Proceedings Paper:
Guo, Y, Sun, Y, Ren, Y et al. (3 more authors) (2019) Upper Limb Muscle Force Estimation During Table Tennis Strokes. In: 2019 IEEE 16th International Conference on Wearable and Implantable Body Sensor Networks (BSN). 2019 IEEE 16th International Conference on Wearable and Implantable Body Sensor Networks (BSN), 19-22 May 2019, Chicago USA. IEEE . ISBN 978-1-5386-7477-2

https://doi.org/10.1109/BSN.2019.8771082

Upper Limb Muscle Force Estimation During Table Tennis Strokes

Yiming Guo, Yingfei Sun*, Yi Ren, Zhipei Huang, Jiankang Wu, Zhiqiang Zhang

Abstract—**Based on an EMG-adjusted method in neuromusculoskeletal model, this study aims to predict the individual muscle force in shoulder and elbow during table tennis strokes. Muscle force estimation makes muscle activation analysis more physiological in sports. Twenty subjects, divided into professional group and amateur group, were adopted in this study. They were asked to do a basic stoke motion: backhand block. Surface electromyography (sEMG) of nine muscles was recorded, as well as the motion data collected by three inertial sensors. A Hill-type musculotendon model was then adopted to estimate individual muscle force by combining adjusted sEMG and motion data. The result shows that the method can estimate individual muscle force during table tennis strokes accurately, and the two groups show significant difference in muscle force of shoulders and elbows.**

Keywords—table tennis, Hill-type musculotendon model, surface electromyography (sEMG), muscle force, upper limb

I. INTRODUCTION

In recent years, sports biomechanics analysis has been widely used in optimizing movement technology and guiding sports training of table tennis. At present, the upper limb strength characteristics [1][2] play an important role in the biomechanical research on human body movement in table tennis. As for backhand block, players predominantly use the shoulder and elbow joints to hit the ball, with a little assistance of waist and wrist. It is, therefore, a significant way to evaluate the motion by analyzing muscle activity during the strokes. As far as we know, this previous analysis basically depended on the process of surface electromyography (sEMG) directly [3]. Meanwhile no research based on the musculoskeletal model to predict the muscle force during strokes has been implemented. Muscle force estimation, which opens up the possibility of objectively evaluating human motion in both mechanical and physiological way [4], should be introduced to quantitative evaluation of players' motion. However, direct measurement of muscle strength is usually not feasible in clinical setting.

Traditional EMG-driven model is a common method in non-invasive muscle force prediction, which has been widely used on so many different anatomical sites like knee, ankle, elbow, shoulder and wrist [5]. However, due to the missing information of deep muscles and noise caused by skin or electrode movement while collecting surface EMG signals, the EMG-driven method is not accurate enough. Inverse dynamic method is also used to analyze the internal mechanism of muscle movement during the table tennis strokes [6], in which muscle forces and velocities come out through the motion data and estimated activation patterns of muscles. Uncertainty of the patterns still limits the accuracy of the method.

With both motion data and sEMG signals, we used a static optimization method based on EMG-driven model to adjust EMG values to optimize the joint moments, so that we could estimate muscle forces. The result indicates that the method can predict individual muscle forces during strokes accurately, making it possible for us to get a deeper understanding of human dynamic movement mechanism. In this paper, we first explain how the approach works during the process. Then we analyse the difference between individual muscle forces of two groups. Last, we draw a conclusion that could help in a scientific and systematic teaching training program.

II. METHOD

A. Data Collection

We collected twenty healthy young subjects (age:23.6±2.1 years; height: 173.9±4.5kg) in this study. ten of them were from the table tennis association of the University of Chinese Academy of Sciences, and another ten subjects were amateurs. They were divided into professional group and amateur group. A ball machine was employed to serve balls under stable frequency, speed and landing point. The participants were required to hold the bat upright, used the backhand block movement to return five balls continuously.

The motion data and sEMG signals were both recorded by the Trigno wireless sEMG recording system (DELSYSINC, Massachusetts, USA). The motion data were collected (148.15 Hz) by four motion sensors, attached to waist, upper arm, forearm and wrist, respectively. Meanwhile, nine electrodes were used to collect sEMG signal of anterior deltoid (DELT_A), middle deltoid (DELT_M), posterior deltoid (DELT_P), clavicular head of pectoralis major (PECM), latissimus dorsi (LAT), long head of triceps brachii (TRIlong), lateral head of triceps brachii (TRIlat), long head of biceps brachii (BIC) and brachioradialis (BRD) at 1925.93 Hz. The electrodes of each muscle were located and placed according to the SENIAM (surface electromyography for the non-invasive assessment of muscles) recommendations [7] and with respect to muscle fiber directions longitudinally. The specific locations are shown in Fig.1. The skin was cleaned by alcohol to reduce noise contamination before settling electrodes. Traditional manual muscle test techniques were applied to collect the isometric maximum voluntary contraction (MVC) trials [8].

*This study is supported by National Natural Science Foundation of China, Grant No.61431017.

Yiming Guo, Yingfei Sun*, Yi Ren, Zhipei Huang, Jiankang Wu are with Sensor Network and Application Research Center, School of Electronic, Electrical and Communication Engineering, University of Chinese Academy of Sciences, Beijing, China.(yfsun@ucas.ac.cn). and Zhiqiang Zhang are with University of Leeds, UK.

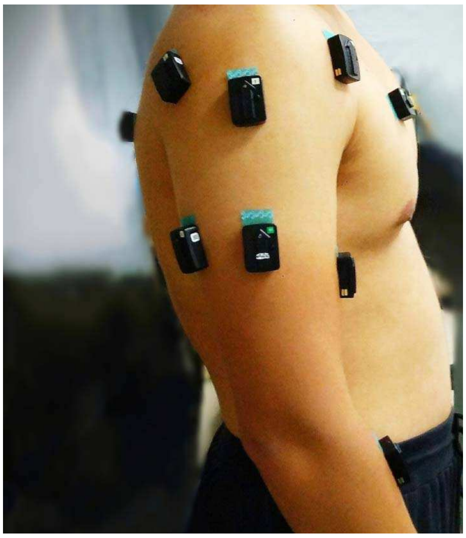

Fig. 1. Locations of the electrodes during trials

B. Preprocessing

Raw EMG signals were high-pass filtered (30 Hz), full-wave-rectified, and low-pass filtered (6 Hz) using a zero-lag fourth-order recursive Butterworth filter to calculate experimental muscle excitations. The excitations were then normalized using data from maximum voluntary contraction trials respectively.

Joint angle was calculated by the integration of the angular rate using a gyroscope. The nine-axis motion data was preprocessed and then we used factor quaternion algorithm to estimate joint Euler angle of the shoulder and the elbow.

Using the calculated joint angle data, muscle kinematics parameters could be acquired by an OpenSim model [9]. We introduced the upper limb model developed by Saul et al [10]. After scaling, we turned joint angle into joint moments, musculo-tendon lengths and moment arms through OpenSim Inverse Dynamics Tool and Analysis Tool in the subject's scaled model. The parameters we got are necessary in individual muscle force prediction.

C. Muscle Activation Dynamics

Muscle activation dynamics was to transform muscle excitation we obtained before to neural activation, and then to muscle excitation. Muscle excitation could represent a relationship between EMG and muscle force considering of the time-delay and non-linearity. The muscle activation dynamics process uses a discrete form of critically damped linear second-order difference system to obtain neural excitation [11]:

$$\mathrm{u}(t) = \alpha e(t-d) - (C_1 + C_2)u(t-1) - C_1 C_2 u(t-2) \quad (1)$$

where $e(t)$ is the muscle excitation at time t, $\mathrm{u}(t)$ is the neural activation, α is the muscle gain, C_1 and C_2 are recursive coefficients, and d is the electromechanically delay. Then either a linear or non-linear EMG-force relationship was used to calculate the muscle activation [11]:

$$a(t) = \frac{e^{Au(t)} - 1}{e^{A} - 1} \quad (2)$$

where $\mathrm{a}(t)$ is the muscle activation, $\mathrm{u}(t)$ is the neural activation, and A is the non-linear shape factor. The values of these system parameters were set to match the subject-specific physiological characteristics using a calibration process, which we will talk about later. In our experiment, we selected DELTA, DELTM, DELTP, PECM, LAT, BIClong, BICshort, TRIlong, TRImed, TRIlat, BRD and BRA as the twelve main action muscles of elbow and shoulder joints during the motions. As for the muscles BICshort, TRImed and BRA, sEMG of which we didn't collect, we adopted a neural mapping method to get their activations [12].

D. Muscle Contraction Dynamics

Muscle activations were then transformed to muscle forces in muscle contraction dynamics. We used a Hill-type musculotendon model to complete the process:

$$F^{mt}(\theta,t) = F^{t} = \left\{ f_A(l) f(v) a(t) F_0^m + f_P(l) F_0^m \right\} \cos(\varphi) \quad (3)$$

where $F^{mt}(\theta,t)$ is the muscle force, F_0^m is the maximum isometric muscle force, l is the normalized muscle fiber length, v is the normalized muscle fiber contraction velocity, $\mathrm{a}(t)$ is the muscle activation, is the pennation angle. $f_A(l)$ is the active force-length relation that express the ability of muscle fibers to produce force at different lengths, $f(v)$ is the passive force-length relation that represents the force response of the fibers to strain, $f_P(l)$ accounts for the force contribution of the fiber contraction velocity.

E. Static Optimization

We adjusted sEMG signal through a comparison between the estimated joint moment and the experimental one that was calculated before by OpenSim. Joint moment estimation took the individual muscle strength and the individual muscle arm as input, according to the Newtonian mechanics, the joint torque was then calculated:

$$\hat{\tau} = \sum_{i=1}^{N_{Muscles}} (MA_i \times F^m{}_i) \quad (4)$$

where $\hat{\tau}$ is the estimated joint moment, $\mathrm{N}_{Muscles}$ is the number of muscles, MA_i is the moment arm of muscle and $F^m{}_i$ is the force of muscle i.

Static optimization was used to adjust system parameters in muscle activation dynamics and muscle contraction dynamics. This calibration process aimed at matching the subject's specific EMG-force generating properties. A simulated annealing algorithm [13] was used to minimize the root mean square error between the experimental and estimated joint moment by varying parameters within pre-defined boundaries.

Following calibration, we employed a novel set of trail as input to drive the calibrated model. During the simulation process based on the model, static optimization unit takes the experimental joint torque and the estimated joint torque obtained by the simulation as input, and uses the optimization algorithm to adjust the parameters in the model within a reasonable preset range, so that the simulated joint torque is more consistent with the experimental joint torque. The objective functions and constraints are as follows [14]:

$$\min F_{obj} = \sum_{i=1}^{N_{DOFs}} |\tau_i - \hat{\tau}_i| \tag{5}$$

$$\text{subject to} \left| \frac{e_j - \hat{e}_j}{e_j} \right| < Th \quad \forall j \in N_{muscles} \tag{6}$$

where τ is the experimental joint moment, $\hat{\tau}$ is the estimated joint moment, e_j is the experimental muscle excitation for muscle i , $\hat{e}_j$ is the adjusted muscle excitation for muscle i , Th is the threshold constrained in the interval (0, 1). We set Th = 0.8 in our experiment to acquire an accurate joint moment estimation [14].

F. Data analysis

The coefficient of determination (R^2) and the normalized root mean squared deviation (NRMSD) [15], were introduced to measure the similarity between the estimated and experimental results, and comparison results with 0.0 ≤ NRMSD ≤ 0.3 and 0.7 ≤ R^2 ≤ 1.0 are thought to be acceptable for joint moment estimation.

Independent sampled t-tests were taken to examine the differences between professional and amateur group. The coefficient of multiple correlation (CMC) was employed to evaluate the similarity of the curves of muscle forces to compare the differences between two groups. The calculation of CMC is as follows [16]:

$$CMC = \sqrt{1 - \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} (Y_{ij} - \bar{Y}_j)^2 / n(m-1)}{\sum_{i=1}^{m}\sum_{j=1}^{n} (Y_{ij} - \bar{Y})^2 / (nm-1)}} \tag{7}$$

where m is the number of curves, n is the number of data of each curve, Y_{ij} is the jth data of the ith curve, $\bar{Y}_j$ is the average of the jth data of all curve, $\bar{Y}$ is the mean of n data for all curves. The closer the CMC is to 1, the higher the similarity of the curve. The result with 0.75 ≤ CMC ≤ 1.0 is thought to be high similarity.

III. RESULTS

A. Estimated Results Comparison

The comparison between estimated and experimental joint moment is shown in Fig.2. It shows the shoulder and elbow joint moment of four consecutive strokes of subject 1. The calculated joint torque of multiple subjects shown in table 1 illustrated that compared with traditional EMG-driven method, the method we used could calculate joint moment more accurately so that the muscle and joint dynamics would also fit the reality closely.

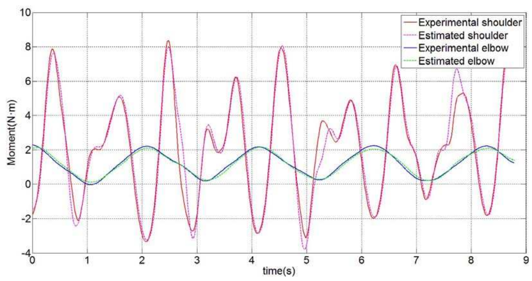

Fig. 2. Joint moment comparison of subject 1

Table 1. Comparison between experimental and estimated joint moment

	EMG-driven	Static Optimization
NRMSD_shoulder	0.4238±0.0756	0.0585±0.0302
NRMSD_elbow	0.3947±0.0687	0.0477±0.0226
R^2_shoulder	0.2073±0.1486	0.9109±0.0428
R^2_elbow	0.4645±0.2508	0.9533±0.0342

B. Muscle Force Analysis

Fig.3 and Fig.4 shows the individual muscle forces of the elbow and shoulder in the second stroke of the subject 1.

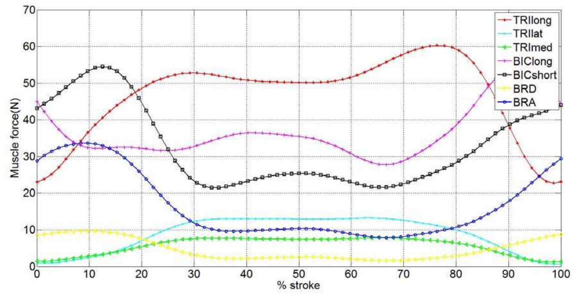

Fig. 3. Individual muscle forces in elbow joint

In the first half of hitting phase, the elbow is basically a process of elbow extension, and the shoulder joint is basically a process of flexion. The long head of the triceps is the main muscle of the elbow, showing an inverted U shape, meanwhile the anterior deltoid is the main muscle of the shoulder. In the second half of the reduction phase, the elbow and shoulder joints are exactly in an opposite situation, the long head of the biceps and latissimus dorsi are the main force muscles. Changes in other muscle forces are also in line with the reality.

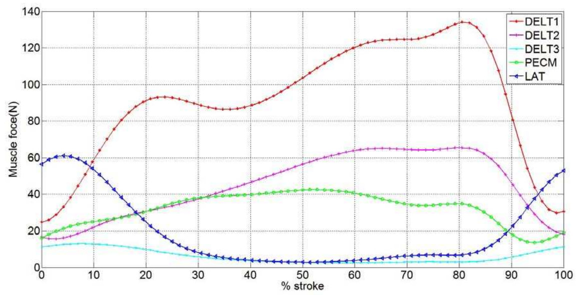

Fig. 4. Individual muscle forces in shoulder joint

During the stroke, the peak force of each muscle reflects the contribution of the muscle throughout the process. Fig.5 is an average of individual muscle peaks during the stroke of all subjects, which have been ranked from large to small. As seen from the figure, the red color shoulder muscles occupy a larger proportion of the whole movement, and the anterior deltoid exerts the greatest force throughout the movement.

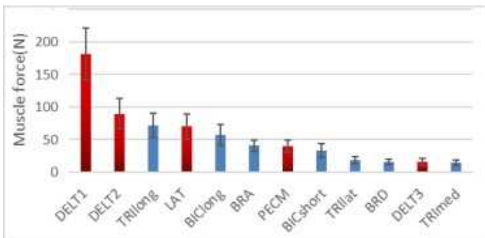

Fig. 5. Average individual muscle peak forces

Table 2 compares the shoulder and elbow movement and muscle force between the professional group and the amateur group. From the results of the kinematic data, it can be concluded that the professional group and the amateur group have some differences in the angle of the shoulder and elbow joint, and the difference in angle indicates the difference in the way the two groups of subjects exert force on the shoulder and elbow movement: The maximum mean value of the elbow joint of the amateur group joint is significantly larger than that of the professional group. On the contrary, the professional group has a lager maximum shoulder angle.

Table 2. Comparison of shoulder and elbow joint between the two groups

	Experts	Novices	P-value
Max shoulder angle	71.92±9.15	52.80±8.53	<0.01
Max elbow angle	131.09±16.68	152.96±22.86	<0.01
Max DELT1/TRIlong	3.38±0.36	2.16±0.61	<0.01

In terms of muscle force, many subjects in the amateur group have great difference in their strength, so that there is no significant difference while comparing their muscle force only, and it is difficult to scientifically distinguish the tendency of the force between the shoulder and elbow. Therefore, we take the ratio between the two muscles with the largest peak of the shoulder and elbow joint, the forehead of the deltoid and the long head of the triceps, to distinguish the difference between the two groups. In terms of overall power, the average peak of the amateur group is smaller than that of the professional group. The main difference is the force of the shoulder muscles. The professional group mainly use shoulder to hit the ball, while the amateur group use more force from the elbow, which is consistent with the conclusion of kinematics.

We selected the main force muscle the forehead of the deltoid and long head of triceps for CMC analysis. Table 3 compares the CMC values of the two groups of subjects. The individual CMC is the CMC value of the muscle force curves of the two main exerting muscles in ten strokes. The results show that both groups have high reproducibility, while the professional group's movement repeatability is significantly higher than that of the amateur group. The group CMC is the CMC value of ten average muscle curves of each subject. The CMC value among the professional group players is much larger than the CMC value among the amateur groups, which indicates that after long-term training and competition, the professional group achieve a higher level of control and consistency in table tennis technology.

Table 3. CMC difference between the two groups of subjects

	Muscle	Experts	Novices	P-value
Individual CMC	DELT1	0.97±0.02	0.90±0.03	<0.01
	TRIlong	0.95±0.02	0.88±0.05	<0.01
Group CMC	DELT1	0.85	0.68	
	TRIlong	0.86	0.61	

C. Conclusion

In conclusion, we can model the table tennis backhand block movement, calculate muscle force more accurately, and perform a certain statistical analysis on the muscle force. Besides, we conclude that difference exists between players at different level, in which the force distribution and stability show the most significant difference. The research results could also be applied in the study of other technical movements of table tennis. Our study lays basis for biomechanical analysis in table tennis sports and also throws lights on the individual training guidance for athletes.

REFERENCE

[1] K. Barczyk-pawelec, Bankosz Z, Derlich M. "Body postures and asymmetries in frontal and transverse planes in the trunk area in table tennis players," Biology of Sport, vol. 29, no. 2, pp: 129, 2012

[2] Y.Wen. Analysis on Coactivation of the Antagonist in Elbow during Isokinetic Flexion and Extension Movement for Elite Table Tennis Players, China Sport Science and Technology, vol. 48, no. 4, pp: 71-77, 2012.

[3] Mansec Y L , Dorel S , François Hug. Lower limb muscle activity during table tennis strokes. Sports Biomechanics, 2017:1.

[4] L.L.Z., J.Z., X.A.Z., and C.T.W.: Upper limb musculo-skeletal model for biomechanical investigation of elbow flexion movement. Journal of Shanghai Jiaotong University (Science) 16, 1, 61-64 (2011)

[5] Koo, T.K.K. and Mak, A.F.T.: Feasibility of using EMG driven neuromusculoskeletal model for prediction of dynamic movement of the elbow. Journal of Electromyography & Kinesiology Official Journal of the International Society of Electrophysiological Kinesiology 15, 1, 12 (2005)

[6] Yoichi Iino, Shinsuke Yoshioka and Senshi Fukashiro. Effect of mechanical properties of the lower limb musles on muscular effort during table tennis forehand. 36th Conference of the International Society of Biomechanics in Sports, 2018

[7] Hermens, H.J., Freriks, B., Merletti, R., Stegeman, D., Blok, J., and Rau, G.: European recommendations for surface electromyography (1999)

[8] Gruen and Peter, J.: Handbook of Manual Muscle Testing. McGraw-Hill, Health Professions Division (1999)

[9] Delp, S.L., Anderson, F.C., Arnold, A.S., and Loan, P.: OpenSim: Open-Source Software to Create and Analyze Dynamic Simulations of Movement. IEEE Transactions on Biomedical Engineering 54, 11, 1940-1950 (2007)

[10] Saul, K.R., Hu, X., Goehler, C.M., Vidt, M.E., Daly, M., Velisar, A., and Murry, W.M.: Benchmarking of dynamic simulation predictions in two software platforms using an upper limb musculoskeletal model. Computer Methods in Biomechanics & Biomedical Engineering 18, 13, 1445-1458 (2015)

[11] Lloyd, D.G.; Besier, T.F. An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo. J. Biomech. 2003, 36, 765–776.

[12] Pizzolato, C.; Lloyd, D.G.; Sartori, M.; Ceseracciu, E.; Besier, T.F.; Fregly, B.J. CEINMS: A toolbox to investigate the influence of different neural control solutions on the prediction of muscle excitation and joint moments during dynamic motor tasks. J. Biomech. 2015, 48, 3929–3936.

[13] Goffe, W.L.; Ferrier, G.D.; Rogers, J. Global optimization of statistical functions with simulated annealing. J. Econom. 1994, 60, 65–99.

[14] Hou, J., Sun, Y., Sun, L., Pan, B., Huang, Z., Wu, J., and Zhang, Z.: A Pilot Study of Individual Muscle Force Prediction during Elbow Flexion and Extension in the Neurorehabilitation Field. Sensors 16, 12, 2018(2016)

[15] Massimo, S.; Gizzi, L.; Lloyd, D.G.; Farina, D. A musculoskeletal model of human locomotion driven by a low dimensional set of impulsive excitation primitives. Front. Comput. Neurosci. 2013, 7, 79

[16] Wang, M., Fu, L., Gu, Y., Mei, Q., Fu, F., & Fernandez.: Comparative Study of Kinematics and Muscle Activity Between Elite and Amateur Table Tennis Players During Topspin Loop Against Backspin Movements, Journal of Human Kinetics, 64(1), 25-33