35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Neuromuscular Interfacing: A Novel Approach to EMG-Driven Multiple DOF Physiological Models*

James W.L. Pau, Shane S.Q. Xie, *Senior Member*, IEEE and W.L. Xu, *Senior Member, IEEE*

Abstract— **This paper presents a novel approach that involves first identifying and verifying the available superficial muscles that can be recorded by surface electromyography (EMG) signals, and then developing a musculoskeletal model based on these findings, which have specifically independent DOFs for movement. Such independently controlled multiple DOF EMG-driven models have not been previously developed and a two DOF model for the masticatory system was achieved by implementing independent antagonist muscle combinations for vertical and lateral movements of the jaw. The model has six channels of EMG signals from the bilateral temporalis, masseter and digastric muscles to predict the motion of the mandible. This can be used in a neuromuscular interface to manipulate a jaw exoskeleton for rehabilitation. For a range of different complexities of jaw movements, the presented model is able to consistently identify movements with 0.28 - 0.46 average normalized RMSE. The results demonstrate the feasibility of the approach at determining complex multiple DOF movements and its applicability to any joint system.**

I. Introduction

There are many difficulties associated in the development of exoskeleton devices for rehabilitative purposes and pattern recognition based approaches for myoelectric control are limited by the ON/OFF nature of the commands they provide [1]. The interface between an exoskeleton device and the operator is only able to identify commands such as "open hand" or "rotate wrist", which are recognizable discrete states and do not offer the user continuous control over the speed or trajectory of movements.

To address this, a neuromuscular interface (NI), which has a physiological model of the joint system at its core was developed and demonstrated with the elbow joint, where random movements were able to be identified from multiple subjects [2]. However, the efficacy of the approach was only shown with a single DOF joint system and the purpose of this study is to present a new approach capable of handling multiple DOF joints.

Fleischer and Hommel developed an exoskeleton for the knee joint [3] and Manal and Buchanan applied a similar approach to the elbow joint [4]. However, both approaches with physiological models simplified the system to single DOF joints. Cavallaro et al. are developing a 7 DOF exoskeleton for the upper limb that includes the multiple DOF shoulder joint, but continue to focus their efforts on the single DOF elbow joint again [5]. Ding et al. furthered the complexity of the physiological model based interface by utilizing a Kalman filter in their approach, but added an additional load to the user's arm to enhance the EMG signal activity and still have not considered multiple DOFs [6].

It is evident that in current interfacing approaches, the problem of identifying movements from multiple DOF joints, without completely reducing the available movement to a single DOF, has not yet been fully addressed. The nature of the EMG signal, recruitment strategies of motor units, and co-activation ability of muscles do not make the transition immediately straightforward because of the multiple roles muscles play in various movements. The interface is also limited by the availability of potential sites to obtain surface EMG signal recordings - reducing the available channels of data and consequently, movement prediction.

This paper presents a methodical approach towards identifying the available superficial muscles that surface EMG signal recordings can be obtained, and then using the available muscles to develop a physiological model for driving an NI. The concept is demonstrated with the masticatory system, which with the temporomandibular joints is arguably the most complex joint system in the human body due to its six DOFs, kinematic redundancy, and large number of mandibular muscles [7]. Some of these muscles are prime movers, and are located superficially and deeply around the craniofacial region.

The selection of available EMG channels limits the amount of movement that can be reconstructed and an initial two DOF implementation is presented. The vertical and lateral movement identification of the mandible is sufficient to emulate a basic cycle chewing pattern that could be applied by a jaw exoskeleton for rehabilitation purposes [8].

II. Materials & Methods

A. Physiological Model

The physiological model of the masticatory system consists of three modular components: the musculoskeletal model, consisting of the geometric structure; musculotendon models, which represent the dynamic behavior of muscles; and the kinematic model, which uses total torque and force to determine movement.

The musculoskeletal model includes skeletal structure properties such as bone, and muscle lengths and attachment points, as well as the sources of all passive and active forces on the mandible. These include the active forces produced by voluntary muscle contraction and the passive weight force

*Research supported by the former Foundation of Research Science and Technology (FRST), now Ministry of Business, Innovation and Employment (MBIE), New Zealand.

J. W. L. Pau, S. S. Q. Xie and P. W. L. Xu are with the Mechanical Engineering Department, University of Auckland, Auckland, New Zealand (e-mail: jpau024@aucklanduni.ac.nz, s.xie@auckland.ac.nz and p.xu@auckland.ac.nz).

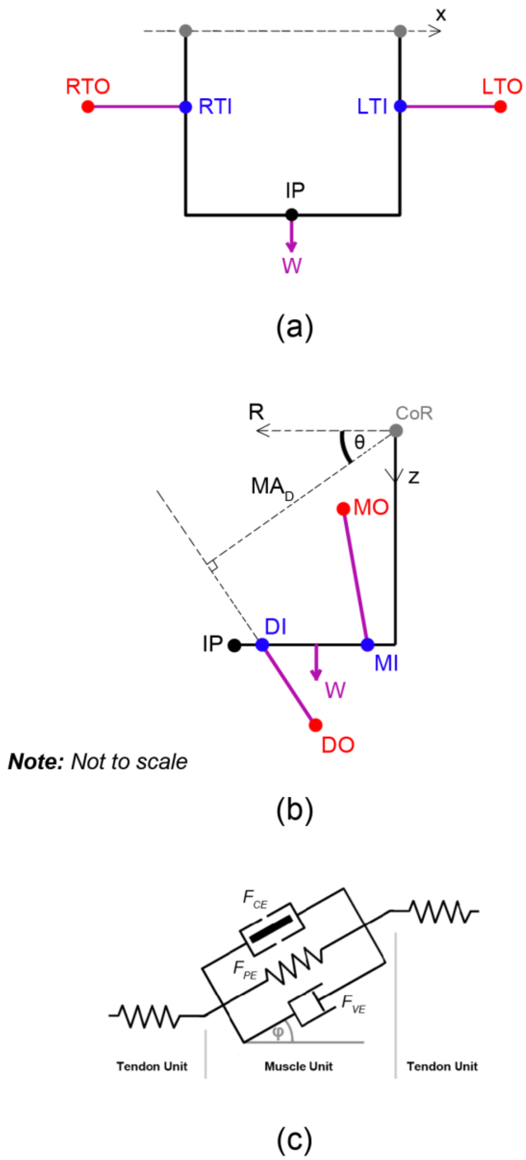

Fig. 1. Musculoskeletal model of the jaw viewed from the (a) front and (b) side. (R, θ, x) is the cylindrical coordinate system, z is the vertical axis, IP is the incisor point, CoR is the center of rotation, W is the weight of the mandible, and the letters are as follows: R = right, L= left, M = masseter, D = digastric, T = temporalis, I = muscle insertion, O = muscle origin, and MA_D is an example of the calculation of a moment arm for the digastrics. (c) shows an example of the musculotendon model (purple muscle lines).

generated by the mass of the mandible. The development of the musculoskeletal model was driven by the findings of the EMG signal channel identification and independent degrees of freedom were implemented as shown in Fig. 1(a) and (b).

The bilateral digastrics and masseters act as a combined antagonistic pair, and are involved in the open-close movement of the mandible as a single DOF. The movement is approximated to occur at a fixed centre of rotation and muscle origin and insertion points can be described in two two dimensional planes. The temporalii muscles act as an antagonistic pair on their own to actuate the lateral movement of the mandible. The lateral motion is assumed to cause the entire mandible to translate without any twisting motion so that there is no dependence on the lateral movement from the open-close movement. The independence is advantageous because physiological modeling depends on parameter selection for accuracy and as more muscles and DOFs are incorporated into a model, the more parameters there are to tune and therefore optimize. By separating the DOFs it is believed that they can be developed and tuned in parallel to allow developments to focus on optimizing the performance of each DOF rather than a larger model in general.

The musculotendon models are based on Hill-type muscle models that are used to determine the forces produced by a muscle based on its linear envelope of myoelectric activity. Fig. 1(c) shows the structure of each musculotendon model and it consists of an active force generation component, and passive elastic and viscous components that model the elastic behaviors of the muscles. The total force of each muscle is given by the sum of its components, i.e.:

$$F_{Tot} = F_{CE} + F_{VE} + F_{PE} \tag{1}$$

where subscripts Tot, CE, VE and PE represent total, contractile element, viscous element and passive elastic element forces respectively. For a more in-depth explanation of the model and its components, see [2].

The kinematic model combines the forces determined from the musculotendon models with the geometry of the musculoskeletal model to calculate the total torque or force for each DOF. Moment arms are easily determinable from the known structure and application of geometric calculations. Once total torques or forces are known, the mass properties of the masticatory system can be applied to determine the accelerations and kinematics of movement with the following relations for the open-close DOF:

$$M_{Tot} = M_{LM} + M_{RM} + M_{LD} + M_{RD} + M_{W} + M_{Damp} + O_z \tag{2}$$

$$d(t+\Delta t) = d(t) + \omega(t)\cdot\Delta t + \frac{M_{Tot}}{2I}\Delta t^2 \tag{3}$$

$$z(t) = IP_R \sin(IP_\theta + d(t)) - IP_R \sin(IP_\theta) \tag{4}$$

where total moment about the centre of rotation, M_{Tot}, is given by the sum of moments caused by the left masseter (LM), right masseter (RM), left digastric (LD), right digastric (RD), mandible weight (W), joint damping (Damp) and an offset value that determines resting position, O_z. In turn, the total moment is used to determine the new angular displacement (in the θ direction) of the mandible, d(t+Δt), using the previous displacement d(t), previous angular velocity ω(t), moment of inertia I, and sampling time Δt. Note that up to this point calculations have been implemented in polar coordinates so to obtain the vertical displacement, z(t), a geometric conversion is required that uses the (R, θ) coordinates of the incisor point: IP_R and IP_θ respectively. A similar approach is applied for the lateral direction of movement that uses the relationships as follows:

$$F_{Tot} = F_{LT} + F_{RT} + F_{Damp} + O_x \tag{5}$$

$$x(t+\Delta t) = x(t) + v(t)\cdot \Delta t + \frac{F_{Tot}}{2m}\Delta t^{2} \tag{6}$$

where the total force, F_{Tot}, is determined by the sum of the force components in the x direction as described for the rotational aspect of movement, with the addition of O_x to account for lateral force offset. The horizontal displacement $x(t+\Delta t)$ is calculated with the previous displacement, $x(t)$, velocity $v(t)$ and mandible mass, m.

The physiological model was implemented in the MATLAB/Simulink environment and the Rapid Simulation Target was used to compile the model into an executable for tuning.

B. *EMG Signal Channel Identification*

To identify the contribution of the six mandibular muscles to vertical and lateral movements, the data from movement types 1, 2, 3 and 5 were analyzed offline. The linear envelope of the signals was determined by high pass filtering with a 2nd order Butterworth filter with 20Hz cutoff, followed by full wave rectification and low pass filtering with a 4th order Butterworth filter with 4Hz cutoff frequency [4].

A statistical analysis was performed on the movement data and the contributions of each muscle to each movement type. Using ANOVA, it was found that as expected, the digastrics are heavily involved in jaw opening and the masseters and temporalii both have an influence on jaw closing. However, it was also found that the temporalii exhibited activity during lateral movement that was significantly different from each other, when considered independently of digastric and masseter activities.

The findings suggested that the muscles could be separated into two independent groups that are involved in controlling the two available DOFs: the masseters and digastrics perform the open-close movement, while the left and right temporalii instigate lateral translations. With this in mind, the physiological model of the masticatory system was developed.

C. *Experimental Protocol*

Ten healthy young adults (5 men and 5 women), aged 21 to 34 years (mean 26 years, SD 3.7) volunteered for data collection. This study was approved by the University of Auckland Human Participants Ethics Committee (Reference #2011/7557), and subjects were briefed and gave informed consent to participate.

The skin surface was prepared by rubbing with an abrasive gel (D.O. Weaver & Co., USA), followed by rubbing alcohol (70% Isopropyl). Bipolar surface electrodes (Blue Sensor N, Ambu, Denmark) were attached to the easily accessible bilateral temporalis, masseter and digastric muscles as shown in Fig. 2. The EMG signals are acquired by a g.USBamp biosignal amplifier (Guger Technologies, Austria), and sampled into the MATLAB and Simulink environment at 1200Hz with a 50Hz notch filter.

Fig. 2. Electrode placement. Bipolar channels are set up on the bilateral (from top to bottom) temporalis, masseter and digastric muscles, with grounding on the clavicle.

The actual movement of the mandible was recorded with an electromagnetic articulograph (EMA) (Carstens, Germany), which uses magnetic fields to induce a measurable current in sensors fixed to the subject with a median error of 0.5mm. The incisor point of the subject was tracked in three dimensional space at 200Hz by attaching a sensor to the front of their lower dentition and two sensors behind each ear to eliminate head movement. The EMA data were later synchronized and interpolated to match the EMG data.

Along with maximum voluntary contraction (MVC) values in the vertical (open and clench) and lateral (left and right) directions, subjects performed seven movement types with five repetitions (without food). Subjects were given at least a minute of rest between trials and each trial lasted for approximately 10 seconds. The movement types were designed to test a variety of possible movement scenarios and were as follows: 1) single open-close cycle; 2) continuous open-close cycles; 3) single lateral cycle (neutral-left-right-neutral); 4) continuous chewing cycles; 5) continuous lateral cycles; 6) random movements as determined by the subject; and 7) random movements without any lateral components.

D. *Tuning*

The model was tuned using genetic algorithms (GA), a popular method used in myoelectric system optimization in the literature [5, 9]. A total of twenty four parameters were optimized with the objective function being to minimize the RMSE over the course of a movement between the model output and actual motion data from the EMA. Both movements were normalized against the range of movement of the subject, which was determined from EMA measurements. This resulted in values between 0 and 1 that indicated the amount of movement in the available range that has been utilized and can be used to compare the different data types (which would have different baselines and inappropriate to align manually or through tuning).

Each data trial for each subject was run four times to minimize the chances of falling into local minima and the results presented are the best of the series of runs. A single GA

TABLE I
SUMMARY OF RESULTS ACROSS ALL SUBJECTS

Movement	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Average	SD
Single open-close cycle	0.28	0.26	0.40	0.24	0.23	0.28	0.068
Continuous open-close cycles	0.38	0.42	0.32	0.54	0.47	0.43	0.084
Single lateral cycle	0.33	0.28	0.25	0.42	0.29	0.31	0.067
Continuous chewing cycles	0.32	0.22	0.29	0.31	0.36	0.30	0.052
Continuous lateral cycles	0.43	0.41	0.55	0.47	0.44	0.46	0.055
Random movements	0.55	0.43	0.39	0.41	0.40	0.43	0.066
Random vertical movements	0.29	0.36	0.32	0.37	0.44	0.35	0.057

*Units are a normalized RMSE value (see section D. Tuning)

optimization run would take on average 11 minutes at a time (SD 6 minutes).

III. RESULTS

The results for all ten subjects are summarized in Table I. The average normalized RMSE over the seven movement types ranged from 0.28 - 0.46, indicating the model could predict movement with reasonable accuracy. As expected, this is lowest for the simplest movement type (single open-close cycle). The identification of more complex movement types such as random movements and cyclical movements are within similar ranges.

IV. DISCUSSION

This paper has presented a novel physiological model of the masticatory system, which has multiple DOFs that act independently of each other to maximize the predictive ability of the model. The modeling approach can be applied to other multiple DOF joint systems with sufficient accessible surface EMG channel locations, such as the shoulder. The results of the study have demonstrated the feasibility of the approach with a range movements being able to be identified with normalized RMSE values ranging from 0.28 - 0.46. Note that for a vertical range of motion of 0.04 m (an arbitrary opening gape) this is roughly equivalent to an 11 - 18 mm RMSE.

It is intended to investigate whether this level of accuracy can be maintained or improved when the approach is applied to a different joint of similar amounts of complexity but with a wider range of movement. Such RMSE error is comparable to previous works but dependence on joint angles rather than translational movement makes it difficult to draw precise comparisons [10]. The significant results presented so far highlight the lack of effect that more complex movements introduce to the model. This would suggest that the separation of movements into independent DOFs is having the desired effect. Further study is required to verify the improvements offered by the model in multiple DOF joint movement prediction, and to determine if this is a suitable method for handling larger electrode numbers. The addition of more DOFs may be disadvantageous with larger sensor footprints, and increased processing overheads and model complexities.

The addition of more DOFs may also be made possible with another detailed study of the EMG signal characteristics and the employment of pattern recognition techniques to help identify movement patterns for characterization purposes. The information could be useful in implementing DOFs that are determined from co-activated muscles and could potentially make it easier to develop more complex models.

The approach still has some limitations and additional work is required to improve it. The tuning process is time consuming and at the moment all the parameters are tuned at once using GAs. This presents a reasonably large searchable parameter space and to ensure an appropriate amount of convergence, the tuning algorithm takes a considerable amount of time to run. There are also limitations in the accuracy of the model and further work will be done to improve its performance with respect to each DOF, as well as increase overall model ability and complexity.

REFERENCES

[1] M. A. Oskoei and H. Hu, "Myoelectric Control Systems - A Survey," *Biomedical Signal Processing and Control*, vol. 2, pp. 275-294, 2007.

[2] J. W. L. Pau, S. S. Q. Xie, and A. J. Pullan, "Neuromuscular Interfacing: Establishing and EMG-Driven Model for the Human Elbow Joint," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 9, pp. 2586-2593, 2012.

[3] C. Fleischer and G. Hommel, "A Human--Exoskeleton Interface Utilizing Electromyography," *IEEE Transactions on Robotics*, vol. 24, pp. 872-882, 2008.

[4] K. Manal and T. S. Buchanan, "Use of an EMG-Driven Biomechanical Model to Study Virtual Injuries," *Medicine and Science in Sports and Exercise*, vol. 37, pp. 1917-1923, 2005.

[5] E. Cavallaro, J. Rosen, J. C. Perry, S. Burns, and B. Hannaford, "Hill-Based Model as a Myoprocessor for a Neural Controlled Powered Exoskeleton Arm - Parameters Optimization," in *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, 2005, pp. 4514-4519.

[6] Q. Ding, X. Zhao, A. Xiong, and J. Han, "A Novel Motion Estimate Method of Human Joint with EMG-Driven Model," in *5th International Conference on Bioinformatics and Biomedical Engineering (iCBBE)*, 2011, pp.1-5.

[7] J. H. Koolstra, "Dynamics of the Human Masticatory System," *Critical Reviews in Oral Biology & Medicine*, vol. 13, pp. 366-376, 2002.

[8] X. Y. Wang, W. L. Xu, K. Etzel, J. Potgeiter, and O. Diegel, "Mechanism Design and Analysis of a Wearable Device for Rehabilitation of Temporomandibular Disorder," in *IEEE International Conference on Robotics and Biomimetics (ROBIO),* 2010, pp. 1674-1679.

[9] M. F. Eilenberg, H. Geyer, and H. Herr, "Control of a Powered Ankle-Foot Prosthesis Based on a Neuromuscular Model," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 18(2), pp. 164-173, 2010.

[10] A. Smith and E. E. Brown, "Myoelectric Control Techniques for a Rehabilitation Robot", *Applied Bionics and Biomechanics*, vol. 8, pp. 21-37, 2011.