Prediction of Clenching Jaw Movements Based on EMG Signals Using Fast Orthogonal Search

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

Alireza Akbarzadeh
Center of Excellence on Soft Computing and Intelligent Information Processing
Mechanical Engineering Department, Ferdowsi University of Mashhad, Mashhad, Iran
Ali_akbarzadeh_t@yahoo.com

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

Abstract—**Recently, the relationship between muscles' electrical activity and body movements has been considered in many medical applications. 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. In this paper, we evaluate the ability of the Fast Orthogonal Search (FOS) methodology to predict jaw motion using Electromyography (EMG) signals recorded from two masticatory muscles, namely masseter and temporalis. Results show the efficiency of FOS in predicting the kinematic parameters (position and orientation) based on EMG signals. Additionally, the proposed model can be utilized to control masticatory robots employing recorded EMG signals.**

Keywords— Electromography (EMG); Fast orthogonal search (FOS); mastication muscles; orthognal Functions.

I. INTRODUCTION

The human chewing process has been investigated in various studies. In general, mastication involves two simple movements: clenching and grinding. In clenching, the mandible moves only in the sagittal plane, whereas in grinding it follows a circle path in the frontal plane [1-2]. The temporalis, masseter and lateral Pterygoid muscles perform the main role in the mastication process. Recently, EMG signals have been employed in rehabilitation applications to study changes of muscles' electrical activity during mastication [3-6]. EMG has also been utilized to distinguish the differences between chewing patterns of individuals [7-10].

Various attempts have been made to estimate movements for controlling prosthetic devices including employing fast orthogonal search (FOS) [11 and 12], parallel cascade identification (PCI) [13 and 14], Laguarre estimation technique (LET) [15 and 16], artificial neural networks (ANN) [17, 18, 19 and 20], principle dynamic mode (PDM) [16], Hammerstein models [21] and principal component analysis (PCA) [22]. Fast orthogonal search, FOS, was developed by Korenberg [11] as a nonlinear identification method for approximating a system's output. This method is based on Gram-Schmidt orthogonal identification. The main goal of this study is to consider the ability of a FOS model to predict the mastication movement using the EMG signals of masticatory muscles.

Electromyography (EMG) has been employed to study changes in the electrical activity of the muscles during mastication [24 and 25]. Experimentally obtained signals, together with the physiological cross-sectional area of the muscles, have been employed to estimate instantaneous muscle forces [26] or to differentiate food-texture characteristics [24]. Additionally, EMG has been used to identify differences in chewing patterns between individuals and to classify individuals into groups according to their chewing efficiency [10]. In this paper the relationship between clenching movement and EMG signals of mastication muscle are considered.

The rest of the paper is organized as follows: Section II describes the experimental setup and theoretical background of the FOS technique. Results are prepared in section III. Finally section IV provides conclusion remarks.

II. MATERIALS AND METHODS

A. Experimental Setup

Six volunteers (four males and two females) participated in this study. All subjects were well-informed about the procedure and provided written consent to the experimental protocol. In each trial, volunteers were asked to perform a maximum voluntary mandible opening and closing (clenching movement) in the sagittal plane (Fig.1) within an interval of 5 sec. Three trials were used for training and another 3 trials were employed for model validation. To record the electrical activity of muscles, an 8-channel electromyography (EMG) system was employed.

In this study for each subject EMG signals were recorded from four muscles, namely right and left masseter, and right and left temporalis (Fig. 2.a). Surface electrodes were placed ~2 cm apart, oriented parallel to the muscle fibers, between the belly of each muscle and its end. The recorded raw EMG signals were passed through a band-pass (15-400 Hz) 3rd order Butterworth filter, rectified and smoothed. Moreover, to trace the chewing trajectory, Simi Reality Motion System (GmbH, Germany) was employed [23]. To record the jaw motion, 6 small reflective markers were adhered to specific facial locations (Fig. 2). Forehead markers were used as reference points. The recorded camera signals were rectified and smoothed by a moving average window of size 200. EMG and force signals are recorded synchronously.

In this work, three kinematic parameters (displacement along x and z directions and rotation about y-axis) were considered as outputs that are to be predicted from EMG signals. Fig. 3 shows the general view of the procedure.

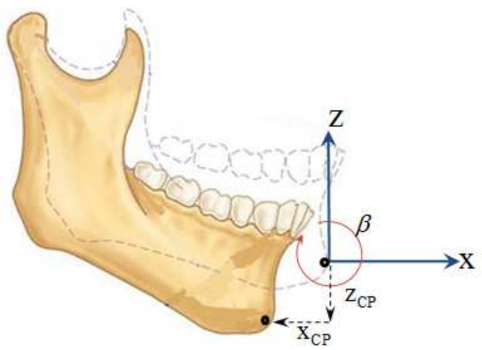
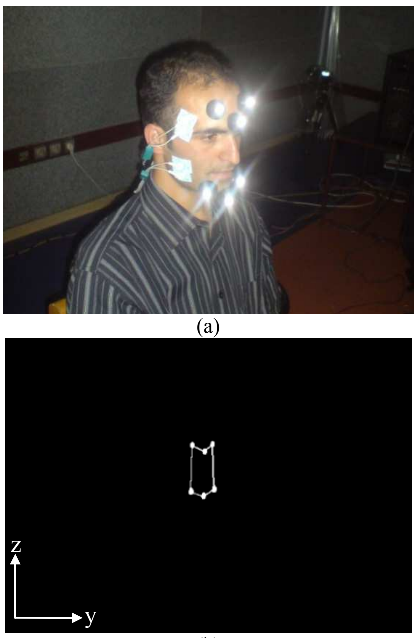


Fig. 1 View of clenching in the sagittal plane



(a)

(b)

Fig. 2 (a) Marker position on the subject's face, (b) Two-dimensional reconstruction of the marker set

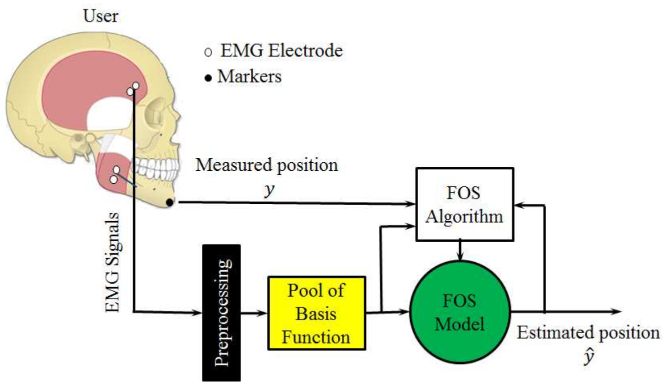


Fig. 3 General view of experimental setup

B. *Fast Ortogonal Search (FOS)*

This method was first introduced by Kornberg in 1985 [11, 12]. The main goal of this method is to minimize the mean-square error of estimation by choosing the best basis functions from all the candidate functions (including polynomial, square and sigmoid functions), which cause the maximum reduction in the mean square difference between estimation and measured data. In fact, in this method, Kornberg proposed an efficient method to obtain the appropriate coefficients corresponding to the selected basis functions. Employing the FOS method we have

$$y(n) = \sum_{m=1}^{M} a_m p_m(n) + e(n) \tag{1}$$

where $y(n)$ is the measured output, $e(n)$ is the prediction error and $\sum_{m=1}^{M} a_m p_m(n)$ is the estimated output. Additionally p_m and a_m are the selected basis functions and their corresponding coefficients, respectively. To obtain a_m by conventional methods, complicated and time-consuming calculations are required. Kornberg [12] used some orthogonal functions q_m that are orthogonal to p_m and then based on this property, obtained the corresponding coefficient g_m related to these function. Therefore,

$$y(n) = \sum_{m=1}^{M} g_m q_m(n) + e(n),\ where\ \overline{q_i(n) q_j(n)} = 0, i \neq j \tag{2}$$

The orthogonal functions q_m can be obtained as follows,

$$\begin{aligned} &q_1(n) = p_1(n) = 1 \\ &q_2(n) = p_2(n) - \alpha_{21} q_1(n) \\ &\vdots \\ &q_m(n) = p_m(n) - \sum_{r=1}^{m-1} \alpha_{mr} q_r(n) \end{aligned} \tag{3}$$

where coefficient α_{mr} is calculate as

$$\alpha_{mr} = \frac{\overline{q_r(n)q_m(n)}}{\overline{q_r^2(n)}}, \quad \begin{array}{l} m=2,\dots,M \\ r=1,\dots,m-1 \end{array} \tag{4}$$

where M is the number of function are chosen. Now for the coefficient g_m that minimizes the MSE of the estimate, we have [11]

$$g_i = \frac{\overline{y(n)q_i(n)}}{\overline{q_i^2(n)}} \tag{5}$$

Kornberg demonstrated that to obtain a_m, only coefficients α_{mr} and g_m would suffice [11, 12]. Moreover, he noticed that there is a recursive solution for obtaining α_{mr} and g_m. Therefore, by multiplying q_m with the two sides of Eq. (3), the numerator and dominator of α_{mr} are obtained, respectively. Also, by multiplying y with the two sides of Eq. (3), the numerator and dominator of g_m are obtained, respectively. To choose the best basis function, the MSE reduction (Eq. 6) must be calculated. The computational algorithm was developed following the steps illustrated in Fig. 4.

$$\overline{e^2_{M+1}} = \frac{\overline{y(n)q_{M+1}(n)}^2}{\overline{q^2_{M+1}(n)}} \tag{6}$$

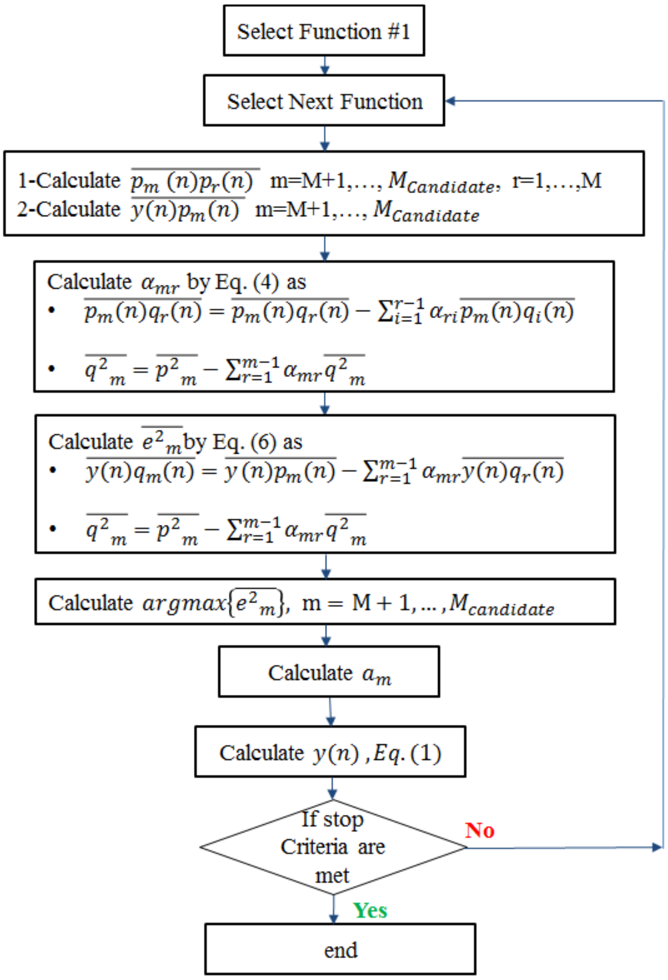


Fig. 4 Structure of the FOS method

III. Results and Discussion

The recorded EMG and kinematics data during 3 trials are shown in Fig. 5 for one of the subjects.

To validate the trained models RMSE, Cross-Correlation (CC) and Average Absolute Error (AAE) were employed as the 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 actual and predicted outputs, respectively, and n is the number of samples.

In this paper, four kinds of basis functions (common, squared, quadratic and sigmoid functions) were employed. TABLE I, summarize these functions. In this table E_{Ma} and E_{Te} are the EMG signals of Masseter and Temporalis muscles, respectively. Also, $E_{Ma(d)}$ and $E_{Te(d)}$ represents the delayed, recorded EMG signals. In this paper, the total delays were selected 100 ms and the first basis function is offset function.

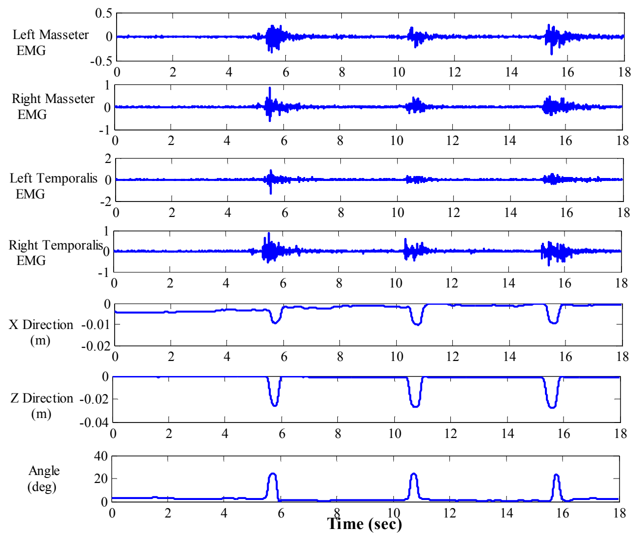
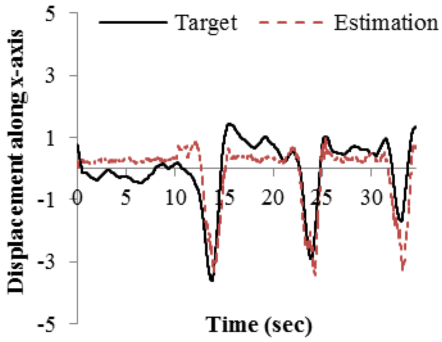


Fig. 5 Sample data recorded from subject 2.

TABLE I. List of basis function

Common Functions	
offset	E_{Te}
E_{Ma}	$E_{Te(d)}$
$E_{Ma(d)}$	$E_{Ma} * E_{Ta}$
$E_{Ma} * E_{Ma(d)}$	$E_{Ma(d)} * E_{Ta}$
$E_{Ma} * E_{Ta(d)}$	$E_{Ma(d)} * E_{Ta(d)}$
$E_{Ta} * E_{Ta(d)}$	
Squared Functions	
$\sqrt{E_{Ma}}$	$\sqrt{E_{Te}}$
$\sqrt{E_{Ma(d)}}$	$\sqrt{E_{Te(d)}}$
$\sqrt{E_{Ma} * E_{Ma(d)}}$	$\sqrt{E_{Ma} * E_{Ta}}$
$\sqrt{E_{Ma} * E_{Ta(d)}}$	$\sqrt{E_{Ma(d)} * E_{Ta}}$
$\sqrt{E_{Ta} * E_{Ta(d)}}$	$\sqrt{E_{Ma(d)} * E_{Ta(d)}}$
Quadratic Functions	
$E_{Ma} * E_{Ma}$	$E_{Ma(d)} * E_{Ma(d)}$
$E_{Ta(d)} * E_{Ta(d)}$	$E_{Ta} * E_{Ta}$
Sigmoid functions	
$sigm(E_{Ma})$	$sigm(E_{Te})$
$sigm(E_{Ma(d)})$	$sigm(E_{Te(d)})$
$sigm(E_{Ma}) * sigm(E_{Ma(d)})$	$sigm(E_{Ma}) * sigm(E_{Ta})$
$sigm(E_{Ma}) * sigm(E_{Ta(d)})$	$sigm(E_{Ma(d)}) * sigm(E_{Ta})$
$sigm(E_{Ta}) * sigm(E_{Ta(d)})$	$sigm(E_{Ma(d)}) * sigm(E_{Ta(d)})$

Fig. 6 shows the ability of the FOS method to predict both the position and orientation of mandible of subject 2, respectively, employing the aforementioned EMG signals of one subject. In this figure all groups of basis functions are employed and the number of basis functions is M=8. Fig. 6 shows that the predictions of y and z directions are more reasonable rather than x direction.



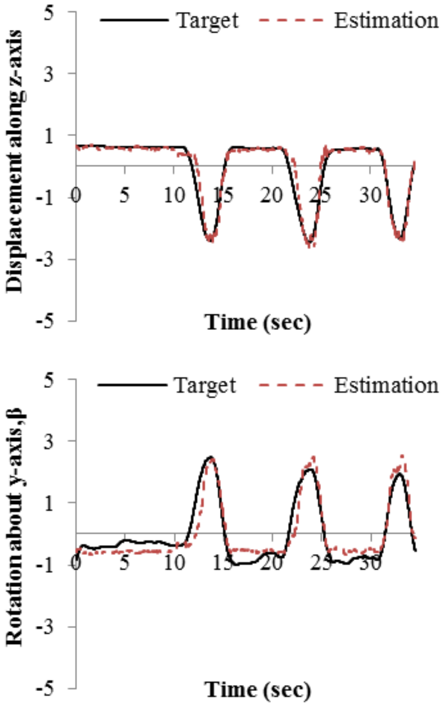
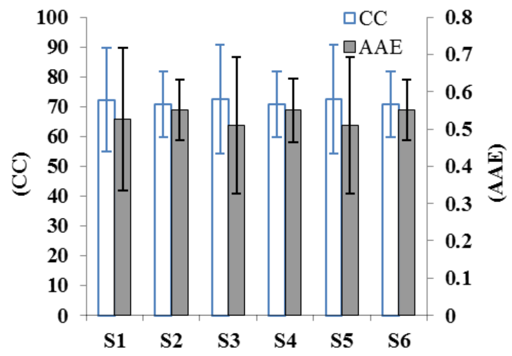


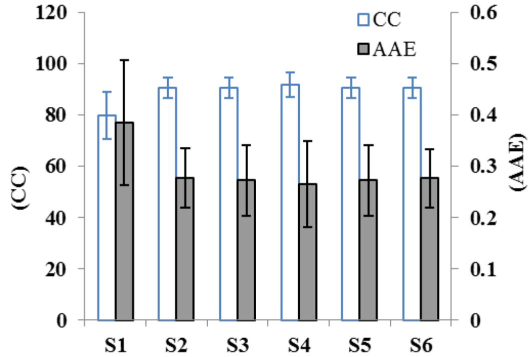
Fig. 6 Performance of FOS in predicting position and orientation variables for validation data. Z-score normalization was applied to both input and output measurements.

For all subjects, RMSE, CC and AAE, for both training and validation phases are summarized in TABLE II. As demonstrated, the ability of FOS differed from one subject to another.

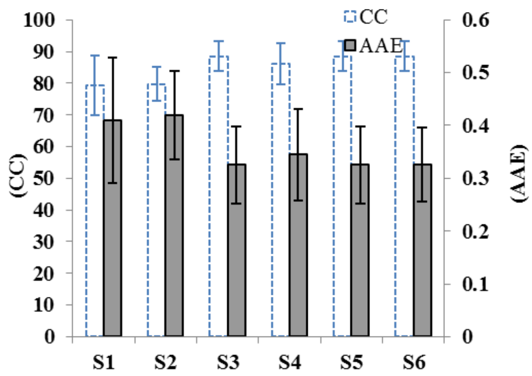
In Fig. 7 the performance of the models is evaluated in terms of CC and AAE. Each bar represents the average of CC and AAE of predicting the kinematics parameters across six volunteers with the vertical bars representing mean ±standard deviation. Generally the identified model for one subject may not be valid for another subject. Discrepancies may be owing to differences between subjects in, for example, electrode positioning with respect to the motor points of the muscles, the amount of tissue between the electrodes and muscles, and characteristics of the muscles/muscle fibers. Fig. 7, demonstrates that the models trained on the data obtained from one of the subjects could be approximately generalized to other subjects.



(a) Displacement along *x*-axis



(b) Displacement along *z*-axis



(c) Rotation about *y*-axis, *β*

Fig. 7 Summary of CC and AAE for each model corresponding to one subject tested on all the other subjects.

In the process of training, FOS performs significantly faster than other methods such as multi-layer perceptron and radial basis function [12]. The reason is that in each step the FOS algorithm searches for the best basis function which causes the maximum reduction in mean square error between predicted and measured data. TABLE III summarizes the time required for the FOS training procedure while different numbers of candidate functions are allowed for 6500 samples on a Core i5 2.5-GHz CPU system.

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

Outputs		***Training***	***Validation***
Displacement along x-axis	**Sub. 1**	2.48(94.5) [0.25]	9.6(90)[0.2]
	Sub. 2	3.9(94.9)[0.24]	14.1(76)[0.5]
	Sub. 3	5.5(95)[0.1]	5.6(94)[0.15]
	Sub. 4	15(85)[0.4]	31(71)[0.58]
	Sub. 5	21(77)[0.4]	57(62)[0.54]
	Sub. 6	4.4(90)[0.3]	8.1(83)[0.4]
Displacement along z –axis	**Sub. 1**	1.1(98.6)[0.1]	5.9(95.8)[0.16]
	Sub. 2	0.91(98.8)[0.09]	3.1(96.8)[0.15]
	Sub. 3	7(93)[0.21]	16(75)[0.4]
	Sub. 4	1.8(98)[0.1]	12.1(92)[0.2]
	Sub. 5	7.9(93)[0.2]	8.1(85)[0.2]
	Sub. 6	103(93)[0.2]	16(88)[0.3]
Rotation about y-axis, β	**Sub. 1**	1.3(97.8)[0.14]	10.5(92.8)[0.22]
	Sub. 2	1.2(98.1)[0.15]	7.1(93)[0.3]
	Sub. 3	5.8(93)[0.2]	10.6(87)[0.3]
	Sub. 4	4(92)[0.32]	22.3(77)[0.5]
	Sub. 5	6.3(91)[0.31]	29(75)[0.4]
	Sub. 6	8.3(92.5)[0.2]	22(82)[0.3]

The number of basis functions allowed to be selected can have a drastic effect on the accuracy of prediction. Although increasing the number of basis functions during training provides a decrease in RSME it may have a negative effect during validation. In order to demonstrate this and justify our choice of M we plot both training and validation RMSE for different values of M in Fig. 8. As illustrated for M>8 the validation RMSE does not decrease any further, even though a decrease is observed for larger values during training. This demonstrates that for each model to perform properly we need to find the optimum number of candidate functions.

TABLE III.
Time required for training with different numbers of basis functions

M=20	0.501 sec
M=15	0.37 sec
M=10	0.23 sec
M=5	0.15 sec

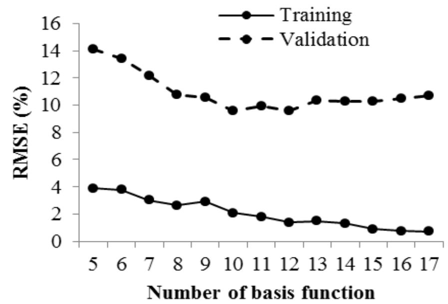


Fig. 8 RMSE (%) for training and validation across of number of basis function.

The provided analysis will aid researchers in characterizing and investigating the mastication process, through the specification of SEMG signal patterns (e.g., muscle displacements) and the observation of the resulting mandible movement. 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 mandible movement from this model can be utilized to better investigate tissue behavior in joints, and to estimate the path of them during mastication.

IV. CONCLUSION

In this paper, we investigated the ability of the FOS method to predict the kinematic parameters (position and orientation) of mandible motion during the clenching movement from recorded EMG signals of masseter and temporalis muscles during jaw opening and closing. In general, results show that this technique is able to provide reasonably accurate predictions of masticatory movements in the sagittal plane. Therefore, the EMG signals contain the significant information about the process under study. Moreover, the results indicate that the time required for training is small and that the FOS can be considered a fast method. The consumed time for training was approximately 0.08 sec and which is advantage when the number of sample points in the data is high and in real time control. Although no effort has been made to consider the computational efficiency of the other algorithm, the FOS method is believed to be more efficient than well-known methods. Finally, we demonstrated that the number of basis functions plays an important role in both training and validation steps. This information can be employed to develop control systems for rehabilitation robots or stimulus patterns for paralyzed muscles. In future works, we aim to employ the developed models for controlling potential robotic devices.

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] D. Braxton, C. Dauchel, W.E. Brown, “Association between chewing efficiency and mastication patterns for meat, and influence on tenderness perception,” Food Qual Pref , vol.7, pp. 217-223,1996.

[10] W.E. Brown, D. Braxton, “Dynamics of food breakdown during eating in relation to perceptions of texture and preference: a study on biscuits,” Food Qual Pref, vol. 11, pp. 259-267, 2000

[11] 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.

[12] 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.

[13] 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.

[14] 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.

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

[16] 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.

[17] M.M. Liu, W. Herzog, and H.C.M. Savelberg, “Dynamic muscle force predictions from EMG: an artificial neural network approach,” J. Electromyogr. Kinesiol., pp. 391–400, 1999.

[18] L. Wang and S. Buchanan, “Prediction of Joint Moments Using a Neural Network Model of Muscle Activations From EMG Signals,” IEEE. Trans. Neural Syst. Rehabil. Eng., vol. 10, no. 1, 2002.

[19] F. Mobasser, and K. Hashtrudi-Zaad, “Rowing stroke force estimation with EMG signals using artificial neural networks,” IEEE Conference on Control Applications, 2005.

[20] H.C.M Savelberg and W. Herzog, “Prediction of dynamic tendon forces from electromyographic signals: An artificial neural network approach,” J. Neurosci. Meth., vol. 78, pp. 65-74, 1997.

[21] Q. Zhang, M. Hayashibe, P. Fraisse, and D. Guiraud, “FES-Induced Torque Prediction with Evoked EMG Sensing for Muscle Fatigue Tracking,” IEEE./ASME. Trans. Mechatro., vol. 16, pp. 816–826, 2011.

[22] D. Staudenmann, I. Kingma, A. Daffertshofer, D.F. Stegeman, and J.H. van Dieën, “Improving EMG-Based Muscle Force Estimation by Using a High-Density EMG Grid and Principal Component Analysis,” IEEE. Trans. Biomed. Eng., vol. 53, no. 4, 2006.

[23] Website: www.simi.com.

[24] R. González, I. Montoya, J. Cárcel, “Review: the use of electromyography on food texture assessment”. Food Sci Technol Int, vol. 7 (6), 461-471, 2001.

[25] Y. Ioannides, J. Seers, “M. Defenez, C . Raithatha, M. Howarth, A. Smith, E. Kemsleys, Electromyography of the masticatory muscles can detect variation in the mechanical and sensory properties of apples”, Food Qual Prefer, vol. 20 (3), 203–215, 2009.

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