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Joseph Kamau Muguro, Minoru Sasaki, Kojiro Matsushita, Waweru Njeri, Pringgo Widyo Laksono, and Muhammad Syaiful Amri bin Suhaimi

Development of Neck Surface Electromyography Gaming Control Interface for Application in Tetraplegic patients' Entertainment

Joseph Kamau Muguro[1,2,a)], Minoru Sasaki[1,b)], Kojiro Matsushita[1,c)], Waweru Njeri[1,2], Pringgo Widyo Laksono[1,3,d)] and Muhammad Syaiful Amri bin Suhaimi[1]

[1] *Department of Mechanical Engineering, Gifu University, Yanagido 1-1, Gifu, Japan*
[2]*School of Engineering, Dedan Kimanthi University of Technology, 657-10100, Nyeri, Kenya*
3Department of Industrial Engineering, Universitas Sebelas Maret, Surakarta, Indonesia

[a)]Corresponding author: x3912104@edu.gifu-u.ac.jp
[b)]sasaki@gifu-u.ac.jp
[c)]kojirom@gifu-u.ac.jp
[d)]pringgo@ft.uns.ac.id

Abstract. In the recent past, surface Electromyography (sEMG) signals has been effectively applied in control interfaces for robots, prosthetic hands, legs and other areas. Few works has focused on neck EMG control in spite of the neck being central to human movements and engagements. We propose a neck EMG model that estimates head movements and apply the signals to control a game developed in Unity 3D engine. The game involves randomly falling and accelerating objects. The user slides the games' player character (paddle) using neck EMG to intercept as many objects. EMG signal is rectified and FIR filtered and used to control the position of a sliding probe of the game in real-time. The paper utilizes an equation model and a Machine Learning model to translate the filtered signal to corresponding neck rotation. From the results, all the subjects reported accuracy of over 70% which confirm the applicability of the interface and ease of use in that there is little or no calibration needed. The control model using equation showed intuitive direction and speed control while the Machine Learning scheme offered more stable direction control but limited speed control of the sliding paddle. The control interface can be applied in multiple areas that involve neck activity e.g. in rehabilitation as well as gaming interface to enable entertainment for the disabled.

INTRODUCTION

The activity of muscles is observed as bio-electric potentials in human beings which constitutes electromyogram (EMG) signal. Surface EMG (sEMG) is the signal acquired from the surface/belly of the muscle group under consideration, usually recorded using surface electrodes. EMG studies in literature can be broadly categorized in to two categories; classification and regression [1]. The former is concerned with accurate prediction of patterns and grouped activity in to a sensible single or multiple action. There is a wide application of this for example in hand or finger prosthetics where voluntary control of certain muscle should correspond to a fine motor action like pinching, pointing and others. The other category of EMG control is concerned with regression and or finding a relationship between continuous muscle activity in a task.

EMG integration into daily activities takes different forms and shapes ranging from gesture and posture recognitions [2], robotic control [3], [4], [5], wheelchair control [6], muscle rehabilitations [7] to list but a few. An application field which is similar to the proposed research is the use of EMG signals in gaming environment [8], [9], [10]. A paper [11], sought to investigate how myo-gaming, a term used to describe application of myoelectric signals to gaming, improves EMG control and whether there are any performance improvements over time. The authors

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reported increased adaptation and accuracy within the game. The authors raised a concern with the current gaming applications with there being little or no translation from gaming to daily activities.

EMG Bio-feedback is one of the promising research area with direct applicability to daily activities. An example of such is reported in [8] where the authors developed an exergaming (gaming for exercises) system to facilitate in rehabilitation exercises for recovering patients. The system is built on a gaming pretext to enhance motivation, performance and measurable quantification of progress. This is proven to increase exercise adherence, engagement, motivation, to mention a few. Authors in [7], reported a better muscular balance in training exercise with EMG biofeedback. Another research [12] reported auditory biofeedback of facial EMG. In the paper, users get to hear their smile translated into an audio signal.

In [13], the authors investigated restoration of cursor control to patients with tetraplegia. The target of the study was restoration of computer control to patients with spinal cord injury (SCI). They used head orientation and EMG from face and neck muscles. The user either rotates the head or alters muscle contractions to change the position of computer cursor. Another paper that evaluated head orientation and neck muscle EMG signals as an input source of 3D robotic command is reported in [14]. The authors utilized neck EMG to control movement of end-effector of a robot arm to a desired position. Another paper predicted head rotation and movements using neck EMG in a 3D telepresence application in a virtual world is reported in [15]. This and other research confirms the significance of neck EMG in feedback and restoration of control to handicapped individuals.

EMG has been used in a previous papers which is related to this paper for controlling brick-breaking game [16]. The paper utilized two muscles in the forearm extensor and flexor to control both position and size of a paddle in a brick game. We propose to utilize Neck EMG from left and right sternocleidomastoid (SCM) muscles to develop a Human-Machine Interface (HMI) for gaming control. This research, derived from [16] but focusing on neck EMG, would give more control to individuals with hand disabilities or SCI patient as a control scheme or an entertainment interface. With the focus being on biofeedback, the user is able to alter the input signal to a desired position. We modelled the relationship between the turning EMG of subjects using an equation and machine learning approach and employed the results to a gaming bio-feedback interface.

Materials and Methods

The setup used for the system for experiment is as shown in Fig. 1a below. Neck EMG recording uses two electrodes; left and right SCM as shown. The recorded EMG is amplified using polyam4B and converted from A/D using NI USB 6211 with 16 bit 250 kS/s multifunction IO device at 2000 Hz sampling rate.

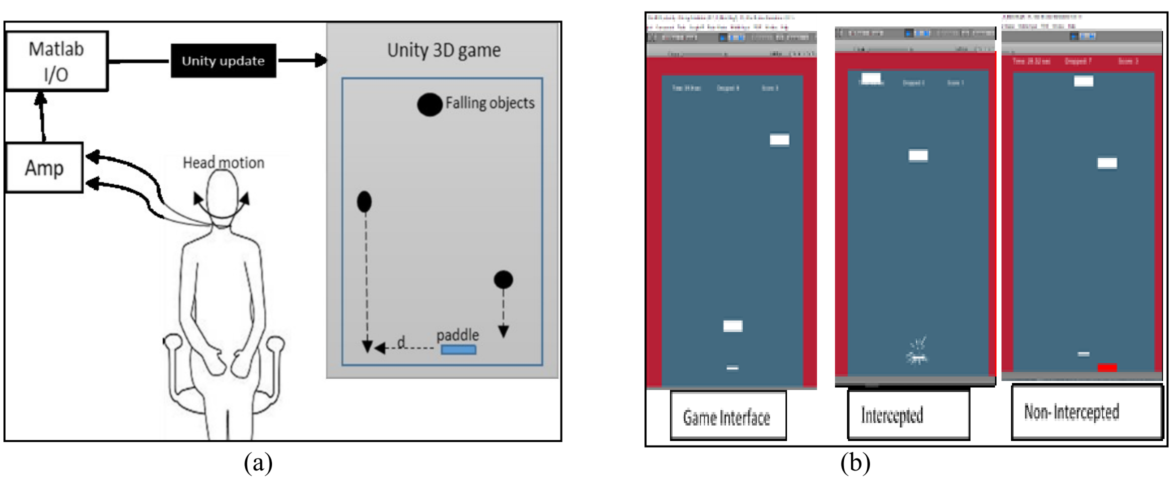


FIGURE 1. **a**) Setup and Data acquisition **b)** Unity 3D game scenes with random objects, intercepted object and missed object

Head Rotation Estimation using Equation Model

An important aspect of the research was an accurate estimation of head rotation. Acquired raw EMG signal is integrated and FIR filtered using moving average to produce a corresponding filtered signal. Teager-Kaiser energy operator is applied to emphasize muscle activity [17]. The equation of energy operator is as shown in (1) below where n is the current sample point.

$$y[n] = x[n]^2 - x[n-1] * x[n+1] \qquad (1)$$

Averaging and mean filtering is applied to realize a smooth signal which represents the quasi-tension (angle of rotation) which is used to move the paddle. The equation for the processed signal is shown in (2) below. In this case, y[n] is energy operator while k represent the number of samples to consider for one Xi value. k value was selected to produce Xi values at a rate corresponding to Unity 3D game scene update function. k was also useful in smoothing the output angle with minimal lagging of the real-time signal.

$$X^{1,2}[i] = \sum_k \left\{ \frac{1}{M} \sum_j^{M-1} \|y[n-j]\| \right\} \qquad (2)$$

The i[th] neck angle estimate is formed by taking the current difference between processed EMG of left and right SCM muscles as described in (3) below. Where X^1 and X^2 is the processed EMG of the left and right SCM respectively. This is the derivation by [13] referred as quasi-tension.

$$\theta_{est} = X_i^1 - X_i^2 \qquad (3)$$

An alternative but similar proposed model is expressed in (4). The advantage of this proposed model is to point out the inverse relationship that exist between left and right SCM to the heads' rotation. Moving the paddle is done by corresponding θest rotations of the head.

$$\theta_{est} = \frac{{X_i^1}^1}{X_i^2} - \frac{{X_i^2}^2}{X_i^1} \qquad (4)$$

Head Rotation Estimation using Machine Learning (ML)

We explored Machine Learning approaches that can be useful in the prediction of left/right neck rotation classification as an alternative to the modelled equation. Raw EMG data was resampled as described above. A calibration phase was utilized to acquire training phase data. From this, we evaluated time domain (TD) features as well as extended TD features [18] like skewness, root mean square and band power of the sampled data. In total, 3 classes (left, right and center), 10 predictor feature (5 features from each SCM signal) totaling to 2500 observations were used for classification. We used 5-fold cross-validation for accuracy estimation and avoid overfitting. In this case, we performed classification using three types of machine learning algorithms; k-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Ensemble as provided in classification learner application in Matlab®. In KNN, cosine distance metric and weighted distance method were evaluated. In SVM, linear and Gaussian kernel functions were evaluated and in Ensemble, bagged trees and boosted trees methods were evaluated.

The performance of the three types was comparable with different computational resource demand; the adopted method was based on classification accuracy and computation time. Performance of the M.L model is validated by the classification accuracy indicator as shown in Table 1 below. From the performance, KNN was chosen for accuracy and response time. The three classification result of -1, 0, and 1 for left, center, and right consecutive classes was parsed to an input integer and averaged to eliminate a misclassification. This ensured that the user will not experience jittery movements. We trained the model with data of one subject and checked the generalization of the performance to all the subjects.

Unity3D Engine Game Development

In this paper, we used unity3D game engine to develop a 2D object-intercepting game. Unity3D has inbuilt physics system which was used to introduce varying hardship settings as the game progresses. This is key to balancing playability and complexity. Objects appeared after a period as per user's needs. Difficulty control was done by the rate of objects appearance. In the game, total intercepted objects as well as time was displayed as shown in Fig. 1b. All users played the game until the set dropped objects were expired typically 5-10 trials. The user sat in front of a PC monitor at a comfortable distance. The game setup required the user to maintain a visual feedback with the dropping object. Thus, the rotation was within normal head turnings with little or no strains. The performance of model is discussed in the results section.

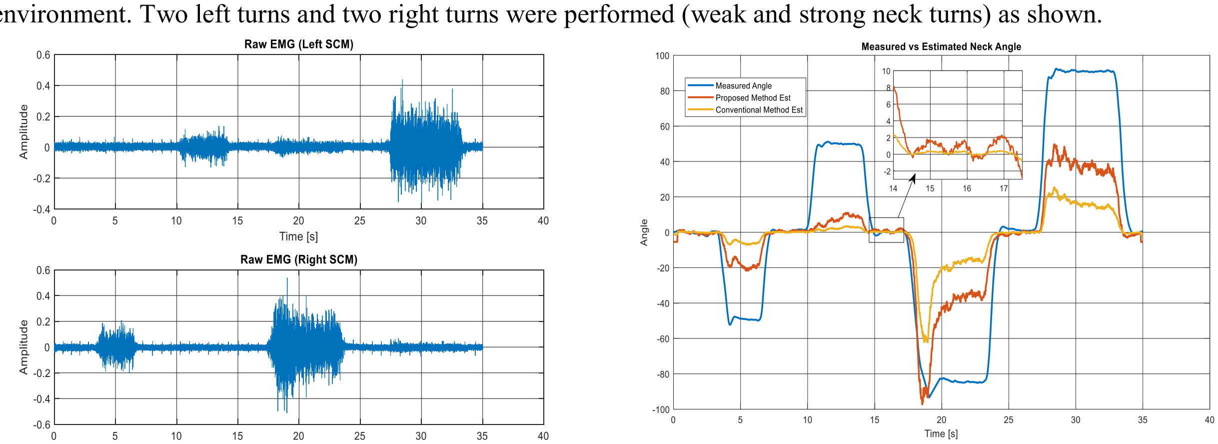
TABLE I. Machine learning training and performance

Type	Accuracy (%)	Prediction Time (s)	Training Time (s)
KNN (Cosine)	0.8965	0.018	0.27
KNN (Weighted)	0.8934	0.028	0.50
SVM (Gaussian)	0.8902	0.012	1.58
SVM (Linear)	0.8945	0.043	2.61
Ensemble (Boosted)	0.8961	0.034	3.86
Ensemble (Bagged)	0.8914	0.050	4.18

RESULTS

Equation Model Validation

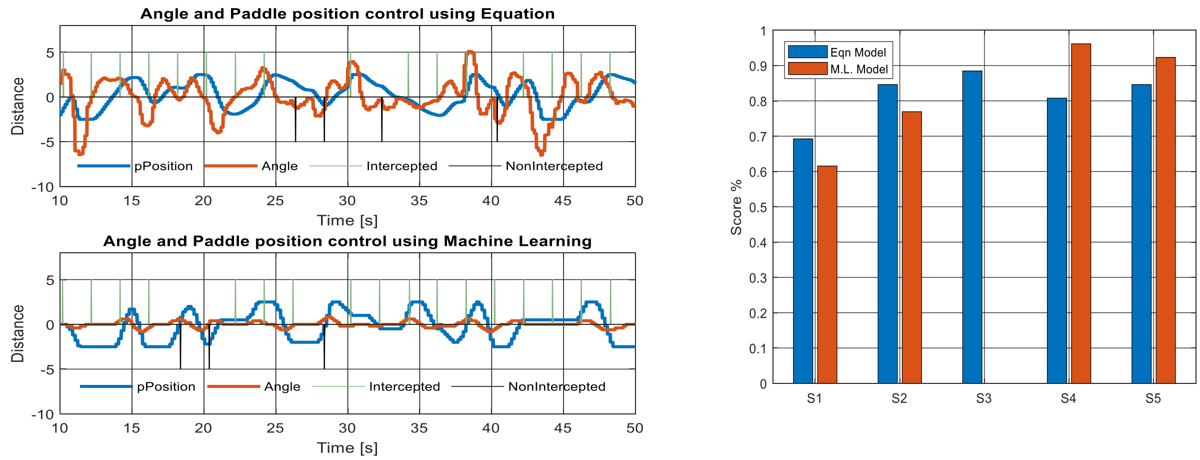
To validate the proposed equation model, we used motion sensors inbuilt in a 3D Virtual Reality (3D-VR) Head Mounted Display (HMD) manufactured by FOVE®. We designed a simple scene with equidistant objects placed in a virtual scene. The scene was designed with two objects on the left and right and a reference point in the middle. The user was to turn head to look at each object in successive turns from the center (reference point), holding for at least 1 second at each point in the VR environment. Unity3D logged data at approximately 60-70 frames per second. To cater for the time synchronization difference between EMG and gyro-sensor data, we performed resampling (a type of least square linear-phase FIR filtering) on the recorded motion data for comparison. This was done offline using Matlab® and reported below. Figure 2a shows raw signal of neck EMG signal produced while turning head in VR environment. Two left turns and two right turns were performed (weak and strong neck turns) as shown.



(a) (b)

FIGURE 2. Validation results of Head rotations a) Raw signal of neck EMG and b) Resultant angle estimates

Figure 2b shows measured position from inbuilt sensors of a 3D-VR HMD unit that corresponds to processed neck EMG activity. The results shows an apparent relation between the model and measured signal. From Fig. 3b, the conventional method performed well in eliminating near-zero oscillations (difference) while the proposed method has an oscillatory nature as shown in the inset. When the signal is weak as is the case in Fig. 3b between 10-15 seconds, conventional method has poor performance in bringing out the difference between the angle estimates. It is worth noting that the results above shows a case where there is no standardization carried out on the signal.



(a) (b)

FIGURE 3. Performance of the proposed method for in-game control using M.L. and Equation (EQN) model. a) Relation between angle and paddle position. b) Percentage score of five subjects S1-S5.

pPosition is the paddle position, angle is the estimated head rotation (driving signal) and intercept and non-intercept are instances of dropped/intercepted objects in the game

Evaluation of EMG Interface

Figure 3 shows game data for comparison and performance indicators. Angle input is calculated from (4) and sent to the gaming interface from Matlab. From the figure, paddle is actively controlled by the input value (Angle) to intercept objects, angle input is in the range between -5 and 5 as shown. Figure 3a shows three missed objects and twelve intercepted objects in a span of 30 seconds. At this time, objects are released after 2 seconds. Missed objects are attributed to separation distance from the current paddle position. This is as shown in the first missed object. The user controls the position of the paddle but not in time to intercept. The other cause is precision control whereby the user over/under steers the paddle around the object location as is the case with the second missed object. Equation model is more intuitive with smooth curve as angle input. This is as expected for a direct feedback model. M.L model on the other hand has discrete-type of input convenient for direction control. Speed control in this case is achieved by compounding input in the same direction.

We tested the system using five subjects as shown in Fig. 4b using both approaches to compare the usability of the two. We considered uniform game-hardship settings and compared the percentage of dropped and intercepted objects. All the subjects under review exhibited accurate control of the game with little or no training time. Subject S3 reported uncoordinated control in M.L model and hence the results are omitted in the comparison.

DISCUSSION

This paper have introduced a methodology for control of paddle position in a gaming interface using neck EMG. The equation model provides a dynamic performance as compared to other method proposed in literature [15], [16]. The advantage of the proposed model equation is that it accentuates the differences that may be present between the SCM muscle tensions. Thus, it has good performance for near zero input signals compared to the conventional method. Neck muscles are weak compared to hand muscles but are more enduring; not easily affected by fatigue. For gaming interface utilizing normal turns (moderate turning force), performance deterioration due to fatigue is less probable.

From literature, EMG signal is present several milliseconds before motion sensors record any changes [15]. This is the guiding principle in the use of EMG as a predictive tool of motion intentions. The results shown below have resampling, filtering and averaging delays introduced as shown in (2). In effect, rate of angle fetch from Matlab is governed by the update function in Unity 3D which is approximately 16 milliseconds. The period is sufficient for apparent real-time game control input. In spite of the introduced delays, the onset of muscle activity with head rotation is closely synchronized. With more elaborate processing, EMG activity before motion sensor readings can be achieved for prediction of movement intentions.

From the data presented in Fig. 3a, the near-symmetry of neck EMG in left and right rotations means that the acquired data may be used without much calibration and standardization processing. This is in contrast to calibration procedure utilized in [16]. This promotes usability, after electrode positioning, all users managed to control the gaming interface with little or no practice sessions. From Fig. 4a, angle input range is between -5 and 5 in the gaming control process. Comparing the input range with that of Fig. 3b above, the muscle activity responsible for the movement is small and less probable to cause any discomfort.

Figure 3 shows that a change in angle input value leads to a corresponding change in rate of change of position. The angle input in this case is indicative of the EMG force employed. The proposed equation model therefore achieves both direction and speed control in the gaming interface. In the case of M.L model, direction of paddle control is accurate but speed control is not direct but relies on accumulated motion in the same direction. This is because of the classification model that categorizes the output as left, right or center. M.L model has a more stable directional stability and poor speed control compared to equation model. The generalization of the trained model had promising performance in that, an un-optimized classification model performed well with no noticeable errors.

The overall performance comparison for 5 subjects show that the users could achieve an acceptable percentage of accuracy before any accumulated game-play skill is developed for the selected hardship settings. The control scheme adopted in this interface is not limited to gaming but may as well be utilized in robotic manipulations, menu selections, biofeedback exercise, etc. The interface is easy with no excessive calibration requirements making it ideal for general applications areas.

CONCLUSIONS

In conclusion, we managed to develop a control interface using neck EMG and test its application in a gaming environment. We modelled the control interface using equation and machine learning approach. Equation model has more intuitive tracking and speed control while as machine learning approach provides a more stable direction control with reduced speed control. The performance of the two schemes are comparable with different computational requirements. The game performance results confirm the applicability of the interface with little or no calibration needed. The system can be applied in control, rehabilitation and or gaming interfaces.

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