Temporal Refinement of Muscle Synergies in Skilled Golf Swings

Hangil Lee, Jinsook Roh, *Member, IEEE*, and Hyung-Soon Park, *Senior Member, IEEE*

***Abstract*—Muscle synergies, defined as coordinated activations of muscle groups, are thought to simplify motor control by reducing dimensionality and providing a repertoire of adaptable motor solutions. While prior research has investigated synergy adaptation in clinical populations and healthy individuals, most evidence stems from constrained or low-degree-of-freedom (DOF) tasks. A critical gap remains in understanding how synergies are refined in high-DOF, performance-driven contexts that demand full-body coordination. To address this, we examined neuromuscular strategies in professional and amateur golfers performing a 7-iron swing. Electromyographic recordings from 27 muscles, along with kinematic and kinetic data, were analyzed to identify kinematic predictors of clubhead speed and their associated muscle activation patterns. Muscle synergy and clustering analysis of these key muscles revealed two group-invariant synergies, pelvis rotation and plantarflexion, whose peak activation timings were significantly correlated with clubhead speed. A significant subject-specific synergy and a significant amateur-exclusive synergy further highlighted how adaptation involves both individualized tuning and filtering of suboptimal strategies. These findings suggest that expert performance in complex, high-DOF tasks relies on temporal refinement of existing synergies rather than structural reorganization, highlighting the importance of managing, rather than minimizing, motor complexity in the acquisition of advanced motor skills. Furthermore, our approach for identifying neuromuscular patterns linked to performance outcomes provides a foundation for targeted training interventions aimed at enhancing or restoring complex movement patterns.**

***Index Terms*—Biomechanics, electromyography, sports performance, motor control, muscle synergies.**

I. INTRODUCTION

EXPERT athletes perform complex motor tasks with exceptional power and precision, illustrating the remarkable capabilities of the neuromuscular system to manage the body's many degrees of freedom (DOF) [1], [2]. The neuromuscular system must integrate the activity of numerous muscles and joints capable of independent motion to produce fluid and efficient movements. Muscle synergies, coordinated activations of muscle groups, offer an elegant solution to this control challenge. These synergies are thought to represent fundamental building blocks of motor control, organizing groups of muscles into functional units that are activated in a coordinated manner to achieve specific movement goals [3], [4]. By simplifying the control of multiple muscles into a smaller set of neural commands, muscle synergies reduce the dimensionality of motor control while preserving the flexibility needed for adaptive and task-specific coordination [5], [6]. This framework has been applied in both movement science and neurorehabilitation to investigate how muscle coordination is organized across healthy and clinical populations.

Emerging models of motor control theory, such as the synergy expansion hypothesis, propose that synergies evolve through experience and diversify to accommodate a wide range of motor tasks [7]. In fine motor skills like piano playing, skilled performers exhibit reduced co-activations and more selective muscle activation patterns compared to novices, reflecting refined neuromuscular control [8]. In contrast, coordination strategies may become more unified in cyclic tasks such as locomotion and cycling, a phenomenon often referred to as synergy merging [9], [10], [11]. These adaptations highlight the capacity of the motor system to reorganize coordination strategies, but their functional implications are not universally beneficial. Notably, in clinical populations, such as individuals recovering from stroke, the merging of synergies is often associated with reduced motor complexity and impaired functional performance [12], [13]. This has led to growing interest in using synergy analysis to understand motor deficits and design neurorehabilitation strategies.

While much of the current literature focuses on relatively low DOF or constrained experimental tasks, there remains a critical gap in understanding how muscle synergies are organized and refined in complex, high DOF movements. In particular, full-body athletic actions place unique demands on coordination and control, providing a valuable model for examining how the nervous system manages performance-oriented movement under minimal constraint. Investigating these adaptations in elite athletes can yield insight into gen-

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Received 11 June 2025; revised 11 October 2025; accepted 4 December 2025. Date of publication 11 December 2025; date of current version 23 December 2025. The work of Jinsook Roh was supported by the National Science Foundation Faculty Early Career Development (CAREER) Award under Grant 2145321. The work of Hyung-Soon Park was supported by the Technology Innovation Program funded by the Ministry of Trade, Industry & Energy (MOTIE), South Korea, under Grant RS-2024-00443121. *(Corresponding authors: Jinsook Roh; Hyung-Soon Park.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Institutional Review Boards of the Korea Advanced Institute of Science and Technology under Approval No. KH2021-215.

Hangil Lee and Hyung-Soon Park are with the Department of Mechanical Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon 34141, South Korea (e-mail: leehangil94@gmail.com; hyungspark@kaist.ac.kr).

Jinsook Roh is with the Department of Biomedical Engineering, University of Houston, Houston, TX 77004 USA (e-mail: jroh@uh.edu).

This article has supplementary downloadable material available at https://doi.org/10.1109/TNSRE.2025.3642830, provided by the authors.

Digital Object Identifier 10.1109/TNSRE.2025.3642830

Fig. 1. (a) EMG, kinematic, and kinetic data were collected to analyze the biomechanics and performance of the golf swing. (b) A multi-step modeling approach was applied to reduce the dimensionality of the dataset and identify key muscles associated with performance. Muscle synergy and clustering analysis was subsequently performed to identify representative neuromuscular coordination patterns for professional and amateur golfers.
Abbreviations: ama = amateurs; GRFp = peak ground reaction force; GRFt = weight transfer timing; MAG = peak magnitude; MOCAP = motion capture; MS = muscle synergy; NMF = non-negative matrix factorization; pro = professionals; TIM = peak timing; WUt = wrist unhinge timing; XF = x-factor; XS = x-factor stretch.

eral principles of neuromuscular organization, with potential relevance for rehabilitation strategies that aim to restore or enhance complex functional movements.

The golf swing exemplifies the complexity of high-DOF motor tasks, requiring precise coordination of body segments to generate and efficiently transfer energy from the ground to the clubhead [14], [15], [16]. It is typically divided into three phases: the backswing, where the club is raised and body segments rotate to store potential energy; the downswing, involving the rapid release of this energy to accelerate the club toward the ball; and the follow-through, during which the body decelerates after impact. This complexity is further compounded by individual differences in musculoskeletal properties, which contribute to a wide range of swing styles and motor strategies [16], [17]. These diverse motor solutions raise fundamental questions about whether shared neuromuscular patterns underlie elite performance despite such variability. Extensive research has examined the kinematic and kinetic determinants of performance, with a particular focus on increasing clubhead speed (CHS), a critical determinant of ball speed and carry distance [16], [17], [18], [19], [20], [21], [22], [23], [24]. However, the neuromuscular mechanisms that underpin these outcomes remain poorly understood. While electromyography (EMG) studies have investigated muscle activity in golfers [25], [26], [27], [28], [29], few have examined how muscle activation patterns contribute to specific performance outcomes.

In this study, we investigated how professional golfers adapt muscle synergies to refine CHS during the golf swing, a representative example of a high-DOF, performance-driven motor task. By analyzing whole-body muscle activation, kinematic, and ground reaction force (GRF) data collected from professional and amateur golfers performing the 7-iron swing, we aimed to determine the neuromuscular strategies that distinguish elite performance (Fig. 1). Our analysis identified kinematic factors strongly associated with CHS and the corresponding muscle activation patterns exhibiting significant correlations with these factors. Leveraging this refined selection of key muscles, we conducted muscle synergy analysis and k-means clustering to reveal distinct patterns of synergy usage across skill levels. This work introduces an approach for linking muscle synergies to performance outcomes and offers insight into how the nervous system refines coordination strategies in complex, high-DOF tasks. We hypothesized that expertise in a high-DOF task like the golf swing arises from the fine-tuning of existing neuromuscular modules rather than structural changes in synergy composition.

II. METHODOLOGY

A. Participants

Two groups of male participants were recruited for this study: professional and amateur golfers. The professional group consisted of 10 participants with 0 handicap (age = 31.5 ± 8.1 [mean ± SD] years old; BMI = 26.1 ± 1.8 [mean ± SD]) who had been licensed under the Korean Professional Golf Association as tour or semi-professionals. The amateur group comprised of 10 non-professional golfers (age = 42.3 ± 13.7 [mean ± SD] years old; BMI = 23.8 ± 1.9 [mean ± SD]) who had been playing golf for at least 2 years and had a handicap ranging from 8 to 25 (15.6 ± 6.2 [mean ± SD]). In golf, a handicap is a numerical measure of a player's skill level, with lower values indicating higher proficiency. Participants with injuries affecting swing mechanics were excluded from the study. All participants were right-handed and references to left and right sides reflect the perspective of a right-handed golfer. The study was approved by the institutional review boards of the Korea Advanced Institute of Science and Technology (KH2021-215). All participants provided written informed consent before the study.

B. Experimental Setup and Data Acquisition

Muscle activity was recorded using wireless surface EMG sensors (Delsys Trigno, MA, USA) from 27 upper and lower limb muscles selected based on prior research [25], [30], [31]. Recorded muscles and abbreviations are listed in Table I. Skin preparation included shaving excessive hair, cleaning with alcohol wipes, and attaching sensors along the belly of the muscle fibers. Sensors were secured with tape to reduce movement artifacts.

Kinematic data were captured using 31 motion capture markers affixed to anatomical landmarks, as detailed in Supplementary Table S1, and recorded with Vicon Nexus software (Vicon MX, Oxford Metrics Group, UK). Markers on the head were attached to a headband, while other markers were secured

TABLE I
MUSCLES RECORDED WITH EMG SENSORS AND THEIR RESPECTIVE ABBREVIATIONS

Muscle	Abbreviation	Side
Sternocleidomastoid	SM	Left & right
Upper trapezius	UT	Left & right
Medial deltoid	MD	Left & right
Pectoralis major	PM	Left & right
Infraspinatus	IS	Left & right
Latissimus dorsi	LD	Left & right
Pronator teres	PT	Left & right
External oblique	EO	Left & right
Erector spinae	ES	Right
Vastus medialis	VM	Left & right
Peroneus longus	PL	Left & right
Gluteus maximus	GM	Left & right
Biceps femoris	BF	Left & right
Gastrocnemius lateralis	GL	Left & right

with tape. The system sampled at 100 Hz, and additional markers were placed on the club and ground for reference. Two force plates (AMTI, Watertown, MA, USA), covered with artificial grass, measured GRF at 1000 Hz. Club and ball kinematics, including CHS, were recorded using a ball launch monitor with reflective stickers on the clubface for tracking (GCQuad, Foresight Sports, San Diego, CA, USA). EMG, kinematic, and kinetic data were synchronized in Vicon to ensure temporal alignment.

C. Experimental Protocol

Maximal voluntary contraction (MVC) was recorded using isometric resistance postures for each muscle [32], [33], [34]. A steel-shaft 7-iron was used for all swings, with participants hitting golf balls on an artificial grass mat into a safety net. Each trial began with a verbal cue, but participants initiated their swings at their own timing. Participants were allowed to take breaks to avoid the effects of fatigue. Ten swings were recorded for each participant, with signal quality monitored between trials.

D. Kinematic and Kinetic Data Analysis

Kinematic data was processed in Vicon Nexus and MATLAB (MathWorks, USA). The golf swing was divided into three phases—backswing, downswing, and follow through—based on previous literature [28], [29], [35]. The backswing began with the initial club movement and ended when the wrist marker reached its maximum height. The downswing started immediately and concluded at impact, while the follow through encompassed all post-impact motion. To facilitate direct comparisons across participants, all swing phases were normalized according to the mean phase ratios of all participants, which were approximately 51:15:34 for the backswing, downswing, and follow through, respectively. This normalization ensured that activation timings could be compared meaningfully despite inter-subject variability in absolute swing durations.

CHS was chosen as the representative performance metric due to its critical role in golf performance and its widespread use as a measure of swing efficacy [24]. Five kinematic variables relevant to CHS were calculated: x-factor, x-factor stretch, peak GRF, weight transfer timing, and wrist unhinge timing. X-factor, representing the rotational displacement between the shoulders and hips during the backswing, was correlated with CHS in several studies [18], [36], [37]. This rotational dissociation between segments allows the trunk muscles to rapidly propel the upper body and produce rotational speed. The x-factor was calculated by aligning the axes of the shoulder and hip segment coordinate systems and determining their maximum angular separation [38]. The related x-factor stretch is defined as the additional rotational separation initiated by pelvis rotation at the start of the downswing and quantified as the difference between the x-factor and the maximum separation during the downswing. This movement is theorized to enhance CHS by utilizing the dynamic stretch-shortening cycle of the muscles [19], [20], [39].

Peak GRF from the left foot and the timing of weight transfer are critical for generating and transferring energy through the kinetic chain. Studies have shown a positive correlation between CHS and high ground reaction force generated by a rapid weight transfer to the left foot early in the downswing [16], [21], [22], [40]. Peak GRF magnitude represented the highest GRF exerted by the left foot, normalized to body weight. Weight transfer timing was identified as the point during the downswing when the left foot's GRF exceeded 70% of body weight and was expressed as a ratio of the frames at which this condition was met to the total number of frames in the downswing.

Lastly, effective wrist control is critical for enhancing clubhead speed, primarily through the technique of maintaining a cocked wrist angle late into the downswing to achieve high acceleration at impact [23], [41]. To represent this, wrist unhinge timing was expressed as a ratio of the frame at which the wrist transitioned from extension to flexion to the total number of downswing frames.

E. EMG Data Analysis

EMG signals were preprocessed in MATLAB to reduce noise and artifacts. A band-rejection filter (5th-order Butterworth, cut-off: 55–65 Hz) removed power-line interference, followed by low-pass (5th-order Butterworth, cut-off: 450 Hz) and high-pass (3rd-order Butterworth, cut-off: 30 Hz) filters [42]. Signals were rectified and smoothed with a low-pass filter at 8 Hz to obtain linear envelopes [43]. EMG data were normalized using MVC values, or the highest observed activation during trials if the trial signal exceeded MVC.

Two EMG-based features were selected due to their interpretability within the context of the golf swing: peak magnitude (MAG) and peak timing (TIM) (Fig. S1). MAG was the maximum normalized EMG value and provided a measure of muscle effort. TIM was the relative timing of the peak activation, calculated by dividing the frame of peak activation by the total number of frames in the respective phase. Both values ranged from 0 to 1 and were calculated for each phase of the swing. These features facilitated interpretation for the golf swing while maintaining model transparency.

F. Elastic Net Modeling

Elastic net regression, a hybrid of L1 and L2 regularization, was employed to address the high dimensionality and multicollinearity of the dataset [44]. This approach allowed for feature reduction while retaining correlated predictors. The method optimally balances sparsity and robustness through the tuning of the α parameter, which determines the ratio of L1 to L2 penalties. The optimization problem is formulated as:

$$\min_{\beta}\left\{\frac{1}{2n}\sum\nolimits_{i=1}^{n}\left(y_i-\sum\nolimits_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\left(\alpha\sum\nolimits_{j=1}^{p}|\beta_j|+\frac{1-\alpha}{2}\sum\nolimits_{j=1}^{p}\beta_j^2\right)\right\} \quad (1)$$

where n is the number of observations, p is the number of predictors, y_i and x_{ij} are the dependent and independent variables, respectively, β_j are the coefficients, λ is the regularization strength, and α is the weighting factor between L1 and L2 regularization.

To ensure that the predictors used in the elastic net model exhibited meaningful linear relationships with the response variable, EMG predictors with a correlation coefficient of less than 0.4 with the kinematic response variable were excluded. The remaining predictors were standardized using z-scores to enable direct comparison of coefficient magnitudes for assessing the relative importance of each variable. A grid search across α values (0.25, 0.5, 0.75) was conducted, and the λ parameter was optimized using jackknife cross-validation to minimize mean squared error.

Given the inherent bias introduced by regularization, traditional p-value testing was avoided, and instead, bootstrapping was applied to evaluate the stability and robustness of coefficient estimates [45], [46], [47]. For each model, 1,000 bootstrapped samples were generated by resampling with replacement, and elastic net regression was applied to each sample. This process produced distributions of coefficient estimates, from which 90% confidence intervals were derived. Predictors with coefficient confidence intervals that excluded zero were considered significant.

Elastic net modeling was performed in two stages. In the first stage, CHS was modeled using kinematic factors as predictors. Significant kinematic factors were then modeled using EMG features from relevant swing phases as predictors to ensure contextual relevance. Specifically, models for x-factor stretch were developed using data from both the backswing and downswing, while weight transfer timing and wrist unhinge timing were analyzed using the downswing and follow-through data.

This multi-step elastic net modeling process provided a structured approach for identifying the critical muscles and activation patterns most relevant to CHS. By incorporating kinematic factors as intermediaries, the analysis reflected the physiological principle that muscle activity drives kinematic motion, ultimately influencing performance. The mean data from the ten trials for each participant were used in the modeling process to analyze the representative performance for each golfer and reduce the impact of trial-to-trial variability.

G. Muscle Synergy Analysis

While elastic net modeling identified key muscle activations associated with performance-relevant kinematic factors, it did not capture how these muscles are coordinated as functional units. To investigate this higher-level neuromuscular organization, we performed muscle synergy analysis on the subset of muscles identified as significant predictors in the preceding elastic net models. This targeted approach ensured the extracted synergies represent coordination patterns directly linked to performance outcomes rather than unrelated muscle activity.

Non-negative matrix factorization (NMF) was applied to the EMG data from each participant to decompose the data into two components: synergy vectors, representing spatial balance of muscle activations, and activation profiles, capturing the temporal dynamics [48]. Previous studies have demonstrated the superior performance of NMF over other dimensionality reduction techniques for muscle synergy extraction in various contexts [49], [50], [51]. The EMG matrix for NMF was constructed for each participant by concatenating data from all 10 trials. All EMG pre-treatment, including filtering, smoothing, and normalization, was identical to the methods described in Section II-E.

The NMF algorithm was applied iteratively for all possible numbers of synergies, ranging from one to the total number of EMG channels. To account for variability in numerical solutions, each analysis was repeated 20 times for each synergy count, and the solution yielding the highest variance in muscle activity was retained. The number of synergies for each participant was determined using a cross-validated R^2 plateau method [52], [53]. In this approach, trial-wise cross-validation is performed across all synergy counts, and the resulting R^2 values are examined as a function of synergy number. The smallest number of synergies at which the R^2 curve reaches a plateau, defined by a mean squared error of linear fit $\leq 10^{-4}$, was identified for each participant.

H. Clustering Analysis

The extracted synergy vectors were subjected to k-means clustering to identify representative patterns of muscle coordination across participants. To ensure robustness, clustering was repeated 1000 times with random initializations, and constraints prevented assignment of multiple synergies from the same participant to the same cluster. The optimal cluster number was selected as the smallest value where the gap statistic, representing the difference between the observed and reference dispersions, exceeded a threshold defined by the standard deviation of the reference dispersion [54].

The identified synergy clusters were grouped into four categories based on their distribution across the professional and amateur groups to reveal patterns in neuromuscular control. A synergy was considered present for a participant if one of their five extracted synergies was assigned to a given cluster. The classification rules were as follows:

- Group-invariant: Synergies present in ≥ 5 professionals and ≥ 5 amateurs.
- Group-dominant: Synergies present in ≥ 5 participants of one group but < 5 of the other.
- Subject-specific: Synergies present in < 5 participants in both groups.
- Group-exclusive: Synergies present only in participants of one group and absent in the other.

I. Statistical Testing

Statistical analyses were performed to evaluate the relationship between synergy clusters and CHS. Participants were divided into two groups for each cluster: those whose synergies belonged to the cluster and those whose synergies did not. Two-tailed *t*-tests were performed to assess whether the presence of a specific synergy significantly influenced CHS. Assumptions of normality and homoscedasticity were verified prior to the *t*-tests using the Shapiro-Wilk test and Levene's test, respectively. For participants whose synergies were part of a given cluster, Pearson's correlation analysis was used to examine the relationship between the peak activation timing of the synergy during its most active phase and CHS. This analysis was limited to subjects utilizing the synergy in the corresponding cluster and evaluated the role of temporal coordination in performance outcomes. The most active phase was defined as the swing phase that exhibited the greatest number of peak activations among the activation profiles being tested. Peak timing was expressed as a ratio of the frame of peak activation to the total number of frames in the corresponding swing phase. Assumptions for Pearson's correlation, including linearity, normality of residuals, and homoscedasticity of residuals, were tested to ensure the validity of the analysis. All statistical analyses were performed in MATLAB.

III. RESULTS

A. Elastic Net Modeling Results

The elastic net analysis identified wrist unhinge timing, weight transfer timing, and x-factor stretch as the most significant predictors of CHS, with mean coefficient magnitudes of 5.82, -4.01, and 2.84, respectively (Table II, Fig. 2a). These factors exhibited confidence intervals that excluded zero, confirming their relevance in predicting CHS. In contrast, x-factor and peak GRF were less reliable predictors, as their confidence intervals included zero, leading to their exclusion from further analysis.

Among the three key predictors, wrist unhinge timing had the greatest coefficient magnitude, indicating its dominant role in predicting CHS. During the downswing, delayed unhinging of the wrist was strongly associated with increased CHS. Weight transfer timing was the second most influential factor, demonstrating an inverse relationship with CHS. Earlier weight transfer, characterized by a more rapid shift of pressure onto the left foot during the downswing, was correlated with greater CHS. Lastly, x-factor stretch was positively correlated with CHS, suggesting that a greater increase in rotational separation between the shoulders and hips at the initiation of the downswing was associated with higher CHS.

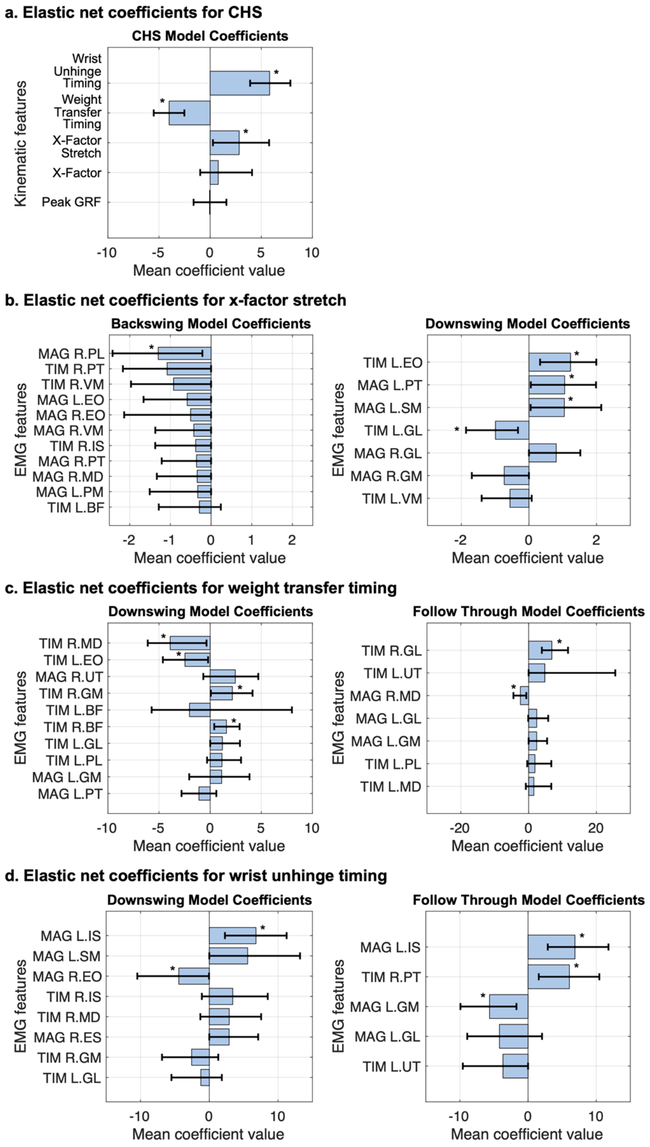


Fig. 2. Mean coefficients and 90% confidence intervals from the bootstrapped elastic net regression models. Predictor variables with confidence intervals that exclude zero are marked with an asterisk, indicating statistical significance. (a) Elastic net coefficients for the CHS model. (b) Elastic net coefficients for x-factor stretch, analyzed during the backswing and downswing phases. (c) Elastic net coefficients for weight transfer timing, analyzed during the downswing and follow through phases. (d) Elastic net coefficients for wrist unhinge timing, analyzed during the downswing and follow through phases.
Abbreviations: BF = biceps femoris; EO = external oblique; ES = erector spinae; GL = gastrocnemius lateralis; GM = gluteus maximus; IS = infraspinatus; LD = latissimus dorsi; L = left; MD = medial deltoid; PL = peroneus longus; PM = pectoralis major; PT = pronator teres; R = right; SM = sternocleidomastoid; UT = upper trapezius; VM = vastus medialis.

The second stage of elastic net modeling revealed the specific muscle activation features associated with each kinematic predictor. For the x-factor stretch, five key EMG features were identified (Fig. 2b). During the backswing, low activation of the right PL was associated with increased x-factor stretch. During the downswing, increased x-factor stretch was corre-

TABLE II

ELASTIC NET REGRESSION MODEL PARAMETERS, SIGNIFICANT PREDICTOR VARIABLES, MEAN COEFFICIENTS, AND CONFIDENCE INTERVALS

Response variable	Phase	α	λ	R^2	Significant features	Mean coefficients	Confidence intervals
CHS		0.5	1.28	0.70	Wrist unhinge timing	5.82	(3.91, 7.85)
					Weight transfer timing	-4.01	(-5.52, -2.52)
					X-factor stretch	2.84	(0.27, 5.76)
X-factor stretch	Backswing	0.75	0.203	0.80	MAG R.PL	-1.30	(-2.42, -0.21)
	Downswing	0.5	0.218	0.81	TIM L.EO	1.23	(0.33, 2.00)
					MAG L.PT	1.06	(0.05, 1.98)
					MAG L.SM	1.05	(0.05, 2.14)
					TIM L.GL	-0.99	(-1.86, -0.32)
Weight transfer timing	Downswing	0.25	0.815	0.70	TIM R.MD	-3.91	(-6.11, -0.36)
					TIM L.EO	-2.46	(-4.63, -0.20)
					TIM R.GM	2.17	(0.06, 4.14)
					TIM R.BF	1.60	(0.40, 2.89)
	Follow through	0.5	0.693	0.75	TIM R.GL	6.84	(3.89, 11.62)
					MAG R.MD	-2.43	(-4.50, -0.68)
Wrist unhinge timing	Downswing	0.5	0.849	0.61	MAG L.IS	6.79	(2.27, 11.25)
					MAG R.EO	-4.44	(-10.47, -0.04)
	Follow through	0.5	0.740	0.61	MAG L.IS	6.87	(2.89, 11.79)
					TIM R.PT	6.06	(1.57, 10.46)
					MAG L.GM	-5.66	(-9.92, -1.71)

lated with late activation of the left EO, early activation of the left GL, and high activation of the left PT and left SM. The analysis of weight transfer timing revealed six key EMG features (Fig. 2c). During the downswing, late activation of the right MD and left EO, along with early activation of the right GM and right BF, were linked to earlier weight transfer timing. In the follow through, early activation of the right GL and high activation of the right MD were also associated with earlier weight transfer timing. For wrist unhinge timing, five key EMG features were identified (Fig. 2d). During the downswing, late wrist unhinge timing was correlated with high activation of the left IS and low activation of the right EO. In the follow through, high activation of the left IS, late activation of the right PT, and low activation of the left GM were similarly associated with delayed wrist unhinge timing.

B. Intermuscular Coordination of Key Muscles for Golf Performance

Muscle synergy analysis based on the cross-validated R^2 plateau method indicated that professionals required an average of 4.8 ± 0.63 synergies, while amateurs required 5.1 ± 0.88. A Welch's two-sample *t*-test confirmed that this difference was not statistically significant ($p = 0.393$, Hedges' $g = -0.38$). On this basis, the number of synergies was fixed at five for all participants, corresponding to the mean dimensionality across groups. Standardizing the analysis ensured equal representation of participants in the clustering procedure, as using individualized dimensionalities would underrepresent those with fewer extracted synergies and bias group comparisons [55], [56], [57]. The gap statistic identified 11 optimal synergy clusters, which were then classified using k-means clustering (Fig. 3).

Among the 100 total muscle synergies, most were classified as group-invariant or group-dominant, with a smaller proportion categorized as subject-specific or group-exclusive. Specifically, 31% of synergies were group-invariant, shared between professionals and amateurs, while 46% were group-dominant, primarily utilized by one group but not exclusively. Subject-specific synergies accounted for 18%, reflecting individual neuromuscular adaptations, while only 5% were group-exclusive, consisting of a single cluster found exclusively in amateurs. Notably, no synergies were exclusive to professionals, suggesting that elite performance is not achieved through the development of novel neuromuscular patterns but rather through the refined modulation of shared synergies.

Four synergy clusters exhibited statistically significant associations with CHS (Fig. 4). These synergies were named based on their inferred functional role at the time of peak activation, considering the coordinated action of the primary muscles within the biomechanical context of the swing as demonstrated by the kinematic data. Three clusters showed a significant correlation between their peak activation timing and CHS for participants within the cluster. The pelvis rotation synergy (C1, $r = -0.64$, $p = 0.006$) was a group-invariant synergy present in all professionals and nearly all amateurs, with peak activation timing during the downswing significantly correlated with CHS. Similarly, the plantarflexion synergy (C2, $r = -0.67$, $p = 0.009$), also group-invariant, exhibited a significant correlation between its peak activation timing during the follow through and CHS. In contrast, the arm pronation synergy (C9, $r = 0.93$, $p = 0.006$) was classified as subject-specific, with peak activation timing during the follow through significantly predicting CHS. This finding suggests that while most synergies were shared across participants, individualized adaptations also contributed to performance enhancement. By contrast,

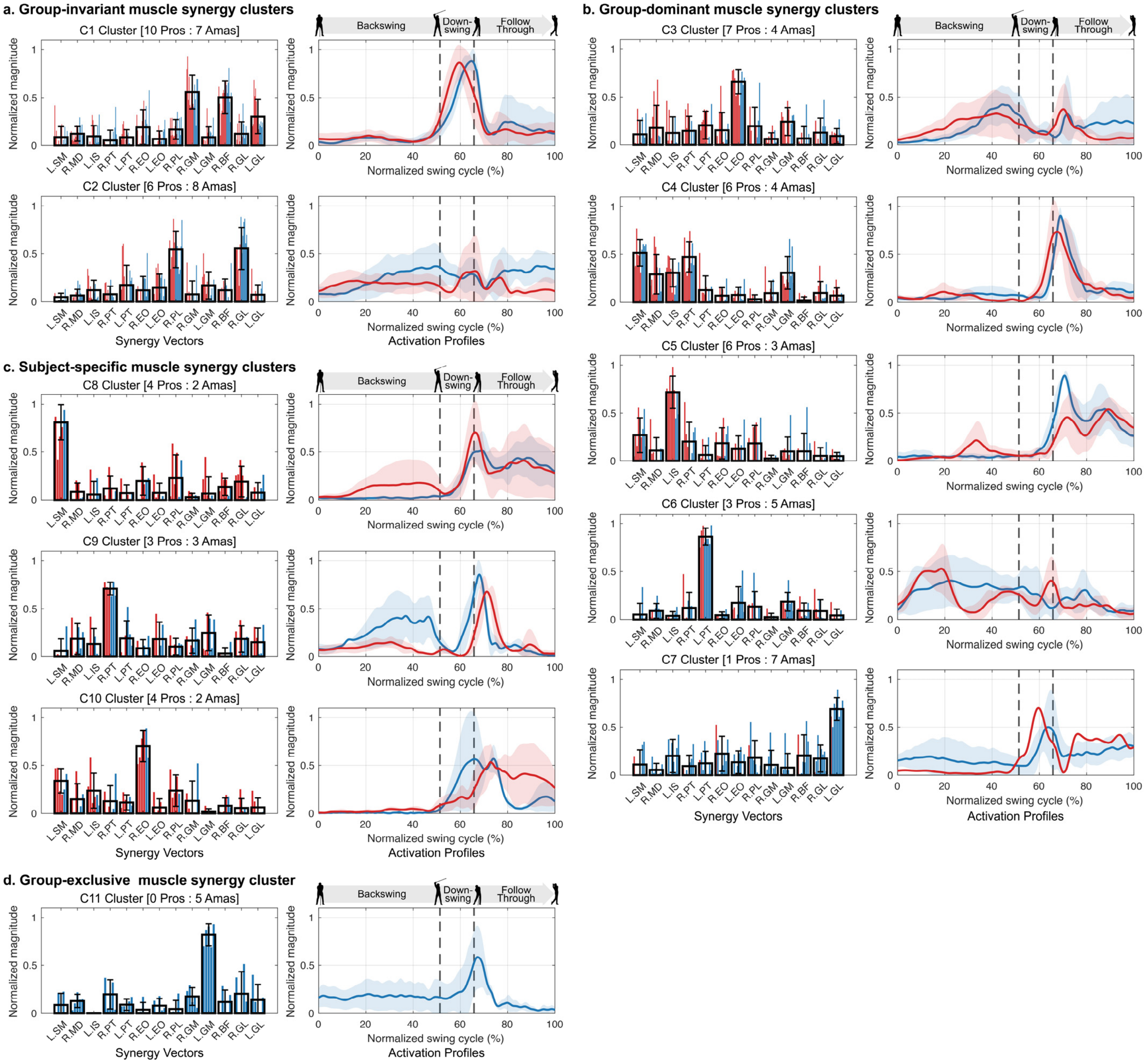


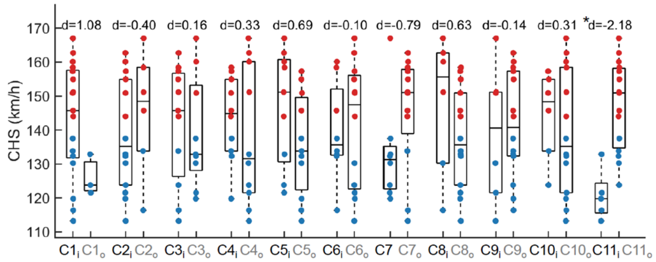
Fig. 3. Muscle synergy clusters and activation profiles. The 11 identified muscle synergy clusters are depicted, with professionals represented in red and amateurs in blue. Each cluster consists of synergy vectors (left) and activation profiles (right). Individual muscle weights of synergy vectors are shown as slim colored bars, overlaid with bold outlines representing the cluster centroid, which characterizes the representative synergy pattern for each cluster. The error bars represent the standard deviation of the individual muscle weights. Activation profiles illustrate the mean temporal dynamics of muscle activity for professionals and amateurs, with shaded regions indicating standard deviations. Golf swing phases are annotated above the activation profiles, with transitions marked by black dashed lines. Each cluster is numbered and lists the number of professionals and amateurs included in the cluster. Clusters are categorized as: (a) group-invariant, shared by both groups; (b) group-dominant, predominantly used by one group; (c) subject-specific, utilized by a small number of individuals; and (d) group-exclusive, unique to one group.
Abbreviations: amas = amateurs; BF = biceps femoris; EO = external oblique; GL = gastrocnemius lateralis; GM = gluteus maximus; IS = infraspinatus; L = left; MD = medial deltoid; PL = peroneus longus; pros = professionals; PT = pronator teres; R = right; SM = sternocleidomastoid.

the hip extension synergy (C11) was the only cluster to reach significance in the group comparison test. This synergy appeared only in five amateurs, and those who expressed it showed significantly lower CHS compared to those who did not (d = –2.18, p = 0.001), indicating it may represent an inefficient neuromuscular strategy.

IV. DISCUSSION

This study investigated how neuromuscular coordination is adapted to refine performance in complex, high-DOF tasks by analyzing coordination patterns in professional and amateur golfers. Through a comprehensive analysis of EMG, kinematic, and kinetic data, we identified key muscles associated

a. CHS distribution based on muscle synergy cluster membership



b. Correlation between CHS and cluster peak activation timing

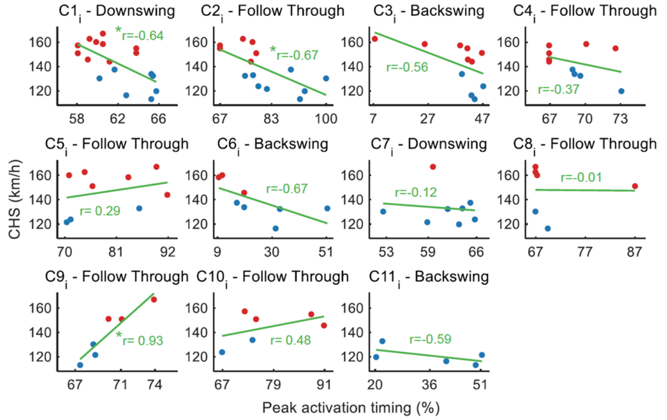


Fig. 4. (a) Comparison of CHS between participants within (Ci) and outside (Co) each cluster, shown as paired box plots. Individual data points are color-coded for professionals (red) and amateurs (blue). A statistically significant difference ($p < 0.01$) is indicated for Cluster 11 by an asterisk. Effect sizes for each cluster are reported as Cohen's *d*. (b) Correlation between CHS and peak activation timing during the most active swing phase for participants within each cluster. Peak activation timing is expressed as a percentage of the swing cycle on the x-axis. Individual data points are color-coded by group, with a green best-fit regression line. Statistically significant correlations ($p < 0.01$) are indicated with an asterisk for Clusters 1, 2, and 9. Corresponding Pearson's *r* values are reported for each cluster.

with performance factors and clustered the resulting muscle synergies. Notably, we found that expert performance was not achieved by creating new synergies or merging existing ones but by refining the activation timing of established synergies. Specifically, the group-invariant pelvis rotation and plantarflexion synergies, and a subject-specific arm pronation synergy exhibited significant correlations between their peak activation timing and CHS. Additionally, the presence of an amateur-exclusive hip extension synergy that was negatively correlated with CHS highlighted a neuromuscular strategy that hindered performance. To further contextualize these synergy-level results, we examined how the specific muscles within these clusters map onto the kinematic factors linked to CHS.

A. Muscle Synergies Mapped to Kinematic Factors

The synergies that exhibited significant activation timings correlated with CHS can be directly related to the kinematic performance factors. The pelvis rotation synergy was dominated by the right GM and right BF, which were modeled to be critical for early weight transfer, an important precursor to high CHS [40], [58]. At the same time, the involvement of the left GL in this synergy also contributed to increasing x-factor stretch, which was linked to increased CHS in agreement with prior studies [19], [20], [39]. Likewise, the plantarflexion synergy, characterized by the right PL and right GL, supported both kinematic performance factors, with the GL contributing to early weight transfer and the PL associated with x-factor stretch. In the upper extremity, the arm rotation synergy primarily activated the right PT, and its delayed activation during the follow through corresponded to delayed wrist unhinging, an established determinant of CHS [23], [41]. Notably, the synergy–kinematic mappings were not necessarily one-to-one but reflected the integrated and overlapping contributions of coordinated modules to multiple aspects of performance. While these mappings clarify how individual synergies contribute to the determinants of CHS, they also raise a broader question of how the nervous system organizes and adapts synergy structure across different motor contexts.

B. Muscle Synergy Adaptation in Complex Motor Tasks

In simpler, low-DOF tasks such as running and cycling, muscle synergy merging has been widely observed as a neural adaptation that enhances control efficiency and reduces task-relevant variability [9], [11]. For instance, elite runners have been shown to merge novice muscle synergies, streamlining motor control to achieve greater running efficiency [9]. Similarly, studies in cycling and locomotion have demonstrated that merging facilitates task-specific adaptations while preserving the flexibility of existing motor solutions [10], [11]. This adaptation appears to be particularly advantageous for tasks with relatively constrained biomechanical demands, as it enables more effective coordination of muscle groups by reducing the dimensionality of neural control.

In contrast, high-DOF tasks present fundamentally different challenges, requiring flexibility and independent coordination of muscle groups, which may limit the utility of such dimensional reduction. Our findings suggest that in these contexts, the nervous system does not simplify coordination by merging synergies but instead fine-tunes the timing of existing ones to meet performance demands. Consistent with this interpretation, the number of synergies estimated from the cross-validated R^2 plateau method did not significantly differ between professionals and amateurs, reinforcing that expertise in golf is not characterized by structural reorganization of synergies. Professional golfers fine-tuned performance by temporally refining retained synergies. The group-invariant pelvis rotation and plantarflexion synergies, utilized by both professionals and amateurs, showed significant correlations between their peak activation timing and CHS. Notably, the pelvis rotation synergy emerged as a foundational motor strategy, employed by every professional golfer and most amateurs. This discovery of shared neuromuscular patterns across skill levels highlights a surprising universality in motor strategies for a task as individualized as the golf swing [17]. These shared synergies likely reflect fundamental biomechanical principles underlying effective swing mechanics. However, the ability to effectively modulate the timing of these synergies distinguished expert performers, emphasizing temporal refinement as a key mechanism of motor adaptation in high-DOF motor tasks.

In addition to these group-invariant strategies, individualized neuromuscular adaptations also influenced performance. A professional subject-specific arm pronation synergy, significantly associated with CHS, reflected individualized, fine-tuned control strategies. This dual reliance on shared and individualized strategies reflects the complexity of high-DOF tasks, requiring universal principles of motor control with adaptations tailored to personal musculoskeletal properties. In contrast, the amateur-exclusive hip extension synergy negatively correlated with CHS revealed how inefficient coordination patterns can hinder performance. Interestingly, no synergy was exclusive to professionals, indicating that expert performance was not defined by access to unique neuromuscular modules, but by the ability to selectively refine and effectively apply modules broadly available across individuals.

To contextualize these findings within broader perspectives of motor learning and control, we examine their relevance to theoretical models of movement coordination. The concept of motor equivalence holds that the human motor system, owing to its inherent redundancy, can generate multiple coordination strategies to achieve the same task outcome [2]. This view is closely tied to the “good-enough” control hypothesis, which posits that motor behavior is shaped not by strict optimization, but by the accumulation of functionally sufficient, adaptable solutions [59]. Consistent with this view, prior studies have reported substantial interindividual variability in learned motor strategies, even in tasks with shared goals [7], [60]. However, our results suggest that in performance-driven contexts, the solution space may become selectively narrowed. Despite variability in musculoskeletal properties, professional golfers exhibited convergence on a subset of neuromuscular strategies characterized by temporally refined synergy activation. While not all professionals relied on identical patterns, the recurrence of shared, performance-linked coordination patterns suggests that under certain task demands, motor equivalence does not preclude but rather enables partial convergence toward effective control solutions.

C. Implications for Neuromuscular-Based Interventions

Beyond theoretical contributions, this study introduces a methodological approach for linking muscle synergies to movement features and performance outcomes. By connecting synergy activation patterns to intermediate kinematic variables and performance-relevant metrics, this framework may inform neuromuscular training strategies applicable to performance-driven skills. For example, synergy patterns observed in expert performers could be used to establish specific motor control targets for training novices, providing a direct pathway to performance enhancement. In our study, the refined activation timing of the group-invariant pelvis rotation synergy offers a universal training target for amateurs seeking to emulate the coordination of elite golfers. Rather than requiring learners to discover effective strategies through trial and error, this approach offers an empirically grounded roadmap for acquiring complex motor skills.

The principle of timely activation of coordinated muscle groups is relevant not only to skilled motor performance but also to rehabilitation. Precise temporal coordination among joints and muscles is a fundamental characteristic of natural movement, and its disruption is frequently observed in abnormal motor control associated with neurological disorders. While demonstrated here through a sports performance context, the proposed framework for mapping and training neuromuscular coordination could be extended more broadly to support both skill acquisition and motor recovery across functional domains.

Despite these implications, translating these insights into neuromuscular training remains challenging. While recent methods have attempted to directly train synergy patterns, delivering intuitive feedback for multi-muscle coordination remains complex [61], [62]. One promising solution is an approach known as muscle-to-action mapping, which uses biomechanical modeling to translate a target synergy activation profile into an intuitive action-based goal, such as movement or force production [63]. By focusing on achieving the action, a learner can implicitly train the complex timing and magnitude of the underlying multi-muscle coordination without conscious, muscle-by-muscle control. While this strategy was initially validated in a neurorehabilitation context, its principle of providing an action-based target for a complex neuromuscular pattern is directly applicable to skill acquisition in healthy individuals. However, the motor equivalence embedded in the musculoskeletal system means that identical muscle activation profiles can produce different kinematic outcomes depending on individual biomechanical constraints. This variability demonstrates the importance of integrating kinematic context into neuromuscular intervention design to ensure that synergy activation facilitates the desired functional outcomes.

While this study offers several insights, it also highlights areas for further investigation. The cross-sectional design limits the ability to track how synergy activation profiles evolve with learning, and future longitudinal work is needed to characterize these dynamics over time. Analyzing intra-individual variability across repetitions could further clarify how stability of neuromuscular coordination contributes to skilled performance. Applications to clinical settings could be broadened by examining how mistiming in synergy activation influence injury risk or maladaptive coordination and further clarify the functional importance of temporal control. Extending this framework to more diverse populations, including female participants and individuals with motor impairments, would also enhance generalizability and reveal how neuromuscular coordination adapts across different functional contexts. Moreover, combining this approach with neuroimaging or stimulation techniques may help identify neural mechanisms that regulate the temporal precision of synergy activation.

Methodological limitations should also be acknowledged. EMG data collected during a dynamic, high-motion task are inherently sensitive to electrode placement differences and cross-talk, which may affect amplitude estimates and the derived synergy structure. Standardizing the number of synergies per participant ensured balanced clustering across subjects but may have masked interindividual variability. Future studies should explore alternative dimensionality and normalization strategies to assess the robustness of these findings and refine synergy extraction in complex, unconstrained movements.

V. CONCLUSION

This study demonstrates that expertise in complex motor tasks is supported not by restructuring neuromuscular modules but by fine-tuning the timing of existing synergies. Unlike synergy merging or increased modular sparsity observed in other contexts, our findings identify precise temporal refinement as the key adaptation for managing high-DOF complexity under performance demands. By systematically linking muscle synergies to movement features and performance outcomes, this work offers insight into how shared neuromuscular strategies are tuned for skilled performance and establishes a foundation for targeted interventions across both performance and rehabilitation domains.

ACKNOWLEDGMENT

Hangil Lee and Hyung-Soon Park are inventors of KR10-2810411, KR10-2810412, and US18/766,884 (pending), all concerning methods and systems for training selective muscle activation during the golf swing.

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