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Title	Utilising dynamic motor control index to identify age-related differences in neuromuscular control
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Publication date	2024-03-10
Original Citation	Burke, L., Khokhlova, L., O'Flynn, B. and Tedesco, S. (2024) 'Utilising dynamic motor control index to identify age-related differences in neuromuscular control', Human Movement Science, 95, 103200 (9 pp). Available at: https://doi.org/10.1016/j.humov.2024.103200.
Type of publication	Article (peer-reviewed)
Link to publisher's version	10.1016/j.humov.2024.103200.
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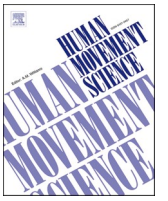
Human Movement Science 95 (2024) 103200



Contents lists available at ScienceDirect

Human Movement Science

journal homepage: www.elsevier.com/locate/humov





Utilising dynamic motor control index to identify age-related differences in neuromuscular control

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ARTICLE INFO

Keywords:
Muscle synergies
Aging
Stepping
Walking
Muscle activity
Motor index

ABSTRACT

Purpose: Considering the relationship between aging and neuromuscular control decline, early detection of age-related changes can ensure that timely interventions are implemented to attenuate or restore neuromuscular deficits. The dynamic motor control index (DMCI), a measure based on variance accounted for (VAF) by one muscle synergy (MS), is a metric used to assess age-related changes in neuromuscular control. The aim of the study was to investigate the use of one-synergy VAF, and consecutively DMCI, in assessing age-related changes in neuromuscular control over a range of exercises with varying difficulty.

Methods: Thirty-one subjects walked on a flat and inclined treadmill, as well as performed forward and lateral stepping up tasks. Motion and muscular activity were recorded, and muscle synergy analysis was conducted using one-synergy VAF, DMCI, and number of synergies.

Results: Difference between older and younger group was observed for one-synergy VAF, DMCI for forward stepping up task (one-synergy VAF difference of 2.45 (0.22, 4.68) and DMCI of 9.21 (0.81, 17.61), $p = 0.033$), but not for lateral stepping up or walking.

Conclusion: The use of VAF based metrics and specifically DMCI, rather than number of MS, in combination with stepping forward exercise can provide a low-cost and easy to implement approach for assessing neuromuscular control in clinical settings.

1. Introduction

Muscle synergy (MS) analysis has been used extensively in the fields of neuroscience, sport science and rehabilitation to gain greater insights into motor control (Hug, 2011). The central nervous system recruits the muscles needed for movement in groups known as muscle synergies. This process optimises movements by allowing the muscles and joints to operate as a coordinated unit to accomplish a movement goal (Abd et al., 2021). These muscle groupings are not fixed synergies for the range of one's life, a multitude of reasons can cause these synergies to shift and regroup, combine or divide (Avrillon et al., 2020; Schache et al., 2010). The leading MS analysis methods, where MS are extracted using non-negative matrix factorisation (NNMF) or principal component analysis, have shown differences in the number of muscle synergy present before and after an injury (Avrillon et al., 2020). Furthermore, it has been seen that often the muscle synergies will not return to their previous most optimal state after rehabilitation for said injury (Avrillon

Abbreviations: BMI, body mass index; CI, confidence interval; CP, cerebral palsy; DMCI, dynamic motor control index; KOOS, knee injury and osteoarthritis outcome score; MS, muscle synergy; MVC, maximum voluntary contraction; NNMF, nonnegative matrix factorization; PCA, principal component analysis; SD, standard deviation; sEMG, surface electromyography; VAF, variance accounted for.

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https://doi.org/10.1016/j.humov.2024.103200
Received 30 September 2023; Received in revised form 22 February 2024; Accepted 4 March 2024
Available online 10 March 2024
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et al., 2020).

It is well known that older people are more prone to trips, falls, and general poor balance (Häkkinen et al., 1996; Pijnappels et al., 2008). While age-related decline in gait and balance control have been documented (Era & Heikkinen, 1985; Springer et al., 2006), the same cannot be said for MS. Numerous studies explored the age-related modifications to muscle function/coordination through the use of surface electromyography (sEMG) sensors monitoring muscle activity during walking. When compared to a younger cohort sample, studies suggest that there is no significant difference between the muscle synergies of a young person and that of an old person (Monaco et al., 2010). Even more complex tasks, such as walking upstairs, could not differentiate the neuromuscular control of a young population and an old population based on the number of MS extracted alone (Baggen et al., 2020). Although extracting MS from sEMG activity using dimensionality reduction techniques has been considered a gold standard for observing injury-related differences in muscle synergies, the same cannot be said regarding age-related differences. Clinical evaluation of elderly people's muscle function is largely carried out through functional assessments such as studying gait and physical energy (Soubra et al., 2019). Research suggests neuromuscular control declines first and functional impairments follow (Clark et al., 2013; Dingwell et al., 2017). Therefore, implementing reliable neuromuscular analysis into these evaluations may allow us to identify these impairments before they even begin to affect physical function. Rehabilitation and preventative measures can then be taken to improve muscular function before the issue becomes too serious.

The further analysis of age-related changes in neuromuscular control was undertaken by using metrics other than the number of synergies, such as the dynamic motor control index (DMCI). The DMCI analysis method was developed in the context of neuromuscular control when studying the gait in people with cerebral palsy (CP) (Steele et al., 2015). It has since been used in two other studies regarding CP patients, children, and adults (Schwartz et al., 2016; Shuman et al., 2019). The DMCI is a summary metric of muscle co-activation during walking. Rather than computing the number of muscle synergies that correlate to a predefined variance accounted for (VAF) threshold, the DMCI constrains the number of muscle synergies to one and scales the VAF score to a z-score based on a control group. In the case of investigating age-related differences between a younger group and an older group, the young group represents the control group. Therefore, the higher the DMCI, the more complex the neuromuscular ability is (Steele et al., 2015).

The study by Collimore et al. (Collimore et al., 2021) showed relatively promising results in distinguishing between age group using the DMCI for walking exercise; however, significant differences were only observed between the 'young' adults (27 ± 3 years) and 'old-old' adults groups (78 ± 2 years). At the same time, a study by Baggen et al. (Baggen et al., 2020) showed that VAF can be successfully used to distinguish between older and younger women in the forward stepping up task. Hence, it can be hypothesized that the results of (Collimore et al., 2021) may be due to the simplicity of the walking task, and that other walking tasks that varied in complexity may be the key to identifying age-related impairments at an earlier age. Moreover, to identify age-related deficits as early as possible, investigation of less senior participants and/or smaller age gap should be considered. Thus, this study aims to explore the usability of DMCI and VAF based metrics to detect age-related changes in in neuromuscular control throughout a range of exercises of varying difficulty.

2. Methods

The study was conducted according to the guidelines of the Declaration of Helsinki and was approved by the Clinical Research Ethics Committee of the Cork Teaching Hospitals at the University College Cork (Ref. number: ECM 4 (e) 17/05/2022 & ECM 3 (kkk) 17/05/2022). Data from 31 participants was collected, with at least 13 participants per group based on the protocol carried out on previous work (Collimore et al., 2021). Participants were recruited within two groups: 'younger adults' (18–35 years) and 'older adults' (50–75 years). The study excluded subjects with a body mass index (BMI) above 35. Moreover, participants in the older group were included if they presented healthy knees, or knees which had sufficiently recovered from past knee trauma and are capable of preforming walking and step-up tasks with ease. The participants were screened using Knee Osteoarthritis Outcome Score (KOOS), and a threshold of 85 was set for younger adults to ensure that the control group exhibits satisfactory knee condition, which resulted in the exclusion of one participant. A summary of the anthropometric measures of the 30 recruited subjects are shown in Table 1.

2.1. Experimental protocol

In this study, the primary muscles in the participant's dominant leg were included for analysis. The tensor fasciae latae was removed from the protocol as sEMG sensors had to be placed in the iliac region which was reported by several participants to be uncomfortably close to the suprapubic region. The following eleven muscles were included: rectus femoris, vastus lateralis, vastus medialis, biceps femoris caput longus, lateral and medial gastrocnemius, soleus, semitendinosus, tibialis anterior, peroneus longus, gluteus maximus, and gluteus medius, in accordance with previous works on the topic (Collimore et al., 2021; Santuz et al., 2020).

Off-the-shelf FREEEMG (BTS Engineering, Italy) electromyography units were used for data collection. Sensors were attached to the

Table 1
Participants' anthropometric measures and KOOS scores.

Group	Number of participants	Males/ Females	Age (SD), years	Height (SD), cm	Weight (SD), kg	KOOS (SD)
Young Adults (Y)	14	7/7	26 (5.04)	171.43 (7.15)	72.59 (13.83)	95.36 (3.82)
Older Adults (O)	16	6/10	55.75 (6.39)	175.15 (9.52)	77.08 (10.42)	79.06 (16.59)

skin of the participants over the muscles of interest using adhesive gel electrodes. Sensors were placed according to the SENIAM guidelines (Hermens et al., 2000). EMG sensors placements are shown in Fig. 1. Off-the-shelf (Xsens Technologies B.V., Enschede, Netherlands) inertial measurement units (IMUs) were adopted to collect limb orientation data (i.e., pitch, roll, yaw). IMUs were placed using elastic straps around the thigh, calf, and foot of the participant as shown in Fig. 2. BTS FREEEMG and Xsens system were synchronised using a hardware trigger.

During the exercise execution participants were asked not to lean on equipment to aid balance unless completely necessary. Three participants in the old group required balance/stability aid during the exercises. Any exercise was practised if requested by the participant. Data collection began with flat walking (Fig. 3, left) with the treadmill speed set to 4 km/h. In this study, both older and younger group were walking at the same speed, contrary to (Collimore et al., 2021), where younger adult walked at 4.32 km/h and older at 3.96 km/h. To include a more challenging version of the task, incline walking was recorded, with the treadmill set to an incline of 5 degrees and a speed of 3.5 km/h. In both instances, data recording began 10 s after the participant started walking to ensure that participants familiarized with the treadmill pace and 40–50 s of data were recorded. After, forward stepping up was performed (Fig. 3, right). A three-step staircase with step height of 20 cm was used, contrary to single wooden block of the same height as used in previous studies (Baggen et al., 2020). The participant was to begin with both feet close together on the ground. The dominant leg was considered as the leading foot. The participants stepped onto the first step of the staircase with their leading foot. Their trailing foot followed so that both feet were then on the same step. The participants were asked to pause for two seconds and then to repeat the movement onto the second step, where both feet finished on the second step and then similarly onto the third step. For the lateral step (Fig. 3, centre), participants were to begin with both feet close together on the ground, facing sideways so that the stairs were on either their left or right hand side based on their dominant leg (e.g., the dominant leg was supposed to be the closest to the step). The participant steps sideways onto the first step with their leading foot. Their trailing foot followed so that both feet were sideways on the same step, similarly to the forward step exercise, two more steps were performed in the same manner.

2.2. Data processing

All data processing steps were completed using MATLAB R2022b software (MathWorks, USA). The sEMG signal processing largely followed procedure described in (Collimore et al., 2021), to allow for a closer comparison between results of the works. The EMG signals were first filtered using a 4th order high-pass Butterworth filter with cut-off frequency at 40 Hz. Additionally, a notch filter was used to eliminate noise at 50 Hz. Then, the signal was de-trended (i.e., the sample mean was subtracted from each observation so that the resulting signal is at zero mean), rectified, and passed through a 4th order low-pass Butterworth filter with cut-off at 4 Hz. Contrary to (Collimore et al., 2021), for the two walking exercises, the middle 20 consecutive strides instead of 30 clean strides were used for signal processing. Gait cycles (strides) were identified using the motion data and resampled to 100-point vectors using cubic interpolation. Similarly to (Baggen et al., 2020), for stepping up exercises, the repetitions were manually divided using motion data and the average of three steps was taken into consideration to ensure the best reconstruction quality for relatively short intervals (Oliveira et al., 2014). While utilising a maximal voluntary contraction (MVC) as a recommended normalisation method within EMG processing (Rubega et al., 2021), muscle impairments may not allow patients, particularly, in older group to be able to contract on command efficiently voluntarily. To remain inclusive to all subjects, the amplitude of sEMG signal was normalised to the maximum activation experienced during each exercise, specifically for 20 strides included during walking and inclined walking, while the maximum activation of the average of three steps for lateral and step forward exercises was used.

The NNMF was used to extract synergies from the collected muscle signals, using MATLAB scripts by Ting and Chvatal (Ting & Chvatal, 2011). This is the most popular extraction method, being used in over 62% of studies between 1999 and 2018 (Rabbi et al., 2020). The variance accounted for (VAF) statistically compared the reconstructed and original muscle patterns (Tresch et al., 2006)

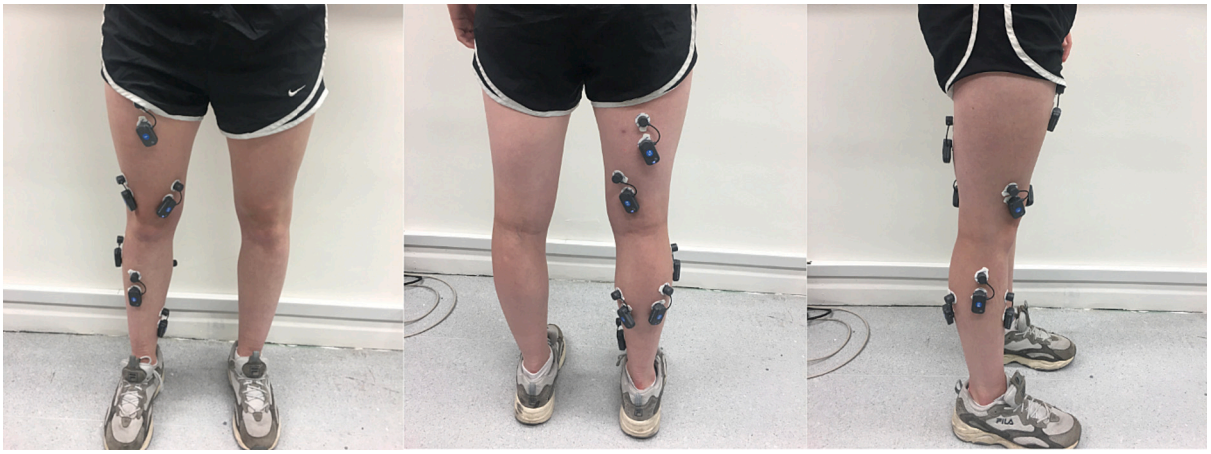


Fig. 1. sEMG sensors placement.

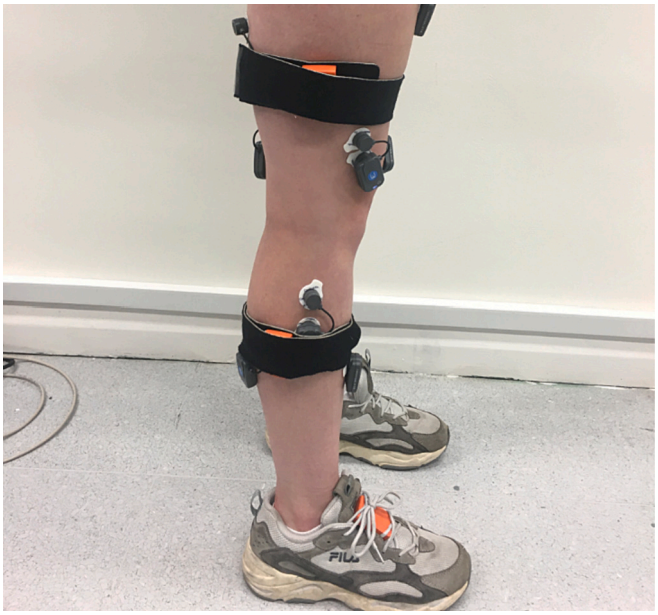


Fig. 2. IMU placement.

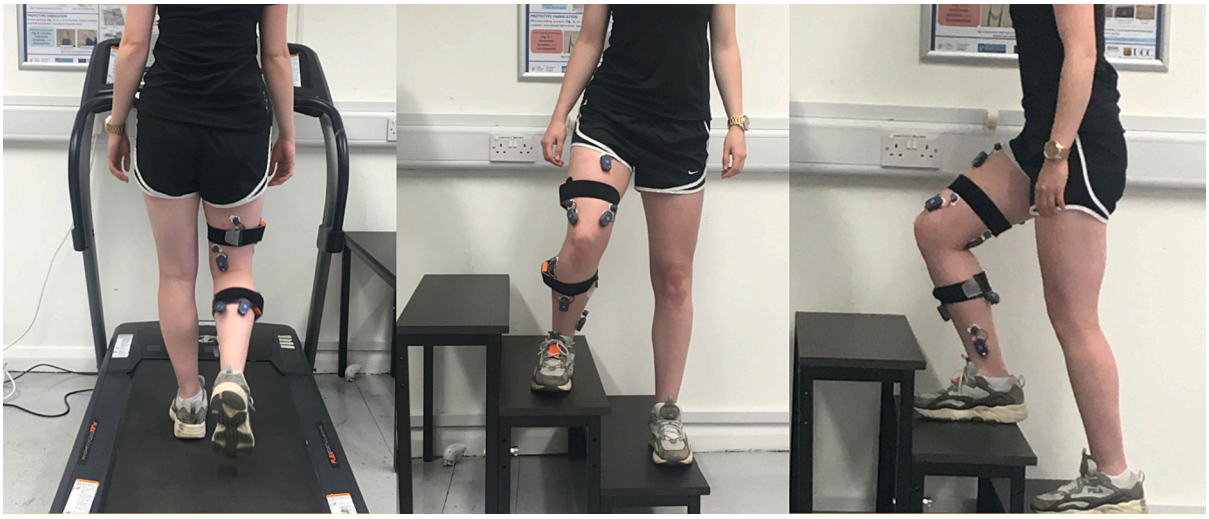


Fig. 3. Examples of participant undergoing exercise trials (walking, steps lateral, steps forward).

and defines the dimensionality of the muscle data in terms of the smallest number of vectors required to explain most of the variability in the data (Kubota et al., 2021). The user predefines a threshold which consistently ranges within 80–95% in the literature (Turpin et al., 2021). In this study, VAF was set to a threshold of 90%, similarly to (Collimore et al., 2021), to allow an effective comparison between studies. The script presents a solution that follows multiplicative update rules (Lee & Seung, 2000) and the number of replicates was set to 50, with a maximum of 1000 iterations, termination tolerance on the change in size of the residual 1e-6 and convergence threshold of 1e-4. Muscle synergies were extracted from 20 concatenated strides for walking and inclined walking (Oliveira et al., 2014) and the average of three steps for lateral stepping and step forward exercises was used, as suggested by (Baggen et al., 2020). Once extracted, the single synergy value was adopted for the DMCI calculation, along with the number of muscle synergies present as the corresponding VAF value based on the stated threshold. Additionally, the VAF values for four synergies were calculated for stepping forward exercise to allow for comparison with results of previous work (Baggen et al., 2020). To calculate DMCI, the single synergy VAF value was then converted to a z-score with the young adult group as the control group, as depicted in Eq. (1):

$$DMCI = 100 + 10\left(\frac{AVG\ VAF_{1synergy-Y} - VAF_{1synergy-Exp}}{SD\ VAF_{1Synergy-Y}}\right) \quad (1)$$

Where $AVG\ VAF_{1Synergy-Y}$ is the average of the one synergy VAF of the whole young adult group, $VAF_{1Synergy-Exp}$ is the one synergy VAF value of each individual in all groups within the study, and $SD\ VAF_{1synergy-Y}$ the standard deviation of the single synergy VAF value of the young adult control group (Steele et al., 2015).

2.3. Statistical analysis

The statistical analysis of the data acquired was performed using SPSS v.28 (IBM, USA). Normality of the data was assessed using Shapiro-Wilk test, Q-Q plots, and histograms. Independent group *t*-test was used to compare mean DMCI scores across the Y and O groups. The Mann-Whitney test was used to assess difference in number of synergies between groups. The paired samples t-test was used to assess the difference in one-synergy VAF between exercises. Significance for all tests was set at $P = 0.05$.

3. Results

Data for walking tasks and step forward was removed for one younger adult participant, step forward task was removed for another younger group participant, and both stepping exercises were removed for one older participant, due to the disconnection of the sensors during the recording process and low-quality signals, respectively. Moreover, erector spinae sensor data was excluded in post processing due to the low quality of the signal for several participants. Due to the motion artefacts observed for gastrocnemius medial recordings in several participants, gastrocnemius lateralis was instead used in the MS analysis for all stepping tasks. Considering that no difference in muscle activation was observed between medial and lateral muscle when tiptoeing with feet in neutral position (Riemann et al., 2011), such exchange should not have had a major effect on the muscle synergies extracted. The resulting number of synergies, one-synergy VAF and the DMCI are presented in Table 2. Full reports of all statistical tests, as well as participants data are included in the supplementary materials.

3.1. Number of synergies

Overall, the majority of participants showed 2 to 3 synergies for all exercises (Table 3). Notably, for inclined walking 4 synergies were required for 8 participants for 90% VAF threshold. No significant differences were observed for the number of synergies between groups.

3.2. DMCI and VAF

The one-synergy VAF values were normally distributed. No significant differences were observed for VAF values/DMCI for both walking exercises and lateral stepping up. For stepping up forward a mean one-synergy VAF difference of 2.45 (0.22, 4.68) and DMCI of 9.21 (0.81, 17.61) was observed between groups, $p = 0.033$. Overall, while not significant for exercises other that step forward, a trend of lower DMCI (Fig. 4) and higher values of one-synergy VAF (Fig. 5) was observed for all trials in the older group, indicating potentially impaired motor control. Four synergies accounted for >98% of variance for both the older and younger groups.

Values of DMCI lower than 90, an impairment threshold suggested by (Collimore et al., 2021), were observed for 50% of the older participants for flat walking, 31.25% for inclined walking, 43.75% and 18.75% for forward and lateral stepping up, respectively. The cumulative percentages of participants' DMCI frequencies within group for each exercise and four-synergies VAF values are presented in the supplementary materials.

4. Discussion

In accordance with literature (Baggen et al., 2020; Monaco et al., 2010; Santuz et al., 2020), no significant differences were discovered for the number of synergies for all included exercises, further confirming the limitation of the number of synergies in providing an effective metric of motor control complexity in MS analysis.

The difference in age between the oldest participant in the young adult group (34) to the youngest participant in the older adult (50 years) group in the presented study is 15 years. This is a vast contrast to the 30 years difference in (Collimore et al., 2021). Nonetheless,

Table 2
Number of synergies, one-synergy and VAF and DMCI for older and younger adults' groups (mean and standard deviation – SD reported).

Exercise	Number of synergies at 90% VAF (SD)		One-synergy VAF (SD)		DMCI (SD)	
	Y	*O*	*Y*	*O*	*Y (control)*	*O*
Walking	2.62 (0.65)	2.13 (0.34)	66.89 (3.73)	69.06 (4.02)	100 (10)	94.17 (10.79)
Incline walking	3.31 (0.48)	3.19 (0.4)	66.97 (3.09)	68.53 (3.63)	100 (10)	95.56 (11.49)
Step up forward	2.33 (0.49)	2.07 (0.46)	82.91 (2.66)	85.34 (2.9)	100 (10)	90.79 (10.92)
Step up lateral	2.29 (0.47)	2 (0)	82.84 (3.81)	83.88 (3.72)	100 (10)	97.27 (9.78)

Table 3
Number of synergies distribution across exercises.

Exercise	Number of participants, total (Y/O)				Total
	1 synergy	*2 synergy*	*3 synergy*	*4 synergy*	
Walking	–	20 (6/14)	8 (6/2)	1(1/0)	29
Incline walking	–	–	22 (9/13)	8 (5/3)	30
Step up forward	1 (0/1)	20 (8/12)	6 (4/2)	–	27
Step up lateral	–	25 (10/15)	4 (4/0)	–	29

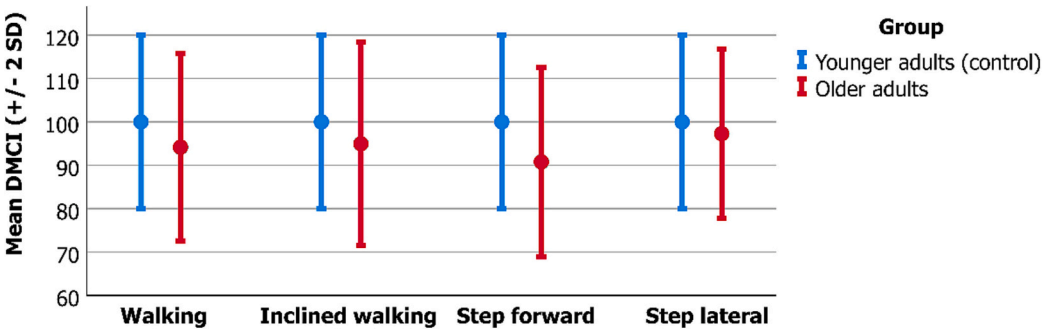


Fig. 4. Mean DMCI scores (error bars ±2SD) for control (younger adults, left bar) group and older adults for four exercises: walking, inclined walking, step lateral, step forward.

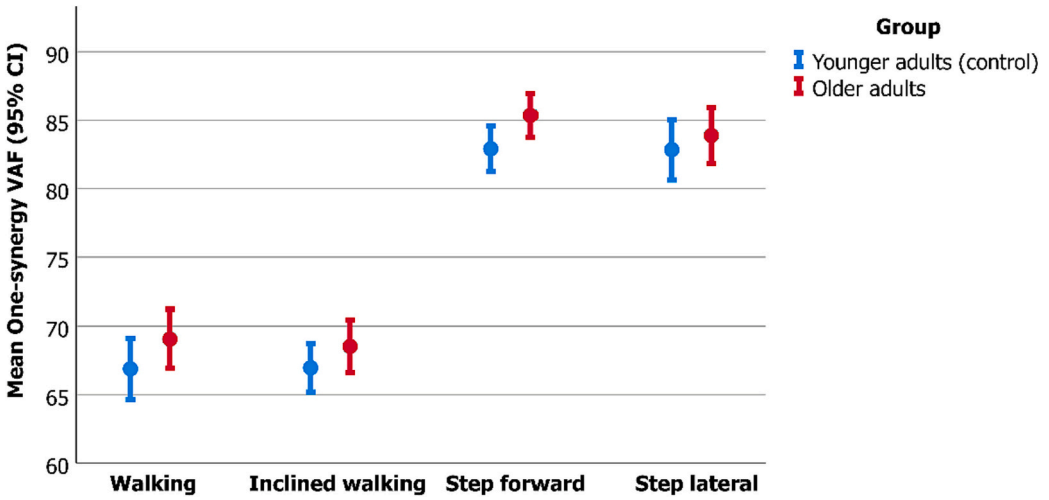


Fig. 5. Mean one-synergy VAF (error bars ±95CI) for younger (left bar) and older adults groups for four exercises: walking, inclined walking, step lateral, step forward.

obtained DMCI score for the older group (55.75 ± 6.39 years) in this study was 94.17 (10.79) for walking on a flat surface, which is slightly lower than 96.4 ± 10.79 for the young-old (70 ± 3) group (Collimore et al., 2021). This indicates that our sample potentially contained more people with neuromuscular control deficit, with 8 people out of 16 in the older group showing DMCI <90, an impairment threshold used in (Collimore et al., 2021), despite a younger age on average. The results of the independent sample *t*-test showed that one-synergy VAF values, and consecutively DMCI for walking tests, do not allow for differentiation between the closer age groups in this study, while it was DMCI that was significantly predictive of older age group (78 ± 2) in the logistic regression model (Collimore et al., 2021). On the other hand, DMCI and one-synergy VAF in forward stepping up exercises did show a difference between age groups, indicating that the increased complexity of movement allows for better detection of neuromotor control changes, confirming the results presented by (Baggen et al., 2020). Interestingly, four-synergies VAF in this study did not differ between groups, contrary to the study (Baggen et al., 2020) where erector spinae muscles were included in the analysis, establishing the importance of the muscle included and resulting dimensionality. Considering this, further investigations, regarding the optimal combination of muscles and the respective number of synergies to obtain VAF values and capture physiological differences in motor control

complexity, might presents a future research direction.

Taking into account wide variations in methodology observed among different studies, particularly in EMG signal pre-processing and the potential impact of this on the number of synergies (Hug et al., 2012), the use of DMCI as a measure based on the control group results may have an advantage. It has been previously shown that z-score measures reduced the influence of low-pass filtering (Shuman et al., 2017) and can allow for an easier comparison between studies.

The study by (Collimore et al., 2021) suggests using DMCI values <90 as a threshold for neuromuscular impairment, reporting a higher proportion of low DMCI (<90) in older group for treadmill walking. The results of the presented study also show that the above-mentioned conclusion is applicable for all exercises considered. Interestingly, the largest difference in ratios was observed for walking, while DMCI was not significantly different in older and younger groups, indicating the potential use of DMCI thresholds as an additional criterion in the assessment of age-related differences in neuromuscular control in a wider range of exercises. Although this study is not sufficient to determine clinically meaningful threshold values of DMCI, the findings suggest the potential for future research. The establishment of DMCI as a clinical measure of neuromotor impairment could be accomplished by including participants with clinically diagnosed conditions or conducting prospective studies, identifying DMCI thresholds, boundaries, and the minimally clinically important difference for various conditions.

When considering exercises included into clinical assessment of neuromotor decline several factors need to be considered. The step-up exercise mimics a daily living task and emphasizes lower extremity strength and coordination. Step-up exercise can provide insights into a person's ability to negotiate stairs or uneven surfaces, which is crucial for maintaining independence, while using a treadmill might be more appropriate for assessment of gait and cardiovascular fitness, overall mobility, and identification of balance issues related to sustained walking. Moreover, step-up allows for intermittent rest periods between steps, and older people might feel more comfortable with stepping up a ladder or a block, rather than a moving treadmill. Considering safety of multi-level step ladder and overhead space required, it might be proven useful to employ a single block, rather than a multilevel ladder. Future studies might be required to investigate the number of step ups better suited for assessment. Specifically, averaging the step-ups could potentially lead to mixing or merging synergies (Turpin et al., 2021) and increasing number of repetitions and using concatenation should also be considered in future studies. Overall, expanding the range of exercises employed in clinical practice can provide a more comprehensive assessment of neuromotor impairment.

This study provides an incentive for a broader clinical application of DMCI score, indicating that the results are generalizable for a wider population, as a less homogenous sample (females and males) and a smaller age gap between groups were considered compared to what previously explored in the literature (Baggen et al., 2020; Collimore et al., 2021). Otherwise, a close replication of methodological approaches with previous works on the topic ensures a fair comparison between the studies, while combining a range of exercises within the same sample allows for counteraction between-subject variability when identifying an optimal exercise for neuromotor impairment assessment. However, some limitations of the study should be considered when interpreting the results. The sEMG data was only collected from muscles of the dominant leg, due to technical limitations of the sEMG system (e.g., number of sensors) and to ensure adequate comparison to previously published results. Thus, any input from the trailing leg, deep muscles, or back muscles was not considered. Moreover, differences in signal pre-processing should be considered when comparing results of this study to others, as different processing techniques might result on different number of synergies extracted.

5. Conclusion

Overall, this study expands the previous findings in the field by exploring a range of exercises and additional metrics of MS analysis. It has been shown that the utilization of one-synergy VAF and DMCI, as opposed to relying solely on the number of synergies, when combined with the forward stepping up exercise can offer a cost-effective and straightforward method for evaluating neuromuscular function in clinical settings, presenting a practical and economical solution for healthcare professionals.

Funding

This work was supported in part by the Science Foundation Ireland which are Co-Funded through the European Regional Development Fund under Grant 12/RC/2289-P2-INSIGHT and Grant 16/RC/3918-CONFIRM. Aspects of this publication have also emanated from research supported by a research grant from the Disruptive Technologies Innovation Fund (DTIF) project HOLISTICS funded by Enterprise Ireland (EI).

CRediT authorship contribution statement

Laura Burke: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Liudmila Khokhlova:** Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Brendan O'Flynn:** Funding acquisition, Supervision, Writing – review & editing. **Salvatore Tedesco:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors have no relevant financial or non-financial interests to disclose.

Data availability

Data will be made available on request.

Acknowledgments

The authors would like to thank Ting and Chvatal (Ting & Chvatal, 2011) for sharing their scripts and all the participants who took part in this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.humov.2024.103200.

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