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Validation of lower limb muscle activation estimated using musculoskeletal modeling against electromyography in the table tennis topspin forehand and backhand

Validación de la activación muscular de las extremidades inferiores estimada mediante modelado musculoesquelético y electromiografía en el *topspin* de derecha y revés del tenis de mesa

Yoichi Iino [1]*, Shinsuke Yoshioka[1], Senshi Fukashiro[1, 2]

1 Graduate School of Arts and Sciences, The University of Tokyo, Tokyo, Japan
2 Japan Women's College of Physical Education, Tokyo, Japan

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Abstract

This study aimed to validate the lower limb muscle activation, estimated using static optimization against electromyography (EMG), in the topspin forehand and backhand strokes. The secondary purpose was to compare the estimated activations of the major muscles/muscle groups between the forehand and backhand strokes. Eight male college table tennis players hit the cross-court topspin forehands and backhands with maximum effort. Stroke motions and ground reaction forces were measured using a motion capture system and two force plates. The EMG signals of the 16 lower-limb muscles were recorded using a wireless EMG system. The static optimization algorithm of OpenSim was applied to stroke motions to estimate lower limb muscle activation, which was compared to EMG activation. Of the seven muscles that showed maximum activation > 0.3 during the forehand, five showed a Pearson correlation coefficient > 0.3 Of the four muscles that showed maximum activation > 0.3 during the backhand, all four showed a Pearson correlation coefficient >0.3. However, some muscles, such as the bilateral gluteus medius muscles, showed a low correlation between estimated and EMG activation. A possible cause is the co-contraction of the relevant muscles. Concordance correlation coefficients were smaller than their respective Pearson correlation coefficients. This result reflects that EMG envelope (activation) is also an estimate of muscle activation and is subject to noise and confounding factors. Comparisons with additional independent measurements, such as ultrasound muscle images and instrumented joint loading, are necessary for more robust validation of the musculoskeletal modeling and muscle activation. The gluteus maximus and hamstrings on the playing side, and rectus femoris on the non-playing side exhibited higher activation during the forehand than during the backhand. The overall results suggest that the static optimization algorithm can adequately estimate lower-limb muscle activity during the topspin forehand and backhand strokes.

Keywords: *Musculoskeletal modeling, muscle activation, electromyography, validation.*

Resumen

El objetivo de este estudio fue validar la activación muscular de las extremidades inferiores estimada mediante optimización estática y electromiografía (EMG) en el topspin de derecha y revés. El objetivo secundario fue comparar las activaciones estimadas de los principales grupos musculares entre los golpes de derecha y

Corresponding author: Yoichi Iino, iino@idaten.c.u-tokyo.ac.jp

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revés. Ocho jugadores hombre universitarios de tenis de mesa realizaron con el máximo esfuerzo los golpes topspin de derecha y revés cruzados en la pista. Los movimientos de los golpes y las fuerzas de reacción del suelo fueron medidos con un sistema de captura del movimiento y dos placas de fuerza. Las señales EMG de los músculos de los 16 miembros inferiores fueron grabadas con un sistema EMG inalámbrico. Se usó el algoritmo de optimización estática OpenSim para estimar la activación muscular de los miembros inferiores durante los golpes, y luego se compararon los resultados con la activación de la EMG. De los siete músculos que mostraron activación máxima > 0,3 en el golpe de derecha, cinco mostraron un coeficiente de correlación de Pearson > 0,3. De los cuatro músculos que mostraron activación máxima > 0,3 durante el golpe de revés, los cuatro mostraron un coeficiente de correlación de Pearson > 0,3. Sin embargo, algunos músculos, como el glúteo medio, mostraron una baja correlación entre la activación estimada y la EMG. Una posible causa es la cocontracción de los músculos involucrados. Los coeficientes de correlación de concordancia fueron menores que sus respectivos coeficientes de correlación de Pearson. Este resultado refleja que la envolvente (activación) de la EMG es también una estimación de la activación muscular y está sujeta a ruido y factores de confusión. Es necesario realizar comparaciones con otras mediciones independientes, como las imágenes musculares por ultrasonido y la carga articular con instrumentos, para lograr una validación más sólida del modelado musculoesquelético y la activación muscular. El glúteo mayor y los isquiotibiales en el lado de juego, y el recto femoral en el lado de no juego, mostraron una mayor activación durante el golpe de derecha que durante el revés. Los resultados generales sugieren que el algoritmo de optimización estática puede estimar adecuadamente la actividad muscular de las extremidades inferiores durante el *topspin* de derecha y revés.

Palabras clave: *Modelado musculoesquelético, activación muscular, electromiografía, validación.*

INTRODUCTION

Topspin forehand and backhand strokes are fundamental techniques used in table tennis, and mastering the effective execution of these strokes is essential for high performance (Seemiller & Holowchak, 1997). A previous study reported that topspin forehand was the most frequently used stroke in elite matches, followed by counter-topspin topspin forehand, with topspin backhand ranking fourth (Malagoli Lanzoni, Di Michele, & Merni, 2014). The same study found that the topspin forehand and counter-topspin forehand were more related to winners than other strokes. Both strokes are performed by utilizing the kinetic chain of the entire body. Previous studies on table tennis strokes have reported that joint angular velocities (Bańkosz & Winiarski, 2018) and hip joint kinetics (Iino, 2018) are associated with racket speed, and have suggested that the lower limbs energetically contribute to the generation of racket speed in the topspin forehand and backhand (Iino & Kojima, 2011; 2016). Kinematic and kinetic analyses have been conducted on the lower limb motions during table tennis topspin forehands and backhands (He et al., 2021; Le Mansec, Dorel, Hug, & Jubeau, 2018; Malagoli Lanzoni, Bartolomei, Di Michele, & Fantozzi, 2018; Qian, Zhang, Baker, & Gu, 2016; Shao et al., 2020; Wang et al., 2018). Two of these studies examined the lower limb muscles using electromyography (EMG). Wang et al. (2018) compared kinematics and EMG data between elite and amateur players during topspin backhands. They found that the hip and knee flexion angles at backswing were larger in elite players than in amateurs and that the maximum activation of the rectus femoris and tibialis anterior was lower in elite players than in amateurs. Le Mansec et al. (2018) reported the EMG of the eight lower limb muscles of the playing side (right side for a right-handed player) in seven typical strokes, including the topspin forehand and backhand. They found that the EMG peak amplitudes of gluteus maximus and biceps femoris were larger than 60% of their maximum voluntary contraction amplitudes in the topspin forehands and forehand smash. These studies provide valuable insights into the unique muscle activation characteristics of elite athletes and different stroke types. However, surface EMG can only be applied to surface muscles, and this alone cannot provide information on muscle forces. Therefore, the function of the muscles in table tennis forehand and backhand is still not fully understood.

Estimation of muscle activation and forces in table tennis strokes can be used to inform performance improvement and injury prevention. As a non-invasive approach, musculoskeletal modeling has been utilized to estimate lower limb muscle activation and forces in human locomotion such as walking and running through predictive and tracking simulations (e.g., Dorn, Schache, & Pandy, 2012; Liu, Anderson, Schwartz, & Delp, 2008; Neptune, Sasaki, & Kautz, 2008) and has revealed the mechanical functions of the lower limb muscles. To our knowledge, there are no studies that have estimated the lower-limb muscle activation in table tennis strokes using musculoskeletal modeling. The estimated lower limb activation has been validated against EMG in locomotion previously (Alexander & Schwameder, 2016; Dupré, Dietzsch, Komnik, Potthast, & David, 2019; Trinler, Leboeuf, Hollands, Jones, & Baker, 2018; Wibawa et al., 2016; Żuk, Syczewska, & Pezowicz, 2018), and these studies reported moderate to good associations between the estimated and EMG activations. Table tennis topspin forehands and backhands require whole-body rotation (Iino & Kojima, 2009; 2016), and different players may have different techniques for these strokes (Bańkosz & Winiarski, 2018). Thus, the extent to which the estimated lower-limb activations in table tennis can be validated against EMG is unclear.

The following two popular algorithms have been used to estimate muscle activations and forces in OpenSim, which is an open-source software tool for musculoskeletal modeling and simulation of movement (Delp et al., 2007): static optimization and computed muscle control. In this study, a static optimization algorithm was used to estimate the muscle activation because the computed muscle control algorithm conducts forward dynamic simulations to track measured kinematics and requires accurate modeling of the upper body, which is difficult for table tennis strokes that involve complex spine and shoulder motions. Additionally, previous studies have shown that computed muscle control is not always more accurate in estimating muscle activation than static optimization (Alvim, Lucareli, & Menegaldo, 2018; Roelker et al., 2020; Trinler et al., 2018).

The purpose of this study was to validate the lower limb muscle activation estimated using static optimization against EMG in table tennis topspin forehand and backhand strokes. The secondary purpose was to compare the estimated activations of the major muscles/muscle groups between the two strokes because no studies have yet made these comparisons. This could provide a scientific basis for developing effective strength-training programs for table tennis.

METHODS

Participants

Eight male college table tennis players participated in this study. All participants were members of a Division I table tennis team in the Kanto Collegiate Table Tennis League in Japan. Their mean ± standard deviation age, height, body mass, and training experience were 20.2 ± 1.5 years, 1.72 ± 0.06 m, 67.5 ± 6.5 kg, and 11.5 ± 2.3 years, respectively. Six players were right-handed and two were left–handed. The dominant hand was judged by the hand holding the racket. All were offensive players. All participants provided written informed consent. The experimental procedures were approved by a local ethics committee.

Experimental procedure

After an individual warm-up session, the participants were asked to hit the topspin cross-court forehands and backhands with maximum effort (Figure 1). They were asked to place their feet on a separate force plate (type 9281; Kistler, Winterthur, Switzerland) during preparation, but they were allowed to move their feet after the beginning of a stroke. At least three successful forehand and backhand strokes were recorded for each participant. Before data collection, the participants were asked to practice the strokes until they became accustomed to the experimental settings. The position of the table tennis table was adjusted for each stroke type for each participant to ensure that the feet were within the boundaries of the force plates at preparation. All participants used the same shake-hands racket (Timo Boll ALC ST, Tamasu Co., Ltd., Japan) with inverted rubber (Tenergy 05, Tamasu Co., Ltd., Japan). A ball machine (Butterfly Amicus 1000, Tamasu Co., Ltd., Japan) was used to feed the players light backspin balls (Nittaku premium three-star, Nippon Takkyu Co., Ltd.). Balls were projected directly to the foreside and backside of participant’s court in topspin forehands and backhands, respectively. The spin rate of the backspin balls after the bounce on the table was 8.6 ± 1.3 rps. The ball feeding frequency was about 43 balls/min. The ball machine was set at -1 for SPIN and 7.0 for SPEED. Finally, they were asked to perform a sequence of hip flexion, extension, abduction, and circumduction of each leg to estimate the locations of the hip joint centers.

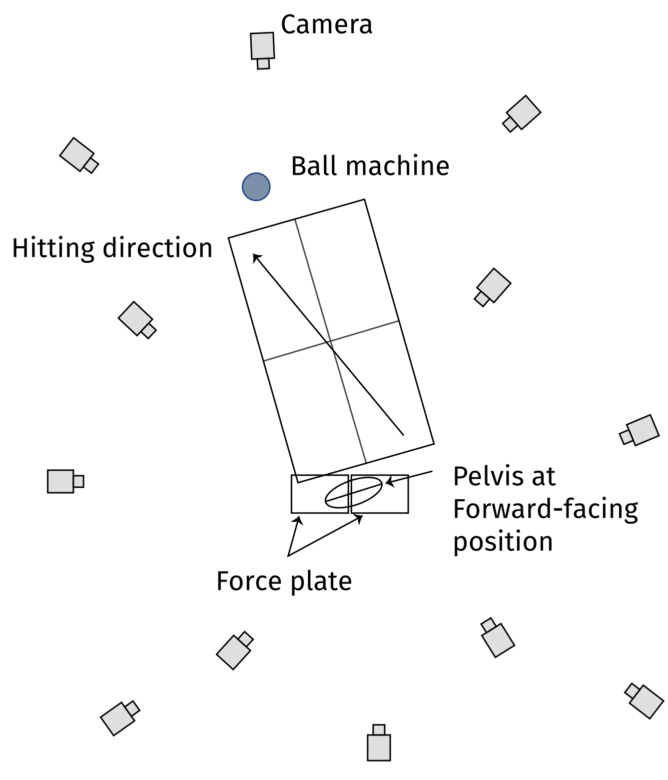

Figure 1. The experimental setup for the topspin forehand. The forward-facing position of the pelvis was defined as the position where the pelvis medio-lateral axis was parallel to the endline of the table tennis table.

Data collection

The participants wore tight-fitting swim pants and table tennis shoes. A total of 51 retro-reflective markers (diameter, 16 m) were attached to landmarks on the whole body. Four markers were attached to the lateral side of the racket face. Three-dimensional marker coordinates were obtained using a 12-camera motion capture system (MAC3D System; Motion Analysis, Santa Rosa, CA, USA) at 200 Hz. The force plate data were recorded at 2,000 Hz. The surface EMG activity was recorded using a wireless EMG system (Trigno Wireless System, DELSYS. Boston, MA, USA). EMG signals were bandpass filtered (20-450 HZ) and sampled at 2,000 Hz. EMG electrodes were placed bilaterally on the gluteus maximus, gluteus medius, biceps femoris, rectus femoris, vastus medialis, tibialis anterior, soleus, and gastrocnemius lateralis muscles. Electrode placement was determined according to SENIAM guidelines (Hermens, Freriks, Disselhorst-Klug, & Rau, 2000). The skin where the electrodes were placed was shaved if necessary and cleaned with alcohol to reduce impedance.

Data processing

The forehand and backhand strokes with the highest racket tip speed for each participant were selected for analysis. Several virtual landmarks were created to scale a generic model using the OpenSim scale tool. The ground reaction force data and kinematics were smoothed using a zero-lag 6 Hz second-order low-pass Butterworth filter. The EMG signals were full-wave rectified and filtered to create a linear envelope using a 6 Hz second-order low-pass Butterworth filter. The positions of the hip joint centers were estimated using a functional method (Gamage & Lasenby, 2002; Halvorsen, 2003).

Musculoskeletal model and estimation of muscle activations

We used a modified version of the OpenSim musculoskeletal model published by Lai et al. (2017). Two additional degrees of freedom of adduction/abduction and internal/external rotation were added to each knee joint. The range of motion was -5° to 5° for adduction (+) and -30° to 30° for internal rotation (+). These values were determined according to Ramsey & Wretenberg, (1999).

Lower limb muscle activation was estimated using a static optimization algorithm with OpenSim 3.3 (Seth, Sherman, Reinbolt, & Delp, 2011). The modified model was scaled for each participant in a static standing position. The maximum isometric force of each muscle actuator was scaled by a factor of 1.8–2.1 to account for possible stronger muscles in younger players. The scale was set so that the estimated activation level would not remain at the maximum (i.e., 1) for more than 15 ms for all muscles because such persistent full activation was not observed in EMG activation. Subsequently, the joint angles during stroke sequences were determined using the Inverse Kinematics tool. The calculated joint angles and ground reaction forces were then used to estimate the lower limb muscle activations through static optimization, which resolves the indeterminacy of muscle forces by minimizing the squared sum of muscle activations.

EMG envelope data were time-shifted by 40 ms to account for the electromechanical delay (Begovic, Zhou, Li, Wang, & Zheng, 2014; Dupré et al., 2019; Zhou, Lawson, Morrison, & Fairweather, 1995). The timings of stroke events were determined in accordance with previous studies (Iino & Kojima, 2011; 2016); However, the origin of the pelvis instead of the shoulder joint was used to define the beginning of a backhand stroke as described below because the present study focused on the lower limb movements. The beginning of a forehand stroke was defined as the time when the pelvis negative (clockwise) axial angular velocity exceeded -0.5 rad/s (for the players who temporarily stopped the pelvis rotation between two strokes) and the time when the pelvis rotated backward beyond the forward-facing position (for the remaining players) (Figure 1). The beginning of a backhand stroke was defined as the time when the origin of the pelvis (midpoint of both hip joint centers) made a preliminary downward movement. The beginning of the forward swing was defined as the time when the pelvis began to rotate forward for the forehand and the time when the pelvis began to move upward for the backhand. Time was normalized to the duration from the beginning of the stroke to the peak racket speed. Muscle activation data were analyzed from 0% (beginning of stroke) to 120% (follow-through) normalized time.

Statistical analysis

Pearson correlation coefficients were determined between the EMG envelope and the estimated muscle activation data for 121 time points. Pearson correlation coefficients were classified as small (r = 0.1–0.29), moderate (r = 0.3–0.49) or large (r = 0.5–1) (Cohen, 2013). In addition, Lin's concordance correlation coefficients (CCC) (Lin, 1989) were determined between the EMG and estimated muscle activations. CCC quantifies the closeness of the two measurements to the 45 degree line that passes through the origin.

The Shapiro-Wilk test was used to evaluate the non-normality of the distribution for the maximum activation of the following lower limb muscles/muscle groups during the forehand and backhand: gluteus maximus, gluteus maximus, adductor magnus, hamstrings, vastus muscles, gastrocnemius, soleus, and anterior tibialis. The test revealed that the distribution for the gluteus maximus on the playing side during forehand significantly departed from normality (P = 0.0017); hence, the Wilcoxon signed-rank test was used to compare the maximum activation between the strokes for that muscle. A two-tailed t-test was used to analyze the remaining muscles. Statistical significance was set at $P < 0.01$.

RESULTS

The maximum racket speed was 20.6 ± 1.6 m/s for the forehand topspin and 21.5 ± 1. 6 m/s for the backhand topspin.

In the forehand, seven muscles showed a maximum estimated activation of > 0.3 (Table 1). The rectus femoris and gluteus maximus of the playing side and the rectus femoris of the non-playing side showed a maximum estimated activation of > 0.5. The tibialis anterior and biceps femoris of the playing side and the gastrocnemius lateralis and gluteus maximus of the non-playing side showed maximum estimated activation between 0.3 and 0.5. The Pearson correlation coefficient between EMG and estimated activations was > 0.3 for eight muscles of the forehand (Table 1). Most muscles that showed substantial maximum activation (> 0.3) exhibited a Pearson correlation coefficient higher than 0.3, except the gastrocnemius lateralis and gluteus maximus on the non-playing side, with mean Pearson correlation coefficients of 0.277 and 0.218, respectively (Table 1). Concordance correlation coefficients were smaller than their respective Pearson coefficients and were > 0.3 for five muscles. Peak EMG activation was observed during the forward swing phase for all muscles that showed substantial activation (Table 1, Figure 2). The rectus femoris and gluteus maximus of the playing side and rectus femoris of the non-playing side showed peak EMG activation after the beginning of the forward swing (Figure 2).

For the backhand, four muscles showed a maximum activation > 0.3 (Table 1). Only the rectus femoris on the playing side showed a maximum activation of > 0.5. The soleus of the playing side and rectus femoris and gluteus maximus of the non-playing side showed maximum activations between 0.3 and 0.5. These muscles exhibited a Pearson correlation coefficient of > 0.3 (Table 1). As was in the forehand stroke, concordance correlation coefficients were smaller than Pearson coefficients and were > 0.3 for seven muscles in the backhand (Table 1). In the backhand stroke, peak EMG activation was also observed during the forward swing phase, except for the vastus medialis on the non-playing side, which showed higher activation during the backswing phase (Figure 3).

The gluteus maximus, hamstrings of the playing side, and rectus femoris of the non-playing side showed a statistically higher maximum estimated activation in the forehand than in the backhand (P = 0.0078, P = 0.00055, and P = 0.0002, respectively, Figure 4). Three muscles showed a maximum estimated activation of > 0.5 during the forehand, whereas only the rectus femoris of the playing side showed a maximum activation > 0.5.

Table 1.
Pearson correlation coefficients and concordance correlation coefficients between EMG and estimated activation levels for lower limb muscles during forehand and backhand topspin strokes.

	Forehand				Backhand			
	Pearson Correlation Coefficient, r	Concordance Correlation Coefficient		Maximum activation	Pearson Correlation Coefficient, r	Concordance Correlation Coefficient		Maximum activation
		r_c	s.e.			r_c	s.e.	
Playing side								
tibialis anterior	**0.300±0.164**	0.204±0.106	0.062±0.014	**0.31±0.17**	0.033±0.266	0.023±0.193	0.055±0.014	0.08±0.08
gastrocnemius lateralis	0.145±0.272	0.087±0.184	0.061±0.010	0.15±0.07	**0.335±0.434**	0.274±0.355	0.057±0.016	0.13±0.07
soleus	**0.528±0.163**	**0.451±0.161**	0.062±0.010	0.24±0.12	**0.650±0.138**	**0.581±0.153**	0.052±0.011	**0.33±0.17**
vastus medialis	**0.349±0.317**	0.282±0.292	0.064±0.022	0.23±0.16	**0.566±0.244**	**0.534±0.247**	0.056±0.024	0.20±0.08
rectus femoris	**0.616±0.201**	**0.572±0.193**	0.055±0.015	**0.58±0.22**	**0.605±0.152**	**0.555±0.149**	0.058±0.014	**0.53±0.16**
biceps femoris	**0.640±0.267**	**0.530±0.257**	0.049±0.017	**0.43±0.23**	0.139±0.293	0.101±0.209	0.050±0.018	0.06±0.05
gluteus medius	0.088±0.230	0.056±0.143	0.052±0.007	0.24±0.17	0.120±0.339	0.059±0.224	0.059±0.018	0.07±0.05
gluteus maximus	**0.883±0.080**	**0.860±0.089**	0.023±0.013	**0.93±0.10**	0.081±0.314	0.063±0.289	0.064±0.013	0.11±0.10
Non-playing side								
tibialis anterior	0.069±0.368	0.066±0.298	0.066±0.012	0.17±0.15	**0.333±0.217**	0.219±0.176	0.055±0.014	0.14±0.06
gastrocnemius lateralis	0.277±0.0457	0.215±0.324	0.058±0.013	**0.34±0.17**	0.245±0.309	0.221±0.288	0.070±0.021	0.25±0.14
soleus	0.169±0.349	0.128±0.281	0.072±0.013	0.26±0.13	0.288±0.335	0.208±0.264	0.066±0.012	0.16±0.11
vastus medialis	**0.343±0.292**	0.251±0.306	0.047±0.028	0.27±0.31	**0.442±0.264**	**0.345±0.246**	0.045±0.025	0.19±0.16
rectus femoris	**0.795±0.099**	**0.746±0.112**	0.038±0.011	**0.85±0.21**	**0.354±0.248**	**0.323±0.257**	0.067±0.022	**0.34±0.23**
biceps femoris	0.234±0.257	0.171±0.190	0.055±0.011	0.13±0.23	**0.666±0.281**	**0.614±0.287**	0.046±0.024	**0.23±0.11**
gluteus medius	0.00±0.237	-0.010±0.177	0.076±0.010	0.19±0.10	0.282±0.319	0.223±0.310	0.060±0.023	**0.13±0.11**
gluteus maximus	0.218±0.272	0.147±0.219	0.065±0.020	**0.35±0.33**	**0.667±0.223**	**0.604±0.235**	0.049±0.023	0.40±0.14

Correlation coefficients > 0.3 (moderate or large in accordance with Cohen (2913)) are shown in bold for clarity.

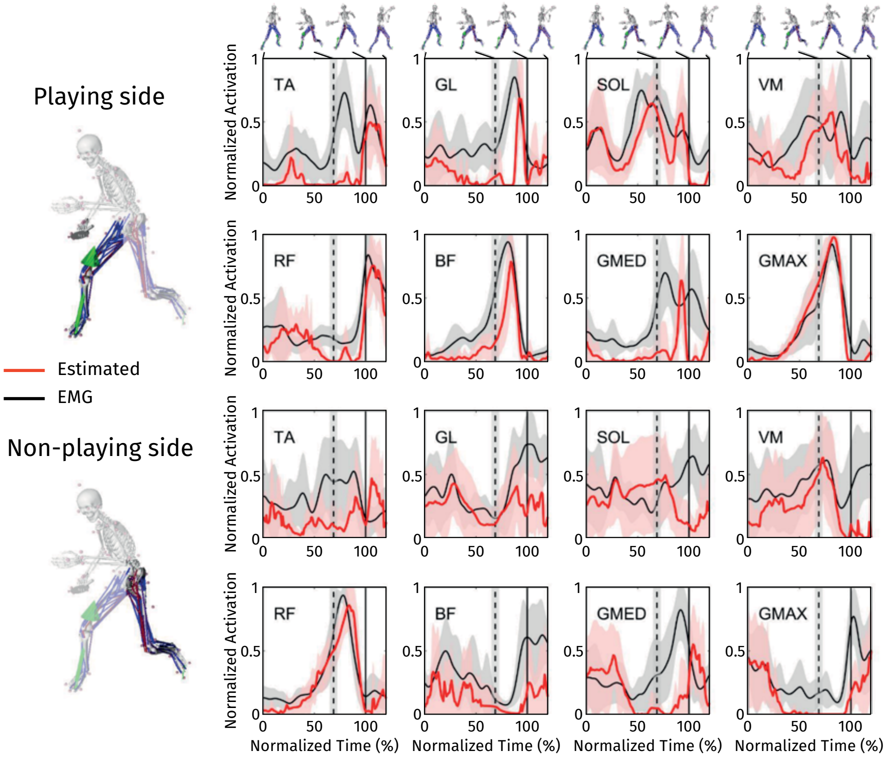

Figure 2. Normalized estimated (red) and EMG (black) activations of the lower limb muscles during the topspin forehand. Vertical lines represent the completion of backswing (dashed) and the occurrence of maximum racket speed (solid). Shared areas show standard deviations for the participants. TA; tibialis anterior, GL; gastrocnemius lateralis, SOL; soleus, VM; vastus medialis, RF; rectus femoris, BF; biceps femoris, GMED; gluteus medius, GMAX; gluteus maximus.

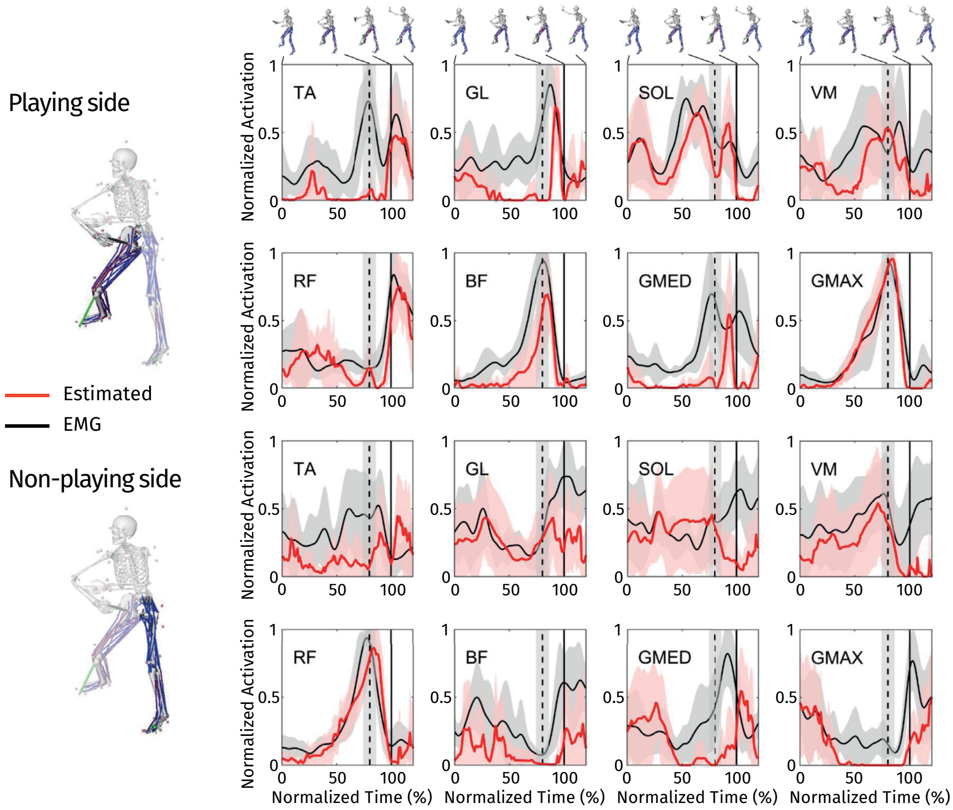

Figure 3. Normalized estimated (red) and EMG (black) activations of the lower limb muscles during the topspin backhand. Vertical lines represent the completion of backswing (dashed) and the occurrence of maximum racket speed (solid). Shared areas show standard deviations for the participants. TA; tibialis anterior, GL; gastrocnemius lateralis, SOL; soleus, VM; vastus medialis, RF; rectus femoris, BF; biceps femoris, GMED; gluteus medius, GMAX; gluteus maximus.

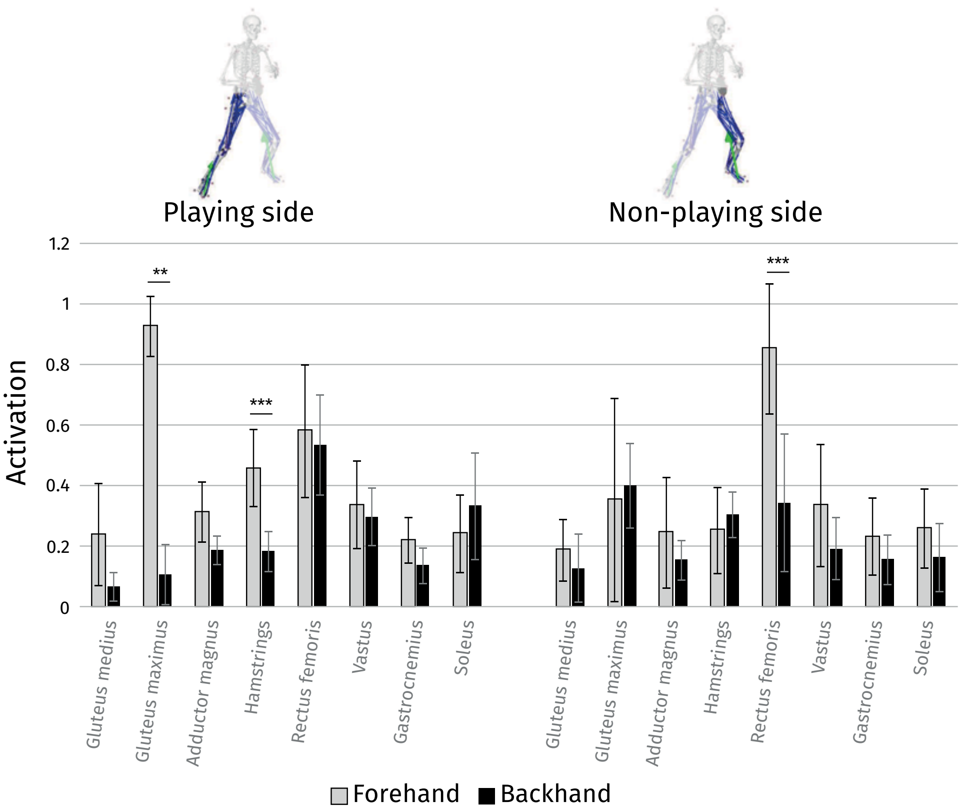

Figure 4. Maximum estimated activation of the lower limb muscles/muscle groups during topspin forehand and backhand. ***P<0.001, **P<0.01.

DISCUSSION

This study aimed to validate the estimation of lower-limb muscle activation during table tennis forehand and backhand through comparison with EMG measurements. We also aimed to compare the estimated activation between forehand and backhand strokes. The maximum racket resultant velocities (20.6 ± 1.6 m/s for the forehand and 21.5 ± 1.3 m/s for the backhand) were similar to or higher than those in previous studies (Bańkosz & Winiarski, 2018; Iino & Kojima, 2009; 2016).

The comparison between the estimated and EMG activation suggests that the static optimization algorithm can adequately estimate lower limb muscle activity during table tennis topspin forehand and backhand. For the four muscles that showed maximum activation of > 0.5, the Pearson correlation coefficients were > 0.5 (Table 1). Of the seven muscles that showed maximum activation between 0.3 and 0.5, five showed a Pearson correlation coefficient > 0.3 (Table 1). However, the Pearson correlation coefficients for the gastrocnemius and gluteus maximus of the non-playing side during forehand were lower than 0.3 (although their maximum activations were higher than 0.3; Table 1).

Co-contraction is a possible cause for the lower correlations observed in the gluteus medius on the playing side and the gluteus maximus and gluteus medius on the non-playing side. EMG recordings showed that the gluteus maximus on the non-playing side was active for 60–80% of the swing phase during the forehand (Figure 2), but the estimated activation was small because the hip joint on the non-playing side exerted flexion torque during that phase (not shown in the Results section). EMG recordings also showed that the bilateral gluteus medius muscles were activated during the follow-through phase of the forehand. However, six of the eight players demonstrated adduction torque at each hip joint during this phase, which resulted in lower estimated activation of the gluteus medius muscles in these players (Figure 2). These results suggest that the co-contraction of the adductor/abductor and flexor/extensor muscles that occurred at both hip joints in the forehand stroke resulted in lower correlations observed in the relevant muscles. Methods for estimating muscle co-contraction using shift parameters (MacIntosh & Keir, 2017) or contraction entropy (Jiang & Mirka, 2007) have been proposed. Future research is needed to establish when and at which joint co-contraction occurs in table tennis strokes to accurately estimate the activation of the lower limb muscles.

Another reason for the lower correlation for some muscles in some participants may be that the model parameters used were not adjusted for each participant as indicated in previous studies (Dupré et al., 2019; Trinler et al., 2018; Wibawa et al., 2016; Żuk et al., 2018). For example, the Pearson correlations for the gastrocnemius of the non-playing side during the forehand and the gastrocnemius of the playing side during the backhand varied substantially among the players (see standard deviation values in Table 1). Muscle parameters, such as the force-length relationship of the muscle and tendon in the generalized model, might not have been appropriate for some players.

Concordance correlation coefficients were smaller than respective Pearson correlation coefficients. Only the gluteus maximus of the playing side during the forehand exhibited a concordance correlation coefficients > 0.8. These results suggest that there was "scale shift" or "location shift" between EMG and estimated activations (Lin, 1989). It should be noted that this reflects that EMG linear envelope is only an estimate of muscle activation and is subject to noise and confounding factors (Staudenmann, Roeleveld, Stegeman, & van Dieën, 2010). For more robust validation of the musculoskeletal modeling and muscle activation, comparisons with additional independent data, such as ultrasound images of muscles and instrumented joint loading, would be necessary (Hicks, Uchida, Seth, Rajagopal, & Delp, 2015).

It is worth comparing the results of the present study with those obtained for walking and other types of locomotion in previous studies (Alexander & Schwameder, 2016; Dupré et al., 2019; Trinler et al., 2018; Wibawa et al., 2016; Żuk et al., 2018). Although these studies have reported that lower limb muscle activation estimated using musculoskeletal modeling generally showed moderate to good agreement with EMG activation, Trinler et al. (2018) suggested that the consistency of agreement between measured and estimated activation levels at different walking speeds was not high enough to recommend immediate clinical adoption. Many factors, such as the musculoskeletal models used (OpenSim, AnyBody), EMG signal processing methods, statistical methods (Pearson or Spearman), and the phase of analysis (stance phase or complete gait cycle), differed between studies, making it difficult to quantitatively compare the correlation coefficients between these studies. Overall, the present study suggests that the static optimization algorithm can estimate lower-limb muscle activity during table tennis forehand and backhand with a similar degree of validity to that of locomotion.

The results suggest that the gluteus maximus and hamstrings of the playing side and the rectus femoris of the non-playing side exhibit higher activation during the forehand than during the backhand. The gluteus maximus and biceps femoris muscles show high activation. These results were consistent with Le Mansec et al.'s (2018) findings on lower limb EMG and the previous studies (Chen et al., 2022; Qian et al., 2016) that suggested that advanced players would use lower limb drive more effectively than intermediate players in the topspin forehand. Our study also suggests that the rectus femoris on the non-playing side is highly activated during the topspin forehand.

In contrast, the lower limb muscles showed relatively low activation during the topspin backhand. This result is consistent with a previous study that found that the angular velocities of playing and non-playing side hip extension and ankle flexion are positively correlated with racket speed in the topspin forehand whereas the angular velocities of the racket arm are correlated with racket speed in the topspin backhand (Bańkosz & Winiarski, 2018). Previous studies (Iino & Kojima, 2011; 2016) have reported that approximately 80% of the mechanical energy of the racket arm at ball impact was due to the energy transfer from the trunk in both the backhand and forehand strokes. Considering that the maximum racket speeds were similar for both strokes in the present study, the trunk muscles may be more highly activated for mechanical work in the backhand than in the forehand, or mechanical energy may be transferred more efficiently through the trunk in the backhand than in the forehand.

The present study has some limitations. First, EMG data were not recorded for maximum voluntary contraction (MVC). Thus, EMG activation could not be normalized to MVC values. Second, the maximum isometric forces of each muscle actuator did not reflect the maximum isometric joint torque for each player because such kinetics were not measured. We focused instead on the patterns of estimated and EMG activations, which were not affected by these normalizing values. Finally, only the static optimization algorithm using the OpenSim model was assessed. Other algorithms such as computed muscle control and other musculoskeletal models should be investigated in future studies.

CONCLUSIONS

The present study suggests that the static optimization algorithm can adequately estimate lower-limb muscle activity during table tennis topspin forehand and backhand strokes. The gluteus maximus and rectus femoris on the playing side and rectus femoris on the non-playing side showed high activation during the forehand. Only the rectus femoris on the playing side showed high activation in the backhand. For these four muscles, the Pearson correlation coefficients were higher than 0.5. A lower Pearson correlation between the estimated and EMG activation was observed for some muscles, including both gluteus medius muscles, during the forehand. A possible cause is the co-contraction of relevant muscles. All concordance correlation coefficients were smaller than their respective Pearson correlation coefficients. The gluteus maximus and hamstrings on the playing side, and rectus femoris on the non-playing side exhibited higher activation during the forehand than during the backhand.

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CONFLICT OF INTERESTS

The authors declare that there are no conflicts of interest.

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