. One of the convenient strategies to face the MCAR missing data problem is utilizing multiple imputation method. In this experiment each participant has repeated measurements and the number of participants was limited, so it was undesirable to drop entire cases with missing data, which would lead to bias due to the small dataset (Sterne et al., 2009). For this dataset 5 imputations were done (multiple imputation method) by SPSS software (IBM SPSS statistics 26) and the average of these 5 imputations was used as the final dataset.

3.4 Peak Amplitude

In this report, peak amplitude represents the maximum angle of flexion in hip and knee and the maximum angle of dorsiflexion in ankle.

For each trial, peaks were identified during the time of perturbation until 1.2 seconds after that. To find the peaks, the maximum value of the signal was found in the aforementioned period per trial, then the value was subtracted from the value for the time 1.99 seconds. If the maximum value after platform movement was less than the time of perturbation, the trial was not considered to contain a valid maximum peak and it means that no meaningful change in joint angle was seen in reaction to that platform perturbation. Otherwise, the trial was accepted as containing a peak, and the amplitude of the peak was included in the analyses.

Considering the initial positioning of joints before a platform movement, some participants started trials with negative angles (extension of the joint), even after slight flexion still the angle was negative. In this case, there was still maximum peaks but the amount of amplitude showed a negative value. In order to eliminate the effect of negative signed in mathematical calculation, the absolute value of angles were utilized in the following statistical analysis. All the amplitudes of peaks in different trials related to AX and BX were averaged for each participant, then the log transformation was applied on them in order to reduce the skewness of their data.

3.5 Peak Latency

Peak latency (s) refers to the time to reach maximum peak. The peak latency of each trial is the result of subtracting the time of maximum peak by the onset time of the platform perturbation. All the peak latencies in different trials related to AX and BX were averaged for each participant. The log transformation was applied on them in order to reduce the skewness.

3.6 Recovery Deviation (RD)

Comparing joint angles between non-active states before and after movement of the platform is informative and can be considered an index of postural recovery, such that small differences would indicate a more complete recovery from the perturbation. For this parameter, 1 second after starting the trial was chosen as non-active state before platform motion. This time was the last moment of showing the cue. In order to find the non-active state after platform movement, a sliding window with length of 1 second was designed. The sliding window moves from the time of perturbation until the end of the trial, and the derivation of each window was calculated while sliding. The window with smallest derivation was chosen for the non-active period and the start point of the window was selected as the non-active state after perturbation. To find out the difference between these two non-active states, the joint angle observed at 1 second after perturbation was subtracted by the angle observed at the start point of the window with smallest derivation after perturbation. The subtracted value in degree units comprised the dataset for the following statistical analysis. Therefore, in this dataset, if the value is higher it indicates a greater difference between the joint angle before and after perturbation. Participants were free to choose their position during the experiment, so joint angles before and after perturbation can differ among participants. These individual differences led to variability of the data, however the difference scores allowed correction for these variations to some extent. The absolute values of recovery deviations were computed per trial, then the average value was obtained for both AX and BX trials for each participant. These data underwent log transformation as a final step to reduce the skewness.

Chapter 4 Statistical analysis

In this experiment the effect of Cue, Block, Age and LNS level was evaluated on each peak amplitude, peak latency and RD for different joint angles of hip and ankle. Statistical analysis were applied to find out the significant difference in use of Cue type in different Blocks among different Age groups with different LNS level. The analysis directly addresses the hypothesis.

4.1 MANOVA

Multivariate ANOVA (MANOVA) is a method that expands the ANOVA to evaluate more than one variable for three or more groups. Whereas the ANOVA is just for evaluating the significant difference between three or more different groups by just one independent variable, MANOVA can evaluate the effect of more than one variable and even the effect of interaction of those variables on different groups. To evaluate the effect of several variables between different groups, the MANOVA analysis was used.

4.2 Bootstrapping

In experiments done on humans, various parameters can lead to a small number of participants. In this experiment the number of participants was fewer than what we expected. Low sample size makes higher marginal errors. In order to estimate the confidence level and margin of error robustly, bootstrapping is a widely used method. Bootstrapping is a resampling method for estimating the population by reproducing different samples with replacement from the original sample. The reproduced samples sizes are in the same size of original sample. This method is called non-parametric bootstrap. The average of all these sample sizes can be considered as a new distribution. A higher number of reproduced samples is desirable (Nisbet et al., 2018).

In order to apply bootstrapping on the four-way multivariate ANOVA analysis the package "MANOVA.RM " in R software was used. This package helps for doing multivariate analysis on non-parametric or semi parametric datasets using bootstraps so there is no need to satisfy the normality or specific covariance matrices (Friedrich et al., 2019). The code "rm" which utilized for repeated measures analysis, provides the Wald-type statistic (WTS) as well as the ANOVA-type statistic (ATS) for repeated measures designs. In ANOVA type statistics (ATS) the F approximation and parametric and wild Bootstrap is used. The wild bootstrap is a method for resampling for regression problems with heteroscedastic error structure. In Wald type statistics (WTS) asymptotic χ 2 -distribution was used (Friedrich et al., 2018).

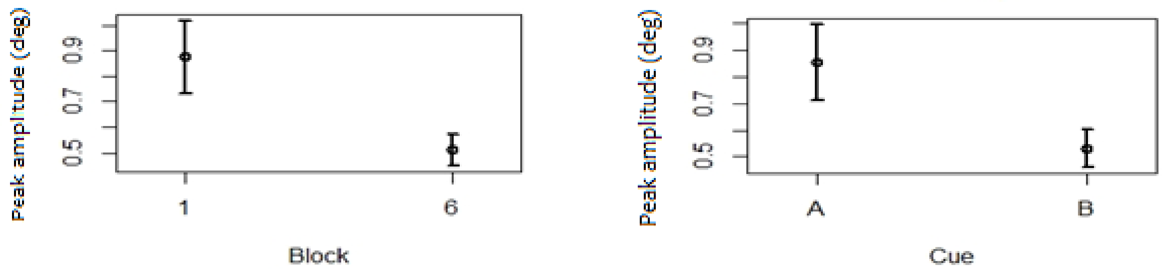
In order to assess the effect of LNS level on postural recovery, a four-way ANOVA using Block (2) × Cue (2) × Age Group (2) × LNS-level (2) was conducted in R software with code "RM" with confidence interval 95% and 1000 resampling. This MANOVA analysis was applied on each kinematic parameter per three joint angles.

4.3 Results

The significant results after resampling are reported in the following sections, however all the results are reported in detail in Table 2.

Peak Amplitude in Hip Joint Angle

For the hip joint angle data, there was a significant effect of Block ((F (1, inf) = 30, $p <$ 0.001) and Cue after resampling (F (1) = 67.765, $p < 0.001$). The effect of Block indicated greater peak amplitudes overall in Block 1 compared to Block 6. The effect of Cue was also significant, indicating that there was greater hip flexion on trials with Cue A than on trials with Cue B.



(a) (b)

Figure 11. Significant effect on peak amplitude of hip joint angle, (a) shows the effect of Block , (b)shows the effect of Cue

The two-way interaction of Block × Cue was also significant after resampling (F (1) = 47.237, $p < 0.001$). The interaction was driven by a significant difference in peak amplitude of hip between Cue A and Cue B in Block 1 and a non-significant Cue effect in Block 6 (Figure 12). All the other main effects and interactions were not significant for peak amplitude of hip.

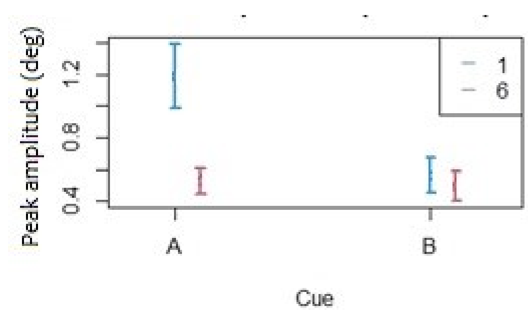
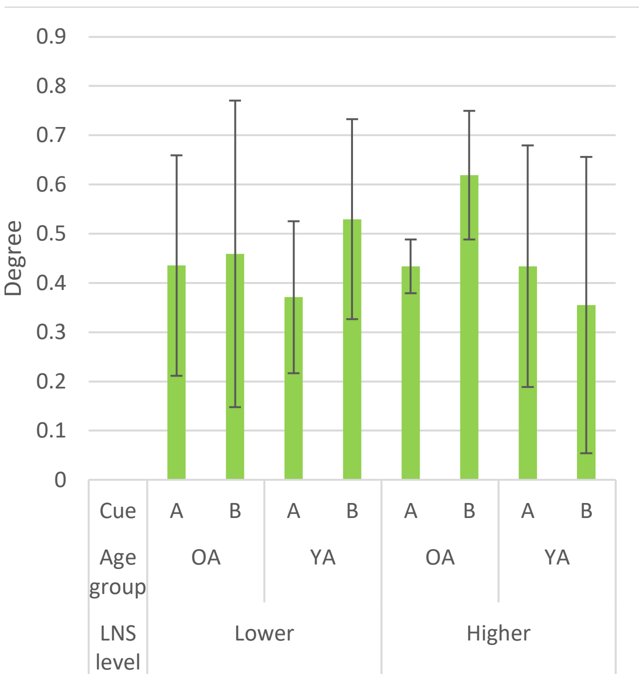


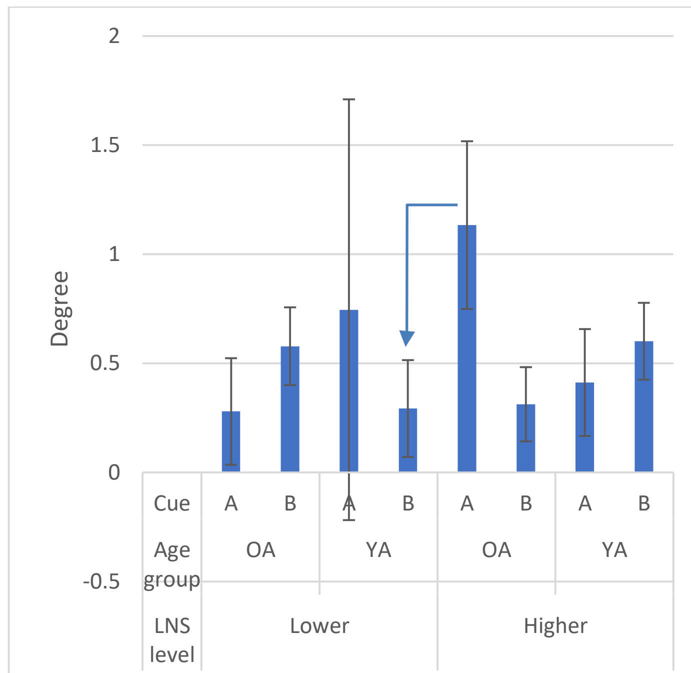
Figure 12. The effect of interaction of Block and Cue on peak amplitude of hip

Peak Amplitude in Ankle Joint Angle

For the ankle joint angle data, a significant 4-way interaction of Block × Cue × Age Group × LNS level was observed after resampling (F (1) = 13.398, $p < 0.001$). In order to do post-hoc analysis, the dataset was split by block number and separate ANOVAs were carried out using the remaining factors: Age group (OA, YA), LNS level (low, high), Cue (A, B). These post-hoc analyses revealed that for Block 6, there was a significant three-way interaction of LNS level × Age Group × Cue (F (1, inf) = 10.064, p = 0.003), however, there was not a significant three-way interaction in the Block 1 data (Figure 13).



A



B

Figure 13. Average of Peak Amplitude for Ankle Joint Angle, a) Block 1 b) Block 6

Splitting the dataset by cue type, in the Cue A trials, a significant three-way interaction of LNS level × Age Group × Block (F (1, inf) = 5.020, p = 0.03) and the significant two-way interaction of LNS level × Age Group (F (1, inf) = 4.059, p = 0.05) were found, in that older adults with higher levels of LNS showed higher amplitude of peak in Cue A compared with older adults with lower level of LNS (Figure 14).

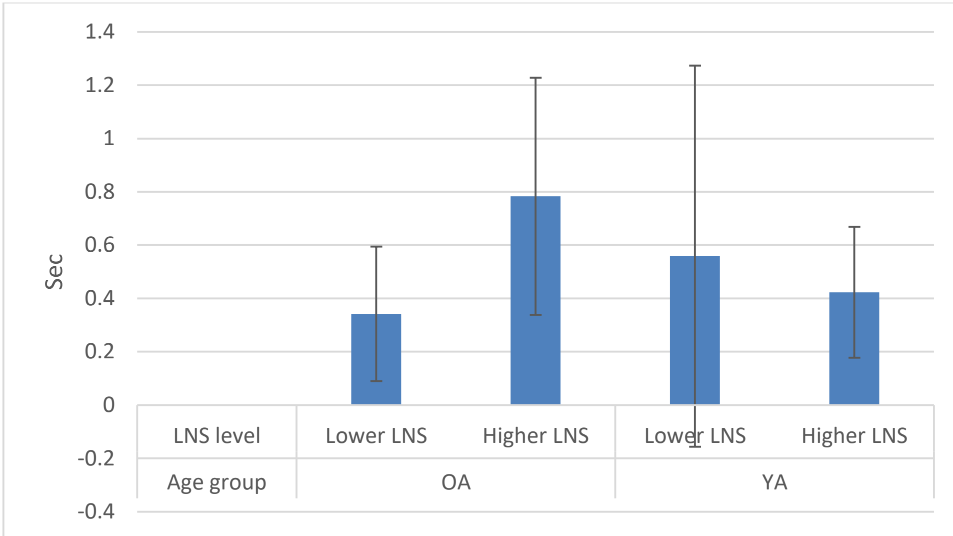
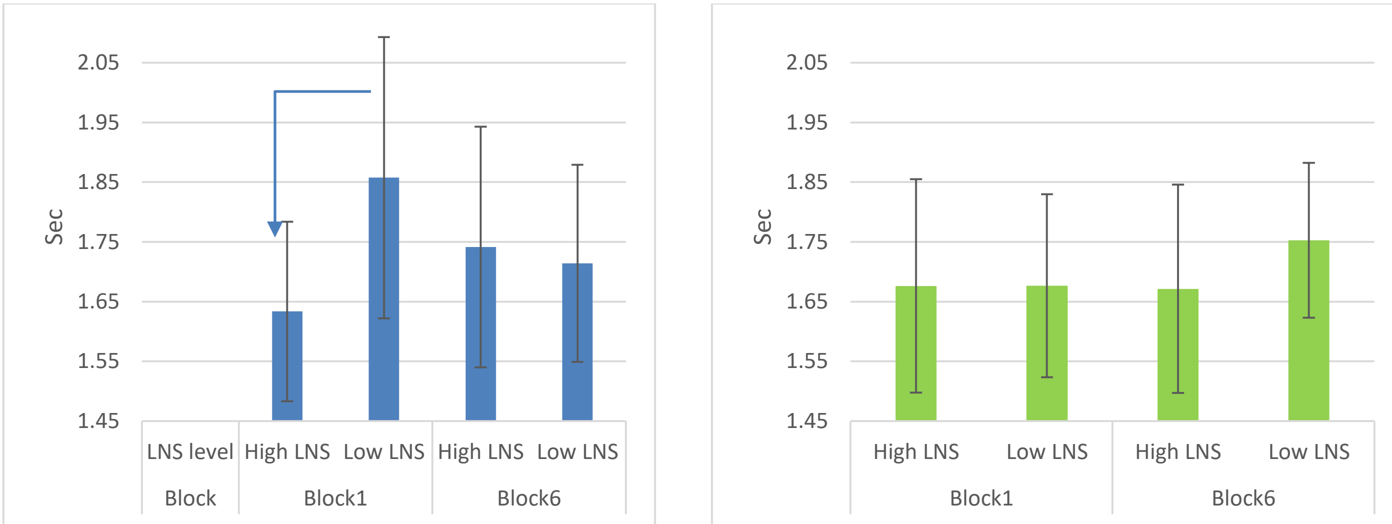


Figure 14. Average of Peak amplitude of Ankle Joint Angle for Cue A

The other main effects and interactions were not significant.

Peak latency of Hip Joint Angle

A significant interaction of LNS level × Age Group × Block was found in peak latency of hip joint angle (F (1) = 5.194, p = 0.023). In order to do the post-hoc analysis, the dataset was split by Age Group (OA, YA), and ANOVA was applied using LNS level and Block as factors. The results revealed that there was a significant interaction of Block × LNS level for younger adults (F (1) = 5.302 , p = 0.026) in that highest peak latency was observed in younger adults in Block 1. However, this was not observed (F (1) = 3.512, p = 0.50) for the older adults (Figure *15*). The other main effects and interactions were not significant.



a b

Figure 15. Peak Latency of hip joint angle in different Blocks and for different LNS level , a) for younger adults, b) for older adults

Peak latency of Ankle Joint Angle

For the ankle joint angle, a marginal difference of Block was shown before (F (1) = 3.337, p = 0.068) and after resampling such that peak latencies were longer in Block 1 compared to Block 6 (Figure 16).

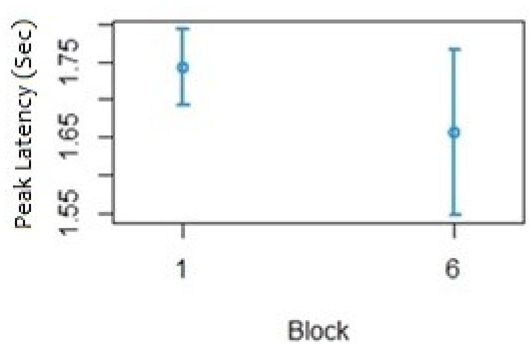
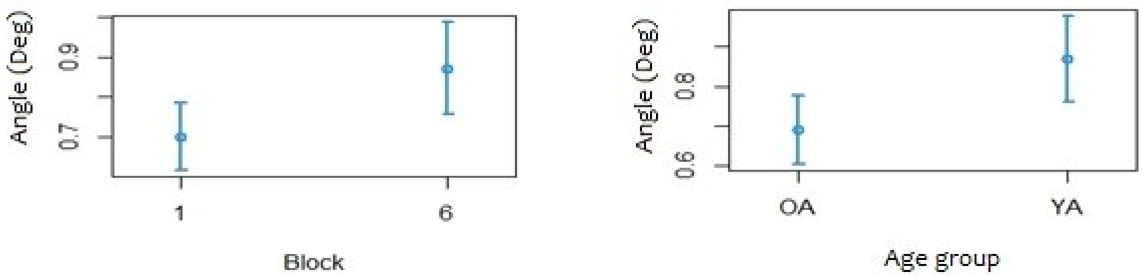


Figure 16. The effect of Block in Peak Latency of Joint Angle

Recovery Deviation of Hip Joint Angle (RD)

For hip joint angle, a significant effect of Block (F (1) = 7.429, p = 0.006) and Age Group (F (1) = 5.64 , p = 0.027) was found after resampling. Other main effects and interactions were not significant. It is notable that lower values of RD shows more complete recovery to the initial pre-perturbation position, suggesting fuller recovery early in the experiment and in older adults overall.



(a) (b)

Figure 17. Significant effects on RD for hip joint angle (a) the effect of Block (b) the effect of age

Recovery Deviation of Ankle joint angle (RD)

For the ankle joint angles, a significant main effect of Block in RD (F (1) = 15.616 , p <0.001) was found after resampling (Figure 18). Other main effects and interactions were not significant.

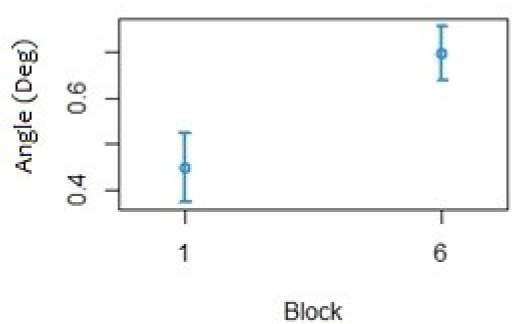


Figure 18. Effect of Block on RD of ankle joint angle

Analysis of variance results of WTS

	df1	*F*	*p*
Peak amplitude of hip joint angle			
within subject			
Block	1	30.779	<0.001
Cue	1	67.765	<0.001
Block × LNS level	1	0.534	0.69
Cue × LNS level	1	1.224	0.633
Block × Age × LNS level	1	0.013	0.685
Cue × Age × LNS level	1	3.41	0.425
LNS level × Block × Cue	1	0.171	0.813
Cue × block × Age × LNS level	1	1.017	0.579
between subjects			
LNS level	1	0.802	0.483
Age group	1	0	0.989
LNS level × Age group	1	1.435	0.325
Peak amplitude of ankle joint angle			
within subject			
Block	1	1.584	0.21
Cue	1	0.239	0.864
Block × LNS level	1	1.002	0.355
Cue × LNS level	1	0.374	0.803
Block × Age × LNS level	1	0.468	0.516
Cue × Age × LNS level	1	2.129	0.517
LNS level × Block × Cue	1	0.524	0.684
Cue × Block × Age × LNS level	1	13.398	0.001
between subjects			
LNS level	1	1.378	0.305
Age group	1	0.772	0.407
LNS level × Age group	1	2.802	0.136
Peak latency of hip joint angle			
within subject			
Block	1	0.059	0.813
Cue	1	0.898	0.485
Block × LNS level	1	1.365	0.251
Cue × LNS level	1	1.73	0.281
Block × Age × LNS level	1	5.194	0.015
Cue × Age × LNS level	1	0.35	0.7

LNS level × Block × Cue	1	0.009	0.92
Cue × Block × Age × LNS level	1	0.028	0.83
between subjects			
LNS level	1	0.769	0.442
Age group	1	0.284	0.652
LNS level × Age group	1	0.132	0.739
Peak latency of Ankle joint angle			
within subject			
Block	1	3.337	0.076
Cue	1	0.387	0.689
Block × LNS level	1	0.009	0.927
Cue × LNS level	1	0.006	0.962
Block × Age × LNS level	1	0.358	0.609
Cue × Age × LNS level	1	3.843	0.186
LNS level × Block × Cue	1	0.371	0.49
Cue × Block × Age × LNS level	1	0.565	0.415
between subjects			
LNS level	1	0.702	0.483
Age group	1	1.442	0.345
LNS level × Age group	1	4.352	0.096
RD of hip joint angle			
within subject			
Block	1	7.429	0.023
Cue	1	5.2	0.263
Block × LNS level	1	0.293	0.69
Cue × LNS level	1	0.028	0.937
Block × Age × LNS level	1	0.239	0.685
Cue × Age × LNS level	1	0.007	0.937
LNS level × Block × Cue	1	0.298	0.566
Cue × Block × Age × LNS level	1	0.557	0.453
between subjects			
LNS level	1	0.006	0.944
Age group	1	5.64	0.02
LNS level × Age group	1	0.014	0.917
RD of Ankle joint angle			
within subject			
Block	1	15.616	<0.001
Cue	1	0.783	0.689
Block × LNS level	1	0.651	0.608

Cue × LNS level	1	0.379	0.777
Block × Age × LNS level	1	1.164	0.47
Cue × Age × LNS level	1	2.85	0.411
LNS level × Block × Cue	1	0.488	0.49
Cue × Block × Age × LNS level	1	0.059	0.796
between subjects			
LNS level	1	0.973	0.361
Age group	1	0.686	0.443
LNS level × Age group	1	1.931	0.122+A1:D86

Table 2. Analysis of Variance Results of ATS

4.4 Discussion

The hypothesis suggests that younger adults utilize the cue types (A, B) more effectively compared with older adults. This hypothesis relies on the assumption that good working memory capacity in younger adults leads to better anticipatory postural responses. Conversely, diminished working memory capacity should reduce the anticipatory postural responses among elderly adults. Therefore, it is not expected that older adults make good use of the cues.

Additionally, we used the LNS test performance as a separate measure of working memory, and considered LNS performance as a factor in the analyses. It was expected that participants with higher LNS level would have better anticipatory postural responses compared with individuals with lower LNS levels. That is, high LNS performance should be associated with better discrimination between cue types.

The significant two-way interaction of Block × LNS level (Figure *15*) for peak latency of hip joint angle among younger adults revealed that participants with lower capacity of working memory reacted to perturbations more slowly that participants with higher levels of working memory in. However, in Block 6 the effect of learning played a role in that there was no significant difference between LNS groups by the final test block.

The two-way interaction of Age by LNS level in the post-hoc analysis of 4-way interaction of peak amplitude (Block × Cue × Age Group × LNS: Figure 13), suggested higher peak amplitudes for older adults with higher levels of LNS compared with older adults with lower level of LNS. It suggested that older adults with higher working memory capacity prepared more for perturbations compared with older adults with lower working memory capacity.

Peak amplitude of the hip joint angle (Figure 11.b) was higher for Cue A than Cue B. This suggests that participants could differentiate between Cue A and Cue B and utilize the cues to maintain their balance. According to the DMC theory, utilization of cues in this manner recruits working memory and suggests that a proactive control strategy has been used.

For the 3-way interaction of Age group, LNS, and Cue, older adults with higher level of working memory capacity utilized Cue A the most compared to the other sub-groups (Figure 14). This pattern could be due to the use of working memory and also being more cautious about protecting themselves and keeping their balance. Also, the younger adults with lower working memory capacity showed the same pattern of using the A Cue to prepare, perhaps because they were less stable in their balance.

The higher level of peak amplitudes in hip joint angle (Figure 11.a) and peak latency in ankle joint angle (Figure 16) in Block 1 when compared with Block 6, suggested the habituation in participants to the perturbation of platform. Habituation generally refers to a decreased reaction to stimuli over repeated trials (Thompson, 2009). In the present dataset, it was expressed in the smaller RD of hip (Figure 17.a) and ankle (Figure 18) joint angles in Block 1 compared to Block

6. Here, participants in Block 6 did not try as hard to get back to their initial preparatory position following a platform movement, whereas they were showed more complete recovery in Block 1.

The observed difference between the peak amplitude for Cue A and Cue B and small difference in Block 6 (Figure 12) can also be interpreted as a result of habituation in Block 1: the peak amplitude of hip for Cue A was higher than Cue B which was due to the utilizing cues and distinguishing between them. This pattern is consistent with proactive control behaviour.

The significant age effects observed in the RD of hip joint angle (Figure 17.b) indicated that recovery was less complete for younger adults than older adults. Considering the fact that older adults tended to be more conservative and cautious, it was clear that they tried harder to keep their preparation position therefore, after each perturbation they tried to get back to their initial position which was their preparation position so they showed lower RD compared to younger adults.

Chapter 5 Machine learning

The dataset which was utilized in this analysis consists of repeated measurement of lower body motion characteristics of participants in response to the sudden movement of the platform therefore, the features were the repeated measures of participants and there were 36 features. The target is prediction of age of participant based on their movement characteristics. The machine learning algorithms were prepared using the library of scikit-learn 0.23.3 in Python 3.

5.1 Basics of Machine learning

In machine learning, the dataset first is generally assessed by a human to make it in the optimal format, then machine learning methods applied to the dataset, based on the results of application of the algorithm on the dataset it can be tuned for better result.

There are four major approaches in machine learning, Supervised learning, Unsupervised learning, Semi-supervised learning, Reinforcement learning.

Supervised learning

Supervised learning is one of the most practical methods of machine learning. If the dataset is labeled, in the way that output related to each input is distinguished, the method is supervised machine learning (Kotsiantis, 2007). Supervised learning is one of the most practical methods of machine learning. A supervised learning problem can be categorized in one of the following groups:

- Classification, if the output variable is a category.
- Regression, if the output variable is numeric.

Unsupervised learning

Where there is no labeled output that works as a guide to finding relationships in the dataset, the method is referred to as "unsupervised learning". The objective of this method is to find out more about the data and whether there is a cluster or a model. (Kotsiantis, 2007).

Semi-supervised learning

If the data set is enormous and only part is labeled, the problem can be called semi-supervised learning. In real life, many datasets are considered semi-supervised because it is not possible or too costly to label them all.

Reinforcement learning

Reinforcement learning is called to the algorithms working in a close loop for solving problems in the way that there is no specific instruction to obey, the algorithm just follows the reward signals. The aim is to achieve as many reward signals as possible. (Sutton & Barto, 2015). An example of this is the training of a dog. The dog will be rewarded if he has done the good work, but he will be punished (or there is no reward) otherwise.

5.2 Assessment of classification algorithm

In order to evaluate the functionality of machine learning systems in this report two factors are calculated: accuracy and precision.

- **Accuracy**, shows how often the classification algorithm classifies correctly.

$$accuracy = \frac{True\ positive + True\ negative}{Total} \qquad \textit{Equation 1}$$

- **Precision**, represent what proportion of True answers that system found is really true.

$$Precision = \frac{True\ positive}{True\ positive + false\ positive} \qquad \textit{Equation 2}$$

5.3 Normalization

Different features in dataset may contain values in different scales. Taking into account all the features with different scales in a machine learning algorithm might cause confusion in the classification and regression. Normalization is solution to this issue by retaining the distribution of feature by changing the scale. By doing normalization all of features in a dataset will be in same scale between 0 -1. The following formula is used for the normalization of dataset in the current report;

$$z = \frac{x - min}{max - min} \qquad \textit{Equation 3}$$

While x is the value of feature for each participant, min is minimum value of each feature and max is maximum values of each feature. Z is normalized value of specific feature for specific participant.

In the current dataset normalization was applied on dataset to scale it between 0-1 as first step before feature selection and applying machine learning algorithms.

5.4 Dimension Reduction and Feature Selection

In this experiment the two-way dataset made by values of peak amplitude, peak latency and RD for each joint angle (hip, ankle and knee) by different Cues (A or B) in different Blocks (1 or 6). Considering all of these variables, there are 36 columns of information (3×3×2×2) which made huge dimension, whereas, the whole number of participants is 28. Therefore, different techniques of dimension reduction and feature selection were utilized in order to improve the functionality of machine learning algorithms such as Partial Least Square (PLS) (Nagaraja & Abd-Almageed, 2015), Principal Component Analysis (PCA) (Song et al., 2010) and Correspondence Analysis(CA) (Benzecri, 1975).

Partial Least Square (PLS)

Partial Least square is a well-known method which is an alternative for ordinary Least Square method to solve multicollinearity and small sample size problem (Chun & Keleş, 2010). PLS is a supervised learning method, therefore, the target variable is labeled and it is possible to get more information about the relation of predictive variable and target comparing with PCA which is unsupervised method.

Higher number of features comapring to the number of samples makes multicolineary in dataset for which using ordinary least Square method is not feasible. PLS method decompose both X and Y (Assuming X is matrix of features and Y is matrix of response variable or class labels) and finds a set of components (called Latent vector) that these components explain the most covariance possible between X and Y(Abdi, 2007)

In this experiment considering the small size of dataset and high dimensionality, two methods of PLS and PCA were combined to get the better feature selection. For the first step PLS method was applied to the dataset. In order to cover 90% of variance in the dataset, 13 features were enough. Thirteen features with highest absolute value of coefficient were chosen as following:

Joint	Type	Block	Cue
knee	Peak latency	1	A
Hip	Peak amplitude	6	A
knee	Peak amplitude	6	B
Hip	Peak amplitude	1	A
Ankle	Peak latency	6	B
Knee	Peak latency	6	A
Knee	Peak latency	6	B
Hip	RD	1	A
Hip	RD	1	B
hip	RD	6	B
Hip	RD	6	A
Knee	RD	1	A
Ankle	Peak latency	1	B

Table 3.features selected by PLS method

Principal Component Analysis (PCA)

Principal Component Analysis is one of the unsupervised learning methods which is widely applied for feature selection for datasets with continuous variables. This method is a transformation method which rotates dataset from one coordinate system to hierarchical coordinate system based on directions that capture the maximum variance.

Higher number of features comparing with number of samples leads to high dimensionality which degrades the accuracy in machine learning algorithms. Therefore, it is necessary to find out the features which are highly correlated in order to select the most independent features and eliminate the others.

A new dataset including 13 features selected by PLS method was generated. The PCA method is applicable in new dataset, however it was not possible to apply it on the initial dataset due to the excess number of features comparing participants. Considering 92% of variance of whole dataset, 9 features were chosen as follows:

Joint	Type	Block	Cue
knee	Peak latency	1	A
Hip	Peak amplitude	6	A
Knee	Peak amplitude	6	B
Hip	Peak amplitude	1	A
Ankle	Peak latency	6	B
Knee	Peak latency	6	A
Knee	Peak latency	6	B
Hip	RD	1	A
Hip	RD	1	B

Table 4.features selected by PCA method from dataset generated by features of PLS method

Correspondence Analysis (CA)

Correspondence Analysis (Benzecri, 1975) can be considered as Principal Component Analysis which is tailored for qualitative data but it also can be used for quantitative data (De Leeuw & Mair, 2009).

CA graphically represents the dependence between rows and columns of contingency tables. The visual display of data helps the interpretation and allows patterns to emerge. The technique reduces the number of dimensions needed to display the data points by decomposing the total inertia (i.e., the variability) of the table and defining the smallest number of dimensions capable to capture the data variability (Doey & Kurta, 2011).

The first step is finding out how many features are good enough to explain the maximum variability of dataset. In this report, the Correspondence Analysis was done by Rstudio. By finding out the cumulative variance percentage, the results presented that 13 dimensions can express 90.6% of whole variance, therefore 13 features were chosen for the new dataset.

The contribution of feature in each dimension shows the proportion of variance in the axis accounted by that feature. By running the correspondence analysis for 13 dimensions, the contribution of each feature in each dimension was assessed. For each dimension, the feature with the highest contribution was chosen. Additionally, as one of the features shows the highest contribution in two different dimension, instead of 13 features there are just 12 features in new dataset.

Joint	Type	Block	Cue
Ankle	RD	1	A
Ankle	Peak amplitude	6	A
Ankle	Peak latency	6	B
Hip	RD	6	A
Ankle	Peak amplitude	1	B
Knee	Peak amplitude	6	A
Ankle	Peak amplitude	1	A
Ankle	RD	6	A
Ankle	RD	6	B
Hip	Peak latency	6	B
Hip	RD	6	B
Knee	Peak latency	1	A

Table 5.features selected by Correspondence analysis

5.5 Classification by Decision Tree

Decision tree is one of the most used method in machine learning (Patel & Prajapati, 2018). This is a supervised learning approach that can be used to address classification and regression issues. One of the advantages of this method over similar methods like SVM and neural networks is that, in this method, the working algorithm is completely accessible.

In a decision tree each node represent a feature(attribute), every link shows a rule and each leaf represents an outcome. In order to design a decision tree, there are different algorithms which can be used.

1- ID3 (Iterative Dichotomiser 3) which utilizes Entropy and information gain to design the tree.

2- CART (Classification and Regression Tree), in which Gini impurity technique is used.

Entropy

Entropy is measurement of disorder of uncertainty. It is defined by following formula

$$H(x) = -\sum_{i=1}^{n} p_i log_2 p_i \qquad \textit{Equation 4}$$

While x is chance of variable, n is number of classes and p is probability of class, H(x) is the entropy of variable x (Shannon, 1948). If the Entropy of a variable in the dataset is equal to zero it shows the variety of classes for that variable is zero and there is just one class of that variable in the dataset. Higher values for Entropy represent a variety of classes for that variable in the dataset. When the entropy of one node is zero, we can stop adding links to that part.

Information Gain

In order to design a decision tree, one of the greatest challenges is choosing the best feature to start first level of classification based on that. Calculation of Information Gain (IG) is utilized to find out the best feature.

$$IG(T,X) = Entropy(T) - Entropy(T,X) \qquad \textit{Equation 5}$$

While T is output column and X is column for which information gain will be calculated (features) and Entropy (T,X) is weighted Entropy of column X.

Larger information gain represents lower Entropy in for that group or variable in dataset. the IG is calculated for each column on each step and the column with highest IG value will be chosen for the splitting based on it. In this report the entropy and information gain is used to design decision tree.

5.6 Ensemble method

Bagging

Bias and variance are the most fundamental feature of a model. Bias defined as the average difference between the predicted value by model and the real values. Variance is capability of model to generalize and functionality of it for prediction in new dataset not just specifically for training set. The model with high variance works very well with specific training set and is not good enough in prediction facing a new dataset. Therefore, the goal is lower bias and lower variance however, these two terms expand toward opposite directions so it should be a bias variance tradeoff in the suggested model. In this way there should be enough degrees of freedom to solve the complexity of the dataset, but it should not be too much in order to maintain its robustness and avoid high variance.

Bagging is one of the most powerful methods of Ensemble techniques. The algorithms of some methods have high variance and are just good with the dataset which are trained based on it. Changing the dataset leads to change in their algorithm a bit such as decision tree (CART).

Bagging is a method that reduces the high variance of algorithm and is generally used for decision trees.

Bagging is the use of bootstrap techniques in machine learning for reducing the high variance. The method makes several independent models and uses the average of their output as the output of the whole system. However, as it is not possible to have different datasets for each model, the bootstrap model is used to reproduce sub datasets from original dataset. This method is widely used for decision trees and it results in lower variance and lower bias.

5.7 Random forest

Random forest is one of the techniques of the Bagging method (Breiman, 2001). Bagging is an ensemble technique which basically means combining multiple models to train a particular dataset to make more accurate prediction. Ensemble techniques fall into three categories: bagging (Bootstrap aggregating), boosting, and stacking.

Random forest use multiple decision trees. In fact, multiple trees which work together can be called a “forest”. The algorithm of trees can be deep or shallow. Shallow trees have less variance and high bias however, deep trees have low bias and high variance. The bagging method is used to reduce the variance for deep trees. In the random forest method, the bootstrap method is used for making different subsets of dataset to train multiple independent deep trees thus, the variance of whole system decreases.

Additionally, random forest utilizes another technique to reduce the correlation between trees. In this method, not only are the different subsets of dataset used for different trees but also sampling over features is used, so that for each tree some features are not used and some of them are used randomly. Therefore, all the trees do not have same strategy for making decision and it reduces the correlation between trees. It also makes random forest more robust against missing data.

5.8 Naïve Bayes

Naïve Bayes classifier (Webb, 2010) is a machine learning method based on probability. This method works based on Bayes theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad \textit{Equation 6}$$

P(A|B) the probability of hypothesis A given data B

P(B|A) the probability of data B given than hypothesis A is true

P(A)the probability of hypothesis A regardless of data and

P(B) the probability of data B (regardless of hypothesis)

It is called Naïve Bayes because the independence of features is one of the fundamental assumption of this method. However, in the real world, it is rarely possible to satisfy this assumption. Nevertheless, this method performs well when the assumptions are not perfectly satisfied. Another assumption in this method is that features have the same effect on the prediction.

5.9 Results

By applying the feature selection method, 4 different datasets were generated. One of the datasets is the one which has no feature selection applied on it. The second dataset consisted of 13 features made by the results of PLS; the third one contained features selected by PLS and PCA, and the final one consisted of features selected by correspondence analysis. Three algorithms of machine learning (decision tree, random forest, and Naïve Bayes) were applied on these datasets separately. For all algorithms 80% of dataset was utilized as the training set and 20% was used as the test set.

Due to the small size of the dataset, we needed a method to evaluate the efficiency of the machine learning algorithms. The K-fold cross-validation is a method applied to small datasets to assess the machine learning algorithm. In this experiment 10-fold cross-validation was applied to all the machine learning methods.

The application decision tree algorithm for classification of results of participants based on Age Group was tested. The accuracy and precision of classification by decision tree for different dataset is as follows: accuracy of 0.63 and 0.676 precision of for dataset with no feature selection, accuracy of 0.831 and precision of 0.883 for dataset for the dataset of feature selection by PLS (Figure *19*), accuracy of 0.764 and precision of 0.84 for dataset for the dataset of feature selection by PCA and PLS, accuracy of 0.665 and precision of 0.735 for dataset for the dataset of feature selection by correspondence analysis. The best result for classification by decision tree was related to dataset with features selected by PLS.

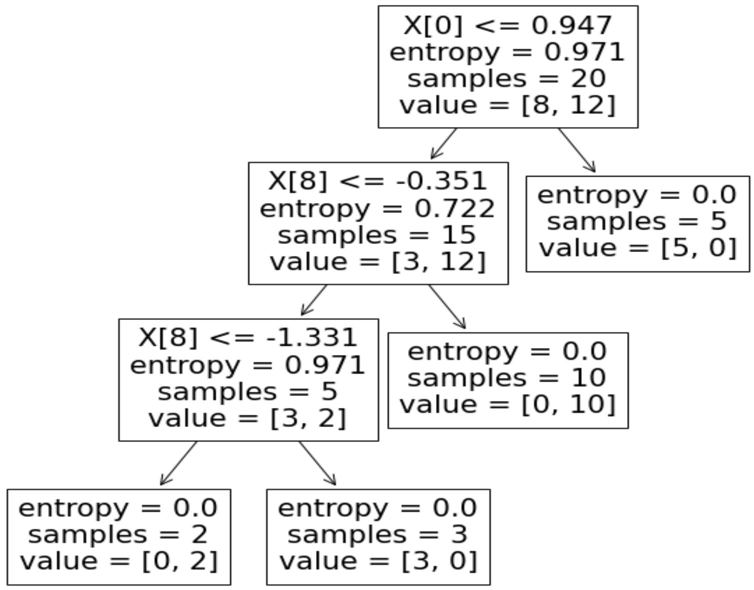
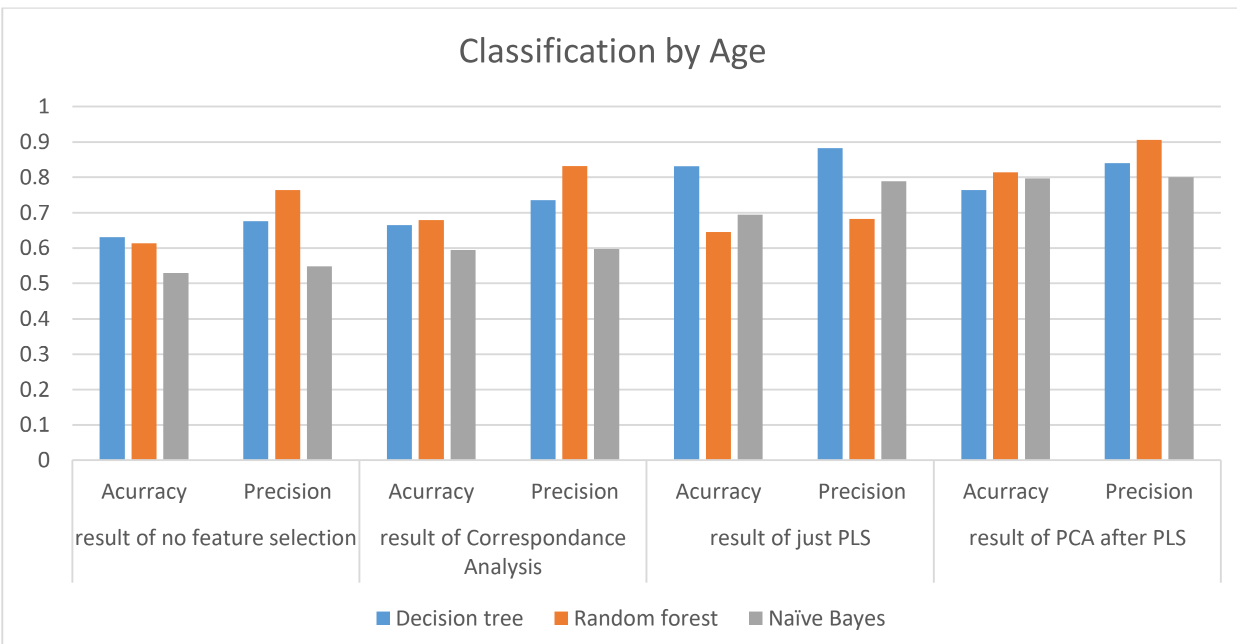


Figure *19*. Decision tree applied on the dataset with features selected by PLS method, X[0] is the peak latency of knee joint angle in Block 1 for Cue A, X[8] is RD of hip joint angle for Block 1 in Cue B. The random forest algorithm was applied to classification by age for the same datasets. The accuracy and precision for the dataset with no feature selection with 50 trees is respectively 0.613 and 0.764. The accuracy and precision for the dataset with features selected by PLS with 100 trees is 0.646 and 0.683. The results for datasets with feature selection by PCA and PLS with 50 trees are 0.814 and 0.906. It is respectively 0.679 and 0.832 with 100 trees for the dataset with features selected by correspondence analysis.

The Naïve Bayes algorithm was applied for classification on datasets with different methods of feature selection. The accuracy and precision of datasets with no feature selection, dataset with features selected by feature selection, dataset with feature selection by PLS and PCA, dataset with features selected by correspondence analysis is respectively, 0.53 and 0.548, 0.695 and 0.789, 0.797 and 0.8 , 0.595 and 0.598.

	Result of No Feature Selection		Result of Correspondence Analysis		Result of PLS only		Result of PCA After PLS	
	Accuracy	Precision	Accuracy	Precision	Accuracy	Precision	Accuracy	Precision
Decision tree	0.63	0.676	0.665	0.735	0.831	0.883	0.764	0.84
Random forest	0.613	0.764	0.679	0.832	0.646	0.683	0.814	0.906
Naïve Bayes	0.53	0.548	0.595	0.598	0.695	0.789	0.797	0.8

Table 6. Results of Classification by Age With Different Algorithms



Chapter 6 Conclusion and Future Directions

6.1 Conclusion

The diminishing effect of age on working memory has been supported by a large body of empirical evidence. The Dual Mechanisms of Control framework offers a useful method of evaluating working memory suggested by Braver. It suggests two different cognitive control processes for different kinds of reaction to stimuli. Proactive control is thought to be active when a person uses cues and prior information to prepare a response. By contrast, reactive control involves just responding to the stimulus after it has happened without forewarning. Proactive control needs more working memory capacity to maintain the mental representation of the cue information. Based on the negative effects of age on working memory, it can be concluded that older adults tend to utilize reactive control more often than proactive control.

To evaluate the EF in older adults, one strategy is to complicate the primary balance or walking task by adding a concurrent cognitive load, as in dual-task designs. In the present experiment, a novel alternative approach was used to asses EF involvement in postural control. Varying the cue validity and content and adapting the AX-CPT procedure allowed for the first time, a postural recovery experiment to test the involvement of working memory specifically in the anticipatory postural response phase.

Statistics

In the statistical analysis, the four-way interaction of working memory capacity (LNS), Age Group, Block, and Cue was evaluated for each parameter related to each joint angle separately, using MANOVAs. Results showed the significant effect of Cue and Age and LNS level in some parameters, in that participants with a higher level of working memory used more proactive control. However, the effects of learning and habituation were also found in some of results, shown as a difference between the Block 1 and Block 6 results.

The significant two-way interactions of Age Group and LNS in RD in ankle, or of Block and LNS in peak latency of hip, suggests that it is not only age that can be considered as a parameter in utilizing proactive or reactive control behaviour, but also the capacity of working memory. The result showed the significant difference in peak latency for younger adults with lower levels of LNS in Block 6, however there was no significant effect of LNS in Block 1. Higher peak latency indicates a slower reaction to the perturbation, suggesting that participants were not able to use the cues to prepare themselves for maintaining balance. Therefore, less use of cues in younger adults with lower levels of working memory capacity can be interpreted as evidence of reactive control and less use of proactive control. The LNS effect was seen in Block 6 and not in Block 1, which may reflect diminishing working memory capacity over time in the participants with lower levels of working memory.

The significant 4-way interaction of Age × LNS level × Cue × Block in peak amplitude of ankle revealed that in Block 6, older adults with higher levels of working memory used the Cue A the most compared with others. However, in Block 1, there was no significant interaction of LNS level × Age Group × Cue. This result is worth noting for two reasons: first, relevant to the hypothesis, the results show that the group with higher working memory capacity showed greater use of the cue information, which suggests more proactive behavior. Second, the greater use of cue information in older adults with higher LNS compared with same subgroup of younger adults could be due to the fact that older adults are normally more cautious about their physical safety than younger adults.

In summary, the results of the multivariate analyses provide evidence for the influence of working memory capacity in postural anticipation and recovery behavior and the age differences in how working memory capacity moderates proactive control behavior.

Machine learning

The efficiency of the dual mechanisms of control for maintaining balance was evaluated parameter by parameter in the statistical analysis. However, it is also helpful to evaluate the whole dataset together. This is possible by using machine learning methods. In this study, not only the relationship between the factors such as Cue, Block, LNS level and Age were found for different joint angles, but also we could predict the age group based on all the parameters utilizing supervised machine learning methods.

In this experiment, in the first step, the important features for classification of the dataset by age were extracted by applying feature selection techniques. The result of feature selection applied with three different methods of PLS, PCA and Correspondence analysis. Two features were common to all three methods. One feature was the peak latency of knee in Block 1 and Cue A and the other feature was peak latency of ankle in Block 6 in Cue B.

In PLS methods features related to the hip and knee had majority of selected features however by correspondence analysis the features related to the hip and ankle had the higher majority.

Comparing between the different methods, the best accuracy was found using decision tree applied on the dataset containing features selected by PLS method. Decision tree is a more intuitive model compared to the random forest and Naïve Bayes approaches. Figure *19* which is diagram of the classification of decision tree on the dataset with features selected by PLS method shows that the only features which are used in the decision tree classification with best accuracy are peak latency of knee joint angle related to Block 1 for Cue A and RD of hip joint angle for Block 1 for Cue B. Utilization of these two features with different cues for classification based on age, shows dependency of classification to use of cue in participants.

Additionally, considering all different methods of feature selection the lowest results were found with the Naïve Bayes methods. Considering that the dataset was not normally distributed, this result is foreseeable.

Combining together the results from the machine learning analyses and MANOVAs, the results of this study show that aging is not the only factor which determines the anticipatory postural responses, but that working memory level is also an important factor. Considering that working memory and cognitive control can be assessed with AX-CPT methods, tests of working memory may be used as a screening method for older adults to evaluate their ability to maintain balance in the case of perturbations. Older adults with lower results might undergo cognitive working memory training to improve their postural anticipation strategy, reduce their fall risk, and increase their quality of life.

6.2 Limitations and future directions

There are some limitations in the current study that should be considered. The small number of participants was one of the restrictions. In the machine learning analyses, the number of features was greater than number of samples (participants). This combination of high number of features and small number of samples might negatively affect the machine learning results and decrease accuracy. Having larger datasets for machine learning analyses would lead to more robust results.

The other challenge was a mechanical problem with the platform speed that led to timing inaccuracies, and resulted in loss of data (reduction from 20 to 19 trials).

In this experiment, the efficiency of DMC in keeping balance was evaluated. Future experiments could expand on this work by adding functional neuroimaging using functional near infrared spectroscopy (fNIRS) in order to discover the regions related to anticipatory postural responses during balance testing, and to compare with the regions associated with cognitive measures of proactive and reactive control.

Appendix

- Normality test

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
				Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Peak amplitude, AX, hip, B1	26	0.342519117	2.20243115	1.1872276	0.50839207	0.078	0.456	-0.452	0.887
Peak amplitude, Bx, hip, B1	26	0.005209954	1.01629086	0.5637481	0.26754928	-0.601	0.456	-0.11	0.887
Peak amplitude, AX, hip, B6	26	0.133532968	0.85610284	0.5254496	0.20457675	-0.249	0.456	-0.831	0.887
Peak amplitude, BX, hip, B6	26	0.008246182	0.82013028	0.4968995	0.23477295	-0.582	0.456	-0.701	0.887
Peak amplitude, AX, Ank, B1	26	0.069212886	0.94269603	0.4199358	0.21467364	0.616	0.456	0.389	0.887
Peak amplitude, BX, Ank, B1	26	0.001890497	0.91473167	0.4555054	0.29273563	0.026	0.456	-1.277	0.887
Peak amplitude, AX, Ank, B6	26	0.009094528	2.84327568	0.4816818	0.59328509	2.855	0.456	9.995	0.887
Peak amplitude, BX, Ank, B6	26	0.008246182	0.91406275	0.4989558	0.23599577	-0.479	0.456	-0.507	0.887
Peak amplitude, AX, knee, B1	26	0.018429935	1.12503422	0.5879317	0.29940622	-0.218	0.456	-0.454	0.887
Peak amplitude, BX, knee, B1	26	0.063026917	1.223434	0.6764357	0.29050862	0.101	0.456	-0.256	0.887
Peak amplitude, AX, knee, B6	26	0.057054446	1.23485753	0.4624293	0.34049035	0.841	0.456	-0.306	0.887
Peak amplitude, BX, knee, B6	26	0.028546627	1.22342099	0.521226	0.34034069	0.463	0.456	-0.801	0.887
peak latency, AX, hip, B1	26	1.426862318	2.07893175	1.7082155	0.17579822	0.48	0.456	-0.789	0.887
peak latency, BX, hip, B1	26	1.425968732	2.22271647	1.7020143	0.22050693	0.931	0.456	0.494	0.887
peak latency, AX, hip, B6	26	1.505149978	2.16720369	1.7454441	0.13714228	1.062	0.456	2.452	0.887
peak latency, BX, hip, B6	26	1.431363764	2.22466253	1.7225964	0.19822676	0.882	0.456	0.459	0.887
peak latency, AX, ank, B1	26	1.431363764	2.10968236	1.7233239	0.16671275	0.349	0.456	0.209	0.887
peak latency, BX, ank, B1	26	1.508529719	2.22336613	1.763948	0.19391564	0.793	0.456	-0.193	0.887
peak latency, AX, ank, B6	26	0.176091259	2.25052165	1.6867685	0.37560814	-2.676	0.456	10.39	0.887
peak latency, BX, ank, B6	26	0.301029996	2.30319606	1.6277914	0.41690199	-1.165	0.456	2.984	0.887
peak latency, AX, knee, B1	26	0.063026917	1.80374967	1.0753112	0.50497873	-0.105	0.456	-1.19	0.887
peak latency, BX, knee, B1	26	1.458637849	1.92427929	1.6425543	0.11297588	0.664	0.456	0.48	0.887
peak latency, AX, knee, B6	26	0.176091259	2.25052165	1.5730176	0.39743883	-1.823	0.456	5.501	0.887
peak latency, BX, knee, B6	26	0.301029996	2.30319606	1.5542442	0.41577546	-0.954	0.456	2.281	0.887
RD, AX, hip, B1	26	0.228464225	1.32464712	0.7361777	0.26003149	0.277	0.456	-0.249	0.887
RD, BX, hip, B1	26	0.023173254	1.41823249	0.6659703	0.33447053	0.166	0.456	-0.006	0.887
RD, AX, hip, B6	26	0.498704521	2.09064069	0.9475338	0.3891773	1.183	0.456	1.666	0.887
RD, BX, hip, B6	26	0.145917435	2.2377729	0.7966266	0.43600957	1.266	0.456	3.501	0.887

RD, Ax, Ank,B1	26	0.030026524	1.07946895	0.4758991	0.2478315	0.566	0.456	0.085	0.887
RD, BX, Ank, B1	26	0.004736455	1.22124357	0.4214404	0.30047669	0.82	0.456	0.448	0.887
RD, AX, Ank, B6	26	0.361716437	1.22894175	0.7203233	0.21013652	0.261	0.456	-0.272	0.887
RD, BX, Ank, B6	26	0.288793614	1.2660531	0.6755115	0.21840785	0.729	0.456	0.994	0.887
RD, AX, knee, B1	26	0.010268389	1.12929835	0.5333983	0.30700191	0.216	0.456	-0.592	0.887
RD, BX, knee, B1	26	0.05703821	1.24746188	0.4950599	0.36915071	0.565	0.456	-0.814	0.887
RD, AX, knee, B6	26	0.236754692	1.52412027	0.8027496	0.30883615	0.177	0.456	-0.123	0.887
RD, BX, knee, B6	26	0.221337399	1.53159425	0.6765982	0.29563125	0.839	0.456	1.42	0.887

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