Robot driving and arm gesture remote control using surface EMG with accelerometer signals

Kiwon Rhee (李基元), Kyungjin You (庾炅辰), Hyunchool Shin (申鉉出)
(*Dept. of Electronic Engineering, Soongsil University, Seoul 156-743, Korea*)

Abstract: This paper proposes a method of remotely controlling robots with arm gestures using surface electromyography (EMG) and accelerometer sensors attached to the operator's wrists. The EMG and accelerometer sensors receive signals from the arm gestures of the operator and infer the corresponding movement to execute the command to control the robot. The movements of the robot include moving forward and backward and turning left and right. The forearm of the robot can be rotated up, down, left and right, and the robot can clench its fists. The accuracy is over 99% and movements can be controlled in real time.

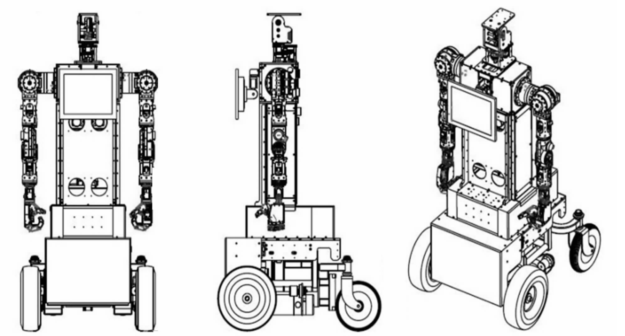
Key words: electromyography(EMG); accelerometer; K-means; entropy

CLD number: TP242.6 **Document code:** A
Article ID: 1674-8042(2012)03-0273-05 **doi:** 10.3969/j.issn.1674-8042.2012.03.015

0 Introduction

Unlike traditional industrial robots, an intelligent robot recognizes the external environment and engages in reasoning to determine whether to move autonomically or interact with a human[1,2]. Intelligent robots have been gradually becoming a bigger part of human life, and it is expected that they will form a greater part of industry in the future[3,4]. Therefore, research on intelligent robots focuses on enhancing their intelligence and the interaction between robots and humans. Such studies are carried out in various fields, for example, robots may be used as homemaker and medical assistants[5,6]. Studies on the navigation of intelligent robots have been widely conducted since the 1980s. Movement types of robots include wheelbase, caterpillar, two legged and multi-legged robots. Wheelbase robots function well on level ground, but their movements are unstable when the ground is uneven. Caterpillar robots are stable even on a rough ground surface, but they are slow and less efficient[7,8]. Studies on two-legged robots have been performed for the past few decades, mainly in Japan; however, their functions are still not outstanding[8].

This paper proposes a new method of controlling a humanoid robot, which utilizes the integration of accelerometer sensors attached to both wrists and electromyography(EMG) signals[9]. The humanoid robot used in this study is a robot named RoMAN. As shown in Fig. 1, the upper half of the body imitates the human body, while the lower half is a wheelbase chassis.



(a) (b) (c)

Fig. 1 Structure and design of RoMAN

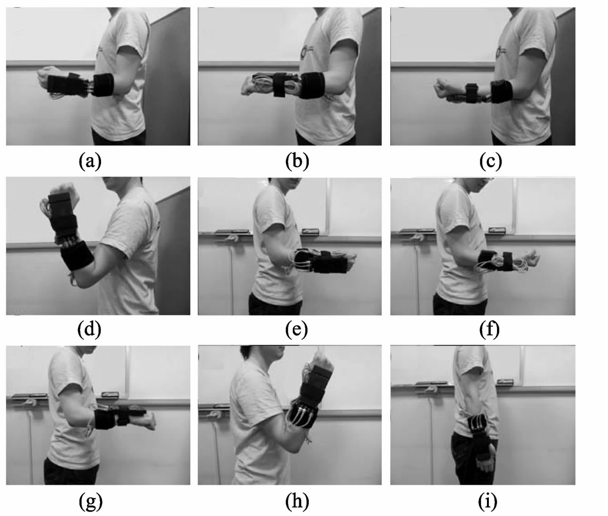
By using the method proposed in this study, the module recognizes gestures by observing the EMG signals occurring on the surface of the arm when the user moves his or her arms, and the accelerometer signals from the arms′ postures. RoMAN executes the corresponding command once it recognizes the gestures of the user. To distinguish each arm gestures, the K-means clustering and K-nearest neighborhood methods are used, and information entropy is calculated and employed to measure the level of activity of the surface EMG signals. The control has

※ **Received data:** 2012-03-18
Foundation item: The MKE(The Ministry of Knowledge Economy), Korea, under the ITRC(Information Technology Research Center) support program supervised by the NIPA(National IT Industry Promotion Agency)(NIPA-2012-H0301-12-2006)
Corresponding author: Hyunchool Shin (shinhc@ssu.ac.kr)

a one-second delay; however, it can be controlled smoothly in real time.

1 Definition of gestures

Gestures used to command the robot include four left-hand gestures that control the movement and five right-hand gestures that control the arms. Figs. 2(a) − (d) show four gestures (forward, backward, left turn and right turn), and Figs. 2(e) − (i) shows gestures used to move the forearm up(U), down(D), left(L) and right(R) with the posture shown in Fig. 2(e) as the initial gesture(I).



(a) − (d): Left-hand gestures (forward, backward, left turn, and right turn); (e) − (i): right-hand gestures (initial position, right, left, up and down)

Fig. 2 Gestures used to command the robot

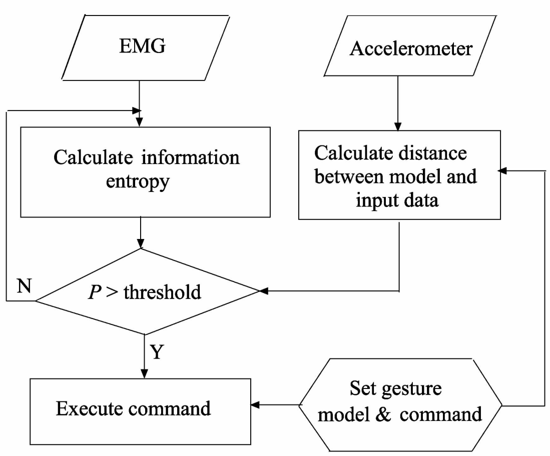


Fig. 3 Flowchart for control

Fig. 3 illustrates a flowchart for control. The robot uses the accelerometer signals received in real time to distinguish the command and employs the EMG signals to judge whether to execute the command.

2 Signal acquisition

2.1 Acquisition of EMG signals

The remote EMG signal measuring equipment in Fig. 4 and Ag/AgCl dipole electrodes were used to acquire the signals. Fig. 5 shows where the electrodes are attached on the forearm of the tester. The distance between the two poles is equal. The sampling frequency of the EMG signals is 64 Hz, and the power line noise has been eliminated.

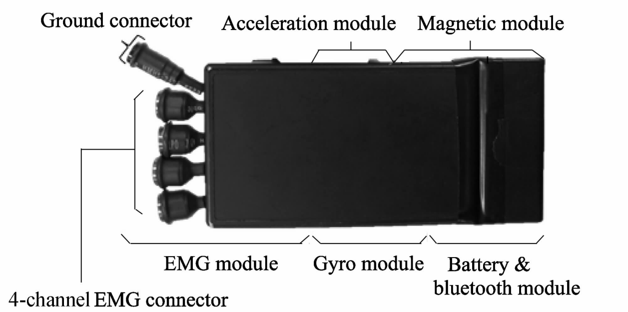


Fig. 4 Remote EMG signal and accelerometer measuring equipment

The tester had no difficulty in moving, and was instructed to move with the strength and speed used in daily life. The surface EMG signals were measured using three channels.

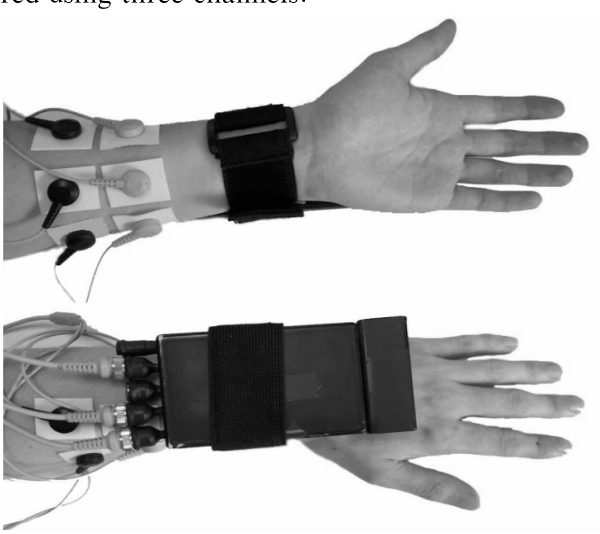


Fig. 5 Sensor modules and EMG sensor attachment

2.2 Acquisition of accelerometer signals

Accelerometer sensors were used to measure the signals. Fig. 4 shows where the acceleration module is located in the equipment and Fig. 5 shows where it is attached on the forearm. Accelerometer signals were measured with a sampling frequency of 64 Hz along the X, Y and Z axes.

3 Proposed method

3.1 Characteristics of gestures for control

Arm gestures for control used accelerometer sensor signals. The measured value of the accelerometer sensors was employed to form a model for each gesture using K-means clustering.

Signals were obtained from the three axes (X-axis signal, $V_x(t)$, Y-axis signal, $V_y(t)$, and Z-axis signal, $V_z(t)$), and they were used to set the centroid. The Euclidean distance between the three accelerometer signals, $V(t)$, and the centroid, $T_{\mathrm{d}}(0)$, was calculated; the $V(t)$ closest to $T_{\mathrm{d}}(0)$ was included in the group S_{d}. Then, S_{d} was used to renew the centroid, T_{d}.

$$S_{\mathrm{d}} = \begin{cases} V(t): \sqrt{(V(t) - T_{\mathrm{d}})^2} \leqslant \sqrt{(V(t) - T_{\mathrm{d}^*})^2}, \\ \forall d^* = 1, \cdots, N \end{cases} \tag{1}$$

$$T_d = \frac{1}{\#\text{number of } S} \sum_{G(t) \in S_d} G(t). \tag{2}$$

The gesture model was determined after repeating the Eq. (1) and Eq. (2) to obtain the optimal centroid.

3.2 Processing EMG signals for control

EMG signals measured from the three channels attached on the forearms are written as $x_c[n]$, where c represents the channel number. The information entropy of the obtained EMG signals was used to decide whether to execute the command. Information entropy was used as the scale to describe the level of change in the information included in the signal.

$$H(X) = \sum_{m=1}^{M} p(x_m) \log_2 \frac{1}{p(x_m)}, \tag{3}$$

where X is a discrete random variable; $p(x_m)$ represents the probability of x_m when the random variable X equals x_m; $p_c(m)$ for the C-th channel is defined as

$$p_c(m) = \frac{\#\text{ of samples} \in I_{\mathrm{m}}}{\#\text{ of total samples}},$$
$$I_m = \left\{ x_c[\cdot] \mid x_{\max} \frac{m-1}{M} \leqslant x_c[\cdot] x_{\max} \frac{m}{M} \right\}, \tag{4}$$
$$m = 1, \cdots, M,$$

where $X_{\max}$ is the maximum value of signal measuring equipment and M represents the total number of bins. In this study, $M = 1\,000$ and $X_{\max} = 1\,050\ \mu\mathrm{V}$; however, this can be adjusted to suit the EMG characteristics of the tester. The information entropy of EMG signals is

$$H_c \equiv H(x_c) = \sum_{\mu=1}^{M} p_c(m) \log_2 \frac{1}{p_c(m)}. \tag{5}$$

The robot was set to react when the total of P values of entropy collected from three channels in one minute exceeded the predetermined value. Once it started to react, the robot would carry out the designated command following the arm gestures.

$$p = \sum_{c=1}^{3} H_c. \tag{6}$$

3.3 Wheel movement control by gestures

The left-hand gestures were used to control the wheel movement of the robot. Once the robot recognized the gesture, the robot would move its wheels in the direction corresponding to the gesture. Table 1 shows the wheel control speed of each gesture; Table 2 gives the accuracy in movement recognition; Table 3 presents the accelerometer signal model used for gesture distinction.

Table 1 Wheel control speed

	Left wheel speed/$(\mathrm{m \cdot s^{-1}})$	Right wheel speed/$(\mathrm{m \cdot s^{-1}})$
Forward	0.50	0.50
Backward	−0.50	−0.50
Left turn	−0.25	0.25
Right turn	0.25	−0.25

Table 2 Accuracy in movement recognition

	Forward/%	Backward/%	Left turn/%	Right turn/%
Forward	100	0	0	0
Backward	0	100	0	0
Left turn	0	0	100	0
Right turn	0	0	0	100

Table 3 Accelerometer signal model for gesture distinction

	X-axis	Y-axis	Z-axis
Forward	1.79	2.40	1.69
Backward	1.69	1.90	0.83
Left turn	1.73	1.58	2.37
Right turn	2.17	1.24	1.75

3.4 Arm movement control by gestures

The right arm gestures were used to control arm movements. First, the initial posture needs to be recognized. Then, the forearm of the robot can rotate up, down, left and right, and the robot can clench its fists. The rotation angle of arm for each gesture is shown in Table 4. The direction of the wheels is determined by the gesture. Table 5 gives the accuracy in movement recognition and Table 6 presents the accelerometer signal model used for gesture distinction.

Table 4 Rotation angle of arm

	Rotation angle of forearm/deg
Up	2.0
Down	−2.0
Left	2.0
Right	−2.0

Table 5 Accuracy in movement recognition

	I/%	U/%	D/%	L/%	R/%
I	100	0	0	0	0
U	0	100	0	0	0
D	0	0	100	0	0
L	0	0	0	100	0
R	0	0	0	0	100

Table 6 Accelerometer signal model for movement distinction

	X-axis	*Y*-axis	*Z*-axis
I	1.59	0.86	1.43
U	2.32	1.55	1.73
D	0.78	1.49	1.60
L	1.61	1.59	2.41
R	1.63	1.56	0.79

4 Experimental results

To test the accuracy of wheel movement and arm movement by gestures, each gesture was tested 50 times. Twenty-five training data and test data were divided so that they did not overlap, and cross-validation was conducted 100 times to calculate the average accuracy. A total of 64 samples were used and the critical value of entropy was 12.

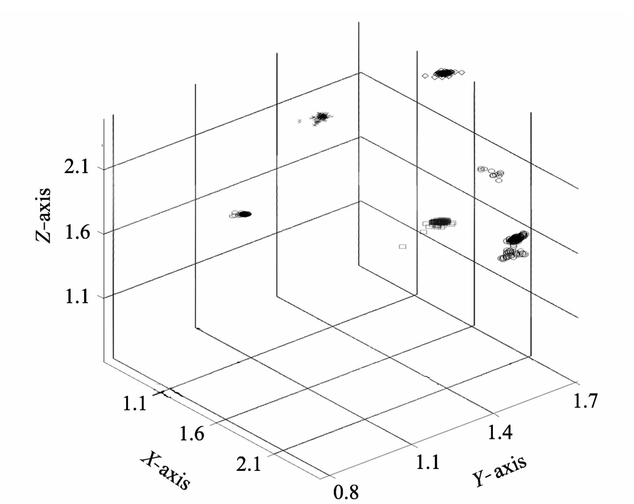


Fig. 6 Distribution of accelerometer sensor output by right-hand gesture

As shown in Figs. 6 and 7, the accelerometer sensor outputs were distributed fairly evenly without overlapping. All nine gestures′ accuracy is near 100% as shown in Table 2 and Table 3, and this proves that the movement recognition ability is stable.

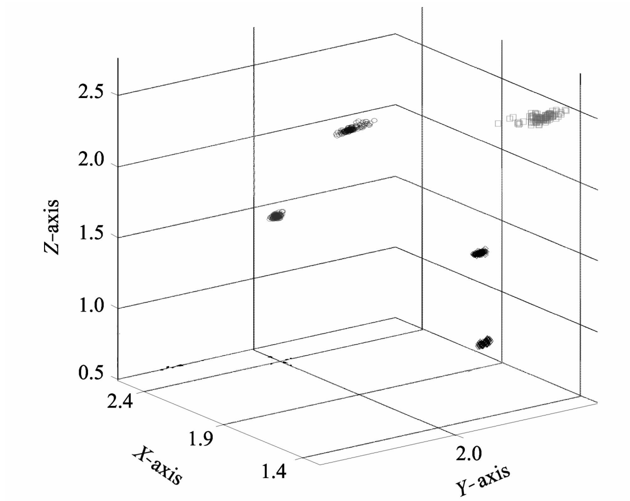


Fig. 7 Distribution of accelerometer sensor output by left-hand gesture

5 Conclusion

In this paper, a new robot control method was suggested that uses accelerometer signal processing for gesture inference and EMG signal processing to confirm control command. This newly developed method allows for smooth control of the wheel and arm movement of the robot.

When deciding whether to execute the command, the critical value of entropy of EMG signals obtained from three channels was used. Three-axis accelerometer sensors were used to recognize gestures (four left-hand gestures and five right-hand gestures), and the gestures were translated into commands to control the robot. To distinguish each gesture, the K-nearest neighborhood method was used, where the Euclidean distance between the model and the acceleration value occurring in the sensor was calculated. The accuracy is nearly 100%.

References

[1] Nakajima H, Brave S, Maldonado H, et al. Toward an actualization of social intelligence in human and robot collaborative systems. Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems, 2004, 4: 3238-3243.

[2] Garcia E, Jimenez M A, De Santos P G, et al. The evolution of robotics research. Robotics & Automation Maga-

zine, 2007, 14(1): 90-103.
[3] Asfour T, Gyarfas F, Azad P, et al. Imitation learning of dual-arm manipulation tasks in humanoid robots. Proc. of the 6th IEEE-RAS International Conference on Humanoid Robots, 2006: 40-47.
[4] Luo R C, Lin M H, Scherp R S. Dynamic multi-sensor data fusion system for intelligent robots. IEEE Journal of Robotics and Automation, 1988, 4(4): 386-396.
[5] Luo R C, Su K L, Shen S H, et al. Networked intelligent robots through the Internet: issues and opportunities. Proc. of the IEEE, 2003, 91(3):371-382.
[6] Nitzan D. Development of intelligent robots: Achievements and issues. IEEE Journal of Robotics and Automation, 1985, 1(1): 3-13.
[7] Eiji N, Sei N. Leg-wheel robot: a futuristic mobile platform for forestry industry. Proc. of IEEE/Tsukuba International Workshop on Advanced Robotics: Can Robots Contribute to Preventing Environmental Deterioration, 1993: 109-112.
[8] Matsumoto O, Kajita S, Saigo M, et al. Dynamic trajectory control of passing over stairs by a biped type leg-wheeled robot with nominal reference of static gait. Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems, 1998, 1: 406-412.
[9] Rhee K W, You K J, Shin H C. Recognition of finger motion combining sEMG and gyro sensor signals. Journal of Measurement Science and Instrumentation, 2011, 2(2): 136-139.
[10] Kreyszig E. Advanced Engineering Mathematics, 9th Edition, Wiley, 2006.