Intuitive Robot Control Using Surface EMG and Accelerometer Signals

Kiwon Rhee, Kyung-Jin You, Hyun-Chool Shin

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 movements to execute the command to control the robot. The movements of the robot include moving forward and backward and turning left and right. The accuracy is over 99% and movements can be controlled in real time.

Keywords—EMG, Acceleromter, K-nn, Entropy.

I. INTRODUCTION

UNLIKE traditional robot, 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. 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 on both wrists and 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.

In the method proposed in this study, the module recognizes gestures by observing the electromyogram (EMG) signals occurring on the surface of the arm when the user moves his or her arm, and the accelerometer signals from the arm postures. RoMAN executes the corresponding command once it recognizes the gesture of the user. To distinguish each arm gesture, the K-mean clustering and K-nearest neighborhood

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methods were used, and information entropy was calculated and employed to measure the level of activity of the surface EMG signals. The control has a one-second delay; however, it can be controlled smoothly in real time.
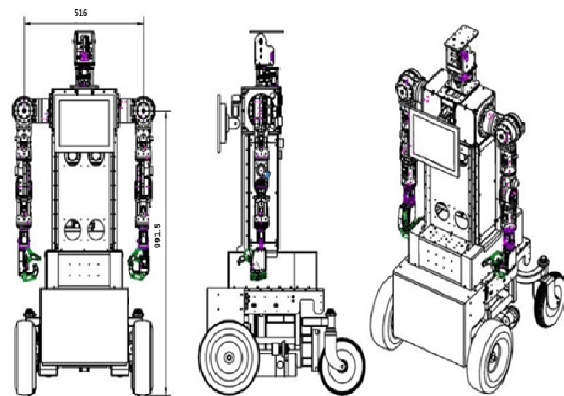

Fig. 1 Structure and design of RoMAN

II. DEFINING GESTURES

Gestures used to command the robot include four left-hand gestures that control the movement. A through D in Fig. 2 show four gestures (forward, backward, left turn, and right turn).
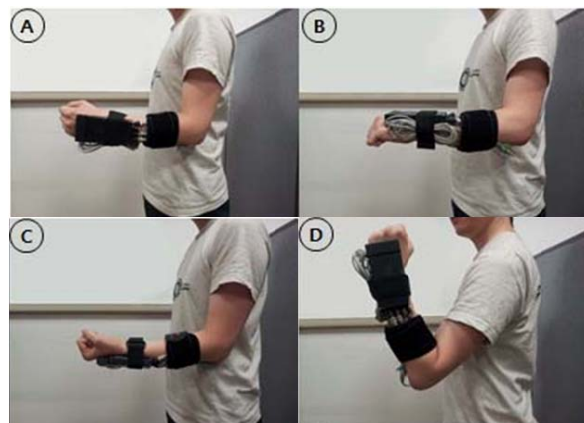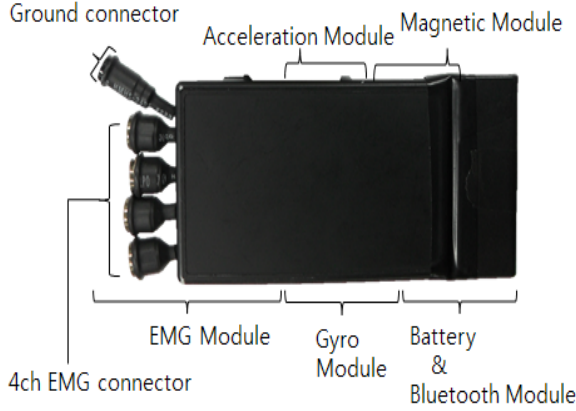

Fig. 2 Left-hand gesture (A: forward B: backward C: left turn D: right turn)

Fig. 3 Remote EMG and accelerometer measuring equipment

III. SIGNAL ACQUISITION

A. Acquisition of EMG Signals

The remote EMG signal measuring equipment in Fig. 3 and Ag/AgCl dipole electrodes were used to acquire the signals. Fig. 4 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.

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.

B. 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. 4 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. Fig. 5 shows the accelerometer data of left-hand gestures.

IV. PROPOSED METHOD

A. 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 [10].

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, $T_d(0)$, was calculated; the $V(t)$ closest to $T_d(0)$ was included in the group S_d. Then, S_d was used to renew the centroid, T_d.

$$S_d = \left\{ \begin{array}{c} V(t): \sqrt{(V(t)-T_d)^2} \le \sqrt{(V(t)-T_{d^*})^2} \\ \forall d^* = 1, \dots, N \end{array} \right\} \quad (1)$$

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

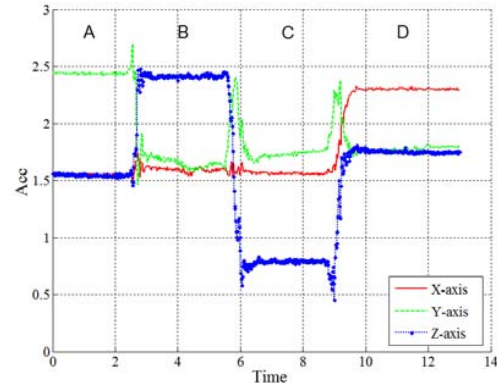Fig. 4 Sensor modules and the EMG sensor attachment

Fig. 5 Accelerometer data of left-hand gestures(A: forward, B: left turn, C: right turn, D: Backward)

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

B. 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.

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

Here, X is discrete random variable, and $p(x_m)$ represents the probability of when the random variable X equals x_m. $p_c(m)$ for the C_{th} channel is defined as follows:

$$p_c(m) = \frac{\#\ of\ samples \in I_m}{\#\ of\ total\ samples},$$
$$I_m = \left\{ x_c[\cdot] \mid x_{max} \frac{m-1}{M} \le x_c[\cdot] \le x_{max} \frac{m}{M} \right\} \quad (4)$$
$$m = 1, \dots, M$$

where X_{max} is the maximum value of signal measuring equipment and M represents the total number of bins. In this study, M=1000 and $X_{max} = 1,050\ \mu V$; however, this can be adjusted to suit the EMG characteristics of the tester. The information entropy of EMG signals is as follows:

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

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

$$P = \sum_{c=1}^{3} H_c$$

TABLE I
WHEEL CONTROL SPEED

	Left wheel(m/s)	Right wheel (m/s)
Forward	0.5	0.5
Backward	-0.5	-0.5
Left turn	-0.25	0.25
Right turn	0.25	-0.25

TABLE II
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 III
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%

C. Controlling Wheels by Gesture

Fig. 6 illustrates a flow chart 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.

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 I shows the wheel control speed of each gesture.

V. EXPERIMENTAL RESULTS

To test the accuracy of wheel movement and arm movement by gesture, 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.
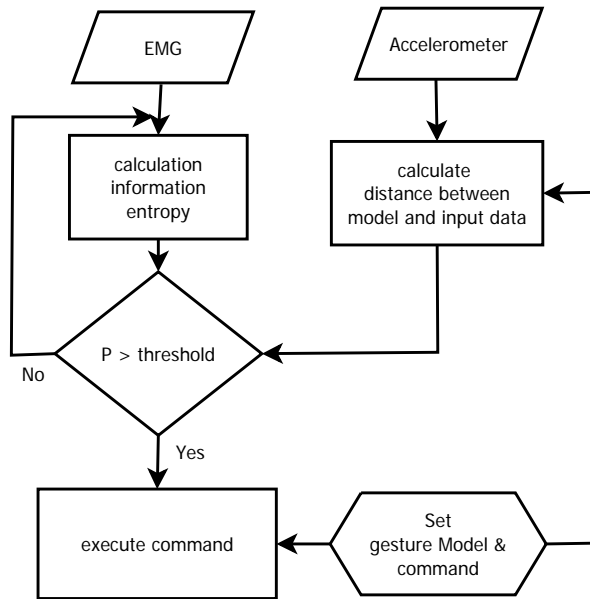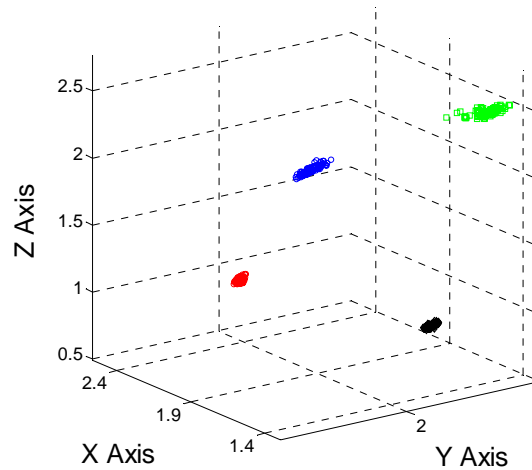

Fig. 6 Flow chart for control

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

As shown in the Fig. 7, the accelerometer sensor outputs were distributed fairly evenly without overlapping. The accuracy in movement recognition is shown in Table II. All four gestures showed accuracy near 100%, and this proved that the movement recognition ability was stable.

VI. 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 of the robot.

In 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 four left-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. This showed accuracy near 100%.

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