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Multi-Task Neuromuscular Generalization and Changes Through the Lifespan

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Multi-Task Neuromuscular Generalization and Changes Through the Lifespan

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Dissertation submitted to the Statler College of Engineering at
West Virginia University

in partial fulfillment of the requirements for the degree of

Ph.D. in Biomedical Engineering

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Abstract

Mobility in everyday life requires executing and shifting between a broad assortment of functional tasks and resisting disturbances that could cause falls. Though the importance of successfully performing a variety of functional tasks is recognized and incorporated in clinical assessments (e.g., the Timed-Up-and-Go Test, Berg Balance Scale), little is understood about the underlying neuromuscular control required, or how it changes with age. The neuromuscular control for functional tasks such as walking is typically studied in isolation, or with variations on the same task. Characterizing the coordination required to produce and shift between a wider variety of tasks and resist external disturbances is crucial to understanding mobility in daily life, not just within a controlled lab environment.

In this work, we identify patterns of multi-muscle coordination (motor modules) across functional tasks in healthy young, middle-aged, and older adults. We demonstrate that healthy young adults recruit common motor modules across voluntary functional tasks (walking, turning, and chair transfers), and characterize changes associated with age. Additionally, we investigate whether motor modules are shared between reactive balance and these voluntary tasks, and whether there are age-related changes here. Identifying age-related changes in multi-muscle coordination can lead to a better understanding of the neuromuscular control underlying mobility changes due to normal aging. Further, fully characterizing changes in neuromuscular control that are due to normal aging can provide a basis for identifying the changes associated with impairments that commonly occur in older adults (e.g., stroke).

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1 Introduction

Falls are a leading cause of injury in older adults [1], [2] These falls commonly occur during a variety of tasks, including walking, turning, chair transfers, and stairs [1]. Individuals with good mobility can comfortably move around in the world, fluidly shifting between tasks and navigating difficult environmental conditions without falling, but these abilities are reduced with aging and neurological or musculoskeletal impairments. This multi-task nature of healthy mobility is clinically well recognized. Many common clinical tests assess a variety of movement tasks; for example, the Timed-Up-and-Go (TUG) test incorporates walking, turning, and chair transfers [3]. However, these assessments are not designed to reveal the underlying causes that produce impaired movement. The neuromuscular control required to flexibly and robustly perform and shift between movement tasks is not fully understood in individuals with good mobility, much less how it changes with age or impairment. Understanding the changes in neuromuscular control that are due to normal aging would provide a basis for investigating other conditions that commonly occur in older adults (e.g., stroke or dementia) and allow us to better separate mobility changes due to normal aging versus changes due to these conditions.

The neuromuscular control of successful mobility relies on a variety of systems, including reflex responses and the musculoskeletal, nervous, and sensory systems, all of which are known to decline with age [4]. Electromyography (EMG) measures the electrical muscle activity generated when a muscle is stimulated by the nervous system and during responses to peripheral reflexes ([5]). Muscle activity can therefore be considered as a bridge between the nervous system and the mechanics of the musculoskeletal system; it provides more information about the underlying control and coordination than mechanical variables alone but is still simple and noninvasive to measure and analyze. Motor module (i.e., muscle synergy) analysis is one method for quantifying patterns in muscle activity. Motor modules are groups of coactivated muscles that can be flexibly combined to produce different functional outputs [6].

Evidence for modularity in movement control has existed since the work of Sherrington and colleagues in the early 1900s with investigations of “flexion reflexes” in animals (e.g., [7]). Building on this, central pattern generators (CPGs) as rhythmic drivers of locomotion within the spinal cord are a well-accepted theory in motor control ([8]). As an example, spinalized cats maintain the ability to walk on a treadmill, supporting the existence of spinally located generators of walking that can operate without sensory input ([9], [8]). Similarly, modular muscle activity is also still observable in animals with removed or suppressed sensory feedback (e.g., [10], [11]), providing further evidence that centrally driven modular control strategies may be encoded in the nervous system.

Although there is ample evidence that motor modules may represent modularity in the nervous system for movement control ([6], [10], [12], [13], [14], [15], [16], [17]) this is still an active area of research with many open questions. Much of the debate revolves around the unsettled question of whether observed modularity arises purely from biomechanical constraints or is encoded in the central nervous system. The truth most likely lies somewhere in between a purely mechanical and a purely neural origin. Because the neural and musculoskeletal systems exist together any control strategies cannot avoid being influenced by mechanical features that either facilitate or constrain movements ([6]). Indeed the mechanics of the muscluloskeletal system likely shape their content, as motor modules have been associated with force generation [14], and functional components of walking such as body support and propulsion (e.g., [18]). There is also evidence that lower dimensional muscle coupling can arise from limb biomechanics and task constraints ([19], [20]). It is also likely that the nervous system organizes

Changes in observed motor modules with learning, development, and neurological injury also provide supporting evidence for modular control. Even muscle activity during the newborn stepping response can be explained with two modular components, which are adjusted and added to with development until they more closely resemble the modular components seen in adult walking ([21]). Conversely, alterations in walking motor module recruitment occur with neurological injuries such as reduced complexity in children with cerebral palsy [22], merging of motor modules in chronic stroke [11], loss of motor modules after spinal cord injury [23], and changes in motor module recruitment after rehabilitation in people with Parkinson’s Disease [24].

Here, we specifically use the concept of motor modules not to assess modularity in neural control but to characterize patterns of multi-muscle coordination. Additionally, decomposing muscle coordination into the motor module space allows tasks that are very dynamically different to be compared, such as discrete sit-to-stand or reactive balance motions versus rhythmic walking movements (e.g., [25]). Motor module analysis is therefore a useful metric for quantifying neuromuscular control across a diverse range of movement tasks and characterizing differences between populations. Previous evidence suggests that motor modules may represent flexible and robust coordination patterns which can be applied to a variety of movements. The same motor modules are observed in variations on the same task, such as standing reactive balance with different postures [26], pedaling with different constraints [27], and running [28] and walking [29] on level and inclined surfaces. The same motor modules are also observed when walking with additional task demands, such as kicking a ball or stepping over an obstacle [30] or changing speeds and step heights [31]. These results suggest that the same muscle coordination patterns (motor modules) can be flexibly adapted to meet additional movement goals or external conditions.

The same motor modules are also observed during functionally different tasks, such as frogs jumping, swimming, and walking [15] or forwards and backwards walking [32]. This suggests that we may draw on a "library" of generalizable muscle coordination patterns that are applicable to different tasks, but such generalization has not yet been confirmed across a broad array of tasks. Accordingly, our central hypothesis is that healthy adults draw upon generalizable muscle coordination patterns for locomotion and other common movement tasks; therefore, one of the primary goals of this work is to determine whether motor modules are shared across an assortment of daily movement tasks. First, we demonstrate that healthy young adults share common motor modules across a set of voluntary tasks (walking, turning, and chair transfers) in Chapter 3. We then characterize motor module generalization across voluntary tasks in middle-aged and older adults in Chapter 4.

Successfully moving through daily life not only requires executing and shifting between tasks, but also resisting any internal or external disturbances to avoid falls. In one study on fall circumstances in community-dwelling older women, 46% of falls could be classified as external perturbations (slips, trips, bumps, or loss of external support). Another 41% of falls were caused by incorrect bodyweight shifts, often during transitional tasks like getting in and out of a chair, gait initiation, or turning [33]. Robust mobility requires the ability to move and shift and respond to any disturbance. Incorporating balance-specific muscle coordination patterns into the coordination of voluntary movement tasks may facilitate responding to challenging conditions. Some evidence for this has already been demonstrated in the similarities between motor modules used during walking and those used during a standing reactive balance task (e.g., [34]).

It has previously been shown that similar motor modules are recruited during a standing reactive balance and walking. In the reactive balance task, participants experience discrete support surface translations ("perturbations") designed to evoke a corrective response and motor modules are extracted from the time window associated with automatic postural responses (APR, [34], [35]). Higher generalization between walking and reactive balance is associated with walking performance in people with chronic stroke [36], Parkinson's disease [24], and young adults [34], [37].

Because this relationship has been demonstrated in multiple different populations, we hypothesize that recruiting reactive balance motor modules during walking is a general strategy enabling more robust and flexible control of walking. In other words, the central nervous system may incorporate components of reactive balance control into the production of voluntary movements like walking. Combining this with our previous discussion of the multi-task nature of daily life, we further hypothesize that healthy adults can draw upon a shared "library" of motor modules for both voluntary and reactive balance task demands. Utilizing this motor module library facilitates flexibility between different functional tasks and resisting disturbances in challenging conditions. Aging reduces the ability to draw from the motor module library or adapt recruitment to meet changing task demands. Therefore, to determine whether reactive balance motor modules play a role in voluntary tasks other than walking, we characterize motor module generalization between reactive balance and each voluntary task in Chapter 5.

Though there is previous evidence that common muscle coordination patterns are shared across tasks, there has not yet been a larger characterization of motor module generalization across a wide variety of movement tasks in any population. Our work is a first step to filling this gap and establishing a deeper understanding of multi-task neuromuscular control. Additionally, identifying changes in multi-task neuromuscular coordination associated with age could facilitate the development of more targeted and personalizable mobility interventions. For example, perhaps balance training methods that encourage the recruitment of reactive balance motor modules during locomotion could help prevent or reverse age-related declines. Analyzing multi-muscle coordination with these methods could also provide a method for quantifying the results of rehabilitation treatments (e.g., in [24]).

2 General Methods

2.1 Experimental Tasks

For all experiments, surface electromyography data was collected bilaterally at 1000 Hz from 12 muscles spanning the hip, knee, and ankle: gluteus maximus (GMAX), gluteus medius (GMED), tensor fasciae latae (TFL), adductor magnus (ADD), biceps femoris long head (BFLH), rectus femoris (RFEM), vastus lateralis (VLAT), medial and lateral gastrocnemius (MGAS and LGAS), soleus (SOL), peroneus (PERO), and tibialis anterior (TA) (shown in Fig. 2.1.)

The data in Chapter 3 were collected from 13 healthy young adults and data from Chapters 4 and 5 were collected from a separate set of 10 young adults (18-35 yrs), 6 middle-aged adults (36-64 yrs), and 5 older adults (65+ years). In Chapters 3 and 4 we examine motor modules recruited during voluntary tasks. In Chapter 3 we focus on the TUG test, as it is a common clinical test that incorporates walking, turning, and chair transfers. However, even when motor modules are separately extracted from the TUG subtasks, they inevitably include transitions between those tasks. For example, participants begin the first step off before they are fully standing, and the portions between the turn and chair transfers are certainly not steady-state walking. Therefore, we included both the TUG test and each component performed separately in Chapter 4, to characterize motor module recruitment more fully during these tasks.

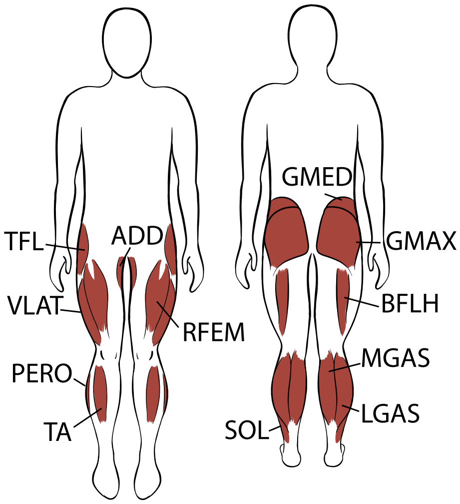

Figure 2.1: An illustration of the muscles used to collect EMG data from all subjects.

Treadmill walking: Data was collected during treadmill walking at both self-selected and fast speeds. First, participants walked on the treadmill for 2-3 minutes at an identified comfortable pace to acclimate to the treadmill. Speeds were then increased by intervals of 0.1 or 0.05 m/s until they said it was a little fast and then brought back down to get their self-selected speed. A minimum of two 30-second trials were collected at the self-selected speed. To identify the participant's fastest possible walking speed, treadmill speeds were increased by 0.1 m/s intervals until the participant felt that they could not go any faster without running. One 30-second trial was collected at each participant's fast walking speed.

Chair transfers: Each participant began seated on a backless chair that was adjusted so their feet were flat on the floor and knees at approximately 90 degrees. In each chair transfer trial, participants were instructed to stand, and then sit down. A gap of at least 2-3 seconds was given between the "stand" and "sit-down" commands, to allow enough space to separate the two tasks. Participants kept their arms crossed the entire time and performed a minimum of 8 chair transfer trials. The x- and z-position of the right shoulder marker was used to partition chair transfer trials into Sit-to-Stand and Stand-to-Sit portions (see Fig. 2.2 C.)

Figure 8: Participants walked in a figure-eight around two cones, spaced 3 meters apart, at a comfortable walking pace. A minimum of 8 trials were collected. All subjects except two young adults made a left turn first; motor modules were separately analyzed by turn direction (see Fig. 2.2 A.)

Timed-Up-and-Go: Participants performed a minimum of 8 trials of the Timed-Up-and-Go (TUG) test [3]. For each trial, participants get up from a chair, walk around a cone 3 meters away, walk back to the chair, and sit back down. They were instructed to walk at a quick pace, as if late, and started each trial with their arms crossed (see Fig. 2.2 B.)

Standing reactive balance: In Chapter 5 we investigated the involvement of balance control in each voluntary movement by comparing motor modules from each voluntary task described above to those from a standing reactive balance task. Reactive balance responses were assessed through a series of ramp-and-hold translations (15 cm) on the split-belt instrumented treadmill. Perturbations were applied in 4 directions (forward, backward, left, and right) and at 3 speeds (0.1, 0.2, 0.3 m/s). These speeds were selected to be strong

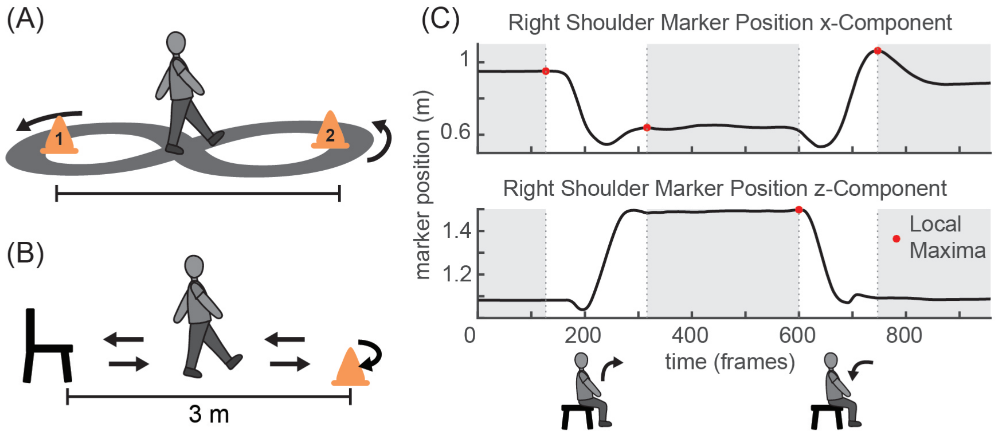

Figure 2.2: During Figure-8 walking (A), subjects made a left turn then a right turn around two cones spaced 3 meters apart. In the Timed-Up-and-Go (TUG) test (B), subjects stood up from a chair, walked 3 m, turned around a cone, and walked back to the chair to sit down. (C) Chair transfer trials were segmented into Sit-to-Stand and Stand-to-Sit portions using local maxima in the right shoulder marker. Sit-to-Stand was defined from the first forward movement to the end of the small backwards motion when fully standing. Stand-to-Sit was defined from the first downward movement of the marker to the peak backwards movement when fully sitting.

enough to require a corrective response, but not strong enough to elicit a fall. Participants experienced 6 blocks with 12 perturbations each, one for each speed and plane. For frontal plane perturbations, participants stood sideways on the right treadmill belt, while for sagittal plane perturbations, subjects stood normally on the treadmill. To standardize stance width, participants were instructed to keep their toes aligned with pieces of tape marking their pelvis width (defined as the inter-ASIS distance between the anterior superior illiac spines). Blocks were given in increasing magnitudes, and directions were randomized within each block. Participants were instructed to look straight ahead, keep their arms crossed, and “do your best to maintain your balance without lifting your feet from the treadmill”.

2.2 Motor Module Extraction

Presented below is an overview of the general steps for motor module extraction. Details about data preparation specific to each study are described further in the subsequent chapters.

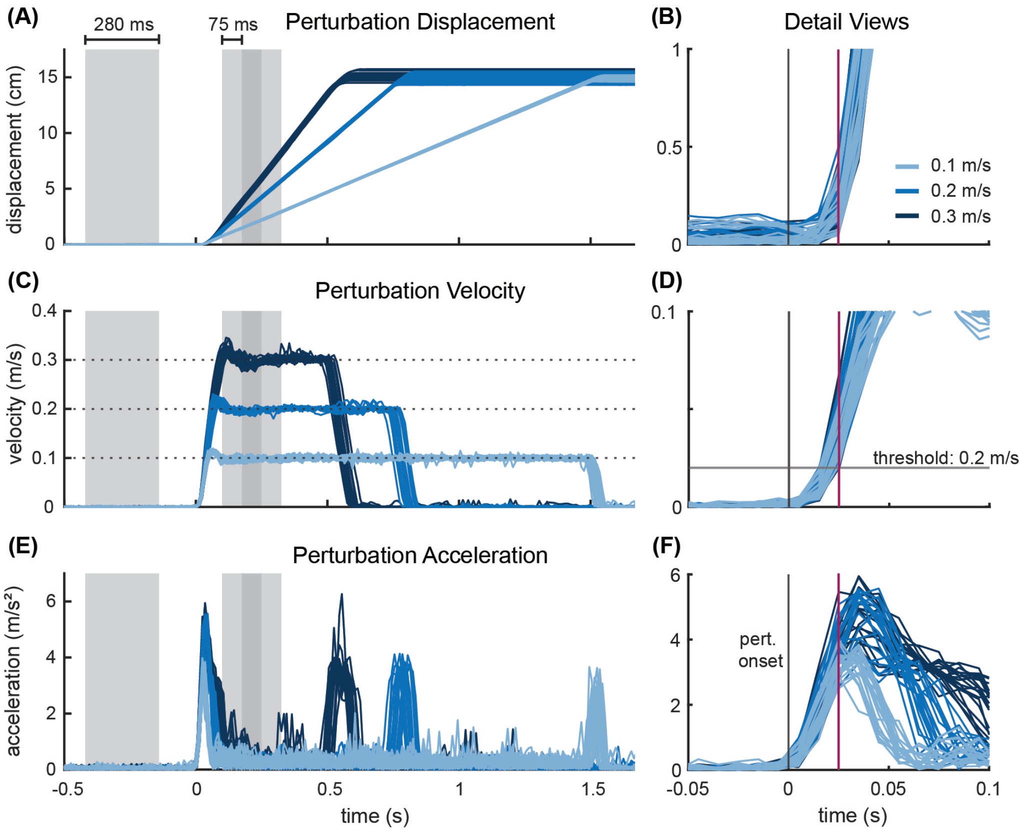

Figure 2.3: Perturbation traces for all trials in an example subject, across all directions and difficulty levels. (A) Perturbation displacements (in cm) and (B) detail view showing the perturbation onset (gray line). (C) Perturbation velocities and detail view (D). Perturbations were aligned by the first point (vertical pink line) that crossed a 0.02 m/s threshold (horizontal gray line). (E) Perturbation accelerations and detail view (F).

Motor module analysis takes a matrix of EMG and decomposes it into modules that sufficiently reconstruct the observed data such that $EMG = W \times C + error$ [38]. Motor modules are extracted such that the module weights (W's, illustrated by the bar plots in Fig. 2.4) remain consistent while allowing the coefficients (C's, illustrated by the line plots in Fig. 2.4) to vary to reconstruct the observed data. The Ws therefore represent muscle groupings and the Cs indicate how the motor modules are recruited over time or space.

Various decomposition methods can be used to extract motor modules, such as principal component analysis (PCA), non-negative matrix factorization (NMF), or independent component analysis (ICA). Here we use NMF to extract motor modules, as it provides a number of advantages, namely it identifies motor module vectors that are independent, non-negative, and define the subspace containing the data ([38]).

PCA identifies orthogonal components that describe the variance within a given data set. The components are ordered from the largest amount of variance explained to the smallest. For an n-dimensional data set, PCA always identifies n components, though usually the first k components that meet a threshold criteria are analyzed (e.g., needed to explain 90% of the overall variance) [38]. Conversely, NMF identifies components that are unordered, independent, non-negative, and tend to define the subspace containing the data ([38], for an illustration, see Fig. 5.2 in [38]). Motor modules identified using NMF can be easier to interpret physiologically, *specifically when using motor modules to investigate patterns of multi-muscle coordination.* For one, because motor modules are nonnegative, they can only represent muscle activity as positive (muscle contracting) or zero (muscle resting) whereas PCA allows subtractive elements that are less interpretable when focusing on patterns of muscle coactivation. Further details about the influence of algorithm selection on motor module results have been described in multiple publications (e.g., [38], [39], [40]) and have been shown to have a limited impact on extracted modular structure ([39]).

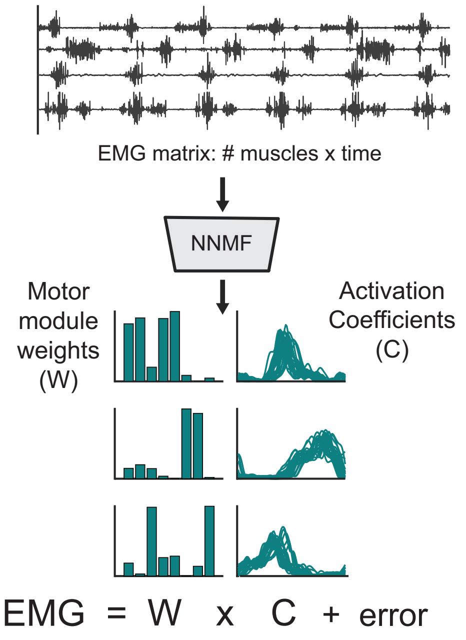

Figure 2.4: Non-negative matrix factorization takes an $m \times t$ matrix of EMG data and decomposes it into a set of motor module weights (W) and activation coefficients (C's). The W's represent which muscle are coordinated together, and the C's represent how each motor module is activated over time or space.

Motor module extraction generally consists of three main steps:

1. Preparing data matrix EMG data are first high pass filtered at 35 Hz to remove movement artifact, demeaned, rectified, and low pass filtered. We use a 10 Hz low pass filter in Chapters 3 and 4 when only voluntary tasks are analyzed. For reactive balance, EMG data are low pass filtered at 40 Hz to keep any high frequency perturbation responses; thus in Chapter 5, EMG from data from all tasks are low pass filtered at 40 Hz for consistency with reactive balance.

Filtered EMG data from each trial are concatenated to create an $m \times t$ data matrix, where m is the number of muscles and t is the total time for all trials. An alternative method is to use averaged data from all trials as the input to the extraction; however, since the purpose of NNMF is to reconstruct variance in the data, it is better to keep the trial-to-trial variability rather than wash it out by averaging ([40], [41]).

Data matrices for standing reactive balance are concatenated across perturbation directions rather than time. For each trial, the average EMG from 4 time bins are concatenated, one 280 ms background bin before the perturbation and three 75 ms bins during the automatic postural response (APR) defined as 100 to 325 ms after the perturbation onset (see Fig. 2.3 A, [24], [42]) Retroreflective tape markers along the edge of the treadmill were used to identify perturbation onset. Trials were aligned by the first frame with treadmill velocity ≥ 0.02 m/s (pink vertical lines in Fig. 2.3 B, D, & F); the perturbation onset was defined as 2.5 frames before this point (chosen to correspond with acceleration onset, gray vertical lines in Fig. 2.3 B, D, & F).

Next, each muscle in the EMG matrix is normalized to a chosen value. Here we normalize EMG for all conditions to the maximum values during self-selected walking. To avoid biasing the extraction towards any muscle, EMG matrices are scaled to unit variance before the extraction, and then unscaled afterward.

If motor modules are extracted for each condition, a separate data matrix is created for each condition and leg.

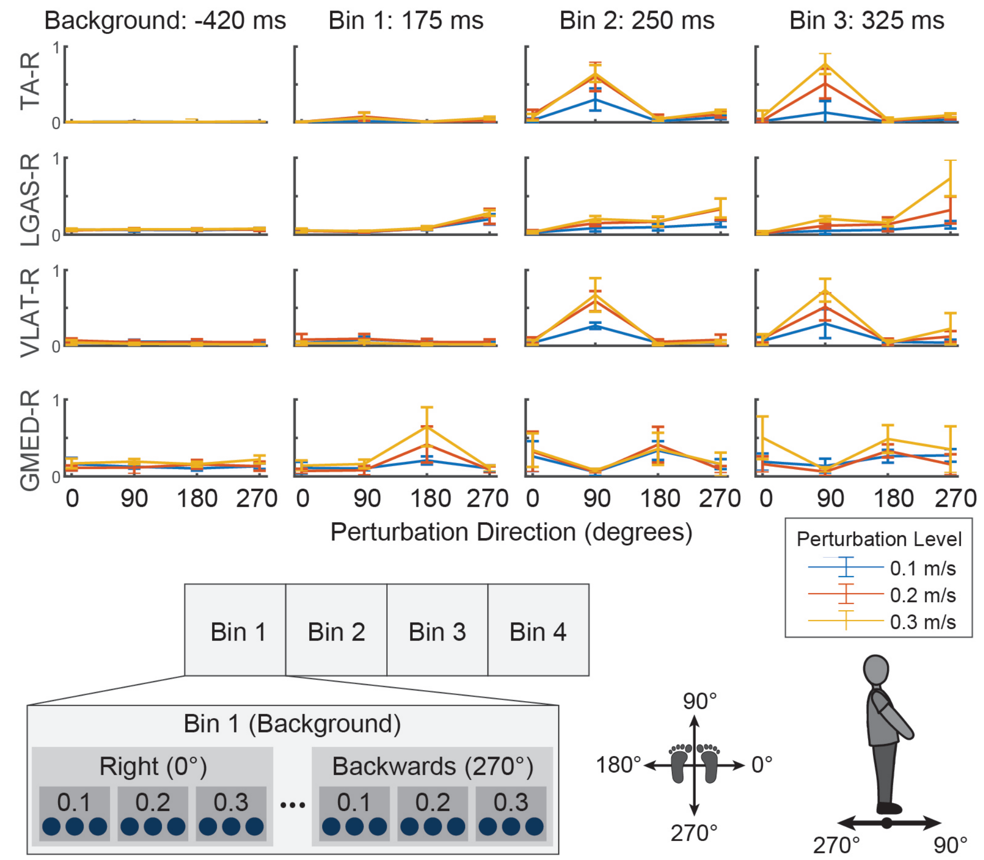

Figure 2.5: Data matrix assembly for standing reactive balance. Shown here are 4 individual muscle tuning curves for an example subject (TA, LGAS, VLAT, and GMED). TA is mostly active during the forwards perturbation (90°) in the Bins 2 and 3, while LGAS is most active during the backwards perturbation (270°). Below is an illustration of the matrix hierarchy for standing reactive balance; here each small circle represents the average muscle activity in a given bin and trial (i.e., each circle represents an $n \times 1$ array, where n is the number of muscles.

2. Extract Motor Modules

We extract motor modules using MATLAB's "nnmf" function (options: "mult" algorithm, 50 replicates, MaxIter = 1000, TolFun = 1e- 6, and TolX = 1e- 4) [43]. The NMF algorithm begins with a guess for W and C (which can either be random or defined) and refines them until the error between the original and reconstructed EMG is minimized. To avoid solutions that are caught in local minima, this process is repeated with

50 random initial guesses for W and C. Additionally, NMF requires the user to define the number of motor modules ahead of time; we extract 1-12 motor modules from each EMG matrix, then select the minimum number of motor modules that best meets the criteria for good reconstruction. The reconstruction quality between the original and reconstructed EMG is evaluated by the variance accounted for (VAF), or the squared uncentered Pearson's correlation coefficient between the original and reconstructed EMG ($EMG = W \times C$) [44]. We generate 95% confidence intervals (CI) on the VAF with a bootstrapping procedure in which motor modules are extracted from a subset of the EMG (resampled 250 times with replacement).

3. Motor module complexity – motor module number and VAF-by-1

Motor modules can be used to quantify neuromuscular complexity, where more modules indicate higher complexity. For example, people with some neurological impairments like stroke [11] or cerebral palsy [22] are shown to exhibit simpler neuromuscular control strategies than healthy populations. The number of motor modules recruited is one common method for describing complexity. We determine the number of motor modules for a given condition as the minimum number of modules such that the lower bound of the 95% CI on the VAF is greater than 90%.

Another method for quantifying complexity is in the variance accounted for by extracting just one motor module (VAF-by-1) [22]. High VAF-by-1 indicates one motor module alone can account for a large portion of the variance and likely only a small total number of modules would be needed to reconstruct the EMG data. Conversely, low VAF-by-1 suggests that more motor modules are required to effectively reconstruct the observed EMG and that the subject has a larger and therefore more complex muscle activity.

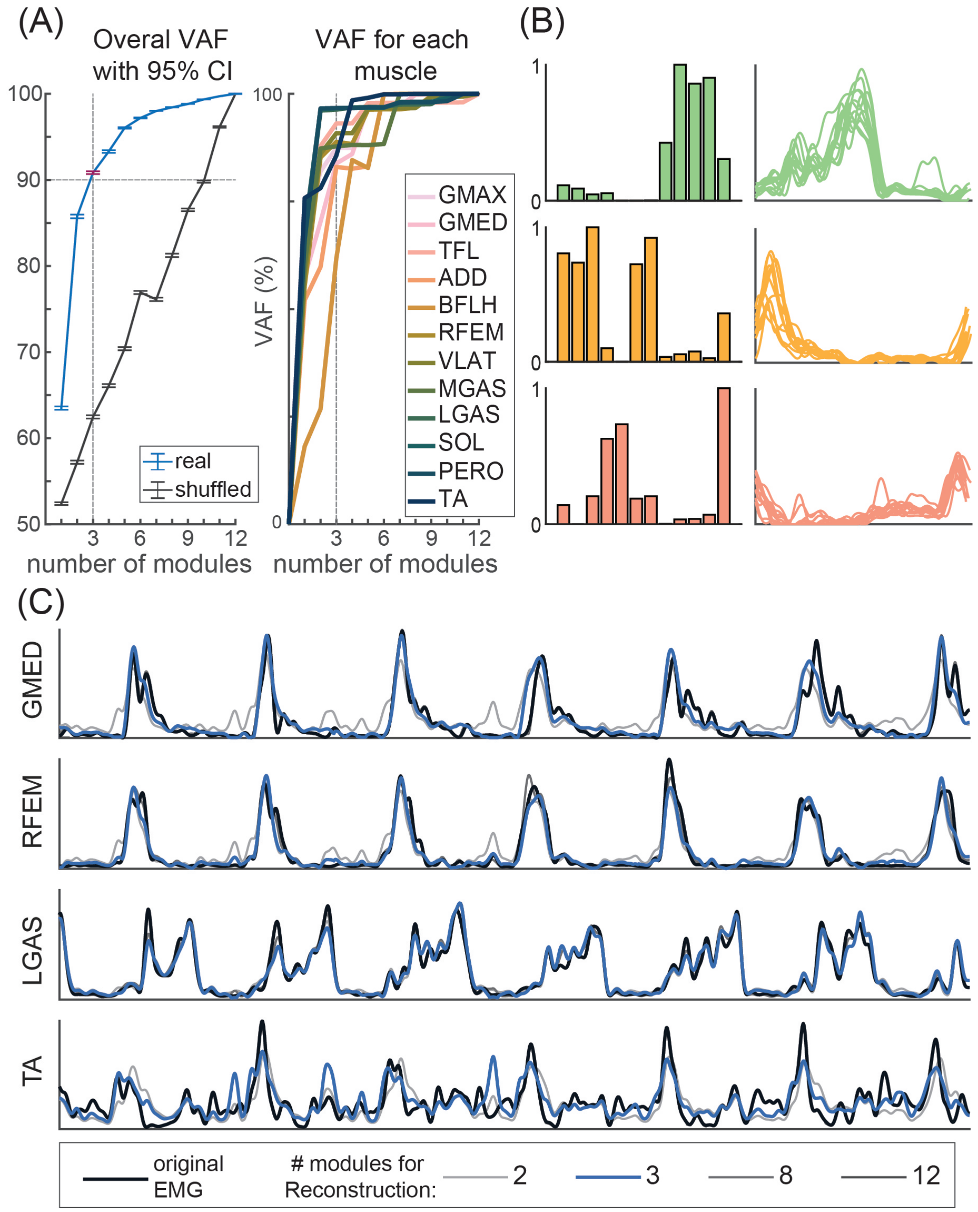

Figure 2.6: Motor module extraction for voluntary tasks - from an example subject during treadmill walking at self-selected speed. (A) VAF plots. The left panel shows the overall VAF and confidence intervals for original (blue) and shuffled EMG data (gray) with increasing number of motor modules. The right panel shows the VAF for each muscle as motor module number increases. The number of motor modules is selected such that the lower bound of the 95% CI is greater than 90% (here 3 modules). The variance accounted for by one motor module (VAF-by-1) here is (about) 65%. (B) Motor modules from an example subject. Bar plots represent the motor module weights (Ws) and the line plots represent the activation coefficients (Cs, here shown per gait cycle). (D) Original EMG data (black) and reconstructed EMG for increasing number of motor modules (gray, with 3 modules shown in blue).

3 Neuromuscular Generalization Across Voluntary Tasks

Sections 3.1-3.5 of this chapter were published as *Young adults recruit similar motor modules across walking, turning, and chair transfers* in *Physiological Reports* in 2021.
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3.1 Introduction

Moving about in the world during daily life requires executing and successfully shifting between a variety of functional tasks, such as rising from a chair or bed, walking, turning, and navigating stairs, etc. This multi-task nature of daily life is recognized clinically, with many clinical tests of mobility assessing multiple functional tasks (e.g. Timed-Up-and-Go test [3], Berg Balance test [45], Mini BESTest [46]). In contrast, the neuromuscular control underlying the execution of and coordination between different functional tasks is less understood. Although the neuromuscular control of different functional tasks have been studied in isolation (e.g., locomotion [47], standing [48], etc.), little is known about how neuromuscular control compares across different functional tasks. A better understanding of neuromuscular control across different functional tasks will provide valuable insight into the strategies that enable us to successfully navigate the many tasks required for daily life.

Motor module analysis is commonly used to investigate neuromuscular control strategies during movement (e.g., [11], [15], [22], [26], [49], [50], [51], [52], [53], etc.). Motor modules, or muscle synergies, are groups of coactive muscles flexibly recruited over time to meet the biomechanical demands required of a functional task [6]. To date, motor module analysis has primarily been used to investigate neuromuscular control within a single functional task. Such studies provide evidence that similar motor modules are recruited within the same functional task under different task demands, such as level versus inclined running [28], varied pedaling speeds [27], straight versus curved walking [54], and reactive balance during different stance positions [35]. In each case, changing musculoskeletal configurations or mechanical demands were addressed with changes in temporal activation and/or incorporation of task-specific motor modules rather than a new set of modules for each condition. While this implies that the nervous system may rely on a common set of motor modules to accomplish a variety of conditions for a particular task, we do not know whether this motor module generalizability extends to a broader range of functionally different tasks.

Motor module generalization, or recruiting common motor modules across functionally different tasks, may enable the successful execution and switching between tasks. Initial evidence for motor module generalization comes from animal studies, where, for example, frogs were found to recruit common motor modules across walking, swimming, and jumping tasks [12]. Although seemingly all locomotive tasks, the joint mechanics required to produce them are different in each task. More recently, evidence that such motor module generalization also occurs in humans has emerged. In particular, we recently found that young adults recruit common motor modules across standing reactive balance and unperturbed walking [34] and that reduced generalization across these two functionally different tasks was associated with impaired gait, balance, and mobility performance in both neurotypical and neurologically impaired populations (e.g. young adults [34], stroke [36], PD [24], the extent to which motor modules are generalized across the wider range of functional tasks encountered during daily life (e.g., walking, turning, chair transfers, etc.) remains unclear.

3.2 Methods

Participants

Thirteen healthy young adults (5 M, 21.4±1.6 yrs) participated in this study. Inclusion criteria was age between 18-35 years old. Exclusion criteria were any diagnosed neurological or psychological conditions, musculoskeletal conditions, sensory deficits, stroke, traumatic brain injury, or a concussion or other injury within a year of participation. All participants provided written informed consent before participating according to an experimental protocol approved by the institutional review board of West Virginia University.

Data Collection and Processing

Each subject performed the TUG test (illustrated in Fig. 3.1 A) first while walking normally (TUG) and then while counting backwards by three's (TUGC). For TUGC, subjects were instructed to pay equal attention to both the counting and walking tasks. Subjects self-selected which direction they turned around the cone until 10 trials of one turn direction were completed. Then we instructed them to turn the opposite direction for an additional 10 trials. Turning direction when sitting back down in the chair was not enforced. Some trials were removed before analyzing due to experimental or equipment error (n=25, 5% of total trials) or subject error (e.g., kicking the cone, n=21, 4% of total trials). In both conditions, each subject completed the TUG test with at least 6 good trials for each turn direction around the cone (avg: TUG 9.46±1.42, TUGC 10.12±1.30).

Three-dimensional marker position was collected at 100 Hz with a 10 camera Vicon motion capture system and a modified plug-in gait marker set with 31 markers placed on the head, trunk, pelvis, thigh, shank, and foot segments. Marker data from the heels, toes, and clavicle were used to segment the TUG test into 4 subtasks: Sit-to-Stand, Walk, Turn, and Stand-to-Sit. The two walking portions were combined into one subtask and turn directions for both the Turning and Stand-to-Sit subtasks were considered separately (e.g., right turn vs. left turn) for a maximum total of 6 subtasks. Turning direction during Stand-to-Sit was not enforced; some subjects consistently chose one direction for every trial and therefore only had 5 different subtasks. Details of TUG segmentation are listed in Table 1 and an example can be found in the supplementary material (Fig. B.1).

Surface EMG data were collected at 1000 Hz from 12 muscles per leg: gluteus maximus (GMAX), gluteus medius (GMED), tensor fasciae latae (TFL), adductor magnus (ADD), biceps femoris long head (BFLH), rectus femoris (RFEM), vastus lateralis (VLAT), medial and lateral gastrocnemius (MGAS and LGAS), soleus (SOL), peroneus (PERO), and tibialis anterior (TA). EMG data were high-pass filtered at 35 Hz (3rd order Butterworth filter), demeaned, rectified, and then low-pass filtered at 10 Hz (3rd order Butterworth filter) using custom MATLAB scripts (example EMG in TUG, Fig.3.1 B). For each subject, leg, and condition, separate EMG matrices were generated by concatenating data from all trials for that condition

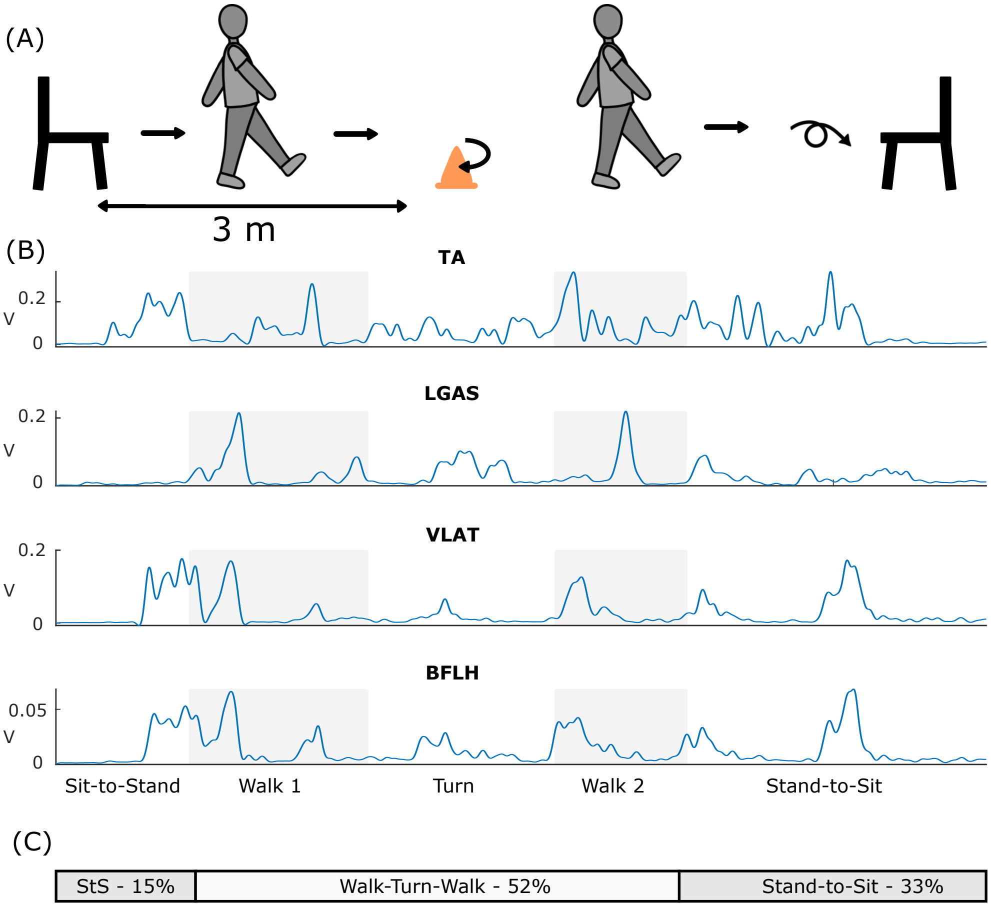


Figure 3.1: The Timed-Up-and-Go(TUG) test. (a) In the TUG test, subjects get up from a chair, walk around a cone3 m away, walk back to the chair, and sit back down. (b) Example muscle activity from selected muscles (tibialis anterior [TA], lateral gastrocnemius [LGAS], vastus lateralis [VLAT], and biceps femoris long head [BFLH]) during the TUG test with labeled subtasks. Gray boxes indicate the walking portions of TUG, while white sections indicate Sit-to-Stand, Turn, and Stand-to-Sit. (c) The subtask proportions used during activation analyses (see Section 2.3.2)

end-to-end to form an $m \times t$ matrix, where m is the number of muscles and t is the number of timepoints (equal to the number of trials × the number of timepoints per trial). For each condition (TUG and TUGC), there were 6 or 7 different EMG matrices per subject and leg - each subtask plus the full TUG test. Those subjects who consistently turned in the same direction when sitting back down had 6 matrices, whereas those who mixed their

Table 3.1: Criteria used to separate subtasks of the TUG test

Event	**Marker**	**Definition**	**Explanation**
1-TUG start	Clavicle	Local minimum in X direction	start of forward movement
2-walk 1 start	Toe	local minimum in Z direction	first toe-off
3-turn start	heel	local minimum in Z direction	last heel strike before turning (feet facing straight ahead)
4-turn stop	toe	local minimum in Z direction	last toe-off before walking straight (feet facing straight ahead)
5-walk 2 stop	heel	local minimum in Z direction	last heel strike before turning to sit
6-TUG stop	clavicle	local minimum in X direction	end of backward movement

turning direction when sitting down had 7. Each EMG matrix was then normalized to the maximum observed value for each muscle in the EMG matrix for the full TUG test.

Motor Module Extraction and Analysis

Motor modules were separately extracted from the EMG data matrix for each subject, leg (left vs. right), condition (TUG vs. TUGC), and sub-task (i.e., the full TUG test and each TUG subtask) using non-negative matrix factorization (MATLAB's 'nnmf' function, with the following options: 'mult' algorithm, 50 replicates, MaxIter=1000, TolFun =1e-6, and TolX=1e-4). Motor modules were extracted such that $EMG = W \times C + \epsilon$, where W is an $m \times n$ matrix of the n motor module weights for m muscles, C is an $n \times t$ matrix containing the activation coefficients for each module, and ϵ is the EMG reconstruction error. Motor module weights (W) are time-invariant, while the activation coefficients (C) may vary across trials as needed to reconstruct the observed EMG. To ensure equal weight of each muscle during the extraction process and avoid biasing towards muscles with high variance and amplitude, the data for each muscle were scaled to unit variance before motor module extraction and then rescaled to original units afterwards [9]. After extraction, module weights (W's) and activation coefficients (C's) were normalized such that the peak weight in each module was equal to 1.

We extracted 1-12 motor modules from each EMG matrix and selected the minimum number needed to sufficiently reconstruct the original data. Module numbers were chosen such that the 95% confidence interval of the overall variance accounted for (VAF) was greater than 90% [50], VAF is the squared uncentered Pearson's correlation coefficient between the reconstructed EMG ($W \times C$) and the original EMG [44]. 95% confidence intervals on the VAF were generated using a bootstrapping procedure (250 samples with replacement) [55], [56]. We then examined motor module generalization and the impact of the cognitive task as follows:

Generalization of motor modules across tasks

To investigate motor module generalization during the TUG test, we used a clustering analysis to group similar modules recruited during the TUG subtasks. For each subject we determined (1) the level of motor module generalization across TUG subtasks, (2) the level of similarity between clustered motor modules, and (3) the level of similarity between modules recruited during TUG subtasks to those recruited during the full TUG test. Examples of these metrics are shown in Figure 2 and their calculations are described below.

1. Motor module generalization. Motor modules recruited during TUG subtasks in the normal condition were separately pooled for each subject and leg and then sorted with a clustering algorithm [11]. The 'cluster' function from the MATLAB Statistics and Machine Learning Toolbox was used to cluster the modules, with the distance metric Minkowski order p=3 and Ward's linkage option. The number of clusters within each group was

determined as the minimum number such that each cluster contained no more than one motor module from each subtask [11], [36], [50],

$$\text{module generalization} = 100\% * \left(1 - \frac{c - n_{min}}{sum(n_i)}\right)$$

where c is the number of clusters, n_i is the number of modules recruited during the i^{th} subtask, T is the total number of subtasks (5 or 6 per subject, depending on whether a subject turned in both directions in the Stand-to-Sit turns or not), and n_{min} is the smallest number of modules recruited in that subject and leg during any subtask. Figure 3.2 illustrates a representative subject whose modules were sorted into 5 clusters with 91.7% generalization.

2. Within-cluster motor module similarity. To assess module similarity within each cluster, we calculated the cluster consistency as the pairwise linear correlation coefficient between all modules in each cluster and averaged for each subject and leg. Module pairs with $r \geq 0.7079$, the critical r value for $\alpha = 0.01$ (for n = 12 muscles, n–2 = 10 degrees of freedom, two-tailed test), were considered similar.

3. Similarity between sub-task and full TUG motor modules. Finally, to determine the similarity of modules identified during the TUG subtasks to modules from the full TUG test, motor modules from the full TUG test were compared to averaged modules from each cluster using Pearson's correlation coefficients, again with a similarity threshold of $r \geq 0.7079$ (example comparison illustrated in Fig. 3.2)

Effects of a cognitive task on motor module recruitment

To characterize the effects of a secondary cognitive task on motor module recruitment, we compared both the spatial and temporal aspects of motor modules recruited during TUG versus TUGC.

We analyzed spatial effects by comparing (1) motor module number and (2) motor module composition between TUG and TUGC. The number of motor modules recruited during TUG and TUGC were compared using paired t-tests for the full TUG test and each of its subtasks (7 total). Motor module composition (W's) from TUG and TUGC for the full TUG and each subtask were compared using Pearson's correlation coefficients, where module pairs

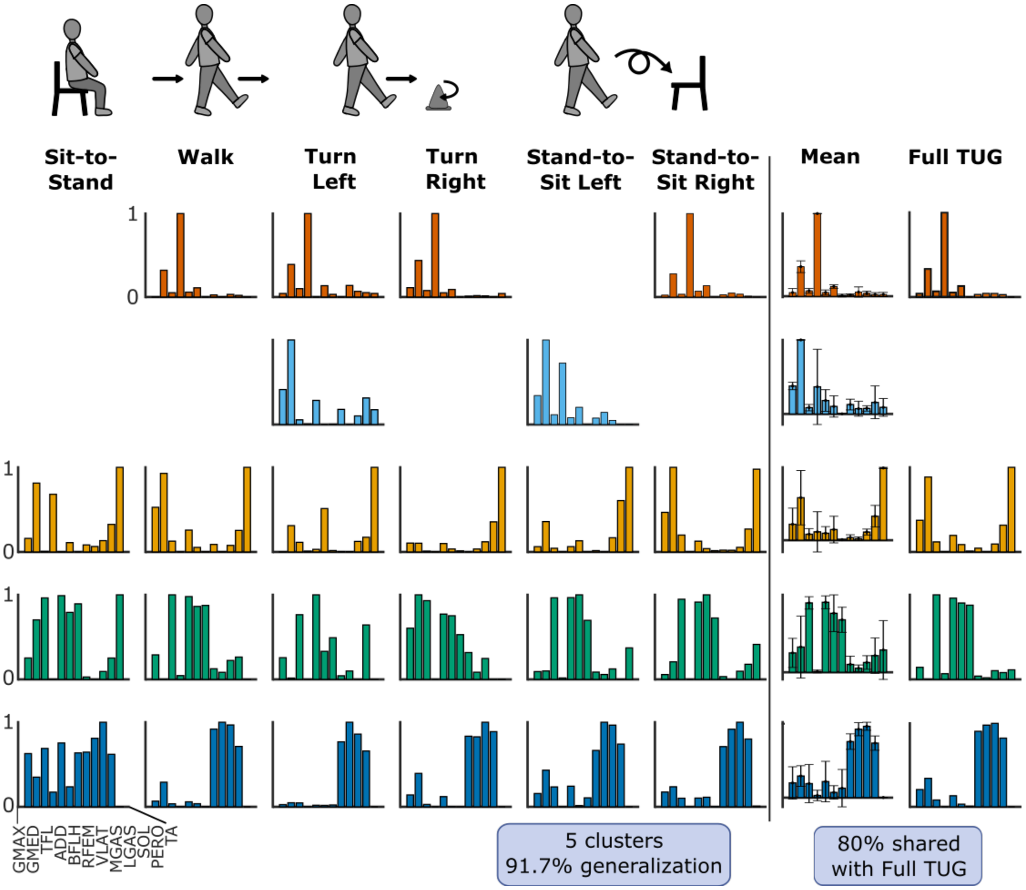


Figure 3.2: Example of clustered motor modules for a representative subject's left leg. The first six columns contain the motor modules recruited during each TUG subtask. Modules in the same row were clustered together. The second column from the right shows the average modules for each cluster and the last column contains the motor modules from the full TUG test. In this example, the subject had five clusters and 91.6% generalization. There are four common motor modules between the full TUG test and the cluster averages, giving 80% in common

with correlation coefficients $r \geq 0.7079$ were considered the same. We also identified how many modules were common between TUG and TUGC by calculating the percentage of common modules, defined as,

$$\% \text{ common} = 100\% * \left(\frac{\# \text{ common}}{\text{sum total in TUG and TUGC} - \# \text{ common}} \right)$$

for each subject, leg, and subtask.

We analyzed temporal effects by comparing motor module recruitment variability between TUG and TUGC. Motor module activation coefficients (C's) for each module were first separated by trial. Each trial was then time-normalized to be the same number of data points and such that the lengths of the chair transfers and walking-turning portions were consistent. Specifically, for each trial we calculated the proportion of each segment as subtask time TUG time. We then averaged these values across all trials and subjects and rounded to the nearest whole number for each TUG segment (Fig. 3.1 C.). Each trial was then normalized to be 1024 points long, with 154 data points in sit-to-stand, 532 points in walking-turning, and 338 points in stand-to-sit. See Fig S2 and "Normalization of Motor Module Activations" in the Supplementary Material for an example and further details. We then separated the trials based on "kinematic strategy", defined as the sequence of first step leg, turn direction, and Stand-to-Sit turn direction. We separated trials in this way because the shapes of motor module activation curves vary based on the TUG kinematic strategy used (e.g., which leg was used to take the first step) without representing true changes in motor module recruitment. To account for this, we only compared the time-normalized module activations from sequences that a subject used in both TUG and TUGC. Specifically, the average root-mean-square error (RMSE) of module activations from common motor modules across all subjects, legs, and tasks were compared using a paired t-test. See Fig. B.3, Table B.2, and "*Kinematic Strategy Separation*" in the Supplementary Material for an example and further details.

Effects of dual task on TUG and counting performance

Finally, to investigate dual-task effects on cognitive performance (i.e., counting backwards by threes from a random number), we compared the counting score and counting rate during TUGC to baseline counting performance. Baseline counting performance was collected while subjects were seated in the chair for 15 seconds (minimum 2 baseline trials). Subjects were instructed to repeat the given number and then for each TUGC trial, the counting score was calculated as

$$s = \frac{c_c}{c_t}$$

and the counting rate as

$$r = \frac{c_t}{t}$$

where s is the counting score, r is the counting race, c_c is the number of correct counts, and c_t is the total number of counts. Counting scores during both TUGC and the baseline were highly skewed towards 1 (Shapiro-Wilk (sw) test statistics: baseline sw=0.50, p<0.001, TUGC sw=0.82, p=0.01), so they were compared using a Wilcoxon signed rank test (α=0.025). Counting rates during TUGC and the baseline fit within a normal distribution and were compared using a paired t-test (baseline sw=0.97, p=0.88, TUG sw=0.92, p=0.22). TUG performance times with and without the cognitive task were compared using a paired t-test.

3.3 Results

Subjects recruited a small number of unique modules that were similar across TUG subtasks. Motor modules from TUG subtasks were grouped into a small number of clusters (avg 5.6±0.99, Fig. 3.3 A), leading to a high percentage generalization (avg 89.23±3.41%, Fig. 3.3 B). Most clusters were consistent across subtasks (avg 0.80±0.06, Fig 3D), with only two of the 11 subjects having an average cluster consistency below the 0.7079 similarity threshold in one of their legs (avgs for each subject: 0.60,0.70). The averaged motor modules across all subtasks within each cluster were very similar to modules recruited during the full TUG test (avg r=0.789±0.115, Fig. 3.3 C).

Motor module composition was unchanged when performing the TUG test with the secondary cognitive task of counting backwards by threes. Subjects recruited an average of 4.5 motor modules during TUG (Fig. 3.4), which was not significantly different during TUGC (p=0.75, Fig. 3.5 A and Supplementary Data Table B.3). Similarly, there was no significant difference in the number of motor modules recruited during TUG and TUGC for any TUG subtask (see Supplementary Data Table B.3 for all t-test results). Subjects recruited motor modules with similar compositions during TUG vs TUGC. Motor modules were highly similar during full TUG (93.7±0.1%, Fig. 3.5 A). Modules were also similar in each subtask (avg across all subtasks: 78.7±0.2), though there was more inter-subject variability (range = 17-100%,

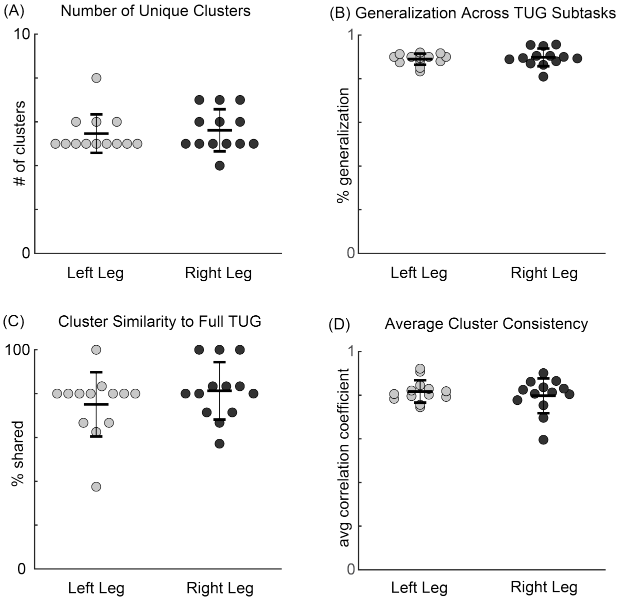


Figure 3.3: Motor module clustering results. For all panels, each dot represents one subject and leg (n = 13). (a) Motor modules were grouped into a small number of clusters across all subjects, (b) leading to a high percentage generalization. (c) Motor modules recruited during the full TUG test were well matched with the cluster averages and (d) Motor modules within each cluster were similar to each other, producing a high cluster consistency

Fig. 3.5 B). Further, most module pairs were more strongly correlated than the similarity threshold, illustrated in a histogram of pooled correlation coefficients (Fig. 3.5 C).

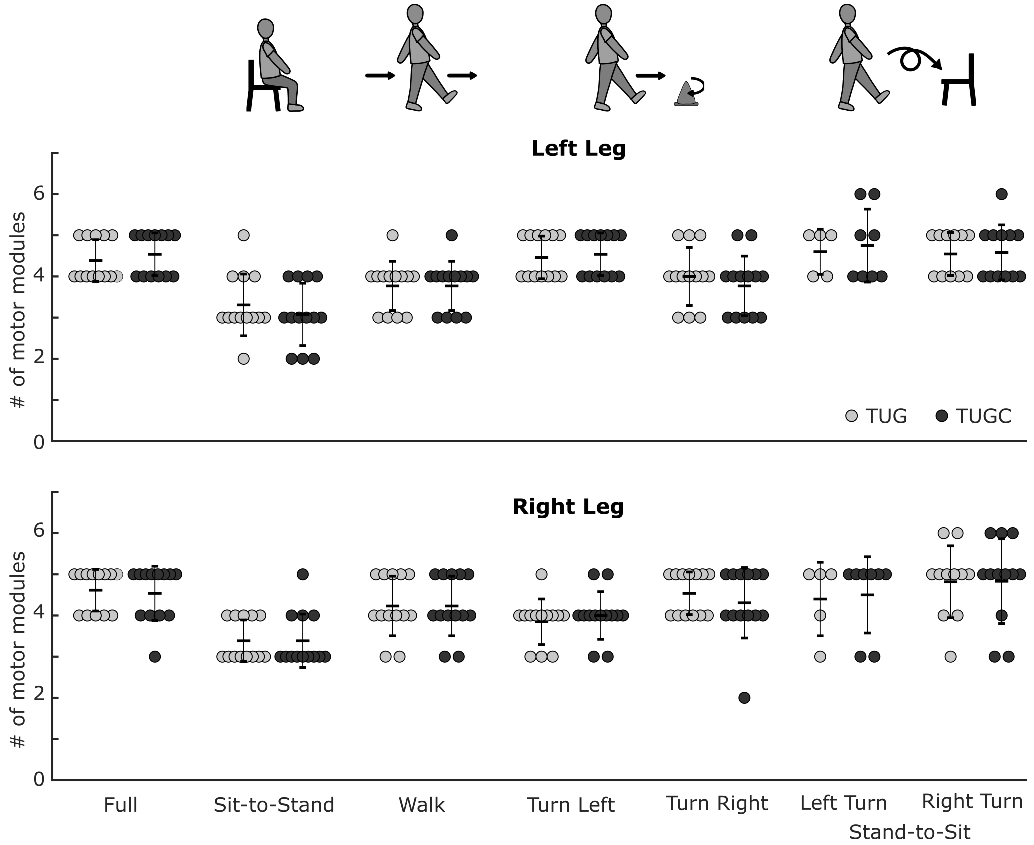


Figure 3.4: Number of motor modules recruited during the TUG test and its subtasks. The number of modules did not change between TUG and TUGC for the full TUG test, or any of the subtasks. (n = 13, paired t-test p = 0.75).

In contrast, motor module activation became more consistent across repetitions of the TUG test when counting backwards by threes. Motor module activation variability was significantly lower in TUGC than in TUG (avg rmse for TUG: 0.066±0.010, TUGC: 0.061±0.011, p=0.008, Fig 6B).

Importantly, the shape of the motor module activation curves varied depending on which leg took the first step, the turn direction, around the cone, and the turn direction when sitting back down (e.g., Fig. 3.6 A). Although most subjects used only two sequences (one for each turn direction around the cone), a smaller subset used 3-4 (Fig. 3.6 C) because they switched their turn direction when sitting down or varied the first step leg. Only

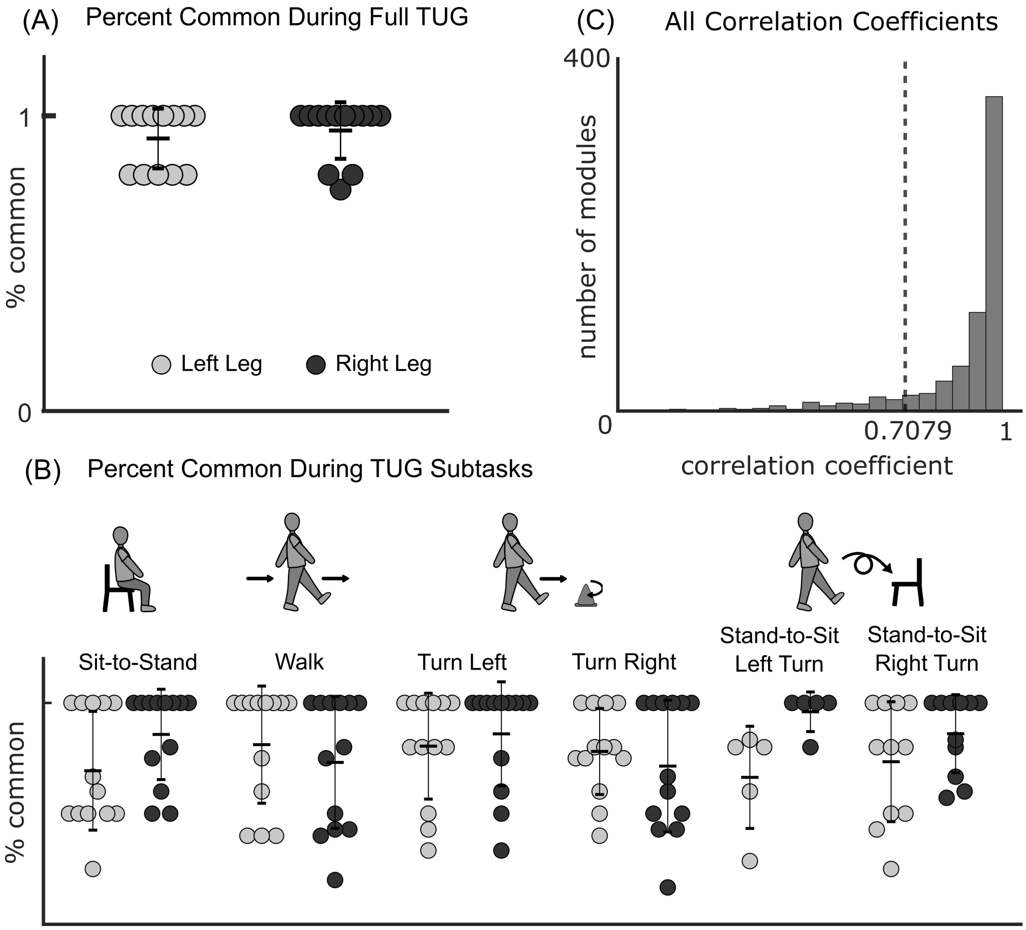


Figure 3.5: Motor module similarity during TUG and TUGC. (n = 13) Motor module composition was very similar during TUG and TUGC, leading to a high percentage common during (a) the full TUG test and (b) each of its subtasks and (c) very high correlation coefficients between all pairs of modules (pooled across all subjects and subtasks, the gray line represents the cutoff for significant similarity, $r \geq 0.7079$)

the module activations from trials with similar sequences were compared between TUG and TUGC (avg 8.9±2.1 trials per sequence; Fig. 3.6 D).

Dual task affected TUG time but not counting performance. The addition of a secondary cognitive task led to a significant but small difference in TUG performance time (TUG: 6.76±0.93 s, TUGC: 7.11±1.10 s, p=0.02, Fig. 3.7 A). Counting score (base: 0.93±0.13, TUGC: 0.93±0.20, p=0.23, Fig. 3.7 B) and counting rate (base: 0.6590±0.24, TUGC: 0.0.63±0.16 counts/s, p=0.31, Fig. 3.7 C) was not different between the baseline trial and TUGC.

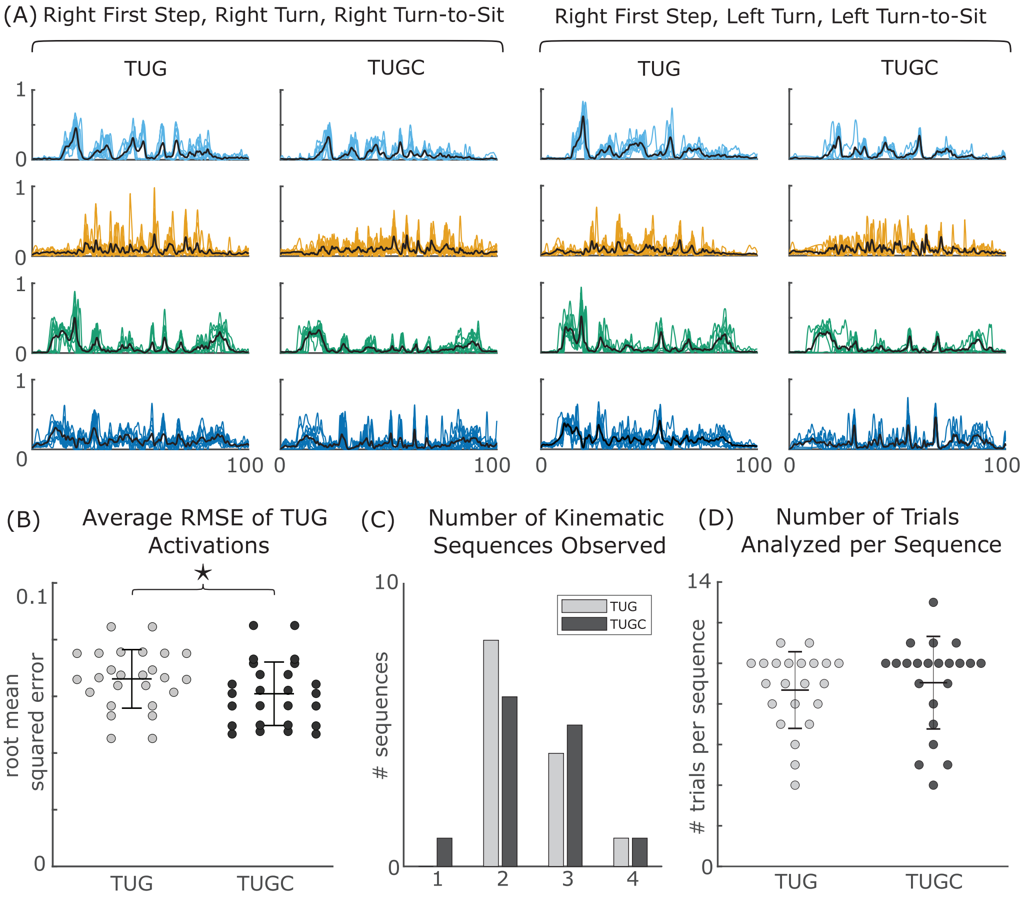


Figure 3.6: Temporal dual task effects. (a) Example module activations from the left leg of one subject in two kinematic strategies. (b) Average root mean squared error of motor module activations during TUG and TUGC (n = 26 legs, paired t-test p = 0.008). Module variability was significantly lower in TUGC than normal TUG. (c) Number of kinematic strategies (sequences) used by each subject. Across all trials, most subjects used 2–3 different kinematic strategies, but only had 1–2 strategies used in both TUG and TUGC. (d) Number of trials used in RMSE analysis, ranged from 4 to 13 trials per kinematic sequence

3.4 Discussion

The central nervous system may rely on generalizable control strategies to meet the multi-task demands of daily life. In support of this hypothesis, we

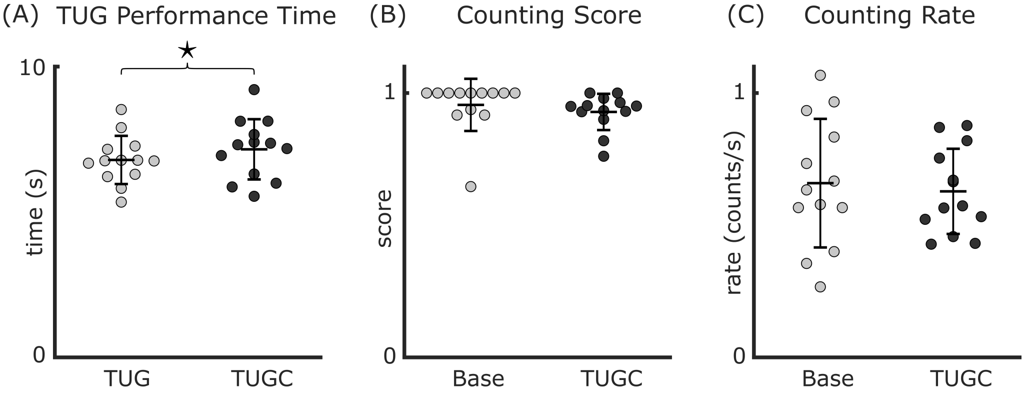


Figure 3.7: Dual Task Costs of the TUG test. (a) There was a small but significant increase in TUG performance time with the added counting task (n = 13, paired t-test p = 0.02). There was no change in either (b) counting accuracy (n = 13, Wilcoxon signed rank test p = 0.23) or (c) the counting speed (n = 13, paired t-test p = 0.22) from baseline to TUGC

show here that healthy young adults recruit a small set of generalizable motor modules across the subtasks of the TUG test and that the composition, but not the activation, of those motor modules is robust to cognitive distraction. This work is the first to demonstrate motor module generalization across multiple tasks that are both functionally different and crucial for healthy mobility.

Generalization of motor modules across tasks

Consistent with our hypothesis, our data suggest that young adults recruit a small set of generalizable motor modules across several functional tasks important for moving about in the world during daily life - walking, turning, and getting in and out of a chair. Prior work has demonstrated that the same motor modules are recruited to perform a single task under varying demands (e.g., pedaling at different speeds [27] or maintaining balance under different postural configurations [35]). Here, we expand upon this prior work to demonstrate that many of the same motor modules are recruited to perform different tasks.

Generalizing the recruitment of motor modules may enable the successful execution of similar basic mechanical demands required of different tasks. Except for turning, the tasks we examined are dominated by sagittal plane motion that likely require the achievement of similar basic mechanical demands such as plantarflexion, leg support, and center-of-mass stabilization. Even though our 180° turning task includes substantial non-sagittal plane motion, its successful performance also requires the achievement of many of these same demands. However, how these demands must be met and coordinated together to achieve successful task performance varies between tasks. For example, walking and sit-to-stand both involve propelling the center of mass forward and extending the limbs while keeping the foot fixed; however, sit-to-stand uses symmetric movements and includes a larger vertical COM movement, while walking alternates leg movements and requires stability during single leg stance [57], [58]. To meet these varying coordination requirements, we found that young adults modulated the recruitment (i.e., activation timing) and not the structure of the motor modules. We also found that most subjects recruited a plantarflexor module, knee extensor module, and a dorsiflexor module across all tasks. These motor modules are similar to those previously identified as important for meeting the mechanical demands of walking ([18], [59], [60]). Follow-up studies are needed to determine whether these generalized motor modules are indeed recruited to produce similar basic mechanical demands across different tasks.

Although many motor modules were generalized across all tasks, task-specific modules did emerge during turning. The emergence of task-specific modules is consistent with prior work. For example, Ivanenko and colleagues observed the emergence of task-specific modules when walking while performing an additional task (e.g., picking up an object or stepping over an obstacle) [30]. However, the emergence of turning-specific motor modules differs from a study by Chia Bejarano and colleagues in which similar motor modules were recruiting during walking and turning [54]. The contrasting results likely stem from differences in the differing radii of the turns and the mechanical demands they require. In [54], subjects walked around a circle with a 1.2 m radius, whereas in the current study subjects turn tightly around a cone or pivot on one leg to change direction 180° (see the left turns in Fig. 2). Such a tight turn may involve much more weight shifting and stepping changes than walking around a wider curve, and therefore are more likely to require additional motor module recruitment. For example, the inside turn leg would have increased demand for both stability and directing the turn. In our study, the turning-specific modules were often composed primarily of hip muscles

(GMAX, GMED, ADD); GMED specifically is known to be important for pelvic stability during single leg stance [61], [62], and contributes to mediolateral control of the center-of-mass [63]. The recruitment of such a module is consistent with increased demand for stability and frontal plane movements during this turn that may not be achievable using the generalized modules on their own. As turns are a common source of falls for people with mobility impairments (e.g., [1], [33], [64]), some of this difficulty could stem from an inability to appropriately recruit turning-specific motor modules. Overall, our results suggest that the nervous system reuses and modifies the same control strategies to execute and shift between similar tasks. When the mechanical demands for a task cannot be met by that module set, additional modules must be recruited.

Although the method used to cluster modules across tasks has been used both by us and others in previous studies (e.g., [11], [36], [65], [66], etc.), it is not without its limitations. In particular, motor modules were clustered primarily based on their dominant muscles and contributions from other muscles could vary between modules within a cluster. It is for this reason that we included a cluster similarity metric, in which we found that modules placed in each cluster were highly consistent in almost all subjects (9 of 11 subjects). Based on this intra-cluster similarity, we do not believe this clustering algorithm limitation affects our main conclusion that participants draw from a small library of motor modules to execute different tasks. However, future studies should explore the impacts of different clustering algorithms on motor module groupings.

Dual Task Effects

Consistent with our hypothesis, we found that motor module number and composition are robust to cognitive distraction. Moreover, we found that both TUG and counting performance were not affected by the cognitive-motor dual task condition. Though we identified a statistically significant increase in TUG performance timing in the dual-task condition, the increased time of 0.35s is substantially lower than the minimal detectable change that is on the order of seconds not sub-seconds (e.g., 1 s in individuals with knee osteoarthritis [67] and 3sin stroke survivors [68]). The lack of meaningful change in TUG time or counting performance suggests that our young adult population was able to successfully focus on the counting tasks enough to keep their performance consistent without compromising TUG performance.

Although motor module number and composition did not change in the presence of a cognitive distraction, motor module activation became more consistent. This result is in contrast with our hypothesis that activation would become more variable when cognitively distracted. Our finding that motor module activations became more consistent when performing the TUG test with a cognitive distraction could mean that subjects allowed their movements to become more automatic while they focused on the counting task, despite instructions to pay equal attention to both counting and TUG performance. Movements like walking require both automatic and executive control, but healthy young adults rely on more automatic control than other populations. In populations that use less automatic control for walking, such as older adults, walking and cognitive tasks compete for executive control resources, impeding performance in both tasks [59]. However, healthy young adults likely have enough automaticity and processing capacity to devote attention to the cognitive task while relying on automatic control to perform the TUG test. Our results of increased recruitment consistency are also in agreement with recent work demonstrating increased dynamic stability of motor modules under dual task conditions without corresponding effects on center of mass stability (in anterior/posterior or mediolateral directions [69]), suggesting an adjustment by the nervous system to prioritize stability during cognitive distractions.

Alternatively, the increased activation consistency could be related to the instructions, order of tasks, and/or difficulty of the cognitive task. TUGC trials were always performed second, and subjects may have been more confident paying less attention to their movements than if TUGC had occurred first. Additionally, subjects may not pay much attention to their initial TUG performance but become more focused during TUGC because of the instructions given. For the normal TUG test, subjects were given no instructions about their focus, and may have allowed their minds to wander during this repetitive and unchallenging task. During TUGC, they were told to pay equal attention to both the counting and TUG and may therefore have given the TUG performance more attention than they had previously, leading to more consistent motor module activations. Finally, it is also possible that our findings are influenced by the difficulty of the cognitive task. In particular, the serial subtraction by threes may have been too easy for our young adult population. Decker and colleagues demonstrated a U-shaped relationship between cognitive demand and gait control (measured through step length and width variabilities [70]); more changes in motor module activations could emerge with more difficult dual task conditions.

Though the underlying reasons for the change in motor module activations in the presence of cognitive distraction remain unclear, our results do suggest that cognitive distraction can impact motor module recruitment. Careful follow up studies could clarify the responses by incorporating a variety of cognitive distractions and controlling for practice effects. Understanding how cognitive distractions impact motor module recruitment and activation would provide further insight into the underlying neuromuscular control mechanisms in both healthy and balance impaired populations who may be more affected by cognitive dual tasking.

3.5 Conclusions

Our results support the hypothesis that healthy young adults recruit from a "library" of motor modules to meet the multi-tasks demands of daily life. Specifically, we found that a small number of common motor modules were recruited during walking, turning, and chair transfers and that their structure was robust to cognitive distraction. Achieving different mechanical and cognitive demands were accomplished through changes in motor module activation. This work is the first step towards a full characterization of motor module recruitment patterns in healthy adults across a wide range of daily life tasks. Our results provide a basis for interpreting the effects of motor module changes on mobility and fall risk during daily life that occur in populations with neural or musculoskeletal injuries.

4 Age-Related Changes in Neuromuscular Generalization

4.1 Introduction

Adults with good mobility can easily perform and transition between daily movement tasks, but older adults have more difficulty doing so. Aging causes declines throughout the neuromuscular system [4], [71], and results in mobility impairments such as poor balance [72], slow walking speeds [73], and susceptibility to distractions [74]. Reduced mobility leaves older adults with increased fall risk, fear of falling, and decreased independence and quality of life. Because healthy mobility requires a wide range of movement tasks, identifying age-related impacts on multi-task neuromuscular control could facilitate the development of more effective prevention methods.

Motor module analysis has been used to quantify changes in neuromuscular control associated with neurological disease and impairment. For example, in individuals with chronic stroke, recruiting fewer motor modules is associated with slower walking speeds and asymmetry [59] and functional impairment [75]. Similarly, fewer motor modules are identified in individuals with spinal cord injury [23], and children with cerebral palsy [22]. In fact, motor modules have often been used to investigate muscle coordination in populations with neurological impairments, yet they have infrequently been considered in healthy older adults.

Natural aging processes affect the neural, muscular, and skeletal systems in myriad ways. Muscles lose strength and mass [71], and bone density is reduced [76], making the potential consequences of a fall more severe. Changes in executive function and attention impact the ability to dual-task while moving [77]. Additionally, aging affects the connection between the nervous system and muscles, altering innervation, neuromuscular junctions, and the relationships between muscle excitation and contraction [4]. Factors such as these and many others could lead to changes in the repertoire of muscle coordination patterns available or how effectively they can be applied.

Though fewer motor modules have been observed in older adults with a fall history, older adults without a fall history appear to recruit the same number of motor modules as young adults [65], [78] but with more variability in the activation coefficients (C's) [65]. Unlike injury or disease such as stroke or spinal cord injury, normal aging likely does not impact the "library" of muscle coordination patterns that can be used, but instead how effectively and flexibly they can be applied. However, multi-task motor module recruitment has not yet been characterized in older adults (much less so in middle-aged adults).

In chapter 3, we demonstrated that healthy young adults recruit common motor modules during the subtasks of the TUG test; here, we investigate whether motor module generalization across these tasks changes with normal aging. We hypothesize that healthy adults, regardless of age, retain the ability to generalize muscle coordination patterns across voluntary tasks; therefore, we predict that young, middle-aged, and older adults will show similar levels of motor module generalization.

Additionally, in our previous work, we could not rule out that some of the motor module generalization was due to the lack of clear boundaries between the TUG subtasks. For example, during the "sit-to-stand" portion, subjects do not stand up, pause, and then begin walking; rather, they execute one fluid "sit-to-walk" motion and step off before fully extending their trunk. Accordingly, in sit-to-stand, subjects often recruited a well-defined plantarflexor module in the leg they used to step off but a less defined module in the opposite leg (for a non-stepping illustration: see the dark blue module grouped with the other plantarflexor modules in Chapter 3, Figure 2). It is, therefore, possible that some of the generalization we observed was due to the transitions between subtasks rather than to similarity between the tasks themselves. In other words, did we observe similar motor modules across tasks only because participants were preparing for (or even beginning) the next subtask before "finishing" the current one?

To more clearly determine whether similar motor modules are recruited during distinct voluntary tasks, we examined the TUG test and each of its subtasks performed separately: walking, turning (in figure-eights), and chair transfers. By including all these tasks, we can investigate distinct tasks (e.g., steady-state walking) and complex tasks with between-subtask transitions more reflective of real-world movement. Because task-specific motor modules tended to emerge during the turn subtasks in our previous work (see Chapter 3, section 4.1), we further hypothesize that the figure-eights and TUG test will each display turn-specific motor modules involving the gluteus muscles.

4.2 Methods

Participants

Ten healthy young adults (7 M, 21.3±2.4 yrs), 6 middle-aged adults (1 M, 58.2±5.1 yrs), and 6 older adults (1 M, 71.2±5.5 yrs) participated in this study. Inclusion criteria were age greater than 18 (classified as young adults: 18-35 yrs, middle-aged adults: 36-64 yrs, older adults: 65+ yrs). Exclusion criteria were any musculoskeletal conditions or concussion or injury within the last year. All participants provided written informed consent before participating according to an experimental protocol approved by the institutional review board of West Virginia University.

Experimental procedures

All participants performed a set of voluntary tasks: treadmill walking at self-selected speed, chair transfers, figure eight walking, and the TUG test. Each task is described in detail in Chapter 2.1.

Data collection and processing

Three-dimensional marker data were collected at 100 Hz with a 10-camera motion capture system (Vicon). We used a modified version of the plug-in gait marker system with 31 markers on the head, trunk, legs, and feet. Marker data were used to identify the beginning and end of the TUG, figure-eight, and chair transfer trials.

Surface electromyography data were collected from 12 muscles of the dominant leg spanning the hip, knee, and ankle, described in Chapter 2.1. EMG data were high pass filtered at 35 Hz, demeaned, rectified, and low pass filtered at 10 Hz using custom MATLAB code. Separate data matrices were created by concatenating EMG data from all trials for each subject and voluntary task. Sit-to-stand and stand-to-sit were analyzed as separate tasks, and each half of the figure-eight task was analyzed separately (to consider each turn direction separately), giving a total of 6 matrices for each subject: Treadmill self-selected (TM SS), figure-eight inside (Fig8 Inside), and outside turns (Fig8 Outside), TUG, Sit-to-Stand, and Stand-to-Sit.

Motor module analysis

Motor modules were extracted separately from the concatenated EMG data matrix for each subject and task (6 extractions per subject) using non-negative matrix factorization (as described in Chapter 2.2). Motor modules are extracted such that

$$EMG = W \times C + \epsilon$$

where ϵ is the EMG reconstruction error, W is an $m \times n$ matrix of n motor module weights for the m muscles and C is an $n \times$ time matrix of the activation coefficients for each motor module. EMG for each muscle was scaled to unit variance before extraction and then rescaled afterward to avoid biasing extraction to any muscle with higher variance.

We examined the following motor module metrics:

Motor module number and complexity: We extracted 1-12 motor modules from each EMG data matrix and selected the appropriate number of modules to accurately reconstruct the observed EMG, as described in Chapter 2.2. To compare motor module complexity, we calculated the VAF from extracting just one motor module (VAF-by-1, described in Chapter 2.2). Higher VAF-by-1 levels indicate fewer motor modules are needed to reconstruct the EMG data, and the task is considered less complex.

Motor module generalization: We used a hierarchical clustering algorithm ([11], also described in Chapter 3.2) to compare motor module composition for each subject across voluntary tasks (one clustering for each subject). The number of clusters was defined as the minimum number such that there was no more than one motor module from each task in each cluster [11], [36], [50]. Motor module generalization was then defined as

$$p = 100 \times \left(1 - \frac{c - n_{min}}{sum(n_i)}\right)$$

Where p is the percent generalization, n_i is the number of motor modules identified in the i^{th} task, n_{min} is the smallest number of modules identified in any task for that subject, and c is the number of clusters (see Chapter 3, Figure 3.2 for an example).

Motor module composition: As a secondary analysis, we characterized the motor modules recruited in each task using the same clustering algorithm to group modules across subjects, for each age group and task (6 tasks x 3 age groups = 18 separate sets of clusters). The number of clusters was defined similarly to above, but here we selected the minimum number of clusters such that there was no more than one module from each subject in a cluster [11], [36], [50].

Statistics

The primary measures of this study are the metrics of motor module generalization (i.e., percent generalization and number of clusters). We used separate one-way ANOVAs (MATLAB 'anova1') to compare each of these metrics across age.

As a secondary measure, we investigated whether motor module complexity changed across age or task. We compared module number and VAF-by-1 across age and task with separate two-way repeated measures ANOVAs (3×6 design: Age (YA, MA, OA) × Task (TM SS, Fig8-In, Fig8-Out, TUG, Sit-to-stand, Stand-to-sit). Pairwise t-tests were performed if there was a significant effect of task; two-sample t-tests with Hommel's corrections were performed for significant effects of age group. For all post hoc tests, p-values were adjusted using Hommel's corrections with $\alpha = 0.05$ [79].

4.3 Results

Motor module generalization:

All subjects shared a small number of motor modules across voluntary tasks (YA: 6.4±1.3, MA: 6.3±1.5, OA: 5.2±1.1 clusters). Accordingly, all subjects exhibited over 70% motor module generalization across tasks (YA: 82±4.8%, MA: 82±4.6%, OA: 86±5.2%). There was no significant difference in the number of clusters (F(2,18)=1.45, p=0.26) or percent generalization (F(2,18)=1.67, p=0.22) across age groups.

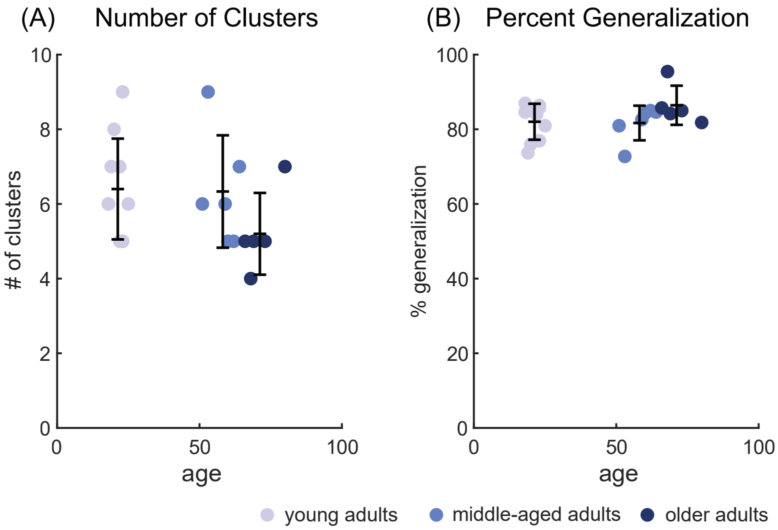
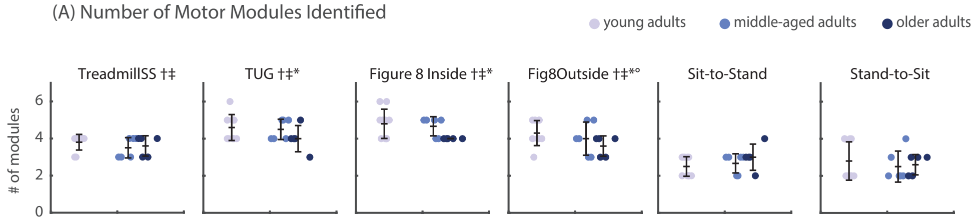
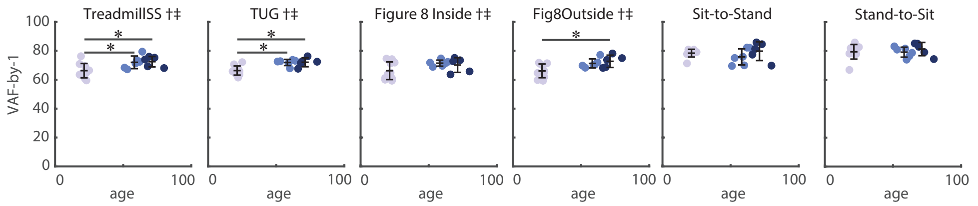


Figure 4.1: Motor module generalization. There was no significant effect of age on the number of motor modules shared across tasks (A) or the percentage generalization across tasks (B).



(A) Number of Motor Modules Identified



(B) Variance Accounted for by 1 Module

Figure 4.2: Motor module number and complexity during voluntary tasks. (A) The number of motor module recruited in each voluntary task. Though there was no difference in motor module number with age, chair transfers had significantly fewer modules than all other tasks. Fewer modules were identified during treadmill walking at self-selected speed than figure-eights and TUG. In figure-eight, more modules were identified in the inside turn than the outside turn. (B) VAF-by-1 in each task. There was a significant effect of task, age group, and their interaction on VAF-by-1. In general, VAF-by-1 increased with age during treadmill walking, TUG, and figure-eights. In young adults, VAF-by-1 was higher in chair transfers than other tasks; in middle-aged adults VAF-by-1 was higher in stand-to-sit than figure-eight inside and TUG. +: significantly different from sit-to-stand, ++: significantly different from stand-to-sit, *: significantly different from treadmill, o: significantly different from figure-eight outside.

Motor module number:

A two-way repeated measures ANOVA indicated a significant effect of task (F(5,90)=34.4, p<0.001), but not age group (F(2,18)=1.3, p=0.31), or the interaction (F(10,90)=1.2, p=0.29) on motor module number (Fig. 4.2 A). Post hoc t-tests indicated that all subjects had fewer motor modules in sit-to-stand than all other tasks except stand-to-sit (all p<0.001). Similarly, there were fewer motor modules identified during stand-to-sit than all other tasks except sit-to-stand (all p<0.001). Fewer motor module were identified in self-selected treadmill walking than figure-eight inside (p<0.001), outside (p=0.03), and TUG (p=0.001). Additionally, there were more motor modules in figure-eight during the inside turn than the outside turn (p=0.02).

VAF-by-1:

There was a significant effect of task (F(5,90) =38.1, p<0.001), age group (F(2,18)=3.8, p=0.042), and the interaction (F(10,90)=2.412, p=0.014) on VAF-by-1 (Figure 2B). Post hoc t-tests indicated VAF-by-1 was lower in young adults during TUG than in middle-aged adults (p=0.003) and older adults (p=0.004). VAF-by-1 was also lower in young adults than older adults in the outside leg of figure-eight (p=0.032), and higher in middle-aged adults (p=0.049) and older adults (p=0.044) than young adults during treadmill walking. Further, young adults had higher VAF-by-1 during chair transfers than figure-eight inside and outside, TUG, and treadmill walking (all p<0.001). Middle-aged adults also had higher VAF-by-1 during stand-to-sit than figure-eight inside (p=0.029) and TUG (p=0.003).

Motor Module Composition

Treadmill walking

For self-selected treadmill walking, we identified 7 clusters in both young and middle-aged adults and 4 clusters in older adults (shown in Fig. 4.3). All young adults recruited a plantarflexor module (Cluster A). Clusters B and C both include the gluteus, TFL, and quadriceps muscles, while cluster G is just the gluteus muscles (2 subjects – 1 subject combined MGAS here). Cluster D is dominated by TA, paired with assorted other muscles. Half of the young adults recruited a module that was dominated by ADD (Cluster E). Cluster F is mainly the hamstring, sometimes with other contributions.

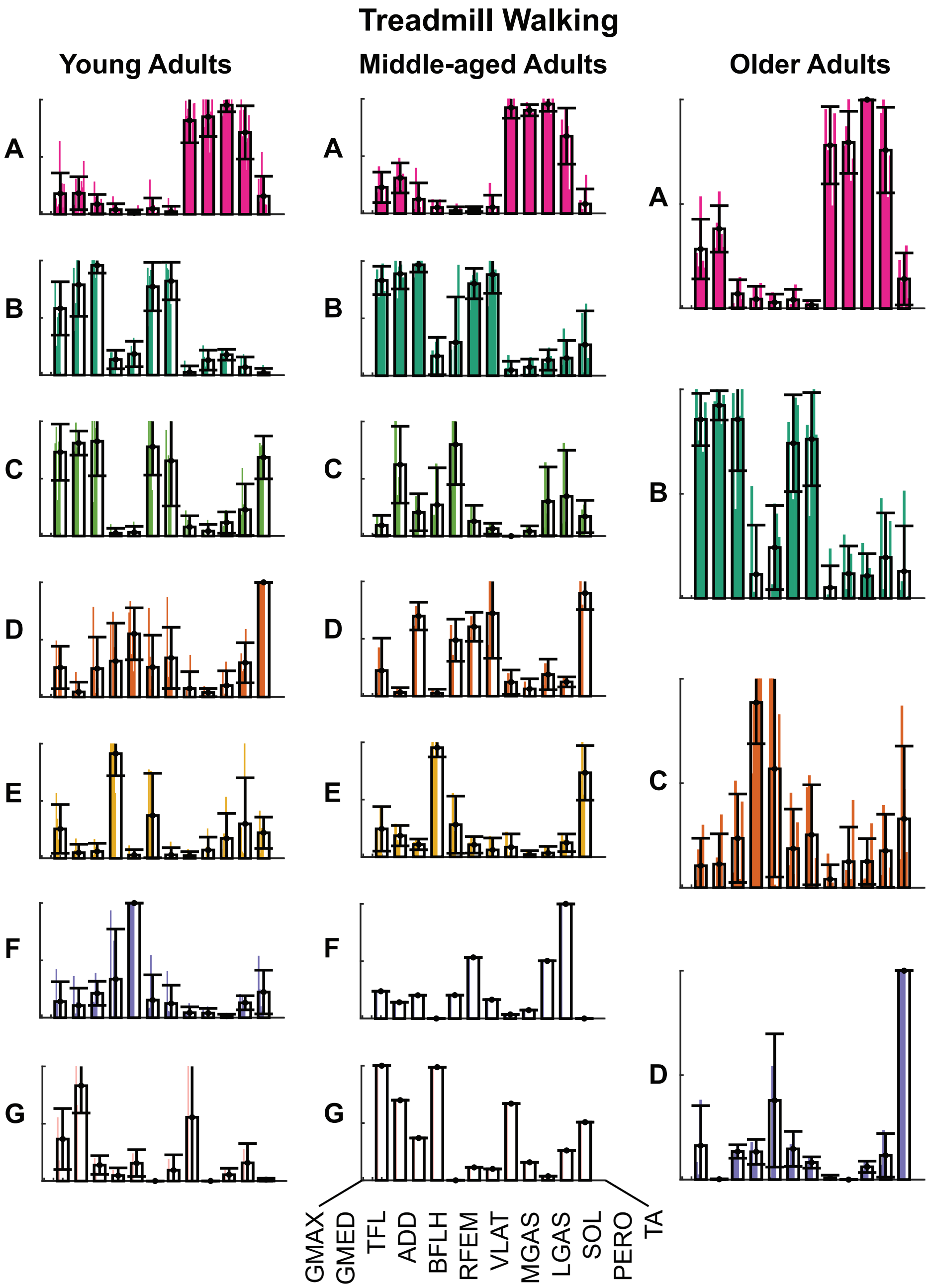


Figure 4.3: Motor modules clustered across subjects during treadmill walking. Module were grouped into 7 clusters for young and middle-aged adults and 4 clusters for older adults.

All middle-aged adults recruited a plantarflexor module (cluster A). Most (5/6) recruited a module with gluteus, TFL, and quadriceps muscles in Cluster B. Cluster C is a loose cluster dominated by the hamstring (3 subjects). Cluster D is TA paired with the quads and TFL (2 subjects). Cluster E contains ADD and TA (3 subjects). The remaining two clusters are subject specific modules.

All older adults recruited a plantarflexor module (A), a module with the gluteus, TFL, and quadriceps muscles (B), and a module with the adductor and hamstring (C). Cluster D was mainly the TA (and sometimes hamstring), recruited by three subjects. For the other two subjects TA was grouped with the hamstring in Cluster C.

TUG

For TUG, we identified 9 clusters in young adults, 7 clusters in middle-aged adults, and 5 clusters in older adults (shown in 4.4.

In young adults, 5 clusters included at least half of the subjects. All subjects had a plantarflexor module (Cluster A) and most (8/10) had a module dominated by ADD (Cluster D). Most also had Cluster B, composed of the gluteus and TFL muscles (and sometimes hamstring, 9 subjects). Cluster E was mainly TA, sometimes paired with RFEM (6 subjects). Cluster F was observed in 3 subjects and was mainly a separate RFEM. The remaining 3 clusters were loosely grouped subject-specific modules.

All middle-aged adults recruited a plantarflexor module (Cluster A). Cluster B was mainly gluteus muscles and some TFL (5/6 subjects) and Cluster C was mainly the quadriceps with some TFL (5/6 subjects). Cluster D was dominated by TA paired with other various muscles (4/6). Three subjects used Cluster E, dominated by ADD. Cluster F was mainly GMED and used by 2 subjects – one did not use Cluster B, the other did not have much GMED activation in Cluster B. The remaining cluster was mainly the hamstring and used by 2 subjects.

All older adults recruited a plantarflexor cluster (A). Cluster B included the gluteus and hamstring muscles (3/5 subjects). Cluster C was mainly TFL and the quadriceps (4 subjects), with more gluteus activity in those subjects who did not recruit cluster B. Cluster D was primarily composed of ADD (4 subjects). Cluster E was dominated by TA, sometimes with contributions from RFEM (4 subjects).

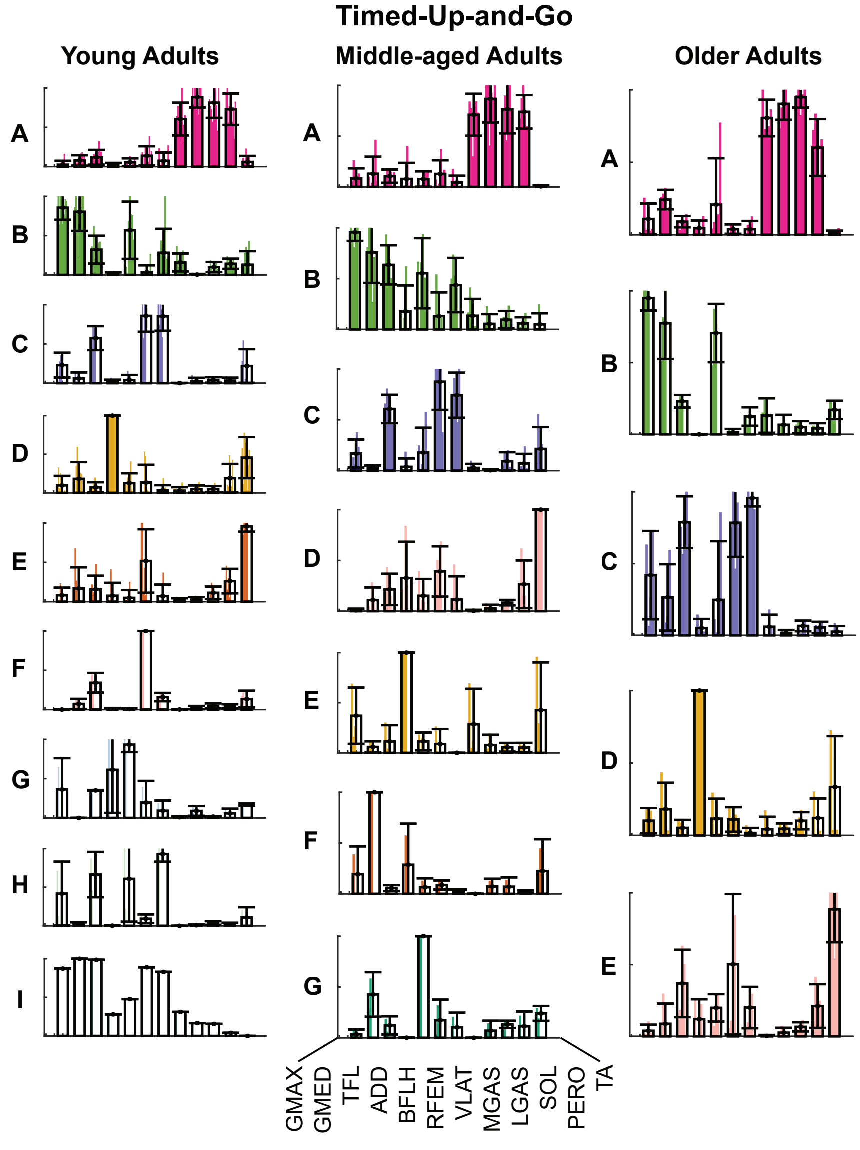


Figure 4.4: Motor modules clustered across subjects during Timed-Up-and-Go. Module were grouped into 9 clusters for young adults, 7 clusters for middle-aged adults and 5 clusters for older adults

Figure-eight - Inside Leg

For the inside leg of figure-eight walking, we identified 11 clusters in young adults, 6 clusters in middle-aged adults, and 5 clusters in older adults (shown in 4.5.

All young adults recruited a plantarflexor module. Most subjects also recruited a hamstring module (cluster B, 8 subjects) and an adductor module (cluster C, 7 subjects). Five clusters represented different combinations of gluteus, TFL, and quadriceps muscles. Cluster C (dark pink) include the quadriceps and TFL (6 subjects). Most subjects who recruited cluster C also had either cluster D (glutes and TA, 4 subjects) or cluster E (glutes, hamstring, and TA, 2 subjects), but not both. Cluster F was a loose grouping usually dominated by RFEM and sometimes TA in those who didn't use cluster C (5 subjects). The remaining clusters were misc. subject-specific.

Three clusters were observed in all middle-aged subjects: a plantarflexor cluster, a gluteus cluster, and a quadriceps/TFL cluster. Four subjects recruited a module dominated by ADD (cluster D). Three subjects recruited a TA module (cluster E) and three subjects recruited a module dominated by the hamstring (cluster F).

All older adult subjects recruited a plantarflexor module (Cluster A) and a module primarily composed of the quadriceps and TFL (sometimes with gluteal activity, Cluster B). Cluster C primarily included ADD and cluster E was mainly the hamstring and TA (3 subjects). The final cluster (D) was a loose grouping; it was mostly the TA and/or peroneus, but included GMED and GMAX in one subject (3/5).

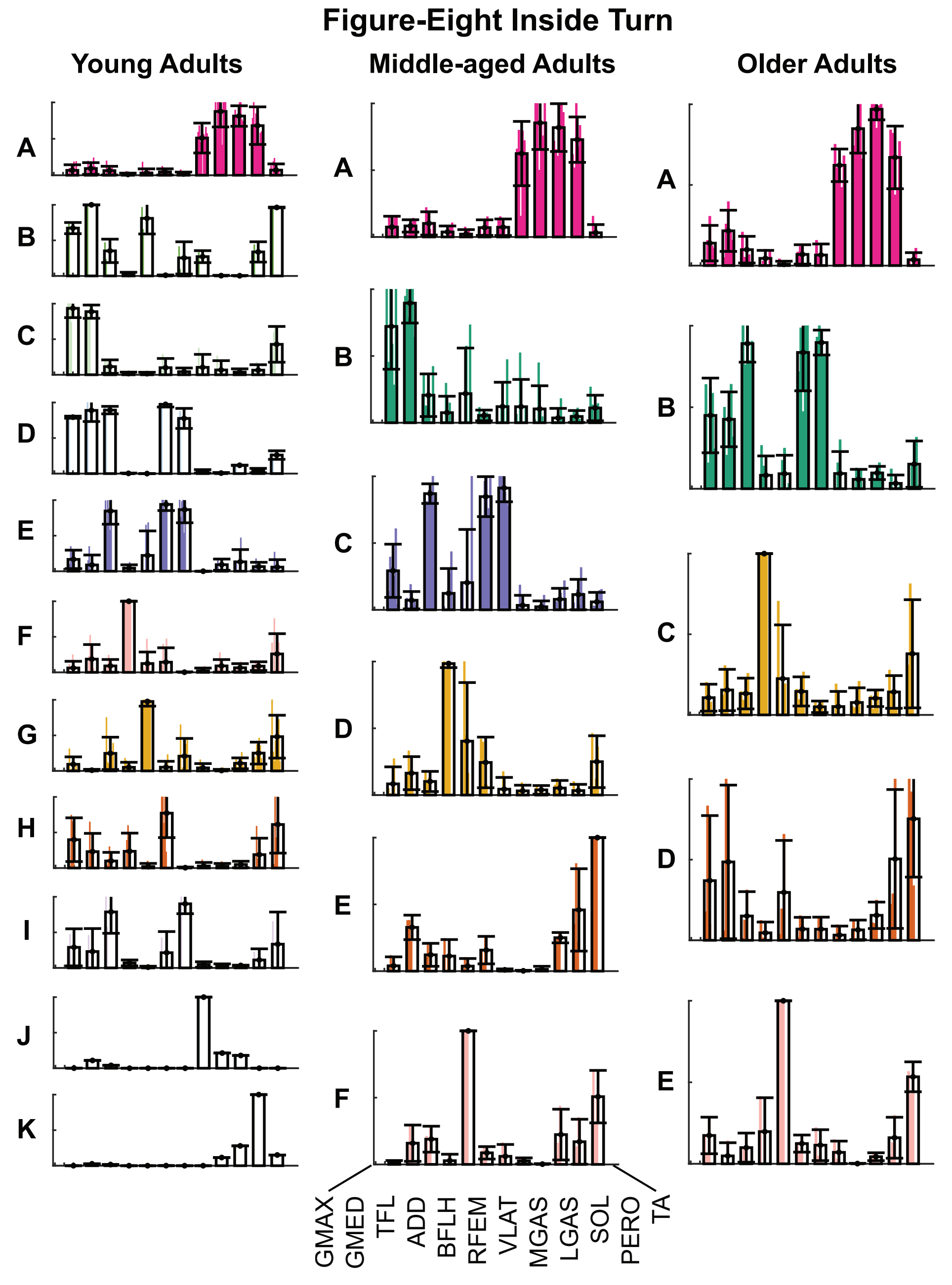


Figure 4.5: Motor modules clustered across subjects during the inside turn of figure-eight. Module were grouped into 11 clusters for young adults, 6 clusters for middle-aged adults, and 5 clusters for older adults

Figure-eight - Outside Leg

Motor modules from the outside leg of figure eight were grouped into 15 clusters for young adults, 7 clusters for middle-aged adults, and 4 clusters for older adults (shown in Fig. 4.6).

All young adults recruited a plantarflexor module, though these were divided into two clusters (cluster A, 8 subjects, cluster B, 2 subjects). Cluster C was primarily the gluteus muscles (6 subjects); those who did not use cluster C recruited their gluteus muscles in either cluster D (subject-specific module), cluster E (mainly GMAX and ADD, 2 subjects), and/or cluster F (primarily gluteus, TFL, and quadriceps together). Clusters M (4 subjects) and N (2 subjects) were primarily composed of ADD, with or without TA respectively. Overall, motor modules from young adults were grouped into 15 clusters, there were 6 main "types" of clusters

- Plantarflexors
- Gluteus muscles alone
- Gluteus muscles pair with others
- Adductor, with or without TA
- Hamstring, with or with out TA and others
- Miscellaneous groupings

Middle aged adults all used a plantarflexor module (Cluster A). Four subjects used cluster C, which was mainly the gluteus, TFL, and quadriceps muscles. Cluster D was mainly the quadriceps and TFL, with some gluteus contributions (3 subjects); two subjects who recruited cluster C also used cluster B, composed of GMED and TA. Cluster E was primarily the hamstring (2 subjects), cluster F was mainly ADD (4 subjects), and cluster G was primarily TA (3 subjects).

All older adults recruited a plantarflexor module (cluster A), a module with the gluteus, TFL, and quadriceps muscles (Cluster B), and a module with ADD and/or TA (Cluster C). Three subjects also recruited a hamstring module, sometimes with TA (Cluster D).

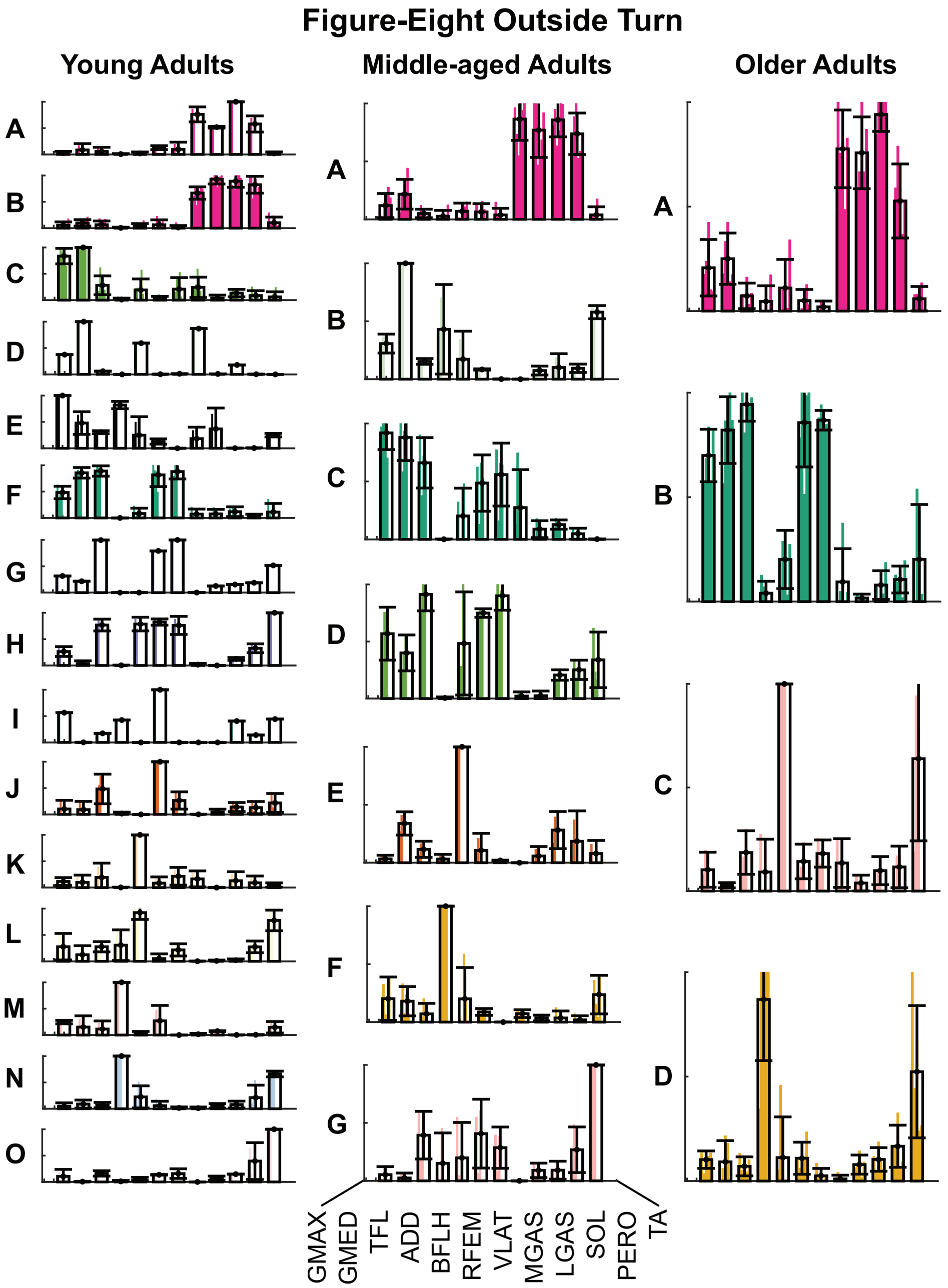


Figure 4.6: Motor modules clustered across subjects during the outside turn in figure-eight. Module were grouped into 15 clusters for young adults, 7 for middle-aged adults, and 4 clusters for older adults

Sit-to-Stand

During sit-to-stand, we identified 5 motor module clusters in young adults, 4 clusters in middle-aged adults, and 5 clusters in older adults (shown in Fig. 4.7).

Most young adults recruited cluster D, which was dominated by TA, sometimes with other muscles included (7 subjects). The remaining 4 clusters were composed of different combinations of gluteus and quadriceps muscles. Cluster A was primarily the quadriceps and TFL, with some contributions from other muscles (6 subjects) while cluster E was mainly VLAT and TFL, sometimes with GMAX (4 subjects). Cluster B was mainly the gluteus and TFL muscles (4 subjects), and cluster C grouped the gluteus and plantarflexor muscles.

In middle-aged adults, all clusters were present in 4 subjects, though all seemed to be fairly loose groupings. Cluster A was primarily the quadriceps, TFL, and TA. Cluster B was mainly the gluteus muscles and TFL, with varying contributions from other muscles. Cluster C included some combinations of plantarflexors with GMED or GMAX.Cluster D mainly included TFL and VLAT.

All older adults used cluster A, composed of the quadriceps and TFL. Cluster B was only present in two subjects and was either GMAX or GMED. Cluster C was present in 4 subjects and was mainly plantarflexors grouped with different hip muscles. Cluster D was primarily the TA, sometimes paired with RFEM (3 subjects). The final cluster was a subject-specific module.

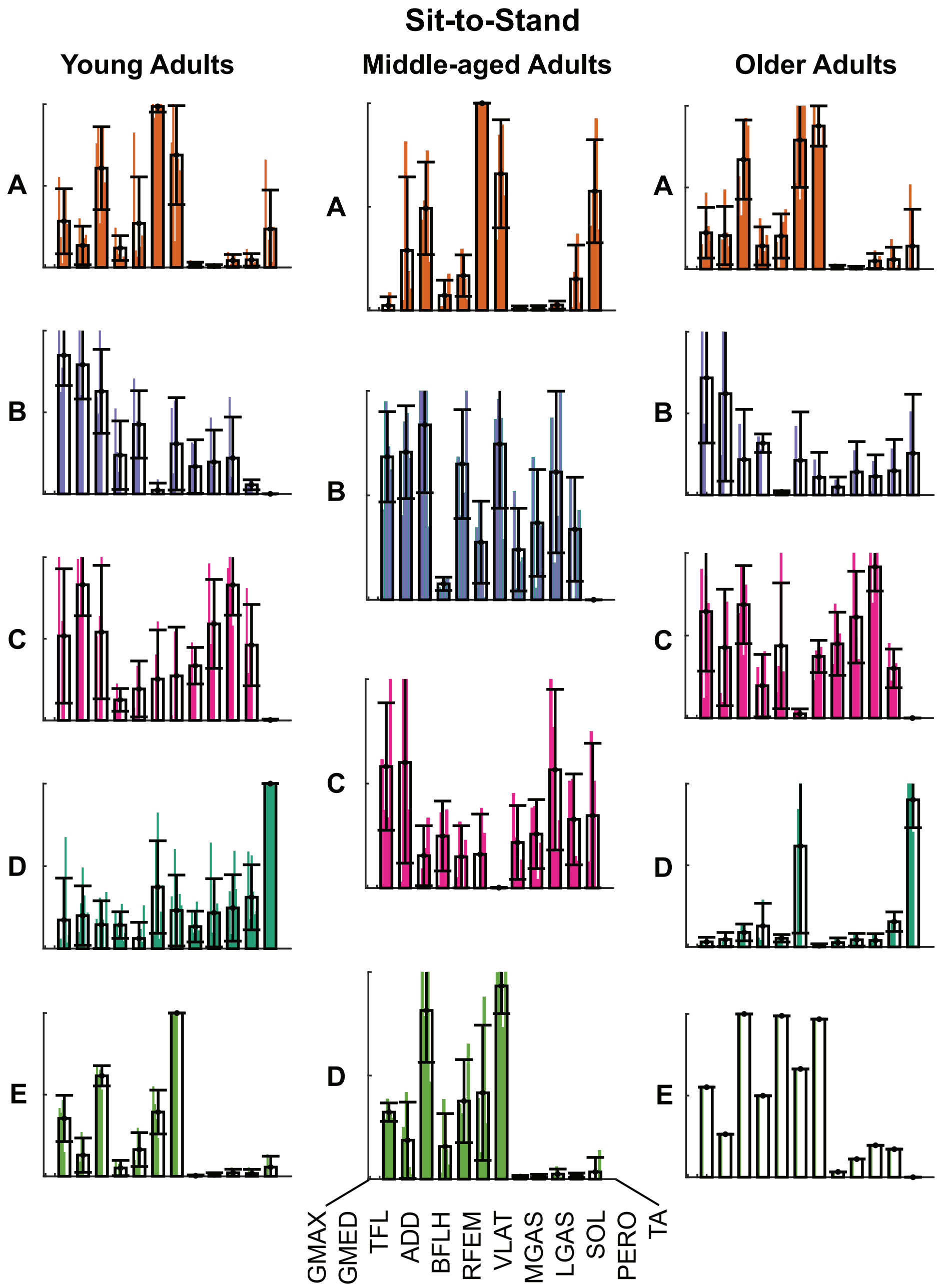


Figure 4.7: Motor modules clustered across subjects during sit-to-stand. Module were grouped into 5 clusters for young adults, 4 clusters for middle-aged adults, and 5 clusters for older adults.

Stand-to-Sit

During stand-to-sit, we identified 6 motor module clusters in young adults, 6 clusters in middle-aged adults, and 4 clusters in older adults (shown in 4.8).

A cluster composed of the quadriceps and TFL was present in most subjects (cluster A, 8 subjects). Three subjects recruited both cluster F (RFEM alone) and cluster D (TFL, hamstring, and VLAT) together. Cluster B loosely grouped modules with the plantarflexors and/or TA (5 subjects) while cluster E was exclusively TA (5 subjects). Four subjects recruited cluster C, which was a loose grouping of gluteus and other muscles.

All middle-aged subjects recruited cluster A, made up of quadriceps, TFL, and sometimes TA. Cluster D was mostly the TA grouped with gluteus muscles and was present in 3 subjects. Two subjects had cluster C which was primarily GMED. A loose cluster of plantarflexor muscles was present in two subjects (Cluster B). The other two clusters were subject-specific modules. Cluster A was present in all older adults and included the quadriceps, TFL, and TA. Three older adults recruited a defined plantarflexor module in cluster B. Cluster C was mainly dominated by TA, but also included gluteus muscles in some modules (4 subjects). Cluster D was a subject-specific muscle grouping of the quadriceps and TFL with GMAX.

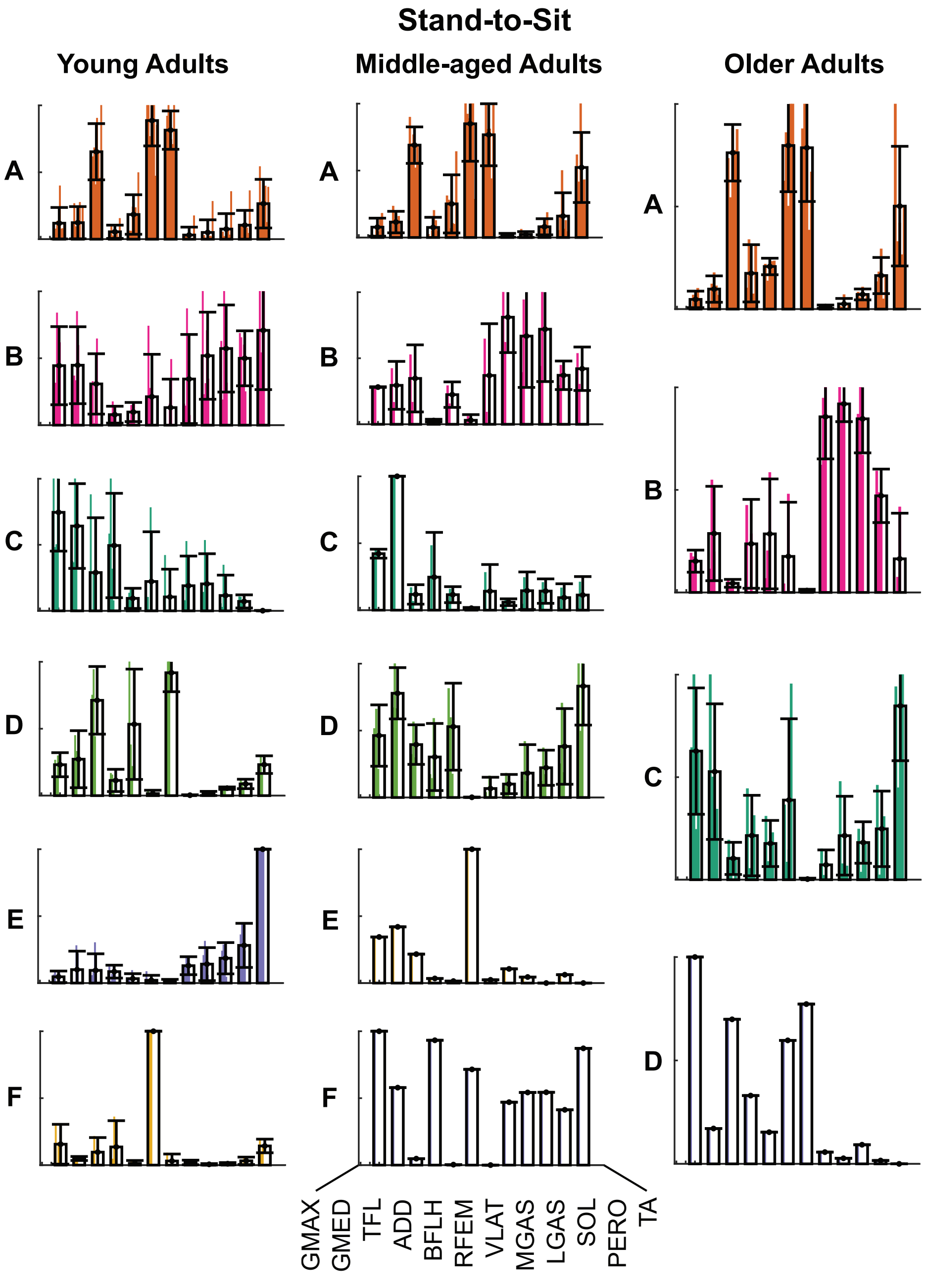


Figure 4.8: Motor modules clustered across subjects during stand-to-sit. Module were grouped into 6 clusters for young adults, 6 clusters for middle-aged adults, and 4 clusters for older adults.

4.4 Discussion

Healthy adults share common motor modules across voluntary tasks

Regardless of age, all subjects showed high levels of generalization between the motor modules recruited in walking, turning, and chair transfers. Values for both the number of clusters and percent generalization were similar to our previous investigation of the TUG test ([80], see Chapter 3). These results provide supporting evidence that similar motor modules are recruited during functionally different voluntary tasks, whether performed in isolation or as part of more continuous and transitory movements. Further, normal aging does not seem to affect overall motor module generalization during voluntary tasks, in support of our hypothesis.

Common and turn-specific modules used during locomotion

We identified 5 main types of motor modules during treadmill walking:

1. A module composed of TFL, gluteus, and quadriceps muscles (e.g., YA clusters B and C in Fig. 4.3),
2. A plantarflexor module (e.g., Fig. 4.3, cluster A),
3. A module mainly composed of TA, sometimes with other muscles (e.g., Fig. 4.3, YA cluster D),
4. A hamstring module (e.g., Fig. 4.3, YA cluster F),
5. An adductor module (e.g., Fig. 4.3, YA cluster E).

The first four modules are similar to those previously identified in walking [18], [59], [60]. Module 1 contributes to body support, module 2 to propulsion, module 3 to braking in early stance, and module 4 to modifying leg energy during late stance and early swing [18], [59]. The fifth module was mainly the adductor muscle. Adductors have been shown to contribute to mediolateral balance control and shifting energy between legs to facilitate contralateral swing, and including an adductor module has been shown to improve mediolateral balance control in walking simulations [18].

During treadmill walking, module 1 (gluteus, TFL, and quadriceps muscles) was present in most people regardless of age (Fig. 4.3). Similar combined hip abductor-knee extensor modules have been previously identified in walking and contribute to body weight support and mediolateral stabilization [18], [59], [54]. However, during turning, this module was not normally observed, especially in young and middle-aged adults. During the TUG test, most subjects had a quadriceps and TFL module (all hip flexors, Fig. 4.4, cluster C) and a module pairing the gluteus and hamstring muscles (all hip extensors, Fig. 4.4, cluster B). We will refer to the hip flexor module as Module 1A and the hip extensor module as Module 1B.

Similarly, during figure-eights, young adults and middle-aged adults typically had a knee extensor module plus some form of gluteus module (e.g., in isolation or paired with the hamstring). During the inside turn of figure-eights, module 1A was consistently identified in almost all subjects (Fig. 4.5, YA cluster E), while a few variations of module 1B were found (YA clusters B-D). Conversely, in the outside turns module 1B (though without much hamstring activity) was consistently used (Fig. 4.6, YA cluster C) but many variations of module 1A or individual quadriceps were found (YA clusters F-J). Middle-aged adults more consistently recruited modules 1A and 1B.

In other words, healthy young and middle-aged adults do not consistently recruit module 1, but separate quadriceps and gluteus motor modules during turning. Module 1A, the TFL and quadriceps, may be more important for the inside turning leg. As discussed above, similar motor modules have been identified as important for body support and stabilization during stance. The stance phase lasts longer during turn than straight-line walking, partly because the COM momentum needs to be slowed, shifted and redirected [81], [82], even during gentle turns [83]. Additionally, turning is associated with larger vertical (i.e., body support) impulses [81]. All of these imply that a motor module like 1A, associated with support and stabilization during stance, would be important during turns. Module 1B contains mostly the gluteus muscles. Hip abductors, and gluteus medius specifically, are important contributors to medial accelerations of the center of mass during normal walking [84] and turning [85]; recruiting the abductor module separately may help meet the additional mediolateral demands of turning in a tight radius (e.g., illustrated by greater medial impulses to shift COM inward [81]).

The emergence of turn-specific gluteus motor modules in young adults is consistent with our qualitative observations of motor modules recruited during TUG subtasks (see Chapter 3). Conversely, older adults did recruit the combined hip module during figure-eights, i.e., they did not recruit the hip abductors separately during figure-eight walking. Older adults have been shown to be less able to modulate gluteus medius activity during tasks like lateral stepping [86] and perturbed walking [65]. The absence of a gluteus-specific motor module during figure-eight walking may reflect reduced control of hip abductors. Though most older adults did not recruit a distinct gluteus motor module during the figure-eight turning, they did during the TUG test. This result suggests that task conditions like turning radius or speed may affect whether a separate gluteus module is needed, or if the combined abductor-knee extensor module is sufficient. However, we did not examine the turn radius in either case here, and while figure-eights were performed at a comfortable walking pace, the TUG test was performed at a quick pace. It is possible that participants may have used different turn strategies during the TUG test and the higher speed may have required more mediolateral control than the wider and slower turns of the figure-eights. The effects of turn radius could also be why our results contrast with a previous study that did not find differences between motor modules used for straight-line and wide-radius curvilinear walking [54]. Future analyses that incorporate kinematic and spatiotemporal parameters could better determine whether the changes in motor modules observed are due to age-related changes in muscle recruitment or simply differences in how the task is performed.

Motor modules are less complex during chair transfers and dominated by knee extensors

Chair transfers were a much simpler task than walking and turning; a smaller number of motor modules were needed to reconstruct observed EMG than in walking or turning. Additionally, both the motor modules and their clusters across subjects tended to be less clear and defined. For example, a clear plantarflexor motor module was recruited in every subject during walking and turning tasks; however, most people did not have such a distinct plantarflexor module during chair transfers. Instead, the plantarflexors were more moderately recruited and often grouped with other muscles like the gluteus muscles and the most common motor module was primarily the knee extensors, quadriceps and TFL (see Figs. 4.7 & 4.8).

Motor modules recruited during voluntary tasks are less variable across subjects with age

In every voluntary task except sit-to-stand, we identified more motor module clusters in young adults than older adults. This could reflect more variability in how younger adults performed the task compared to older adults. For example, some young adults preferred to step around the turns while others performed a tighter pivot. Though we did not investigate kinematics here, characterizing how participants performed each task (e.g., turning [87], or sit-to-stand strategy [88]) may clarify the variability in young adult motor modules shown here.

Conversely, this variability may be an effect of the small number of middle-aged and older participants included here, or the clustering algorithm used. We used the same algorithm that others have [11], [36], but there has not yet been a thorough methodological study to identify the best algorithm for clustering motor modules. For example, a different algorithm may not have identified two separate plantarflexor clusters in figure-eight (Clusters A & B, Figure 4.6). To determine the best method for clustering motor modules, future studies should examine the effects of different algorithms and settings on clustering results and select the one that best defines functionally different modules without excessively separating similar modules.

Consistent with previous studies of walking in older adults [65], [78], we found some differences in motor module complexity (VAF-by-1) but not module number with age. Generally, VAF-by-1 increased with age during walking, TUG, and the outside turn leg, so older adults show reduced complexity during walking and turning tasks. These tasks also generally have higher complexity across all age groups than the chair transfers; possibly the older adults are more susceptible to performing differently during walking and turning than in simpler tasks like chair transfers.

4.5 Conclusion

Here, we found that healthy adults between the ages of 18 and 80 share common motor modules for walking, turning, and chair transfers. Though with this study we have begun to characterize patterns of multi-muscle coordination across a broader set of tasks, walking, turning, and chair transfers are still only a small fraction of the diverse ways humans move around in daily life. Additionally, the timing patterns and functional roles of modules recruited during different tasks like turning will need to be determined, as has been done in walking (e.g., [18]). Thoroughly characterizing what motor modules are recruited, when they are recruited, and how they contribute to functional outputs in a diverse assortment of daily movement tasks would provide a deeper understanding of multi-task neuromuscular control. An understanding of this “library” of motor modules in healthy adults would provide a strong basis for quantifying both movement deficits and rehabilitation improvements in people with neuromuscular impairments.

5 Neuromuscular Generalization Between Reactive and Voluntary Tasks

5.1 Introduction

Motor modules provide a useful way to quantify neuromuscular control and identify similar patterns between tasks [6], [12], [15], [55]. It has been shown that reactive balance motor modules are recruited during walking and that recruiting more balance modules during walking is associated with various measures of walking performance. Low generalization associated with slow walking speeds, etc. in impaired populations, and high generalization and high performance in healthy adults and skilled dancers [24], [34], [36], [66]. Specifically, people with chronic stroke were shown to have low generalization and slow walking speeds compared to healthy controls, despite recruiting similar numbers of modules [36]. Conversely, expert ballet dancers share even more motor modules between reactive balance and walking than novice healthy young adults, and this was correlated with better walking balance performance (Allen, Carey, et al. 2020, Appendix A). Because the relationship between motor module generalization and walking performance has been demonstrated in multiple age ranges and patient populations, we hypothesize that drawing on reactive balance motor modules enables more robust and automatic control of linear walking.

Common motor modules identified during standing reactive balance are also found in both perturbed and unperturbed walking, further suggesting that recruiting reactive balance motor modules during walking may facilitate better walking balance control [42]. Incorporating reactive balance motor modules during voluntary tasks like walking may help the central nervous system coordinate the movements required to meet task-level goals. For example, during standing reactive balance, motor module tuning can be predicted by COM state error, sometimes contradicting activation that could be expected based on local sensory feedback [89]. This suggests that reactive balance motor modules may be recruited to execute task-level goals such as COM control, which would be even more important during perturbed or challenging walking.

However, humans do more than just walk in straight lines. Daily life involves frequent nonlinear walking, turning, and transitioning between different positions and environments. Such movements likely require even more balance and stability than straight-line walking [81], [83], [85]. If reactive balance motor modules are recruited during straight-line walking, it seems reasonable that similar strategies would apply to the control of other common tasks; however, whether reactive balance motor modules are recruited during nonlinear walking or other voluntary tasks has not yet been determined. The primary goal of the present study was, therefore, to characterize motor module generalization between standing reactive balance and a wider array of voluntary tasks. We hypothesize that recruiting reactive balance motor modules is a general strategy employed to enable more robust and automatic movements and drawn on for a wide range of tasks.

Additionally, aging impacts multiple systems important for sensory feedback and postural response [90], such as proprioception [91] and neural noise that could affect sensory processing [92]. Sensorimotor declines can impact both the accurate assessment and execution of task goals like COM control, and lead to higher instability and fall rates or compensatory strategies (e.g., [93], [94]). If reactive balance motor modules are incorporated during voluntary tasks to help meet task level goals like COM control, age-related changes may lead to altered motor module generalization; however, reactive balance motor module generalization has not yet been characterized with normal aging.

Here we compare the motor modules recruited in standing reactive balance to those recruited during voluntary tasks: treadmill walking, figure-eight walking, chair transfers, and the TUG test. We included healthy young adults, middle-aged adults, and older adults. We predicted that healthy adults recruit reactive balance modules during all of these voluntary tasks. Further, we predicted that motor module generalization would decrease with age and that across all ages, higher generalization would be associated with faster walking speeds and task performance.

5.2 Methods

Participants

Ten healthy young adults (7 M, 21.3±2.4 yrs), 6 middle-aged adults (1 M, 58.2±5.1 yrs), and 5 older adults (1 M, 71.2±5.5 yrs), participated in this study. Inclusion criteria were age greater than 18 (classified as young adults: 18-35 yrs, middle-aged adults: 36-64 yrs, older adults: 65+ yrs). Exclusion criteria were any musculoskeletal conditions or concussion or injury within the last year. All participants provided written informed consent before participating according to an experimental protocol approved by the institutional review board of West Virginia University.

Experimental procedures

All participants performed a standing reactive balance task and a set of voluntary tasks: treadmill walking at self-selected and fastest possible speeds, chair transfers, figure eight walking, and the TUG test. Each task is described in detail in Chapter 2: General Methods.

Data collection and processing

During each task, we collected three-dimensional marker data at 100 Hz; maker data were used to identify the beginning and end of each TUG, figure eight, and chair transfer trial. Additionally, retroreflective tape markers on the treadmill belts were used to identify perturbation onset during the standing reactive balance task as described in Chapter 2.2.

Surface electromyography data were collected on the dominant leg at 1000 Hz from the same 12 muscles listed in Chapters 3 and 4 (GMAX, GMED, TFL, ADD, BFLH, RFEM, VLAT, MGAS, LGAS, SOL, PERO, and TA (see Chapter 2.1). EMG data were high pass filtered at 35 Hz, demeaned, rectified, and low pass filtered at 40 Hz using custom MATLAB code.

We created separate data matrices for each task and subject by concatenating EMG data from all trials. As in Chapter 4, we considered sit-to-stand and stand-to-sit as separate tasks, and each turn direction of figure eight as separate tasks, giving a total of 7 voluntary task matrices for each subject. For standing reactive balance matrices, data from 4 time bins were concatenated, one before the perturbation, and three 75 ms bins during the automatic postural response. The background bin represented the average EMG for each muscle during a 280 ms window which ended 140 ms before the perturbation onset. The first APR bin began after a 100 ms delay (see Fig. 2.4). For all data matrices, EMG for each muscle was normalized to the maximum value observed during walking.

Motor module analysis

Motor module extraction is described in detail in Chapter 2. Briefly, we separately extract n motor modules from each subject and task (8 extractions per subject) such that EMG = W x C + err, where W is the m x n matrix of module weights, C is the n x time matrix of activation coefficients, and err is the error between the original and reconstructed EMG. To avoid biasing the extraction towards any high-variance muscles, EMG was scaled to unit variance for each muscle, and then rescaled after the extraction. For each subject and task, we extracted 1-12 motor modules and selected the number of motor modules such that the 95% confidence interval on the VAF between the original and reconstructed EMG was greater than 90%.

We used two methods to characterize the similarity between reactive balance and voluntary motor modules. First, the reactive balance motor modules were used to reconstruct EMG data from each voluntary task. The VAF by these reconstructions were compared across task and age in a two-way repeated measures ANOVA, with age group and task as factors.

Second, we performed a shared-specific motor module extraction for each voluntary task as detailed in [11]. In this method, EMG data from the reactive balance and a voluntary task are concatenated into one matrix and a set of motor modules is extracted. Because the matrices from each task can vary widely in length, EMG data from the shorter data matrix were first resampled to be the same length as the longer to avoid biasing the extraction to any task. The numbers of motor modules identified in separate extractions for each task (e.g., n_1 and n_2 are used as an estimate for the maximum number of shared-specific synergies (i.e., no synergies are shared). Motor modules are extracted from the combined data matrix, and the number of motor modules is decreased with each iteration until reaching the larger of n_1 and n_2. Each iteration yields a W and C, with some combination of shared and task-specific modules. The appropriate number of motor modules is chosen similar to the separate extractions, such that the lower bound of the 95% confidence interval on the overall VAF (here from $W \times C = EMG_{combined}$) is greater than 90%.

Generalization with reactive balance motor modules: We then determined the amount of generalization and task-specificity with each voluntary task. A two-way repeated measures ANOVA (custom R script) was used to compare the number of motor modules shared across age and task. The percentage of shared motor modules was then defined as

$$p_{shared} = \frac{n_{sh}}{n_{vol} + n_{RB} - n_{shared}} \times 100\%$$

and the percentage shared was compared across age and task using a two-way repeated measures ANOVA. Similarly, the percentage of task-specific modules was defined as

$$p_{sp} = \frac{n_{sp}}{n_{vol} + n_{RB} - n_{sp}} \times 100\%$$

for reactive balance and the voluntary task. The percentage of task-specific modules in reactive balance and each task were compared with two-way repeated measures ANOVAs, with age group and task as factors. For all ANOVAs here, pairwise t-tests were performed if there was a significant effect of task; two-sample t-tests with Hommel's corrections were performed for significant effects of age group. For all post hoc tests, p-values were adjusted using Hommel's corrections with $\alpha = 0.05$ [79].

Performance metrics

As a secondary analysis, we calculated the following performance metrics for each task and compared them to metrics of motor module similarity described above:

- self-selected walking speed,
- maximum walking speed,
- time required to stand up or sit down fully,
- time spent in each turn,
- average TUG time.

Each performance metric was separately compared to the number and percent of motor modules shared with reactive balance, and VAF from reactive balance reconstruction for that task using simple linear regression such that

$$s = mp + b$$

where s is the performance metric (e.g., fastest walking speed), p is the motor module similarity (e.g., number of shared modules during treadmill walking), m and b are the slope and intercept of the regression line respectively. We then evaluate the correlation coefficient r between the linear model and the observed data.

5.3 Results

Motor module number and VAF-by-1 were similar to the results reported in Chapter 4, despite the differences in EMG processing. Therefore, motor module complexity will not be discussed again here.

Reconstruction of Voluntary Task EMG using Reactive Balance Motor Modules

Reactive balance motor modules were able to reconstruct EMG from voluntary tasks (range across all: 63.1-97.8% VAF). In treadmill SS, reconstruction VAF was lower in older adults than middle-aged (p=0.003) and young adults (p=0.004). Similarly, in figure-eight outside leg, reconstruction VAF was lower in older adults than middle-aged adults (p=0.041) and young adults (though not significant, p=0.054). Reconstruction VAF was also higher in stand-to-sit than treadmill SS in older adults (p=0.017).

Shared-specific motor module extraction

A small number of motor modules were identified for reactive balance (range: 2-6), and each voluntary task (range: 2-5) using the shared-specific extraction. Older adults shared fewer modules than young adults between reactive balance and treadmill SS (p=0.015), figure-eight outside leg (p=0.002), and TUG (p=0.004). Compared to middle-aged adults, older adults also shared

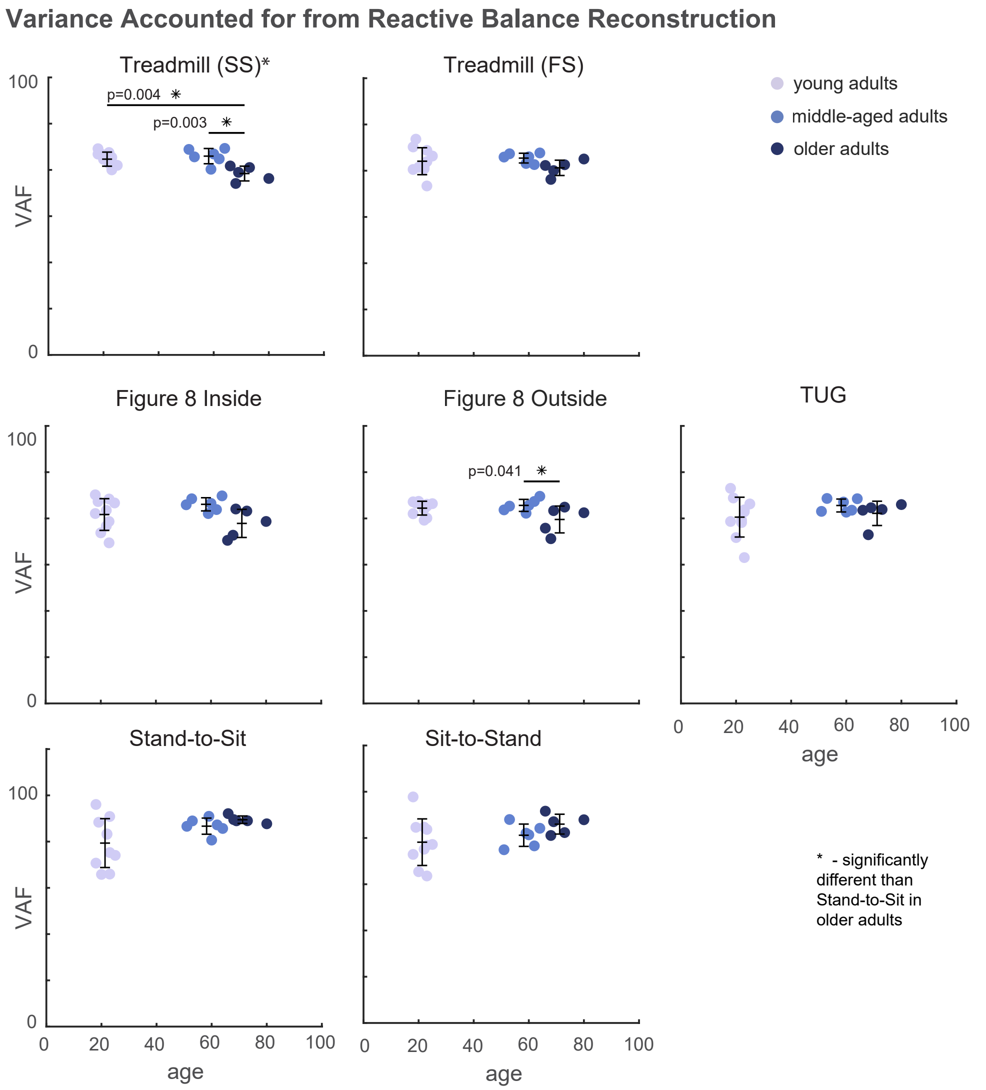


Figure 5.1: Overall variance accounted for when reactive balance motor modules are used to reconstruct voluntary task EMG.

fewer modules during figure-eight inside (p=0.016), figure-eight outside (p=0.004), and TUG (p=0.002).

The percentage of motor modules shared between reactive balance and voluntary tasks was lower in older adults than young adults in figure-eight outside (p=0.017). Older adults also had a lower percentage shared than middle-aged adults in figure-eight inside (p=0.035) and outside leg (p=0.008). Conversely, older adults shared a higher percentage of motor modules between reactive balance and sit-to-stand than young adults (p=0.036).

When compared to figure-eight tasks, there were more task-specific reactive balance motor modules in older adults than young adults (inside leg: p=0.035, outside: p=0.008) and middle-aged adults (inside: p=0.026, outside: p=0.002).

There were lower percentages of task-specific motor modules present in older adults during both sit-to-stand (vs. YA: p=0.001, vs. MA: p=0.008) and stand-to-sit (vs YA: p=0.008, vs. MA: p=0.057). Across tasks in young adults, more task-specific modules were identified in sit-to-stand than figure-8 outside leg ($p \leq 0.001$), treadmill SS (p=0.032), and TUG ($p \leq 0.001$). Middle-aged adults also used a higher percentage of task-specific in chair transfers than figure-eight inside (sit-to-stand: p=0.011, stand-to-sit: p=0.005), outside leg (sit-to-stand: $p \leq 0.001$, stand-to-sit: p=0.008) and TUG (sit-to-stand: $p \leq 0.001$, stand-to-sit: p=0.005).

Comparisons with task performance speed or time

There were no significant correlations between the overall VAF from reconstructing voluntary task EMG using reactive balance motor modules. However, there was some relationship between higher reconstruction VAF during sit-to-stand and faster standing time (r=0.28,p=0.12), and between higher VAF during self-selected walking and maximum walking speed (r=0.26, p=0.14)

Similarly, there were no correlations between the number or percentage of motor modules shared with reactive balance and performance speeds or times; however, there was a slight relationship between more shared modules and faster maximum walking speeds (r=0.29, p=0.11).

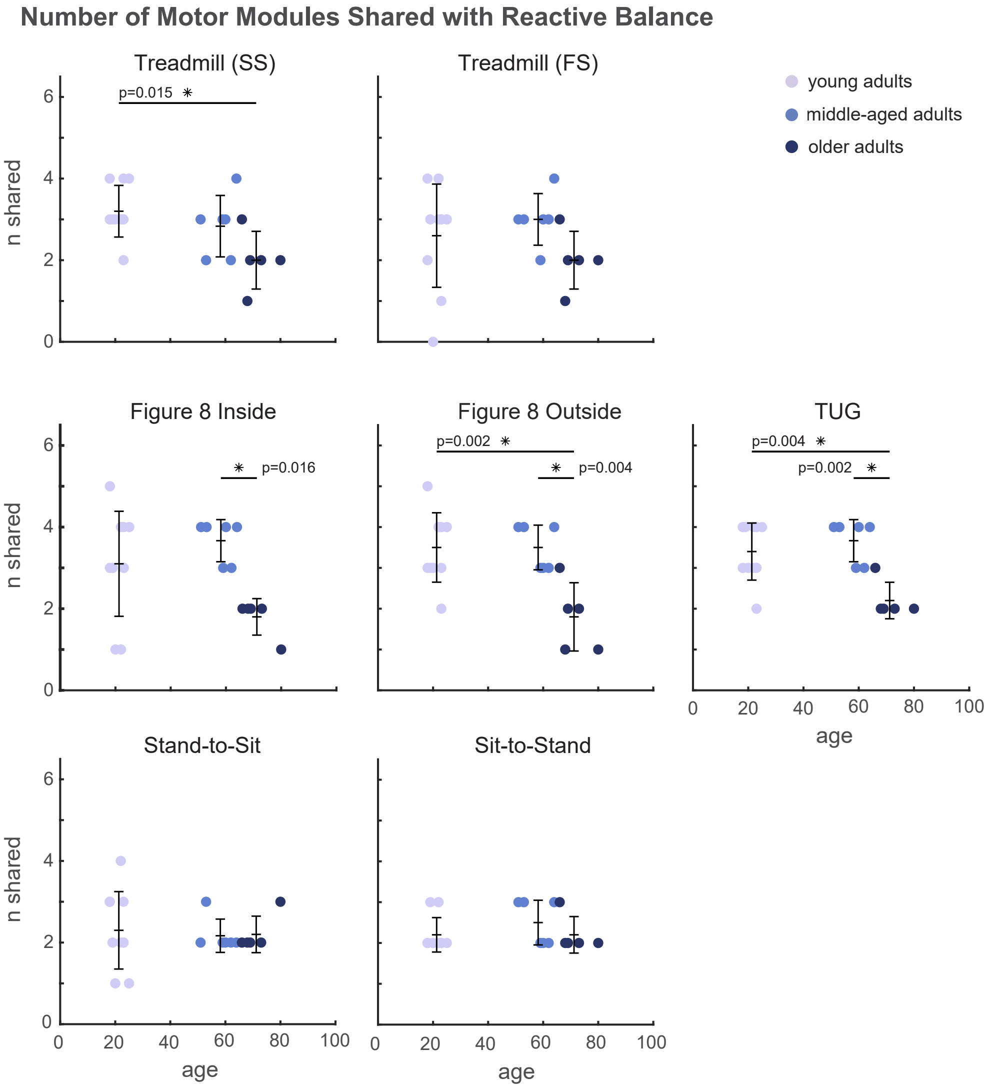


Figure 5.2: Number of motor modules shared between reactive balance and voluntary tasks

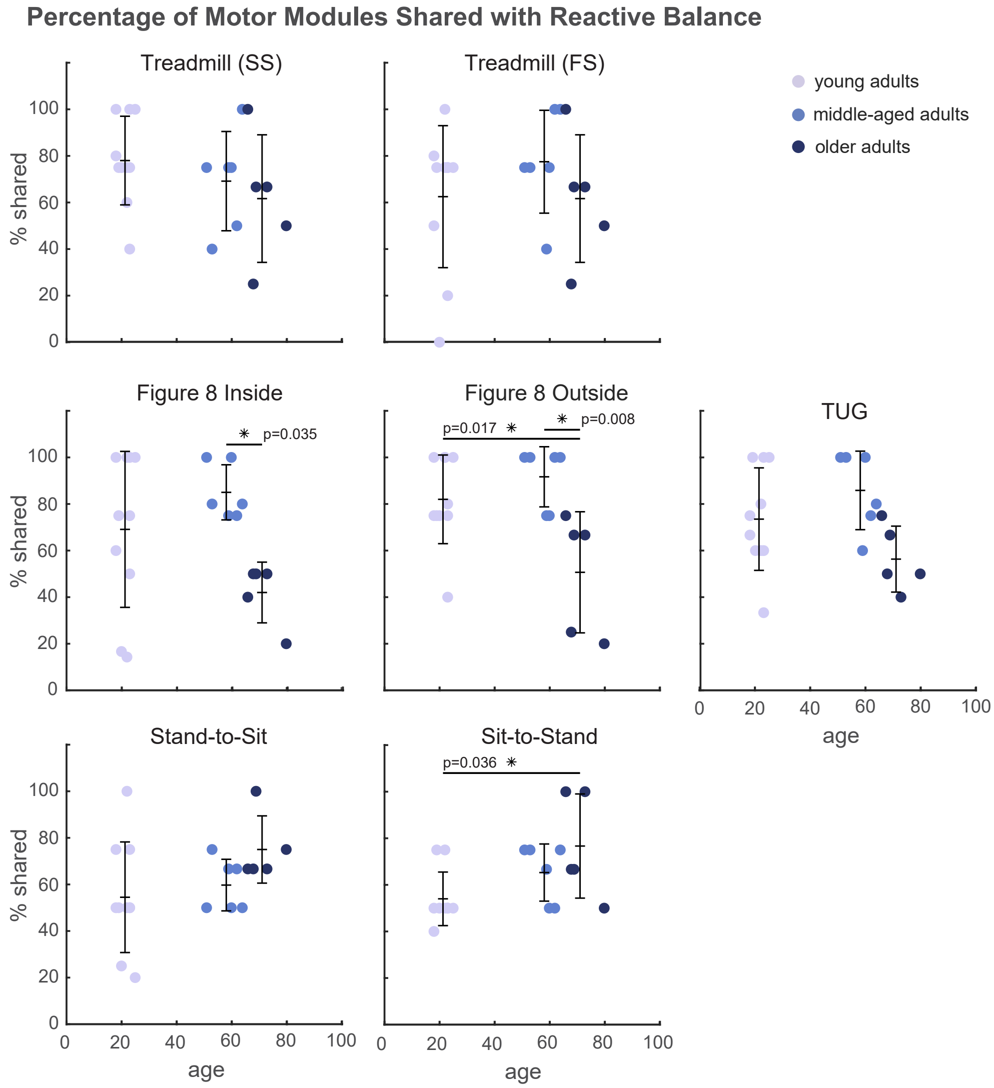


Figure 5.3: Percentage of motor modules shared between reactive balance and voluntary tasks

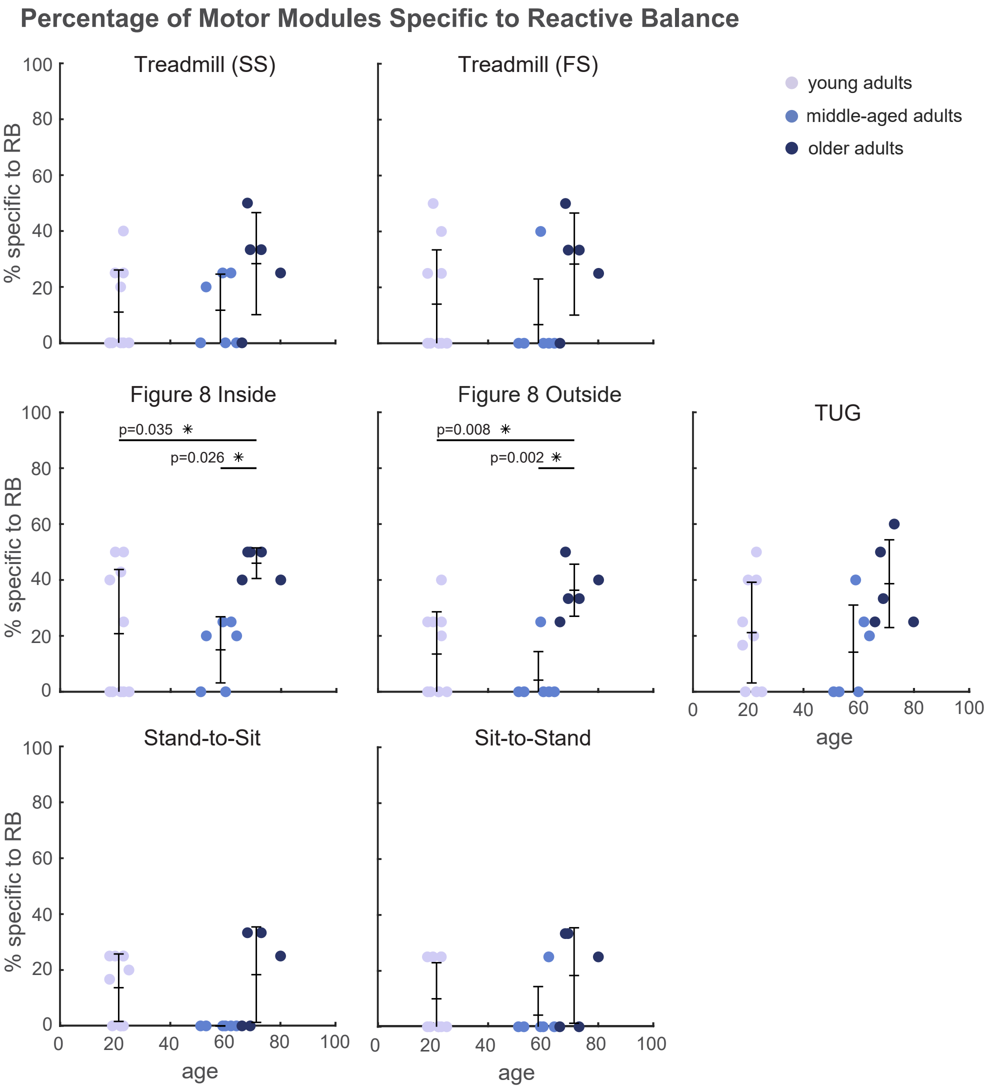


Figure 5.4: Percentage of motor modules specific to Standing Reactive Balance

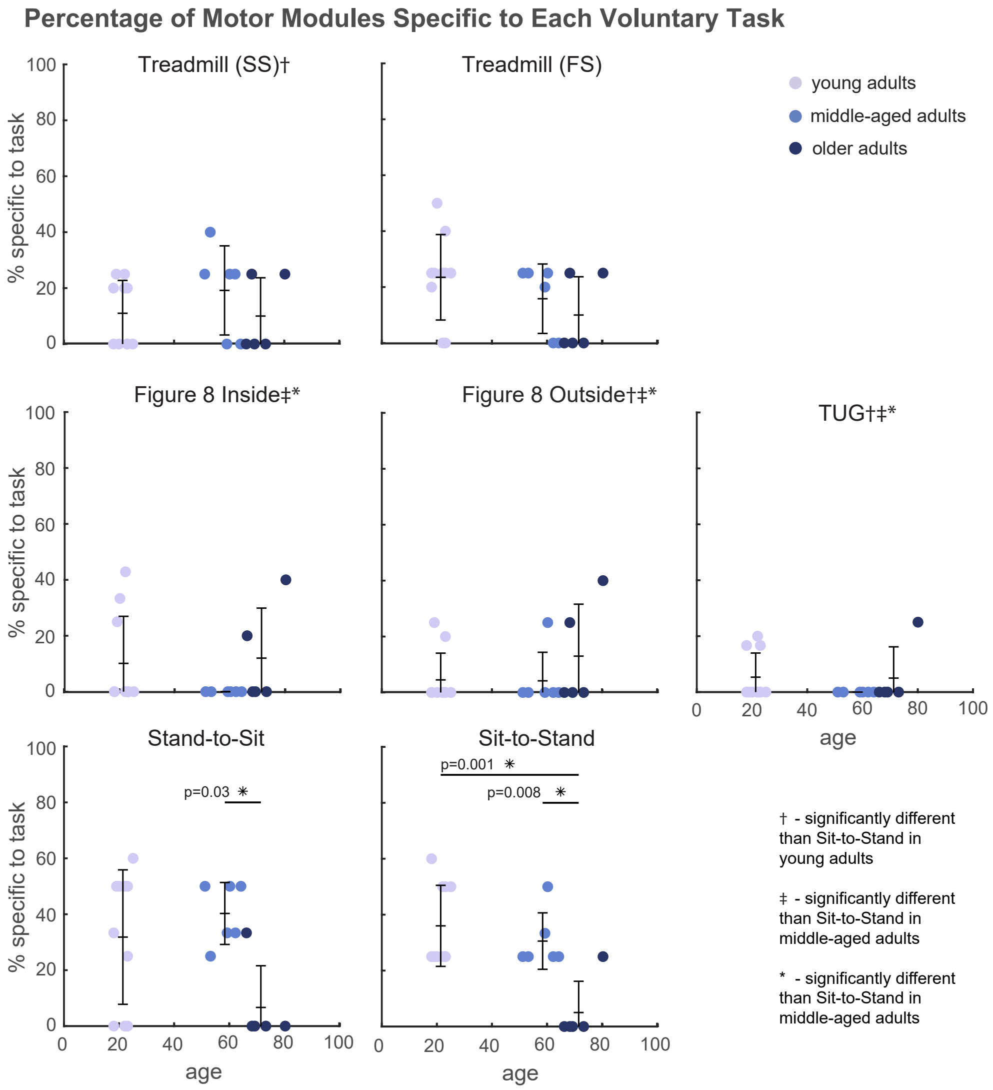


Figure 5.5: Percentage of motor modules specific to each voluntary task

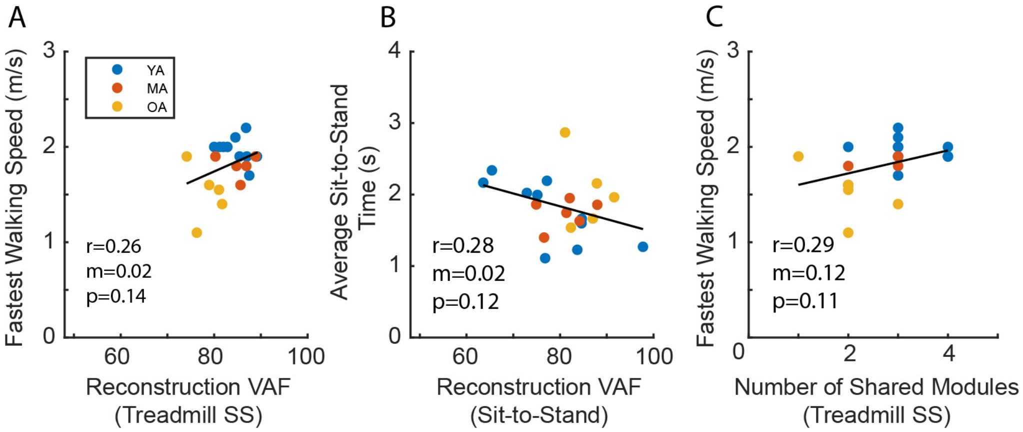


Figure 5.6: Comparisons between motor module generalization and task speed or time

5.4 Discussion

In summary, we found that healthy adults do recruit reactive balance modules during other voluntary tasks besides walking but that there are changes in generalization associated with aging. Consistent with our predictions, there was less motor module generalization with age during walking and turning tasks. Interestingly, we also found that older adults showed higher motor module generalization during chair transfers, contrary to our expectations. Finally, we found a small relationship between higher generalization and faster walking/turning.

Reactive balance motor modules are recruited during voluntary tasks

In support of our hypothesis, healthy adults share similar motor modules between standing reactive balance and voluntary tasks. Reactive balance motor modules were able to reconstruct over 63% of the variance in every voluntary task. Also, at least one motor module was shared between reactive balance and every other task (except for one subject in treadmill FS). These results fit with our expectations based on prior work (e.g., [34]) and support our hypothesis that healthy adults recruit reactive balance motor modules during voluntary movements to enable more robust control.

Generalization is reduced in older adults during walking and turning tasks

Consistent with our hypothesis, older adults had less motor module generalization between reactive balance and the walking and turning tasks, though this was not always significant. Older adults had lower reactive balance reconstruction VAF in self-selected treadmill walking and figure-eight outside leg, with similar trends in other tasks. Older adults also had significantly fewer shared motor modules during both figure-eights, self-selected treadmill walking, and TUG, and a significantly lower percentage shared in figure-eights, with similar trends in TUG and treadmill walking (though these tasks had large standard deviations).

Older adults may be less able to draw upon reactive balance strategies during walking and turning. This is illustrated by the task-specific percentages. Older adults used more reactive balance-specific motor modules when compared to figure-eight, without any difference in the percent specific to the voluntary task. In other words, older adults have more reactive balance modules that are not being shared with the figure-eights than young or middle-aged adults. Interestingly, generalization differences with age are stronger in the turning tasks and not always present during straight-line walking. The additional frontal plane demands of turning may require additional balance control compared to walking [95].

Older adults did recruit fewer motor modules during reactive balance, walking, and turning tasks than young adults, suggesting that reductions in both balance control and movement quality may contribute to reduced motor module generalization between balance and walking. Regardless of age, slower maximum walking speeds are associated with less generalization between walking and reactive balance, which fits with results from previous work demonstrating a relationship between walking performance and motor module generalization [34], [36].

Generalization is higher in older adults during chair transfers

Contrary to what we expected, motor module generalization was higher in older adults during the chair transfer tasks. Though the percent shared during sit-to-stand was the only significantly lower variable in older adults, a similar trend exists during stand-to-sit. Similarly, there is a general trend that, in older adults, reactive balance motor modules are able to reconstruct a higher percentage of the variance in chair transfer EMG. Together, these results suggest that older adults may use more reactive balance motor modules during chair transfers.

There was no difference in the number or percent of reactive balance modules that subjects recruited when compared to chair transfers; however, older adults had significantly fewer modules that were specific to the chair transfers. In other words, young adults use a mix of reactive balance and task-specific motor modules during chair transfers, but older adults almost exclusively use the reactive balance modules with almost no task-specific modules.

Older adults may use more reactive balance modules during chair transfers because of differences in COM control compared to young adults. Greater postural sway and COM displacement during sit-to-stand has been demonstrated in older adults [96], [97] and adults with knee osteoarthritis [98]. Age-related declines in neuromuscular features like muscle strength or sensorimotor feedback may contribute to poorer control over COM motion, requiring reactive postural corrections. For example, greater postural sway during sit-to-stand is correlated with changes in rectus femoris activation [96]. Similarly, a variety of sensorimotor variables important for balance maintenance (e.g., limb proprioception, tactile sensitivity, and postural sway) are predictors of sit-to-stand performance time in older adults [99]. Additionally, different compensatory strategies in older adults (e.g., due to different movement objectives or neuromuscular capacity [96]) could change how the chair transfer tasks are performed and therefore require additional recruitment of balance motor modules.

Middle-aged adults recruited reactive balance motor modules during voluntary tasks.

The results in middle-aged adults were sometimes similar to young adults and sometimes similar to older adults. We found no reduction in how much middle-aged adults shared reactive balance motor modules, whether through reactive balance reconstruction VAF, number, or percent shared. Also, similarly to young adults, middle-aged adults recruited a low percentage of motor modules specific to reactive balance. They also recruited few to no task-specific motor modules during the walking and turning tasks. Altogether, in walking and turning, middle-aged adults still have a large overlap between balance and walking/turning motor modules. Like the young adults, they are drawing on balance motor modules during walking and turning, without much task specificity needed/shown.

Though generalization in middle-aged adults was similar to young adults during walking and turning, it followed similar trends as the older adults during chair transfers. Though it was not significant, middle-aged adults do seem to share slightly more balance modules during chair transfers than young adults (especially visible in the sit-to-stand subplot of Figure 3). Like other age groups, middle-aged adults recruited few motor modules that were specific to reactive balance; however, they did have more task-specific modules during the chair transfers. This suggests that middle-aged adults may be starting to use more reactive balance modules during chair transfers like older adults but are also still recruiting chair transfer-specific modules, unlike older adults.

These results also illustrate the importance of including middle-aged adults when investigating changes due to aging. Middle-aged adults are a frequently overlooked population; investigations of aging often include only young and older adults. Though middle-aged adults often exhibit similar results to young adults in many variables (e.g., many of the results in [100]), there are observable differences in postural stability [100], [101]. Age-related impacts on neuromuscular control do not happen overnight but likely begin causing subtle changes during middle age, which become easier to detect as they advance. By characterizing changes in neuromuscular control during middle age, we may be able to better understand how and when the differences seen in older adults begin to occur and develop earlier interventions to better preserve mobility with advancing age.

Limitations:

There were some limitations to this study. For one, the way we identify the percent shared and specific is dependent on the number of motor modules identified in separate extractions. Identifying the number of motor modules is dependent on how the VAF cutoff is defined. This is likely why there are much higher standard deviations in these parameters compared to those that do not depend on that number (e.g., high SD in percent shared despite tighter SDs in reconstruction VAF). Adapting the shared-specific extraction method to not depend so strongly on an initially identified number of modules might produce more consistent standard deviations and provide a better image of shared vs. specific motor modules. Additionally, we implemented our standing reactive balance paradigm on a treadmill rather than a multi-directional platform. Thus we only included 4 perturbation directions here, whereas previous studies included 12 directions (e.g., [36]). There could be important components of balance control that are more detectable in those intermediate directions.

Future directions

Here we have investigated motor module generalization across more tasks than usual by including walking, turning, and chair transfers. However, this is still a small number compared with all the different ways we move in daily life. Future studies should include additional tasks such as stair climbing, lifting objects, getting out of bed, and gait initiation. Additional future studies should also expand beyond isolated lab tasks and consider more “complex” or real-world tasks such as getting out of a car, walking through the grocery aisle, or standing up to reach something high on a shelf. Characterizing multi-muscle coordination across such a broad array of tasks would give a clearer picture of how people coordinate their movements in daily life.

We also only consider discrete support surface perturbations here. It would be interesting to characterize the “mini library” of reactive balance motor modules used in a variety of perturbations and see how that compares to voluntary movements. For example, balance modules used during waist-pull perturbations, which act on the center of mass rather than the feet, might be more similar to balance modules needed when lifting a large box from the floor. Further, future work should compare how different reactive balance motor modules compare to perturbed voluntary tasks; the balance modules that are helpful when walking on a slippery surface may not be the same modules needed when navigating a crowded store aisle. There also needs to be a deeper characterization of when and how reactive balance motor modules are recruited during voluntary tasks. For example, when are balance modules recruited during the turn, and how does it relate to different types of turn strategies, like pivoting or stepping?

Here we only compared motor module generalization to task time; there could be clearer relationships with other variables, such as body sway when getting out of a chair [96], turn strategy [87], or stepping characteristics [102]. Additionally, we have previously shown that in young adults, the relationship between generalization and walking performance emerged only when their balance was challenged ([34], see Appendix A). It is possible that stronger associations between generalization and task performance during turning and chair transfers are more observable with higher speeds, slippery floors, or other more challenging conditions.

Finally, though we show changes in generalization associated with aging, we only had a small population of middle-aged and older adults. All our older adults were also very active, with little history of falls. Follow-up studies should investigate reactive balance motor module generalization in larger sample sizes to see whether these trends hold. This work could also be further extended as a basis to investigate this relationship in populations with impairments. We have previously shown reductions in walking balance generalization in people with chronic stroke [36], but whether this would extend to other voluntary tasks remains an open question.

6 Conclusions

Despite the inherent multi-task nature of daily life, the underlying neuromuscular control required to execute and switch between a wide range of movement tasks is not yet well understood. Previous work in humans (e.g., [34], [35], [37]) and animals (e.g., [12], [14], [15]) has suggested that similar muscle coordination patterns (motor modules) are shared across different movement tasks. Further, sharing more common coordination patterns between walking and standing reactive balance is associated with walking performance in different populations, from low generalization and poor walking performance in people with chronic stroke [36], to higher generalization and excellent walking balance performance in expert dancers [34].

Based on this evidence, the overarching hypothesis for this work is that drawing upon a generalizable "library" of common muscle coordination patterns may facilitate performing and shifting between movement tasks flexibly and robustly. Aging and impairment impact this generalization, whether by reducing or changing the "library" itself or by affecting how appropriately it can be applied. The primary goals of this work were therefore to determine whether healthy adults share common muscle coordination patterns across a wider range of tasks than previously investigated and characterize changes in generalization associated with aging.

We found that healthy adults do share similar muscle coordination patterns across functionally different tasks as described in Chapters 3 and 4. Whether walking, turning, and chair transfer tasks were performed in isolation or as part of a continuous task like the Timed-Up-and-Go test, common motor modules were shared across tasks. Task-specific motor modules were observed during turning, possibly reflecting the increased mediolateral demands not present during chair transfers or straight-line walking [81], [83], [85]. We also found that healthy adults use reactive balance motor modules during these voluntary tasks, providing further supporting evidence that incorporating reactive balance motor modules in voluntary movements may be a general strategy to help meet task level goals ([25], [89]). These results support our hypothesis that generalizable muscle coordination patterns are used across a broad variety of reactive and voluntary movement tasks to enable well-coordinated movements and resist external disturbances.

With increasing age, people still shared common motor modules across voluntary tasks but had changes in their recruitment of reactive balance motor modules. Older adults used fewer reactive balance motor modules during walking and turning, consistent with our predictions. However, older adults shared more reactive balance motor modules during chair transfers than young adults, possibly reflecting increases in postural sway and instability [96]. Middle-aged adults usually had similar results to young adults but showed some trends toward older adults (e.g., in recruiting reactive balance modules during chair transfers) that may indicate the changes in muscle coordination patterns beginning to take place with age.

Whereas neurological injuries have been shown to be associated with fewer and different motor modules recruited (e.g., spinal cord injury [23], cerebral palsy [22], and stroke [75]), normal aging likely does not dramatically alter the library of coordination patterns available, but how and when they are recruited. For one, physical changes in the muscles likely contribute to how motor modules can be recruited. Sarcopenia, a condition in the elderly comprising low muscle strength, muscle mass, and physical ability, has wide-ranging and often progressive effects on fall risk and quality of life [71], [103]. With the development of conditions like sarcopenia, the coordination strategies that an individual has used throughout their adult life may become unsuitable. As a result, motor module recruitment may need to be adjusted to compensate for such age-related changes and their potential side effects such as reduced ability to control center of mass position when sitting down [96]. Indeed, reduced rectus femoris volume is associated with longer performance times in a 5x Sit-to-Stand test [104].

Additionally, changes in the nervous system and its connections to muscles may inhibit appropriate motor module recruitment, whether as noise or error in the output signals or sensory input signals required for monitoring the body's state [92],[105]. It has been shown that reactive balance motor modules are tuned according to COM feedback [89]. Declines in sensory integration and neural communication could therefore affect both the correct estimation of COM state and the effective tuning of balance module recruitment, leading to reduced usage of reactive balance motor modules during walking or even overuse of balance modules during chair transfers.

Though we have shown that there are age-related differences in generalization of muscle coordination patterns across a wider set of tasks, we only had a small population of older adults, and daily life requires far more types of movements than just walking, turning, and chair transfers. To truly gain a better understanding of the underlying patterns of multi-task neuromuscular control required for healthy mobility and the changes associated with aging, further research should be done. Specifically, future work should include a much broader variety of tasks, including activities both inside and outside the lab, such as climbing stairs, getting out of a car, or walking while carrying heavy objects. Additionally, larger and more diverse populations should be included. Ideally, a longitudinal study with a large sample size could be used to characterize individuals' changes in motor module recruitment over a span of decades. Given that such a study would be very expensive and difficult to perform, a larger cross-sectional study incorporating subjects from a range of ages, occupations, activity levels, and socioeconomic groups would also be appropriate.

Our work does contain some methodological limitations, though we do not believe they devalue our results. For one, there are valid critiques of motor module analyses that rely on using some cutoff to identify a specific number of motor modules. With a rigid cutoff such as we used here, it is possible that in some subjects the most "appropriate" set of motor modules may not be identified with this method, particularly for those who are very close to the threshold. This is a likely reason those larger standard deviations were observed in metrics that did depend on motor module number. We also included a mix of analyses that used identified numbers of motor modules (e.g., percent generalization) and those that were independent of module number (e.g., VAF-by-1 and VAF from using balance motor modules to reconstruct voluntary task EMG). The potential sensitivity of motor module numbers is a valid concern worthy of further research; however, because we saw similar trends in both types of metrics, we are confident in the claims presented here. Additionally, there have been discussions about potentially interesting structure in the residual left behind in that cutoff (i.e., there may be valuable coordination information contained in the 10% of variance *not* accounted for by an identified set of motor modules [106], [107]. Though we do not disagree with this, the residual structure is not likely to make an impact on our findings here; we were not attempting to characterize all of the relevant structure that exists in the muscle activity, but rather identify common patterns in muscle recruitment across tasks.

Here we have presented novel results demonstrating that human movement can be described with common generalizable motor modules across a variety of functionally different tasks, and that generalizable modules are recruited under both voluntary and reactive balance conditions. Our results are a first step towards thoroughly characterizing the patterns of muscle coordination used to produce the multitudes of movements that people are capable of, and understanding how that movement control is affected by age, training, or neurological injury. Fully characterizing the patterns of muscle coordination required for healthy daily movement and the resulting changes with age would provide opportunities for identifying underlying changes in movement control with age and impairment, developing more targeted interventions for declining mobility, and quantifying results of rehabilitation treatments.

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A Generalization of motor module recruitment across standing reactive balance and walking is associated with beam walking performance in young adults

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Abstract

Background: Recent studies provide compelling evidence that recruiting a common pool of motor modules across behaviors (i.e., motor module generalization) may facilitate motor performance. In particular, motor module generalization across standing reactive balance and walking is associated with both walking speed and endurance in neurologically impaired populations (e.g., stroke survivors and individual's with Parkinson's disease). To test whether this phenomenon is a general neuromuscular strategy associated with well-coordinated walking and not limited to motor impairment, this relationship must be confirmed in neurologically intact adults.
Research Question: Is motor module generalization across standing reactive balance and walking related to walking performance in neurologically intact young adults?
Methods: Two populations of young adults were recruited to capture a wide range of walking performance: professionally-trained ballet dancers (i.e., experts, n = 12) and novices (n = 8). Motor modules (a.k.a. muscle synergies) were extracted from muscles spanning the trunk, hip, knee and ankle during walking and multidirectional perturbations to standing. Motor module generalization was calculated as the number of modules common to these behaviors. Walking performance was assessed using self-selected walking speed and beam-walking proficiency (i.e., distance walked on a narrow beam). Motor module generalization between experts and novices was compared using rank-sum tests and the association between generalization and walking performance was assessed using correlation analyses.
Results: Experts generalized more motor modules across standing reactive balance

and walking than novices (p = 0.009). Across all subjects, motor module generalization was moderately associated with increased beam walking proficiency (r = 0.456, p = 0.022) but not walking speed (r = 0.092, p = 0.349).
Significance: Similar relationships between walking performance and motor module generalization exist in neurologically intact and impaired populations, suggesting that motor module generalization across standing reactive balance and walking may be a general neuromuscular mechanism contributing to the successful control of walking.

Introduction

Maintaining balance is critical for well-coordinated walking and the neuromuscular control of walking and balance may therefore share common structure. Motor module (a.k.a. muscle synergy) analysis has frequently been used to investigate the structure of neuromuscular control underlying walking and balance performance. Motor modules are defined as groups of coactive muscles flexibly recruited over time to transform movement goals into biomechanical output [6]. Our recent studies provide novel and compelling evidence that recruiting a common set of motor modules across standing reactive balance and walking (i.e., motor module generalization) contributes to successful walking performance in neurologically impaired populations [24], [36], then its relationship to walking performance should also be present among neurologically intact populations. The purpose of this study was therefore to identify whether motor module generalization across standing reactive balance and walking is related to walking performance in neurologically intact young adults.

The number of motor modules recruited during walking is frequently used as a measure of neuromuscular complexity, with higher complexity (i.e. more motor modules) associated with better walking performance. However, neuromuscular complexity during walking does not directly translate to a specific level of walking performance. Increased neuromuscular complexity is observed with motor development in infants [51] and with motor expertise in adults [37]. Conversely, neuromuscular complexity is reduced in many neurologically impaired populations that exhibit motor deficits and is associated with reduced walking speed and endurance [22],[23],[59],[108],[109]. Nevertheless, individuals with similar neuromuscular complexity during walking can exhibit very different levels of walking performance [36],[59],[108]. Further, improvements in walking performance, such as those due to rehabilitation in neurologically impaired populations or long-term training in neurologically intact populations, can occur without an increase in neuromuscular complexity [37],[110],[111].

Our recent studies demonstrate that generalization of motor modules across gait and balance tasks may be another important neuromuscular mechanism underlying differences in walking performance. We found that motor module generalization across standing reactive balance and walking is reduced in individual's with neurological impairments, such as Parkinson's disease [24] and stroke [36]. In other words, few standing reactive balance modules were recruited during unperturbed walking. Many of these individuals were community-dwelling with high function and although their walking speed was slower than neurotypical controls, they did not exhibit reduced neuromuscular complexity (i.e., number of motor modules). Instead, a reduction in motor module generalization was associated with their slower walking speeds. Because the relationship between motor module generalization and walking speed was present in individuals who do not exhibit reduced neuromuscular complexity we reasoned that it might also explain differences in neurologically intact individuals. Although many of the motor modules recruited for standing reactive balance are also recruited during unperturbed walking in healthy young adults [42], the relationship between generalization and walking performance has not been tested.

In the present study, we analyzed electromyography (EMG) from muscles spanning the trunk, hip, knee, and ankle during overground walking and multidirectional perturbations to standing in healthy young adults. We recruited two populations of young adults to capture a wide range of walking performance: professionally trained ballet dancers (experts) and untrained novices. Two measures of walking performance were investigated: self-selected walking speed and beam-walking proficiency. Beam walking proficiency (i.e., walking on a narrow beam [37]) provides a challenge to walking balance that may better differentiate walking performance than walking speed. Based on our hypothesis that motor module generalization across standing reactive balance and walking is a general neuromuscular strategy contributing to the successful control of walking, we predicted that generalization across all subjects would be positively associated with our measures of walking performance.

Methods

Participants

Twelve experts (professionally-trained ballet dancers; 12 female, 22.0±2.5 yrs old, 1.64±.06 m height, 54.3±6.3 kg weight) and 8 sex, age, height, and weight-similar untrained novices (no dance or gymnastics training; 8 female, 21.9±3.4 yrs old, 1.66±0.06 m height, 66.1±21.4 kg weight) participated in the experiment.

Inclusion criteria for all participants was age greater than 18 yr. Experts were required to have at least 10 years of ballet training and were recruited from the professional development program of the Atlanta Ballet Center for Dance Education and the Company of the Atlanta Ballet. Novices were required to have no formal dance or gymnastic training. Exclusion criteria for both groups were self-reported medical conditions that could impair walking and balance. All participants provided written informed consent before participating according to protocols approved by the institutional review boards at Emory University and Georgia Institute of Technology.

Experimental Procedures

All participants completed four walking conditions (narrow beam-walking, wide beam-walking, overground walking at slow speed, overground walking at preferred speed) and one standing reactive balance condition. Motor modules in beam-walking and overground walking at slow speed in these participants were previously analyzed in Sawers et al. [112]. Here, we focus on motor modules in standing reactive balance and overground walking at preferred speed.

- Standing reactive balance. Reactive balance performance was assessed through postural responses to ramp-and-hold translations of the support surface while subjects stood on an instrumented platform. The platform translated in 12 equally spaced directions in the horizontal plane (see Fig. 1B) with 13 cm displacement, 15 cm/s peak velocity, and 0.3 g acceleration. Three trials in each direction were collected in random order. Subjects were instructed to cross their arms and maintain balance without stepping or using their arms. Stance width was self-selected and enforced to be the same across all trials.
- Overground walking at preferred speed. Subjects were instructed to walk at their preferred speed over a 7.5m distance while keeping their head up and looking straight ahead. Six trials were collected per subject.

EMG data collection and processing

Surface EMG activity was recorded at 1080 Hz from 16 muscles on the right leg and trunk of each participant: tibialis anterior (TA), peroneus longus (PERO), medial gastrocnemius (MGAS), soleus (SOL), vastus medialis (VMED), vastus lateralis (VLAT), biceps femoris long head (BFLH), semimembranosus (SEMM), gluteus maximus (GMAX), gluteus medius (GMED) rectus femoris (RFEM), tensor fasciae latae (TFL), adductor magnus (ADMG), rectus abdominus (REAB), external obliques (EXOB), and erector spinae (ERSP). EMG signals were high-pass filtered at 35 Hz (third order-Butterworth), de-meaned, rectified, and low-pass filtered at 40 Hz (third-order Butterworth) using custom Matlab routines. Subject-specific EMG data matrices for each condition (i.e., standing reactive balance and walking) were assembled as described below. The assembled EMG data matrices for each condition were then normalized to the maximum activation observed during walking at preferred speed.

For standing reactive balance, EMG data were analyzed during four time bins: one before the perturbation and three during the automatic postural response (APR; Fig. 1B) [42]. Specifically, mean muscle activity was calculated during a 280-ms background period that ended 140 ms before the perturbation and during each of three 75 ms bins beginning 100 ms after perturbation onset. Mean muscle activity values for each muscle during each bin for each trial were assembled to form an mxt data matrix, where m is the number of muscles (16) and t is the number of data points (3 trials x 12 directions x 4 time bins = 144).

For consistency with reactive balance processing, EMG data for walking were averaged over 75 ms bins. Data from the first and last two steps were removed to avoid gait initiation and termination (Fig. 1A). Trials were concatenated end-to-end to form an mxt data matrix. The number of data points, t (trials x time bins), varied across subjects, with a minimum size of 121. There was no significant difference between groups (176.4±39.3 for experts, 213.9±47.9 for novices, t(18)=1.91, p=0.10).

Motor Module Analysis

Motor modules for each subject were extracted separately from EMG data matrices derived from standing reactive balance and walking using non-negative matrix factorization (NNMF; [113]). NNMF decomposes the recorded EMG according to EMG=WxC, where W is an mxn matrix with n motor modules and C is an nxt matrix of motor module activation coefficients. To ensure equal weight of each muscle during the extraction process, each row in the EMG data matrices (i.e. each muscle) was scaled to unit variance before motor module extraction and rescaled to original units afterward.

Motor module number in each condition (nwalk, nbalance) was chosen as described previously [24],[36]. Briefly, 1-16 motor modules (W) were extracted from each EMG data matrix. Goodness of fit between actual and reconstructed

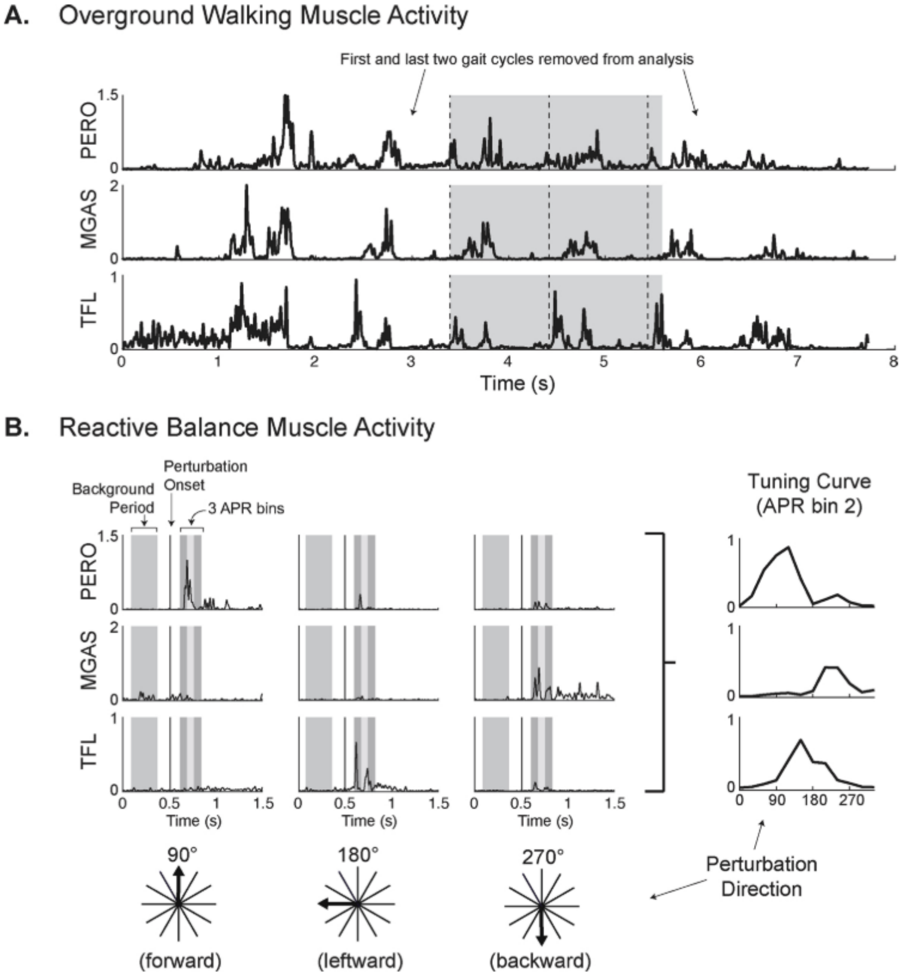


Figure A.1: Example processed EMG from select muscles during overground walking (A) and standing reactive balance (B). A: muscle activity for walking was recorded while participants walked overground at their self-selected speed for at least 6 trials of 7.5 m each. For each trial, the first and last two gait cycles were removed to avoid gait initiation and termination. Dashed lines represent right heel-strikes, and the shaded region represents the data analyzed for 1 trial. Data from all trials for a subject were concatenated before motor module extraction to form an m x t data matrix, where m is the number of muscles and t the number of time points across all trials. B: muscle activity for standing reactive balance was assessed through ramp-and-hold perturbations in 12 evenly spaced directions. Left: responses to forward, leftward, and backward perturbations are illustrated. EMG responses occurred 100 ms after perturbation onset (denoted by black vertical line). Mean EMG activity was calculated during a background period before the perturbation and three 75-ms time bins during the automatic postural response (APR). Right: tuning curves of mean muscle activity from perturbations as a function of perturbation directions for the second APR bin. Before motor module extraction, the tuning curves were assembled to form an m x t data matrix, where m is the number of muscles and t the number of data points (3 trials x 12 directions x 4 time bins = 144). (PERO, peroneus longus; MGAS, medial gastrocnemius; TFL, tensor fascia latae).

EMG was evaluated with variability accounted for (VAF), defined as 100 x squared uncentered Pearson's correlation coefficient [44]. 95% confidence intervals (CI) on VAF were calculated using a bootstrapping procedure where EMG datasets were resampled 250 times with replacement and VAF of the reconstructed EMG was recalculated after each resampling. n was chosen such that the lower bound of the 95% VAF CI exceeded 90%. We compared nwalk and nbalance between groups using separate two-tailed Wilcoxin Rank Sum tests (H_0: experts=novices; H_1: experts $\neq$ novices).

Motor module generalizability, nshared, was defined as the number of motor modules shared between standing reactive balance and walking [24],[36],[42] and identified using Pearson's correlation coefficients. A pair of motor modules were considered shared if $r > 0.623$, which corresponds to the critical value of r^2 for 16 muscles at α=0.01. To account for the fact that each subject recruited a different number of total motor modules, motor module generalization was also expressed as a percentage:

$$\%n_{shared} = 100\% \times \left(\frac{nshared}{n_{walk} + n_{balance} - n_{shared}} \right)$$

. To determine if experts generalized more motor modules across standing reactive balance and walking, we compared nshared and %nshared between groups using a one-sided Wilcoxin rank sum test and t-test, respectively (H_0: experts=novices; H_1: experts>novices).

Walking Performance Metrics

1. Preferred walking speed: Walking speed for each trial was defined as the average velocity of the C7 marker in the middle of the walkway and was then averaged across all trials for each subject.

2. Beam-walking proficiency: Participants walked in a heel-to-toe pattern along a narrow beam (3.8cm wide, 3.25cm high, and 3.66m long) six times while keeping their arms crossed over their chest. Participants were instructed to stop if they uncrossed their arms or stepped off the beam (i.e., failure). Beam-walking proficiency was defined as a normalized distance walked, calculated as the ratio of the sum of the distance walked across all six trials and the total possible distance [37]. Perfect performance – i.e., no failures – equals 1.0.

Differences in preferred walking speed and beam-walking proficiency were compared between experts and novices using two-sided t-tests. To test our prediction that motor module generalization is positively associated with walking performance, one-tailed Pearson's correlations (H_0: r=0, H_1: r>0) were performed to relate each metric of motor module generalizability (nshared, %nshared) to each metric of walking performance (walking speed, beam-walking proficiency).

Results

Motor module number (Fig. 2B) did not differ between experts and novices in either walking (p=0.299) or standing reactive balance (p=0.497). The median number of motor modules recruited for walking was 7 in experts (range: 5-8) and 6 for novices (range: 5-9). The median number of motor modules recruited in standing reactive balance was 6 in experts (range: 4-7) and 6 for novices (range: 4-8).

Motor module generalization (Fig. 2C) was higher in experts compared to novices (nshared: p=0.009, %nshared: p=0.010). The median number of motor modules shared across standing reactive balance and walking was 3 in experts (range: 1-4) and 2 in novices (range:1-3). These numbers correspond to an average percentage of motor modules shared across conditions of 30.9±11.2% in experts and 18.2±10.1% in novices.

Beam-walking proficiency but not preferred walking speed differed between experts and novices, with better beam-walking proficiency associated with higher levels of motor module generalization (Fig. 3). Average preferred walking speed was 1.16±0.18 m/s in experts and 1.08±0.16 m/s in novices (p=0.303). Beam walking proficiency was 0.76±0.20 in experts and 0.59±0.20 in novices (p=0.037). Across all subjects we identified a significant moderate positive relationship between beam walking proficiency and number of motor modules generalized across conditions (r=0.46, p=0.022) and a similarly sized positive relationship with the percentage of modules shared across conditions that did not quite reach significance level of α=0.05 (r=0.34, p=0.072). No significant relationship between motor module generalization and preferred walking speed was identified (nshared: r=0.09, p=0.349; %nshared: r=0.19, p=0.205).

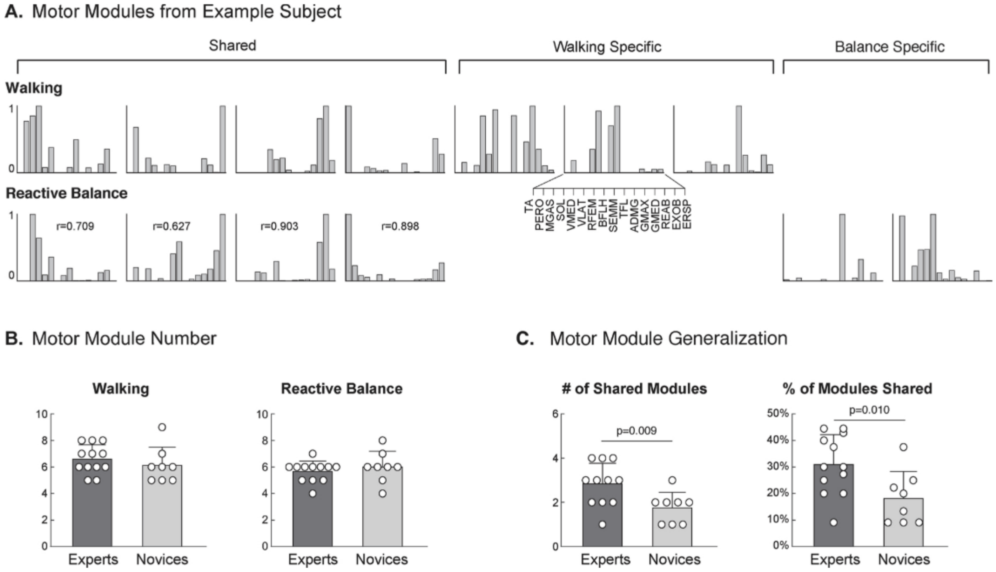


Figure A.2: Motor module number and generalization across walking and reactive balance. A: representative motor modules from an expert subject during walking and standing reactive balance. Motor modules were extracted from each behavior independently and identified as shared across behaviors if r ¿ 0.623. 4 out of 9 motor modules, or 44.4%, were shared across conditions in the example subject. B: The number of motor modules recruited during overground walking (left) and standing reactive balance (right) did not differ between experts (n = 12, dark gray) and novices (n = 8, light gray). C: Both the number (left) and percentage (right) of shared modules was decreased in novices compared to experts. White circles in B and C represent individual values for each subject. (TA, tibialis anterior; PERO, peroneus longus; MGAS, medial gastrocnemius; SOL, soleus; VMED, vastus medialis; VLAT, vastus lateralis; RFEM, rectus femoris; BFLH, biceps femoris long head; SEMM, semimembranosus; TFL, tensor fascia latae; ADMG, adductor magnus; GMAX, gluteus maximus; GMED, gluteus medius; REAB, rectus abdominus; EXOB, external obliques; ERSP, erector spinae).

A.1 Discussion

Accumulating evidence suggests that motor module generalization across standing reactive balance and walking, defined as recruiting a common set of motor modules across both tasks, may help to distinguish differences in walking performance. Here, we demonstrate that motor module generalization across these two tasks is positively associated with the ability to perform a challenging beam-walking task in neurotypical adults. This corroborates our prior studies in stroke survivors and individuals with Parkinson's disease demonstrating a positive relationship between motor module generalization and measures of walking performance such

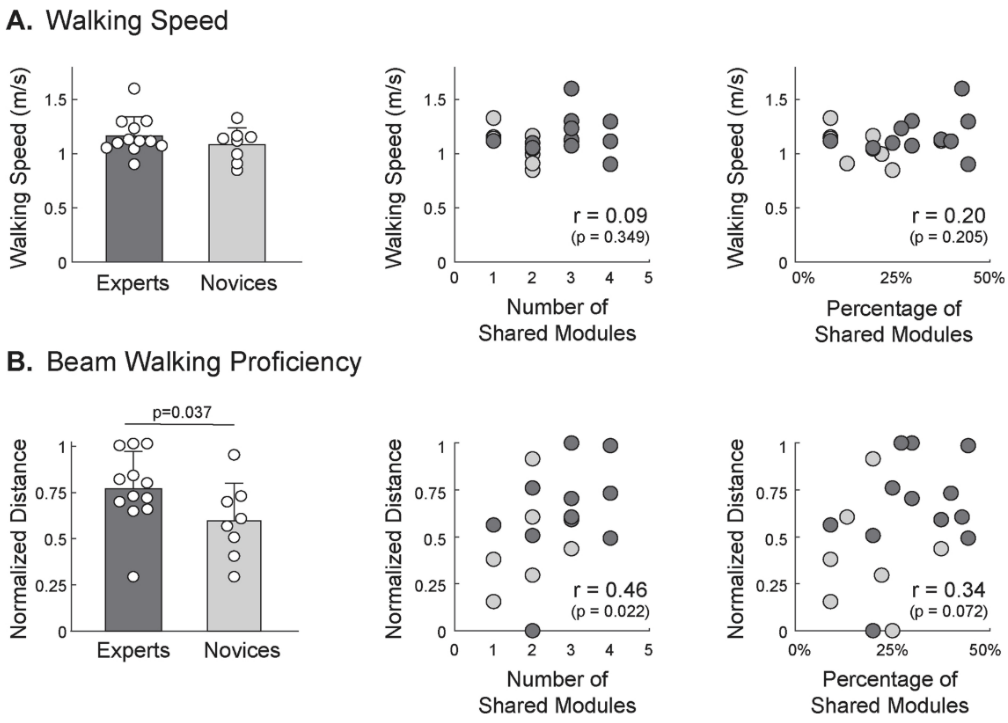


Figure A.3: Walking performance metrics. A: Self-selected walking speed did not differ between experts and novices (left panel) and was not associated with the number (center panel) or percentage (right panel) of motor modules shared across standing reactive balance and walking. B: The normalized distance walked on a narrow balance beam was higher in experts compared to novices (left panel) and was positively associated with both the number (center panel) and percentage (right panel) of motor modules shared across standing reactive balance and walking. Experts are denoted in dark gray and novices in light gray. Circles represent individual values for each subject. this

as speed and endurance. Taken together, these studies add to our understanding of how walking is controlled and provide compelling evidence that motor module generalization with standing reactive balance may be a neuromuscular strategy utilized during walking in both healthy and motor-impaired populations. In particular, this strategy may co-opt the neuromuscular control important for automatic postural responses to enable the robust and automatic control of balance during walking.

Our results are consistent with our prior studies in neurologically impaired populations [24],[36], suggesting that recruiting reactive balance motor modules during walking may be a general neuromuscular strategy for well-coordinated walking regardless of motor ability. We found that motor module generalization across standing reactive balance and walking but not motor module number in either task differed between young adult experts and novices (Fig. 2). As both groups were young adults with no motor deficits it was not surprising that a similar number of motor modules were identified between groups in each task. However, the generalization of motor modules across standing reactive balance and walking differentiated the neuromuscular control structure between these two groups. Interestingly, the amount of motor module generalization that we observed previously in different group of young adults (37.4±23.4%) [42] was higher than the novices studied here (p=0.03, t-test) but similar to experts (p=0.42). This discrepancy could be due to lower motor ability of the novices studied here versus the young adults in the prior study, where we did not control for expertise [42]. Additionally, the perturbations to standing were of lower velocity and acceleration in this study (15 cm/s versus 35 cm/s velocity and 0.3g compared to 0.5g acceleration), which also could have altered the number and/or structure of motor modules recruited in reactive balance.

Recruiting standing balance motor modules during walking may contribute to the maintenance of walking balance. Our prior studies revealed that motor module generalization across these two tasks was associated with overground walking performance in motor impaired populations (i.e., speed and endurance) [24],[36]. Unsurprisingly, we did not find a similar relationship with overground walking in healthy young adults in the current study. In contrast to motor impaired populations, overground walking does not provide a challenge to young adults and therefore we also included a beam-walking task. This beam-walking task was specifically designed to provide a challenge to walking balance and we previously found that it could differentiate walking balance ability in young adults [37],[112]. Here, we expand upon our prior study and find that performance on the beam-walking task in the same cohort of young adults is positively associated with motor module generalization across standing reactive balance and overground walking. That this relationship only emerged when balance is challenged (i.e., overground walking in stroke survivors [36] and beam-walking in young adults) suggests that generalization across these two tasks represents a neuromuscular strategy for maintaining balance while walking. Given that this relationship is of only a fairly moderate strength (r=0.46), this neuromuscular strategy should be placed in context as one of multiple concurrent strategies likely contributing to walking balance.

Motor module generalization across standing reactive balance and walking may also contribute towards the automatic control of walking. Responding to discrete perturbations, such as those experienced by participants in the current study in the standing reactive balance paradigm, requires rapid changes in the coordination of muscle recruitment. These rapid changes are typically thought to be mediated by brainstem circuits [114], although more voluntary contributions can play a role in the later response. Recruiting a common set of motor modules across standing reactive balance and walking suggests a convergence on this automatic recruitment of motor modules important for the maintenance of balance. That such convergence is increased (i.e. more common modules) in the expert group is consistent with prior evidence suggesting that automaticity and movement efficiency is increased with expertise [115],[116],[117]. These results are also consistent with our prior studies in stroke survivors and Parkinson's disease [24],[36] in which reduced gait automaticity is common [118],[119],[120],[121],[122] and we found that motor module generalization across standing reactive balance and walking was reduced. Further, improvements in walking function in Parkinson's disease were accompanied by increased motor module generalization due to the walking motor modules becoming more similar to the standing reactive balance motor modules. Taken together, these results suggest a potential relationship between gait automaticity and motor module generalization that is common to both neurologically impaired and intact populations. Future work is needed to directly test this putative relationship.

Conclusions

We identified a positive relationship between beam-walking performance and motor module generalization across standing reactive balance and walking in young neurotypical adults. This relationship is consistent with our prior studies in individuals with Parkinson's disease [24] and stroke survivors [36]. Although the sample sizes in each study were small (between 6 and 11 per group), taken together these studies provide compelling evidence that recruiting reactive balance motor modules during unperturbed walking may be a general neuromuscular strategy that contributes to the maintenance of balance during walking.

B Supplementary material to Chapter 3

TUG Subtask Segmentation Example

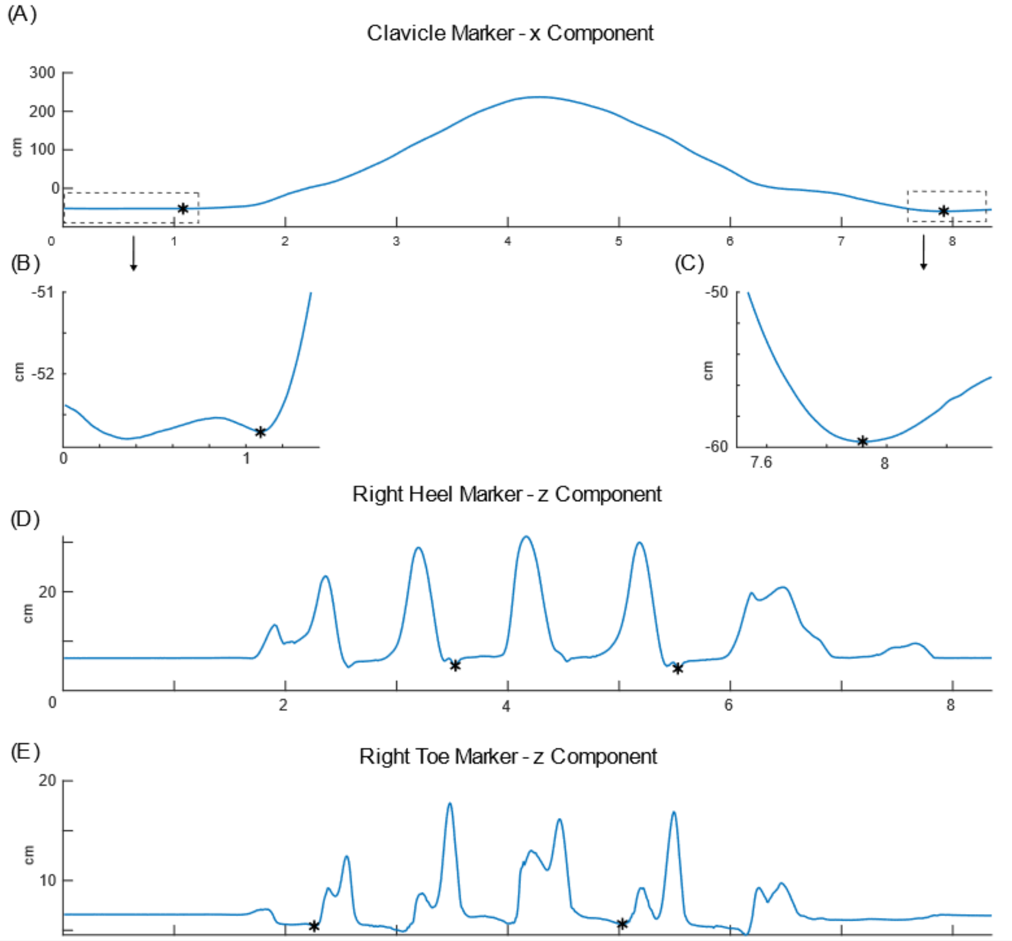


Figure B.1: Example of TUG subtask segmentation in a representative subject. (A) Clavicle marker in the x-direction, used to identify TUG start and stop. (B) Toe markers in the z-direction, used to identify Walk 1 start and Turn start. (C) Heel markers in the z-direction, used to identify Turn stop and Walk 2 stop. Also see Table 1 in the manuscript.

Normalization of Motor Module Activations

Each trial was normalized to be the same number of points (1024) and such that the number of data points in Sit-to-Stand, Walk-Turn-Walk, and Stand-to-Sit was consistent. These values were determined by pooling the subtask proportions (subtask time / full TUG time) across all subjects and trials in the single task TUG test, averaging them for each subtask, and rounding to the nearest integer. This yielded

- Sit-to-Stand: 15%
- Walk 1: 17%
- Turn: 25%
- Walk 2: 10%
- Stand-to-Sit: 33%

The Turn and the two Walk subtasks were combined to avoid introducing any experimenter bias from which steps were selected as the beginning and end of the turn. As described above, TUG subtasks were manually identified, so even though subjects were generally consistent with the number of steps, a particular step could be classified as turning or walking in different trials depending on the subject's orientation. Motor modules activations were then normalized as follows:

- Sit to stand - 15% - 154 points
- Walk-Turn-Walk - 52% - 532 points
- Stand-to-Sit - 33% - 338 points

Kinematic Strategy Separation

Trials were classified based on "kinematic strategy", defined as the sequence of the first step leg, turn direction, and stand-to-sit turn direction (e.g., RRR or LRL). The shapes of the activation curves depended on kinematic strategy; for example, the first peak in the plantarflexor synergy would depend on which foot was used to step off. We didn't want to artificially analyze variation that was purely due to such kinematic differences.

Because the first leg step-off and stand-to-sit turn direction were not enforced, some subjects varied their kinematic strategies, and did not always use the same

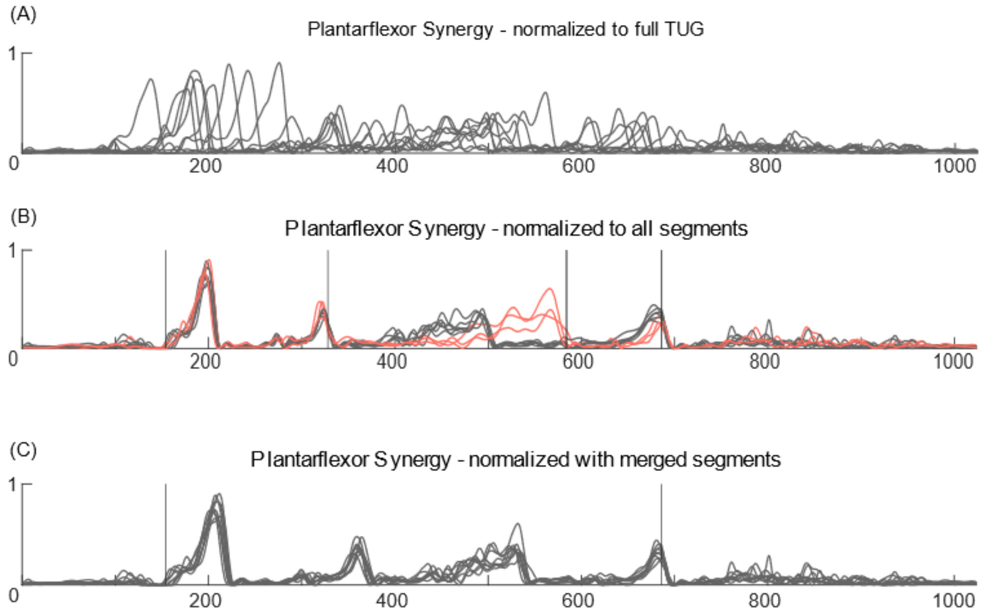


Figure B.2: Example of normalization in a single motor module from a representative subject in the cognitive dual-task TUG test. (A) Motor module activation profiles normalized to the full TUG test only. Here the only defined points are the beginning and end of the TUG test. (B) Activation profiles with every subtask normalized. A couple different curve profiles can be seen that could be due to the turn identification, colored in orange. Vertical lines indicate the divisions between TUG subtasks. (C) Activation profiles normalized to three sections (Sit-to-Stand, Walk-Turn-Walk, and Stand-to-Sit), as used in the manuscript. Here, the peaks for each step are more aligned, allowing for better RMSE analysis.

ones in TUG and TUGC. Table 2 contains the number of trials in which the subjects used each kinematic strategy. For example, YA23 used 3 kinematic strategies in both TUG and TUGC, but only two (RRR and RLL) were used in both conditions. So that only like performances from TUG and TUGC were compared, we only included trials that had the same kinematic sequences in both TUG and TUGC in the RMSE analysis.

Detailed Results

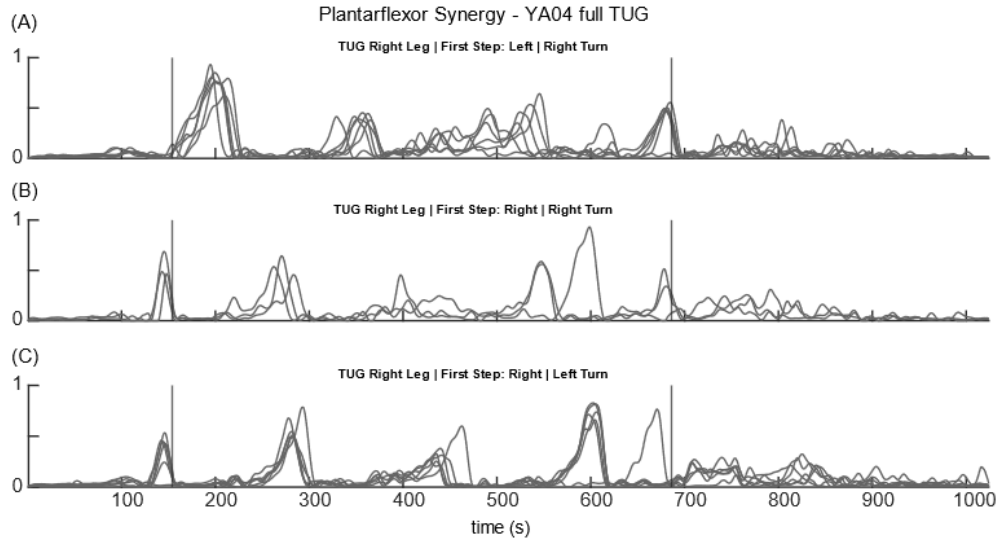
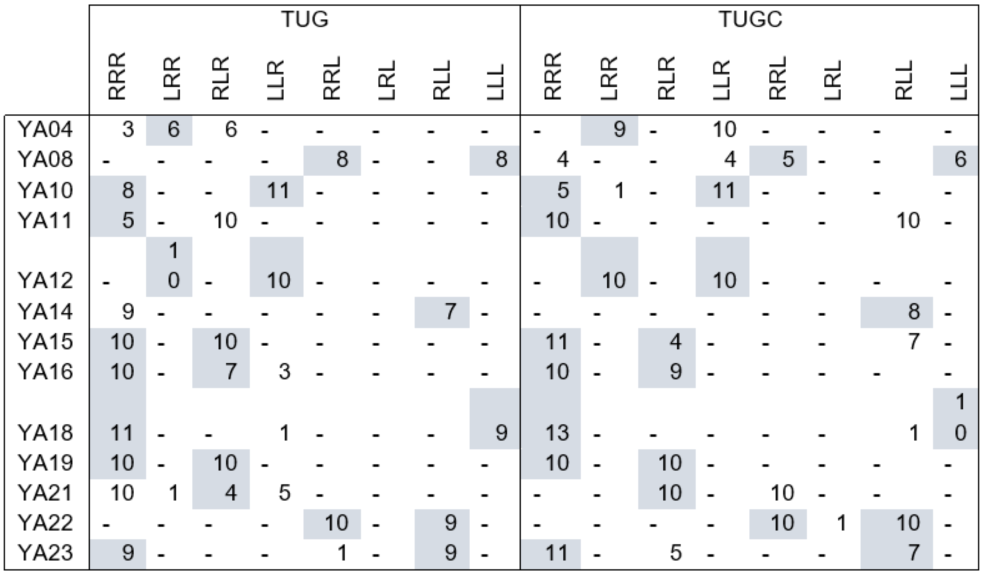


Figure B.3: Example of activation profiles from two motor modules in three kinematic strategies. Activations from the kinematic sequences LRR (A), RRR (B), and RLR (C).

Table B.1: Results of t-tests comparing motor module composition in TUG vs TUGC for all TUG subtasks

	p-value
full	0.713
Sit-to-Stand	0.185
Walk	1
Turn Left	0.265
Turn Right	0.161
Stand-to-Sit Left Turn	0.678
Stand-to-Sit Right Turn	0.576



	TUG								TUGC							
	RRR	LRR	RLR	LLR	RRL	LRL	RLL	LLL	RRR	LRR	RLR	LLR	RRL	LRL	RLL	LLL
YA04	3	6	6	-	-	-	-	-	-	9	-	10	-	-	-	-
YA08	-	-	-	-	8	-	-	8	4	-	-	4	5	-	-	6
YA10	8	-	-	11	-	-	-	-	5	1	-	11	-	-	-	-
YA11	5	-	10	-	-	-	-	-	10	-	-	-	-	-	10	-
YA12	-	10	-	10	-	-	-	-	-	10	-	10	-	-	-	-
YA14	9	-	-	-	-	-	7	-	-	-	-	-	-	-	8	-
YA15	10	-	10	-	-	-	-	-	11	-	4	-	-	-	7	-
YA16	10	-	7	3	-	-	-	-	10	-	9	-	-	-	-	-
YA18	11	-	-	1	-	-	-	9	13	-	-	-	-	-	1	10
YA19	10	-	10	-	-	-	-	-	10	-	10	-	-	-	-	-
YA21	10	1	4	5	-	-	-	-	-	-	10	-	10	-	-	-
YA22	-	-	-	-	10	-	9	-	-	-	-	-	10	1	10	-
YA23	9	-	-	-	1	-	9	-	11	-	5	-	-	-	7	-

Figure B.4: Table 1: Kinematic Strategies and Number of Trials. This table contains the number of trials per kinematic sequence for each subject, in the single-task TUG test (TUG) and the dual-task TUG test (TUGC). Each of the 8 kinematic sequences consists of a first step leg, turn direction, and stand-to-sit turn direction. For example, the sequence 'RRR' indicates the subject stepped off with their right foot and turned to the right for both turns; the sequence LRL indicates step off with the left foot, a right turn around the cone, and a left turn before sitting down. Table cells contain either the number of trials that the subject used that sequence, or a dash for sequences that were unused. Colored cells indicate sequences that were used in both TUG and TUGC and were therefore included in the RMSE analysis.

Table B.2: Clustering Results

	# clusters		% generalization		Avg Consistency		% shared w/ Full TUG	
subject	L Leg	R Leg	L Leg	R Leg	L Leg	R Leg	L Leg	R Leg
YA04	5	5	90	89	0.85	0.86	80	80
YA08	8	5	88	96	0.81	0.82	63	100
YA10	5	6	90	86	0.77	0.83	100	83
YA11	5	5	90	90	0.83	0.80	80	80
YA12	6	5	91	90	0.82	0.60	83	67
YA14	5	4	92	95	0.82	0.84	67	100
YA15	5	5	88	95	0.72	0.78	80	100
YA16	5	7	89	81	0.81	0.85	80	71
YA18	6	7	88	89	0.82	0.77	38	71
YA19	5	6	83	90	0.78	0.70	80	83
YA21	6	6	85	87	0.71	0.74	67	83
YA22	5	5	90	89	0.83	0.79	80	80
YA23	5	7	92	88	0.78	0.89	80	57