EMG-BASED SIGNAL PROCESSING SYSTEM FOR INTEPRETING ARM GESTURES

Osamah A. Alsayegh
Systems & Control Department
Engineering Division
Kuwait Institute for Scientific Research
POBox 24885, 13109 Safat, Kuwait
E-mail: osayegh@kisr.edu.kw

ABSTRACT

This paper presents an electromyographic-based (EMG-based) signal processing system for interpreting human arm gestures. To retain a constraint-free user's environment, EMG sensing is limited to three arm muscles. EMG signals are processed to attain parameters that are related to the muscles temporal activities. The attainment of these parameters through time constructs a unique signature for each particular gesture. Experimental investigation was carried out to examine the system's reliability in recognizing 12 arm gestures. The results show that the system can recognize the 12 gestures with a success rate of 96%.

1 INTRODUCTION

More and more researchers and practitioners in the fields of human-computer interaction and robotics emphasize the necessity for humanizing machine interaction, thus calling for more intuitive interfaces. Attaining this goal is dependent upon both software and hardware systems that can relieve users from technical detail of their working environments. The user should be able to behave in a natural way and bring into action natural modes of expression such as gesture. Therefore, gesture and sign language have become a recent focus in advanced interface design. The growing attention that gesture-based interfaces have been receiving is due to the large number of potential applications and activities that can be eased and improved when they are operated or dealt with in a natural manner.

Existing intuitive or natural interfaces include Data-gloves and arm/hand goniometers [11]. In these class of approaches, the user wears bulky equipment that can constrain normal movement; furthermore, in cases involving actual handling of objects, Data-glove may not be appropriate. Alternative approaches include speech [7], video, e.g., [5], and EMG, e.g., [1], information processing systems.

The current speech recognition technology is still not robust, especially outside controlled environments, under noisy conditions, and with multiple speakers. Video information acquisition is non-contact and thus does not impose any constraints on the user; however, obtaining detailed information about a motion is generally very difficult even when using multiple cameras. Consequently, researchers tend to limit the application domain, e.g., [5]. Moreover, visual information cannot estimate force, pressure, or effort that is produced by the user's arm/hand, which are important in interacting with the machines.

EMG signals have been used in the medical engineering field in relation to the tracking of trajectories, e.g., [2]. A successful application that has been in the market for more than three decades is the EMG-driven prosthetic arm and hand [10]. Recently, EMG-based control systems have taken a new direction. Several studies have suggested the use of EMG signals as a method of interaction with machines, e.g., [3], [9]. However, most of the EMG-based movement recognition systems are restricted to planar movements, e.g., [1]. The rest involve single joint movements, e.g., [8], or hand pose interpretation [3]. Moreover, all of the EMG-based arm movement analysis systems have used at least six muscles, e.g., [6], and such a number of monitored muscles might restrict the user's movements.

This paper presents an EMG-based signal processing system that interprets arm gestures in the three-dimensional (3D) space. Gestures are interpreted by sensing the activities of three muscles, namely, anterior deltoid (AD), medial deltoid (MD), and biceps brachii (BB) muscles. This limited sensing insures the constraint-free user's environment.

2 EXPERIMENTAL SETUP

Three healthy male subjects with a history of no neuromuscular diseases were used for the collection of EMG data samples. EMG data samples were collected in a four-week time period. Fifty trials were performed for each gesture (total of 600 trials for 12 gestures). Bipolar surface electrodes were used to record the activity of the shoulder and elbow joints. The EMG signals were acquired and recorded by the Biopac MP30, which is specifically designed for acquiring physiological signals. The MP30 was programmed to perform the following ordered steps on the EMG signal in real time: (i) sampling at a rate of 500 s/sec., then digitally (ii) high-pass filtering with f_c = 30 Hz, (iii) low-pass filtering with f_c = 250 Hz, and finally, (iv) band-stop at f_o = 60 Hz. The net amplification was 2500.

The experiments were carried out by studying the motion of free hand shape/figure drawings in the air. We considered 12 symbolic-drawing gestures as shown in Fig. 1. The initial articulation of the arm was to have 90° between the upperarm and forearm, where the upperarm was parallel to the torso. However, for the gesture of drawing the shape "∪"

(see Fig. 1j), the initial articulation of the arm was formed by having 0° between the upperarm and forearm.

3 EMG SIGNAL PROCESSING

The processing of the EMG signals is based on the fact that each particular arm gesture has a unique temporal coordination of activities between the muscles [4]. The onset and offset time instances and the time duration of the muscle activities of different movements have different values. The processing of EMG signals is carried out in a three-phase process. First, to analyze the coordination of muscle activities, it is desirable to generate smooth signals that follow the rises and falls of the muscle activation patterns. These smooth signals are referred to as the envelop signals of the EMG signals. Fig. 2 shows the processing performed on an EMG signal to attain its correspondence envelop signal. In Fig. 2, an EMG signal is rectified, normalized with respect to the corresponding maximal activation, and then low-pass-filtered.

In the second phase, control points and their corresponding time instances are extracted from the envelop signals. These control points represent the local and global minima and maxima of the envelop signal. For example, Fig. 3 shows control points and their correspondence time instances of typical envelop signals that reflect the activities of the AD, MD, and BB muscles in performing the "zigzag" gesture (see Fig. 1h).

In the third phase, a temporal signature is constructed using the time instances derived in the second phase. For instance, for the case of the "zigzag" gesture where control points exist at times , , and (see Fig. 3), we define the parameters , , and at each time interval (e.g., $[t_o\ t_1]$, $[t_1\ t_2]$, etc.) as follows:

$$\theta_1 = \int_{t_i}^{t_j} |\,\mathrm{EMG}_{\mathrm{MDmuscle}}\,|\,dt,$$

$$\theta_2 = \int_{t_i}^{t_j} |\,\mathrm{EMG}_{\mathrm{ADmuscle}}\,|\,dt,$$

$$\theta_3 = \int_{t_i}^{t_j} |\,\mathrm{EMG}_{\mathrm{BBmuscle}}\,|\,dt,\ j = i+1,$$

where $|\mathrm{EMG}_{\mathrm{MDmuscle}}|$, $|\mathrm{EMG}_{\mathrm{ADmuscle}}|$, $|\mathrm{EMG}_{\mathrm{BBmuscle}}|$ represent the rectified and normalized EMG signals of the MD, AD, and BB muscles, respectively. The calculated parameters at each time interval are plotted in the feature space. Thus, a temporal signature is formed for a gesture. Fig. 4 shows the temporal signatures of some of the arm gestures that are performed by the three subjects. The calculated parameters (θ_1, θ_2, and θ_3) are fitted to ellipsoidal figures. As the variation increases, the ellisoidal figure size increases. From Fig. 4, one can see that each gesture has a unique signature.

The classification procedure is carried out by constructing successive feature vectors for each gesture. These feature vectors describe the gesture's temporal signature. This type of classification is referred to as the context-dependent classification, which is carried out in this study within the framework of Bayes theorem as follows.

Let Φ: ϕ^1, ϕ^2, ..., ϕ^N be a sequence of N (feature vectors) observations, where $\phi^k = [\theta_1{}^k\ \theta_2{}^k\ \theta_3{}^k]^T$ corresponds to the kth parameter vector, and c_i, ,i = 1, 2, ..., M, the classes in which these vectors must be classified. Let C_i: c_{i1}, c_{i2}, ..., c_{iN} be one of the sequences of these classes corresponding to the observation sequence. The classification is performed in the following manner: to which class sequence C_i, a sequence of observations Φ corresponds. This is equivalent to appending ϕ^1 to class c_{i1}, ϕ^2 to class c_{i2}, and so on. Having observed a specific Φ, the Bayes rule assigns it to C_i for which

$$p(C_i \mid \Phi) > p(C_j \mid \Phi),\ \forall\ i \neq j.$$

This is equivalent to

$$p(\Phi \mid C_i)\, p(C_i) > p(\Phi \mid C_j)\, p(C_j),\ \forall\ i \neq j.$$

Assuming that all classes are independent and have Gaussian pdfs, the $p(\Phi \mid C_i)$ is calculated as follows:

$$p(\Phi | C_i) = \prod_{k=1}^{N} p(\phi^k | c_{ik}),$$

where the pdf of $p(\phi^k \mid c_{ik})$ is expressed as

$$f(\phi^k | c_{ik}) = (2\pi)^{-3/2} |\Sigma|^{-1/2} \exp[-(1/2)(\phi^k - \mu)\ \Sigma^{-1} (\phi^k - \mu)],$$

where μ is the mean vector, and Σ is the 3×3 diagonal covariance matrix corresponding to the c_{ik} class. Furthermore, it is assumed that all gesture classes are equally likely, i.e., $p(C_i)$ = 1/12. Table 1 shows the success rate in classifying the 12 gestures. The overall success rate is 96%. It was observed that the structured type movements (see Fig. 1g-l) have a higher classification success rate than the pointing (simple) movements (see Fig. 1a-f). The main reason that structured type gestures have a better classification rate is due to the clear coordination of the muscular activities. Such muscular activities (via EMG data) are expressed very distinctly in structured movements.

4 SUMMARY AND FUTURE WORK

This paper presents an EMG-based human-machine interface system that is able to recognize 12 arm gestures from sensing three arm muscles with a success rate of 96%. The processing of the EMG signals utilizes the temporal coordination activity of the monitored muscles to identify a particular gesture.

The future plan includes designing a light-wieght EMG sensor that uses data transmission and thus does not impose any constraint on the radius of the user's activities.

References

[1] Alsayegh, O. and Brzakovic, D., "Guidance of Video Data Acquisition by Myoelectric Signals for Smart Human-Robot Interfaces," IEEE Inter. Conf. Robotics and Automation, Leuven, Belgium, May 16-20, pp. 3179-3185, 1998.

[2] Cheron, G., Draye J., Bourgeios, M., and Libert, G, (1996), "A Dynamic Neural Network Identification of Electromyography and Arm Trajectory Relationship During Complex Movements," IEEE Trans. Biomed. Eng., Vol. 43, No. 5, pp. 552-558, 1996.

[3] Farry, K. A., Walker, I. D., and Baraniuk, R. G., "Myoelectric Teleoperation of Complex Robotic Hand," IEEE Trans. Robotics and Automation, Vol. 12, No. 5, pp. 775-88, 1996.

[4] Flanders, M., Pellegrini, J. J., and Geisler, S., "Basic Features of Phasic Activation for Reaching in Vertical Planes," Experimental Brain Research, Vol. 110, pp. 67-79, 1996.

[5] Hienz, H., Grobel, K., and Offner, G., "Real-time Hand-Arm Motion Analysis Using a Single Video Camera," Proc. Inter Conf. Automatic Face & Gesture Recognition, Killington, Vermont, USA, pp. 323-327, 1996.

[6] Koike, Y. and Kawato, M., "Human Interface Using Surface Electromyography Signals," Electronics and Communications in Japan, Part 3, Vol. 79, No. 9, pp. 15-22, 1996.

[7] Lange, H., "Speech synthesis and speech recognition: tomorrow's human-computer interfaces?," In Annual review of information science and technology, Vol. 28, Williams, M. (Ed), Learned Inf., pp.153-85, Medford, NJ, USA, 1993.

[8] Latwesen, A. and Patterson, P., "Identification of Lower Arm Motions Using the EMG Signals of Shoulder Muscles," Medical Engineering & Physics, Vol.16, No.2, pp.113-121, 1994.

[9] Nelson, W. T., Hettinger, L. J., Cunningham, J. A., and Roe, M. M., "Navigation Through Virtual Flight Environments Using Brain-Body-Actuated Control," IEEE 1997 Virtual Reality Ann. Inter. Symp., pp. 30-8, Albuquerque, NM, March 1-5, 1997.

[10] Parker, P. and Scott, R., "Myoelectric Control of Prostheses," CRC Critical Reviews in Biomedical Eng., Vol. 14, No. 4, pp. 283-310, 1986.

[11] Sheridan, T. B., Telerobotics, Automation, and Human Supervisory Control, MIT Press, Cambridge, MA, USA, 1992.

Table 1 Success rate in classifying 12 gestures

Gesture (see Fig. 1)	correct	Incorrect	% success rate
a	45	5	90
b	48	2	96
c	50	0	100
d	43	7	86
e	50	0	100
f	50	0	100
g	49	1	98
h	47	3	94
i	50	0	100
j	50	0	100
k	50	0	100
l	47	3	94
Total	**579**	**21**	**96**

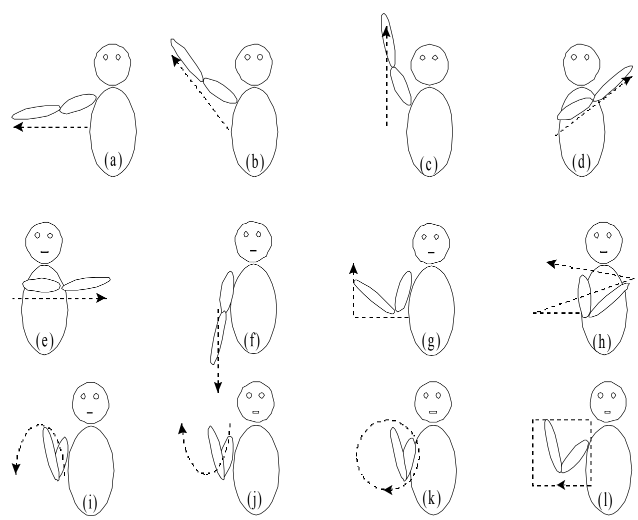


Fig.1 The 12 arm gestures considered in the study

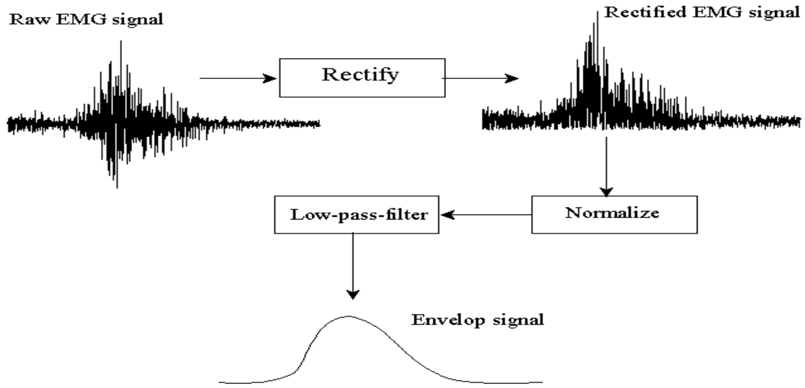


Fig. 2 Processing of an EMG signal to attain its corresponding envelop signal

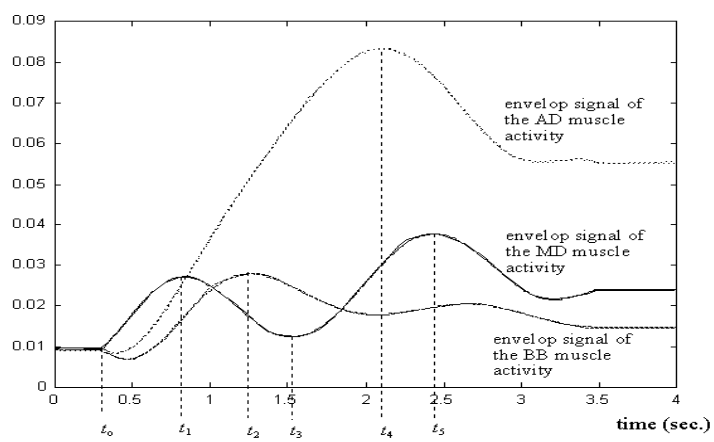
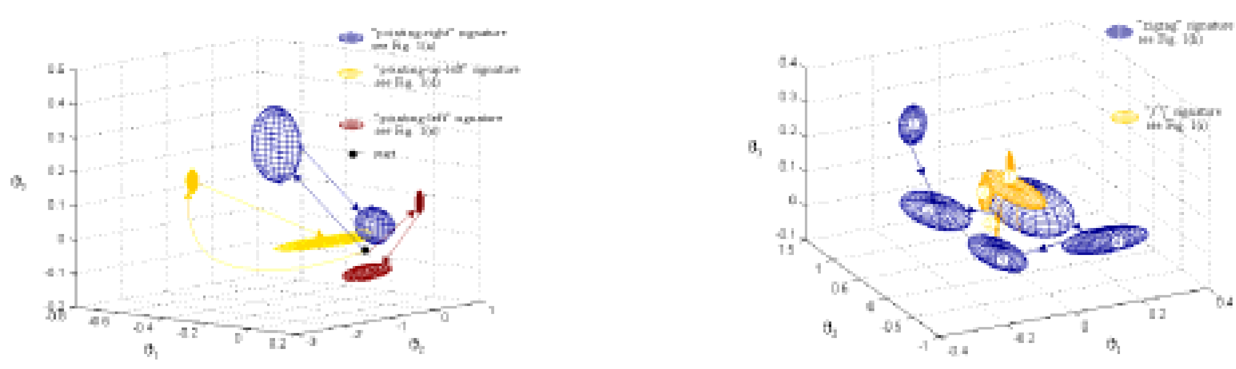


Fig. 3 Typical envelop signals that are attained from the activity of the AD, MD, and BB muscles to perform the "zigzag" gesture



(a) (b)

Fig. 4 Five temporal signatures representing five gestures are plotted in the feature space. The signatures result from the performance of three subjects. (a) Three pointing movement signatures, representing the gestures pointing-right, pointing-up-left, and pointing-left. (b) Two signatures representing the "zigzag" and "∩" gestures. The signature paths from start to end are illustrated via numbers.