# Estimation Biting Force Based Using EMG Signals and Laguerre Estimation Technique

Nazanin Goharian
Electrical Engineering Dept, Ferdowsi University of Mashhad
Mashhad, Iran
Goharian_n@yahoo.com

Sahar Moghimi
Electrical Engineering Dept, Ferdowsi University of Mashhad, Center of Excellence on Soft Computing and Intelligent Information Processing
Mashhad, Iran
s.moghimi@um.ac.ir

Hadi Kalani
Mechanical Engineering Dept, Ferdowsi University of Mashhad
Center of Excellence on Soft Computing and Intelligent Information Processing
Mashhad, Iran
Hadi.Kalani@yahoo.com

***Abstract*—Biting force varies based on type of food that is being chewed. To study human mastication comprehensively, it is better to consider the electromyography (EMG) activity of the masticatory muscles and bite force. The aim of this study is to evaluate SEMG-force relationship by utilizing Laguerre expansion technique (LET). In this work, the electrical activity of only two masticatory muscles, namely masseter and temporalis are measured. Results denote the ability of LET in predicting mastication biting force based on EMG signals. Additionally, the proposed model can be able to control masticatory robots using recorded EMG signals. In these applications, uses of non-expensive and portable of electromyography (EMG) electrodes have advantageous compared to the use of force sensors and cameras which are often very expensive and require massive structures.**

***Keywords— Electromography (EMG) signals; Laguerre expansion technique (LET), Biting Force; mastication muscles; Volterra technique.***

## I. INTRODUCTION

The significance of the chewing process on digestion and health necessitates studies of the mastication system. The mastication process is generated by a complex group of muscles that are on both side of the jaw. The main muscles of mastication are left/right masseter, left/right temporalis and left/right pterygoid muscles [1-2]. Surface electrodes are only able to record the electrical activity of the bilateral masseter and temporalis muscles [1-2]. Food scientists are interested in investigating the relation between food texture, bite force and electromyography signals [1-12]. Electromyography (EMG) has been employed to study changes in the electrical activity of the muscles during mastication [11, 13-15]. Changes in EMG parameters are better able to assess the sensory characteristics compared mechanical measurements [11]. Experimentally obtained signals, together with the physiological cross-sectional area of the muscles, have been employed to estimate instantaneous muscle forces [16-17] or to differentiate food-texture characteristics [11].

The relationship between muscles' electrical activity and force is of special importance in many applications including gait analysis, orthopaedics, rehabilitation, ergonomic design, haptic technology, telepresence surgery and human-machine interaction [1, 18-21]. Recently, various researchers used surface EMG (SEMG) to estimate muscle force [18-25]. Parametric and non-parametric models have been employed to obtain an accurate estimation of the SEMG-force relationship. Parametric methods mainly employed muscle activation and contraction dynamics as well as physiological measurements [18 and 19]. To estimate SEMG-force relationship various methods has been utilized including fast orthogonal search (FOS) [20-21], parallel cascade identification (PCI) [22-23], Laguerre estimation technique (LET) [24-25], and principle dynamic mode (PDM) [25]. The aim of this study is to evaluate SEMG-biting force relationship by utilizing Laguerre expansion technique (LET).

The rest of the paper is organized as follows: Section II describes the experimental setup and theoretical approach of the LET. In section III, results are presented and discussed. Finally section IV provides conclusion remarks.

## II. MATERIALS AND METHODS

### A. Experimental Setup

Five volunteers (age 23±2 years) participated in this study. All Subjects were free of any muscular pain and had no past history of orthopaedic and neurological disorders. Ethical approval for the study was granted by the Ferdowsi University of Mashhad. All subjects provided written informed consent. SEMG signals were recorded from masseter and temporalis muscles. Fig. 1a represents the location of electrodes on both muscles. Subjects were seated in a comfortable chair and instructed to sit still during recording sessions. They were unable to view the computer screen. Each experiment consisted of eight repeated trials. In each trial, subjects were asked to perform biting (Fig. 1a) within an interval of 5 s. To record the electrical activity of muscles, an 8-channel EMG system was employed. Surface electrodes were placed ~2 cm apart, oriented parallel to the muscle fibers, between the belly of each muscle and its end. Also to measure bite force, a device was designed and produced (Fig. 1b). This device is made of three FSR sensors that are able to record forces up to 100 N. Moreover, the shape of this device would allow recording of a natural bite. Subjects were seated in a comfortable chair and instructed to sit still during recording sessions. They were unable to view the computer screen. EMG and force signals are recorded synchronously.

For modeling, first EMG and force signals were pre-processed to remove both low and high frequency noise. Recorded raw SEMG signals were passed through a band pass (15–400 Hz) 3rd order Butterworth filter. The resulting signals were rectified and smoothed by a moving Gaussian window. Finally, the rectified and smoothed SEMG signals were normalized to Z-score. By doing the aforementioned procedure we obtain the normalized data with zero mean and unite variance. To process the force signal, a moving Gaussian window with 400 points was applied to raw signals.

(a)


(b)

Fig. 1(a) Experimental setup and electrode positioning on subject's face, (b) biting sensor

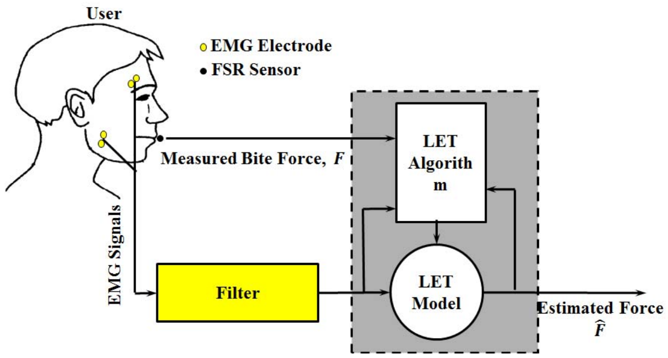



Fig. 2 General view of the experimental setup

In this work, biting force of incisor teeth is considered as output that is to be predicted from EMG signals. Fig. 2 shows the general view of the experimental setup.

### *B. Laguerre expansion technique (LET)*

The best way to Volterra kernel estimation is to use the LET. The Laguerre functions have exponential behavior and are orthogonal from zero to infinity. This method uses a set of discrete, normalized and orthogonal Laguerre functions to estimate Volterra kernels. As shown in Fig. 3, in this method, filter banks are discrete Laguerre functions that take $x(n)$ as input and translate it to $v_j(n)$ by using discrete time convolution with the corresponding Laguerre function [24-25].

Laguerre functions can be defined as

$$b_j(m) = \alpha^{(m-j)/2}(1-\alpha)^{0.5}\sum_{k=0}^{j}(-1)^k \binom{m}{k}\binom{j}{k}\alpha^{j-k}(1-\alpha)^k \qquad (1)$$

where, $b_j(m)$ is discrete Laguerre function of order $j$ and $m$ varies between 1 to $M$ (system memory). $\alpha$ $(0<\alpha<1)$ represents the rate of exponential decline. As shown in Fig. 3, $v_j(n)$ can be obtained by using discrete time convolution

$$v_j(m) = T\sum_{m=0}^{M-1} b_j(m)x(n-m) \qquad (2)$$

where $T$ denotes sampling rate. By substituting $v_j(m)$ in $f(.)$ (nonlinear function with order Q) the output of discrete Volterra model can be calculated

$$y(n) = c_0 + \sum_{r=1}^{Q}\sum_{j_1}^{L}\sum_{j_r}^{j_{r-1}} c_r(j_1,\ldots,j_r)v_{j1}(n)..v_{jr}(n) + \varepsilon(n) \qquad (3)$$

where $y(n)$ is the output, $L$ is the number of filter banks, $\varepsilon(n)$ is the estimation error and $c_r$ represents the coefficients of discrete Laguerre expansion. Equation 3 can be rewritten as

$$y = Vc + \varepsilon \qquad (4)$$

where, $V$ is the matrix of filter bank's outputs. For instance, the nth row of the matrix V is

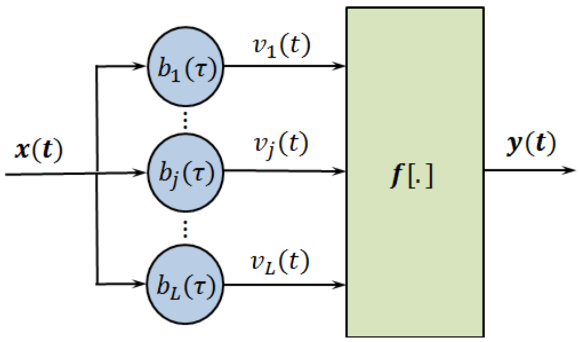



Fig. 3 Schematic of Laguerre expansion technique

$$\{1, v_1(n), \ldots, v_L(n), v_1^2(n), v_2(n)v_1(n), \ldots, v_L^2(n)\} \tag{5}$$

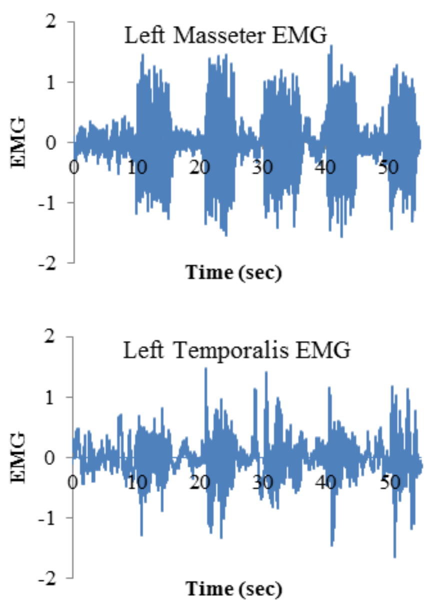
There are some ways to estimate these coefficients. For instance, square Gram matrix can be employed to achieve the solution of the estimation problem. But when the matrix $V$ is not full-rank, the square Gram matrix is singular. Also the number of columns in matrix $V$ is dependent on $L$ (number of filter banks) and $Q$ (order of the nonlinear function). Therefore, in estimations of high nonlinear order, the phenomenon "dimension curse" occurs. In this case, a pseudo inverse, $V^+$, can be utilized to calculate the coefficient estimates as

$$\hat{c} = V^+ y \tag{6}$$

Where, $V^+$ represents pseudo inverse of matrix $V$. All programming of the algorithm of LET is performed in MATLAB (v. R2012b). Results are prepared in the next section.

## III. Results and Discussion

The recorded EMG and bite forces during 5 trials are shown in Fig. 4 for one of the subjects.



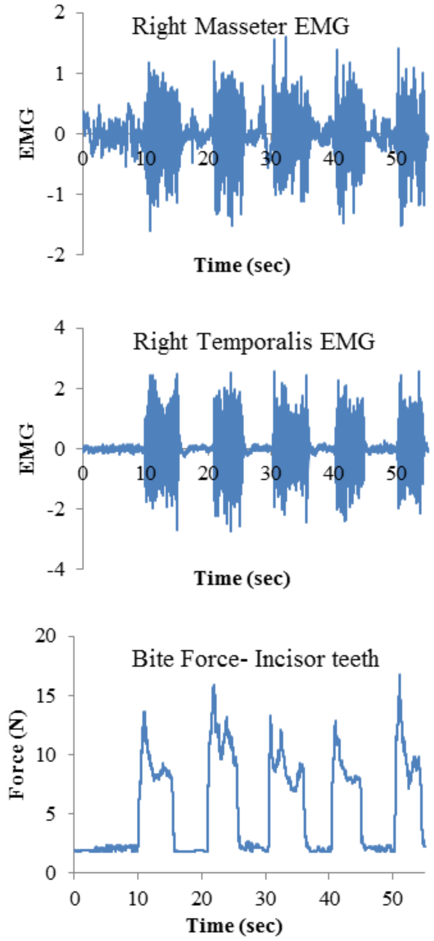




Fig. 4 Sample data set recorded from subject1

To validate the trained models RMSE, Cross-Correlation (CC) and Average Absolute Error (AAE) are employed as evaluation criteria,

$$\text{RMSE} = 100 * \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i)^2} \tag{7}$$

$$\text{CC} = 100 * \frac{\sum_i (y_i * \hat{y}_i)}{\sqrt{\sum_i (y_i)^2}\sqrt{\sum_i (\hat{y}_i)^2}} \tag{8}$$

$$\text{AAE} = \frac{\sum_i |(y_i - \hat{y}_i)|}{n} \tag{9}$$

where $y_i$ and $\hat{y}_i$ are the recorded and predicted outputs, respectively, and $n$ is the number of samples.

Fig. 5 represents the ability of LET to estimate bite force on incisor teeth by employing the aforementioned EMG signals of one subject. As shown in Fig. 5, estimated force (black dashed line) follows the measured force (blue solid line) appropriately. Therefore the Laguerre model has ability to find the relationship between EMG and force.

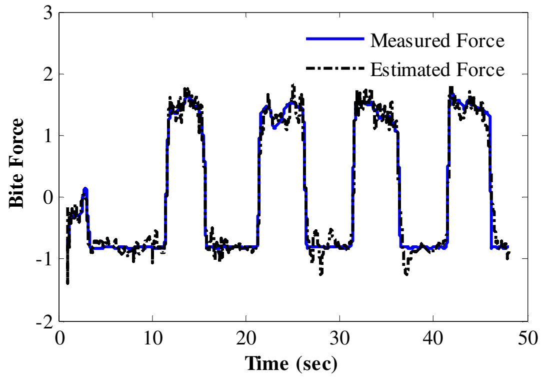



Fig. 5 Performance of LET in predicting bite force for validation data. Z-score normalization was applied to both input and output measurements.

For all subjects, RMSE, CC and AAE, for both training and validation phases are summarized in TABLE I. In general, the LET performed well in predicting bite force. As can be seen, the accuracy of LET varies from one subject to another. This can be due to differences in electrode positioning with respect to the muscles' motor points, the amount of tissue between the electrodes and muscles.

In LET trainings, there are two parameters (number of filter banks, $L$ , and rate of exponential decline, $\alpha$ ) that have an effect on accuracy of the model. For fast dynamics it is better to select a small value for $\alpha$ , and vice versa. As can be seen in Fig. 6, by increasing $\alpha$ , the accuracy of the model increased (in both training and validation phases). In other words, RMSE and AAE increased and CC decreased with increasing $\alpha$ , in both trainings and validation steps. It shows that our system is slow and it is better to set a high value for $\alpha$ .

TABLE I. RMSE (CC) [AAE] values for both training and validation phases.

| ***Output*** | | ***Training*** | ***Validation*** |
|---|---|---|---|
| **Bite Force** | **Sub. 1** | 19 (0.23) [89.7] | 38 (0.5) [82.5] |
| | **Sub. 2** | 6.6 (0.1) [96.6] | 11 (0.2) [94.4] |
| | **Sub. 3** | 6.44 (0.1) [96.7] | 13 (0.2) [93.3] |
| | **Sub. 4** | 7.01 (0.2] (96.4) | 23 (0.3) [87.9] |
| | **Sub. 5** | 12 (0.2) [93.2] | 25 (0.3) [86.3] |

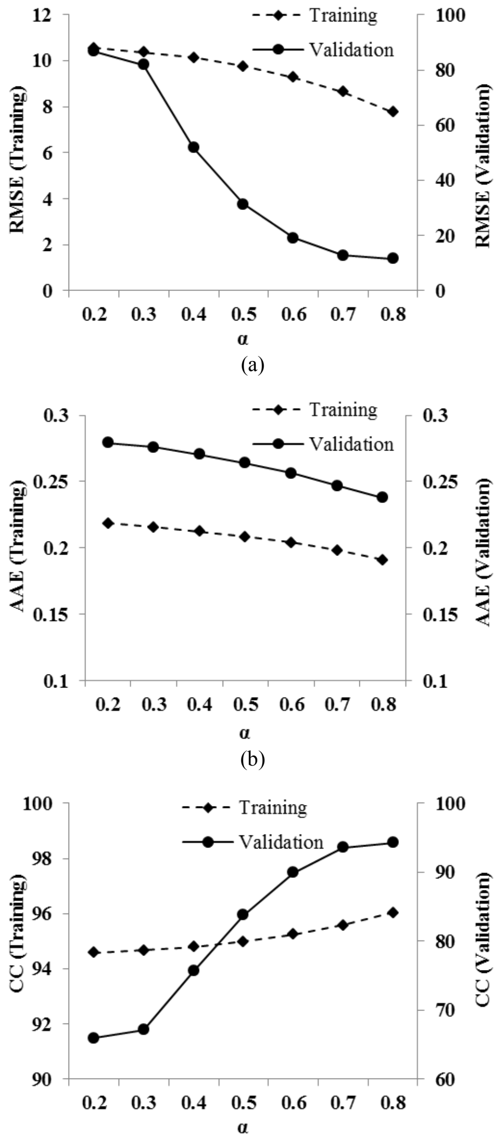
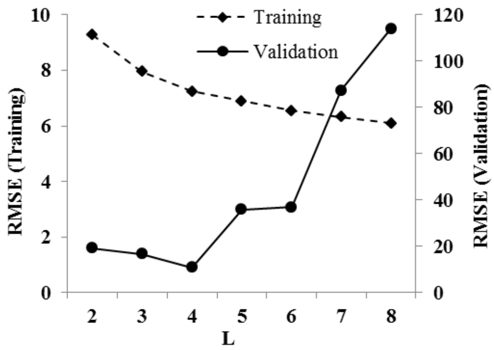
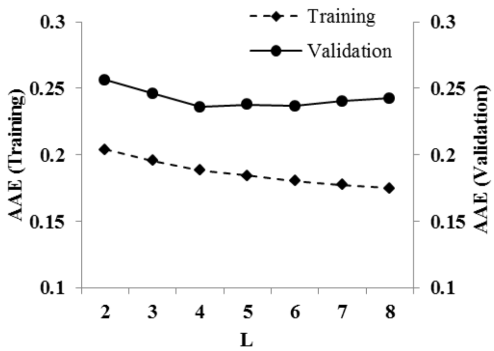



Fig. 6 Effect of varying $\alpha$ in training and validation on (a) RMSE, (b) AAE and (c) CC

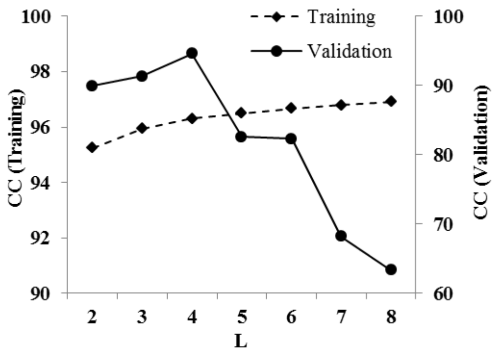
Another parameter that has to be optimized for optimal prediction is the number of filters in the filter banks. As shown in Fig. 7, by increasing the number of filters, RSME and AAE decreased and CC increased in the training phase, however it had a negative effect during the validation phase. Fig. 7 indicates that despite increased accuracy in the training phase by increasing the number of filters, the RMSE and AAE increased and CC decreased for the validation data (for $L \geq 5$ ). This demonstrates that the phenomenon overtraining has happened. Therefore, to avoid overtraining the optimum number of filters has to be found for each model.




(a)




(b)




(c)

Fig. 7 Effect of varying $L$ (the number of filters) in training and validation on (a) RMSE, (b) AAE and (c) CC

Moreover, Fig. 8 represents the intrasubject variability results. Each bar represents the average of CC and AAE of predicting the bite force across five volunteers with the vertical bar representing mean ±standard deviation. As it is mentioned in previous work [26], identified for one subject is may not be valid for another subject. Because there are some difference, such as position of EMG's electrode, muscle fiber, muscle volume and muscle length, between each subjects. Although, from Fig. 8 can be concluding that identified models, for subject 2 are able to use to other subjects appropriately. It means this model have a more comprehensive to other models.

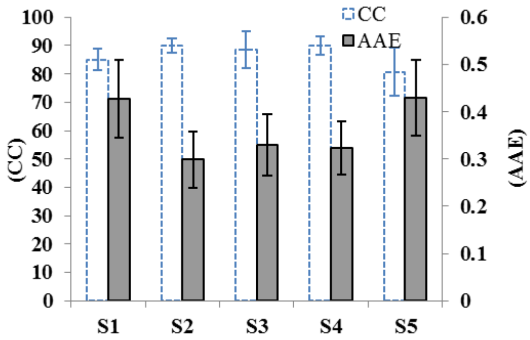



Fig. 8 Summary of CC and AAE for each LET corresponding to one subject tested on all the other subjects.

In this study, the relationship between EMG signal of jaw muscles and biting force is investigated. Such models can provide clinical insight into the development of more effective rehabilitation therapies, and can aid in assessing the effects of an intervention. The prediction of biting forces from this model can be utilized to better investigate tissue loading in joints, and to estimate of tensile ligament forces and compressive cartilage loads.

## IV. Conclusion

In this paper, we investigated the ability of the LET to predict bite force from recorded EMG signals of masseter and temporalis muscles. To record biting forces, a new device was developed. In general, results showed that this method is capable of providing reasonable accurate estimates of biting forces on incisor teeth. Therefore, the EMG signals contain the significant information about the process under study. Moreover results indicated our dynamic system is slow, therefore it is better to select high value for the rate of exponential decline. Finally, it was demonstrated that the number of filters in the filter bank has an important role in training and validation steps. Moreover, the intrasubject variability results show that this model has a good ability to estimate biting force based on recorded EMG signals. This information can be employed to develop control systems for rehabilitation robots or stimulus patterns for paralyzed muscles. Although no effort has been made to consider the computational efficiency of the other algorithm, the LET method is believed to be more efficient than well-known methods. Thus, by predicting the subject's biting, we can provide applicable tools for EMG-based masticatory robot control. In future works, we aim to employ estimated models for detecting and characterizing food texture and for controlling potential robotic devices. Moreover, we plan to estimate biting force of molar teeth based on EMG signals.

## References

[1] J. S. Pap, W.L. Xu, and J. Bronlund, "A robotic human masticatory system –kinematics simulations," Int J Intell Syst Tech Appl, vol. 1, pp. 3-17, 2005.

[2] W. Xu, J. E. Bronlund, "Mastication robots: biological inspiration to implementation," Springer-Verlag Berlin Heidelberg Press, 2010.

[3] H. J. Smit a, E. K. Kemsley, H. S. Tapp, J. K. Henry, "Does prolonged chewing reduce food intake?," Fletcherism revisited, Appetite, vol. 57, pp. 295–298, 2011.

[4] E. K. Kemsley, M. Defernez, J.C. Sprunt, A.C. Smith, “Electromyographic responses to prescribed mastication,” Journal of Electromyography and Kinesiology, vol. 13, pp. 197-207, 2003.

[5] Y. Ioannides, J. Seers , M. Defenez, C. Raithatha, M. S. Howarth, A. Smith, E. K. Kemsleys, “Electromyography of the masticatory muscles can detect variation in the mechanical and sensory properties of apples,” Food Qual Pref, vol. 20, pp. 203-215, 2009.

[6] W.E. Brown, “Method to investigate differences in chewing behaviour in humans: I. Use of electromyography in measuring chewing,” J Text Stud, vol. 25, pp. 1-16, 1994.

[7] F.R. Jack, J.R. Piggott, A. Paterson, “Relationships between electromyography, sensory and instrumental measures of cheddar cheese texture,” J Food Sci, vol. 58, pp. 1313-1317,1993.

[8] W.E. Brown, K.R. Langley, L. Mioche, S. Marie, S. Gerault, D. Braxton, “Individuality of understanding and assessment of sensory attributes of foods, in particular, tenderness of meat,” Food Qual Pref, vol. 7, pp. 205-216, 1996.

[9] A. Woda, A. Mishellany, M. A. Peyron, “ The regulation of masticatory function and food bolus formation,” J Oral Rehabil, vol. 33, pp.:840–849, 2006.

[10] D. F. Stegman, et al., “Surface EMG models: properties and applications,” J. Electromyogr. Kinesiol, vol. 10, pp. 313–326, 2000.

[11] R. Gonalez, et al., “ Review: the use of electromyography on food texture assessment,” Food Sci. Tech. Int, vol. 7, pp. 461–471, 2001.

[12] E. Helkimo, B. Ingervall, “ Bite force and functional state of the masticatory system in young men,” Swed. Dent. J. vol. 2, pp. 167–175, 1978.

[13] H. J. Smit a, E. K. Kemsley, H. S. Tapp, J. K. Henry, “Does prolonged chewing reduce food intake? Fletcherism revisited,”, Appetite, vol. 57, pp. 295-298, 2011.

[14] E.K. Kemsley, M. Defernez, J.C. Sprunt 1, A.C. Smith, “Electromyographic responses to prescribed mastication,”, Journal of Electromyography and Kinesiology, vol. 13, pp. 197-207, 2003.

[15] Y. Ioannides, J. Seers , M. Defenez, C. Raithatha, M. S. Howarth, A. Smith, E. K. Kemsleys, “Electromyography of the masticatory muscles can detect variation in the mechanical and sensory properties of apples,” Food Quality and Preference, vol. 20, pp. 203-215, 2009.

[16] J. Barbenel, “The mechanics of the temporomandibular joint – a theoretical and electromyographical study,” J. Oral Rehab. 1 (1) (1974) 19–27.

[17] B. May, S. Saha, M. Saltzman, “A three-dimensional mathematical model of temporomandibular joint loading,” Clin. Biomech. 16 (6) (2001) 489–495.

[18] C.A. Phillips, D.W. Repperger, A.T. Neidhard-Doll, and D.B. Reynolds, “Biomimetic model of skeletal muscle isometric contraction: I. an energetic–viscoelastic model for the skeletal muscle isometric force twitch,” Computers in Biology and Medicine, vol. 34, pp. 307–322, 2004.

[19] T. Siebert, M. Sust, S. Thaller, M. Tilp, and H. Wagner, “An improved method to determine neuromuscular properties using force laws– From single muscle to applications in human movements,” Hum. Mov. Sci., vol. 26, pp. 320–341, 2007.

[20] F. Mobasser, J.M. Eklund, and K. Hashtrudi-Zaad, “Estimation of Elbow Induced Wrist Force With EMG Signals Using Fast Orthogonal Search,” IEEE. Trans. Biomed. Eng., vol. 54, no. 4 , 2007.

[21] Korenberg and J. Michael, “Fast orthogonal algorithms for nonlinear system identification and time-series analysis,” Advanced methods of physiological system modeling, pp. 165-177, 1989.

[22] J. Hashemi, E. Morin, P. Mousavi, K. Mountjoy, and K. Hashtrudi-Zaad, “EMG–force modeling using parallel cascade identification,” J. Electromyogr. Kinesiol., vol. 22, pp. 469–477, 2012.

[23] Korenberg and J. Michael, “Parallel cascade identification and kernel estimation for nonlinear systems,” Annals of biomed. eng., vol. 19, no. 4, pp. 429-455, 1991.

[24] V. Z. Marmarelis, Nonlinear dynamic modeling of physiological systems. Wiley-Interscience, 2004.

[25] V. Z. Marmarelis, “Identification of nonlinear biological systems using Laguerre expansions of kernels,” Annals of biomed eng., vol. 21, no. 6, pp. 573-589, 1993.

[26] L. Ljung, “System identification, ” John Wiley & Sons Inc, 1999.