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INTUITIVE MUSCLE-GESTURE BASED ROBOT NAVIGATION CONTROL USING WEARABLE GESTURE ARMBAND

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Abstract:

In this paper, we propose a muscle gesture-computer interface (MGCI) system for robot navigation control employing a commercial wearable MYO gesture control armband, the motion and gesture control device from Thalmic Labs. This system allows the user to control a three-wheeled omni-directional robot remotely by his/her intuitive motion. Two approaches were proposed with surface electromyographic (sEMG) sensors and combination of sEMG and inertial measurement unit (IMU). Computer simulations and experiments were conducted to evaluate the feasibility of the proposed system.

Keywords:

Muscle gesture-computer interface; wearable MYO gesture control armband; omni-directional robot; surface electromyographic sensor; inertial measurement unit

1. Introduction

Gesture recognition pertains to recognizing meaningful expressions of human motion, including the hands, arms, face, head, and body. It is of utmost importance in the field of human-computer/human-machine interface (HCI/HMI). In recent years, there has been a tremendous interest in introducing intuitive interfaces that can recognize the user's hand gestures and translate them into machine commands. This paper presents a muscle gesture-based human interface for mobile robot navigation control employing a wearable MYO gesture control armband [1].

Interaction with a gesture is simpler and more natural than manipulating physical devices such as keyboards, mice, and joysticks. There are mainly three techniques to extract human motion information for gesture recognition applications: visual analysis, inertial sensors and bio-signals. Vision-based approaches have the advantage of avoiding human-worn equipment; however, it lacks the robustness of lighting conditions, occlusions, and the human-robot spatial relationship for outdoor and mobile requests [2]. In addition, it has distance limitations. On the contrary, Biological signal technology has much future potential. Biotechnologies have two major categories: Electroencephalogram (EEG) based Brain Computer Interfacing and Electromyogram (EMG) based interface. Moreover, there are two smaller areas in Electrocardiogram (ECG) and Electrooculography (EOG). Amongst EMG signal is generally used due to its better properties of high amplitude and signal to noise ratio than other biosignals [3]. Beside, the acquisition of EMG signals is easy and less complex when compared to the other signals. Recently more and more researches fuse EMG and IMU information for HCI/HMI applications.

There are two kinds of EMG in prevalent use: needle EMG and surface EMG (sEMG). The first one is not practically feasible in HCI/ HMI since a needle electrode has to be inserted through the skin into the muscle tissue. Muscle gesture-computer interfaces [4-8] based on sEMG recognition have been rapidly developed for various applications such as Electric-Powered Wheelchair [3], recognizing sign language [9], lie detection [10], HCI/HMI [11, 12], smart home [13], mobile device [14], Prosthesis Robotic Hand [15], robotic arm manipulation [16-19] and mobile robot navigation control [20-24].

Moon *et al.* [3] controlled the direction (left, right and forward) of an electric-powered wheelchair with left-, right- and both-shoulders elevation gestures. The experimental results showed the proposed system is feasible to navigate wheelchair in real indoor environment. In [16], two EMG signals were collected using surface electrodes mounted on the operator’s lower arm to control a 7 DOF Humanoid Robot Arm. Pilarski *et al.* [17] measure EMG signals with sEMG electrodes attached on four muscle groups: biceps, triceps, wrist flexors, and wrist extensors. Then the EMG signals were implemented to mimic three activities (reach, relax and retract) of an AX-12 Smart Arm. Cannan and Hu [18] proposed the GE-fusion and MEA-fusion bands to control an Edubot Robotic Arm. A dual channel sEMG was employed to control the opening and closing of the gripper while the inertia sensors were utilized to control the

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movements (up, down, left, right) of the manipulator. Worn on the user's forearm, the JPL BioSleeve incorporates 16 sEMG sensors and one IMU was developed by Worf *et al.* [19]. The BioSleeve can reliably decode 16 discrete hand gestures and estimate the continuous orientation of the forearm simultaneously. Subsequently BioSleeve gesture control was implemented for three robotic platforms: a manipulation system, a small ground robot, and a five-fingered hand.

Using a single EMG signal from the levator scapulae muscle, two gestures (fist and finger spread) were recognized for mobile robot control ("Start" and "Stop") through Bluetooth [20]. Afterward the motions of the robot (forward, backward, turn left, turn right) is manipulated using IMU sensor. In [21], a two-channel sEMG was implemented to decide whether to control the RoMAN robot. Nevertheless, the motions (Forward, Backward, Left turn, Right turn) of robot is actually inferred from acceleration sensor. *Kim et al.* [22] used a single channel sEMG to recognize four hand gestures (Press, Left, Right, and Circling) and navigate an RC car without exploitation of inertial sensors. Finally, three and four sEMG sensors were adopted in different study to control the movement of a Nao humanoid robot [23] and AIBO Robot [24], respectively.

Obviously the number and placement of the sEMG electrodes is a critical issue for the successful identification of hand motions. Recent studies [6, 25-26] have developed multi-channel sensor rings so that the user can easily wear the sensor ring without alignment. However the number of electrodes adopted is quite different. Saponas *et al.* [6] developed muscle-computer interfaces (muCI) using 10 sensors worn in a narrow band around the upper forearm. Du *et al.* [25] developed an electrode configuration system consisting of 7 active electrodes that place around the forearm to recognize 11 hand motions. For most users, Tang *et al.* [26] claimed that 6-channel half wristband is enough to record the contraction information of the four extensor muscles.

In this study, a muscle gesture-computer interface system employing the MYO gesture control armband was developed for mobile robot navigation control. It is an electromyography device worn on the forearm just below the elbow. MYO contains 8 medical grade stainless steel EMG sensors and a highly sensitive nine-axis IMU. It currently only recognizes five distinct poses including fist, spread fingers, wave in, wave out and double tap gestures.

The rest of this paper is organized as follows. System architecture is introduced in Section 2. The three-wheeled omni-directional mobile robot is subsequently described in Section 3. Section 4 describes the simulations and experiments conducted in this study. Finally, Sections 5 and 6 present the results, discussions and conclusions.

2. Muscle Gesture-Computer Interface (MGCI) System

As can be seen on Figure 1, the intuitive remote control system consists of three parts - the user with MYO armband, MGCI, and the mobile robot. In addition to the 8-channel EMG raw data, MYO armband furthermore provides identified gestural data and spatial data (orientation and movement of the user's arm) to computer using the Bluetooth protocol. The identified hand gestures were then mapped to robot operating commands by MGCI system and control the mobile robot remotely through Wi-Fi.

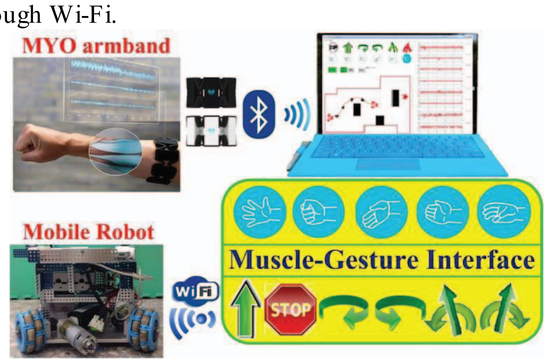

FIGURE 1 The proposed mgci system architecture

As Figure 2 depicted, MYO is an armband device developed by Thalmic Labs in Waterloo, Canada. It is a device for hand gesture recognition and arm movement tracking. The goal of MYO is an easy and comfortable HCI for computer, smartphones and other products by using hand gestures. In addition to the 8-channel sEMG sensors, MYO is also equipped with a nine-axis IMU. An ARM Cortex M4 processor is used for applying machine learning algorithms to classify executed hand gestures. After a hand gesture is classified, MYO notifies a pared device through BLE (Bluetooth Low Energy) which hand gesture was performed. Thalmic Labs provides SDK (Software Development Kit) to access MYO functions for Windows, iOS, Mac and Android cross-platform. This SDK provides a high level API, meaning that developers do not have direct access to raw sensors data, but only to classified hand gestures and motion data from IMU. However the Raw Data SDK for the MYO armband was live recently and the developers can access to a stream of raw EMG data straight from the MYO armband.

FIGURE 2 Myo armband

One disadvantage of MYO is that only 5 gestures including fist, spread fingers, wave left, wave right and double tap were supported by Thalmic Labs. Besides "double tap" was utilized as a locking/unlocking mechanism previously and is misclassified very easily. Fig. 3 illustrates the relative position worn in the forearm, the indexed number of the MYO's 8-channel sEMG sensors and the corresponding 8-channel EMG raw data acquired for five gestures.

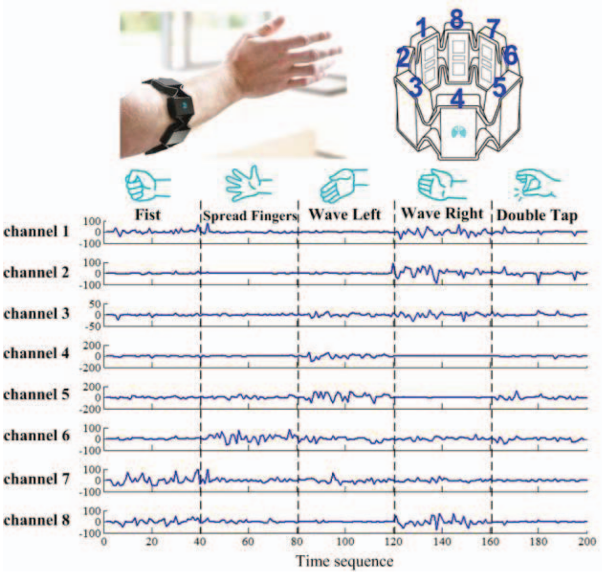

FIGURE 3 8-channel conditioned semg signals for five gestures

3. Three-Wheeled Omni-Directional Robot

An omni-directional mobile robot is a type of holonomic robots. It has the ability to move simultaneously and independently in translation and rotation. The inherent agility of the omni-directional mobile robot makes it widely studied for dynamic environmental applications. Omni-directional mobile platforms have attracted much attention in both academia and industry in the field of robotics. In comparison with conventional two-wheeled or four wheeled car-like mobile platforms, omni-directional mobile robots have the superior agile capability to move toward any position and to simultaneously attain any desired orientation. This manoeuvring capability is particularly useful in designing mobile platforms for autonomous service robots.

Figure 4 shows the three-wheeled omni-directional robot and its symmetric structure and geometry employed in this study. Three independent driving wheels (double row 4200 series, Kornylak Corporation) equally spaced at 120° from one another are driven by 24VDC gear motor IG42 (Shayang Ye Industrial Co., Ltd.) with Pololu SMC04A motor controller.

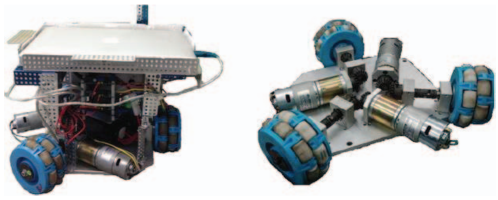

FIGURE 4 The three-wheeled omni-directional mobile robot

The kinematic equation of the omni-directional wheel platform could be described as follows [27-28],

$$\begin{bmatrix} V_1 \\ V_2 \\ V_3 \end{bmatrix} = \begin{bmatrix} r\omega_1 \\ r\omega_2 \\ r\omega_3 \end{bmatrix} = P(\theta) \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix}$$

where
$$P(\theta) = \begin{bmatrix} -\sin\theta & \cos\theta & L \\ -\sin(\pi/3 - \theta) & -\cos(\pi/3 - \theta) & L \\ \sin(\pi/3 + \theta) & -\cos(\pi/3 + \theta) & L \end{bmatrix}$$

r denotes the radius of the driving wheels; L represents the distance from the wheel's center to the geometric center of the platform. V_i and ω_i, i = 1, 2, 3, denote the linear and angular velocities of each wheel, respectively. The matrix $P(\theta)$ is always nonsingular for any θ. The second-order dynamic model derived from the Newton's second law for translation and rotation can be found in [27-28] for reference.

4. Simulation and Experiment

Currently only four gestures for MYO armband were adopted in the proposed MGCI since "double tap" is misclassified very easily. A graphic user interface (GUI) written with visual C++ as shown in Fig. 5 was developed to check the positive gesture recognition rates of these gestures. The gesture recognition rates for "fist", "spread fingers", "wave right" and "wave left" gestures are 98.17%, 95.68%, 99.45% and 99.82%, respectively. Clearly MYO has much superior recognition rate compared to the other studies [7-9].

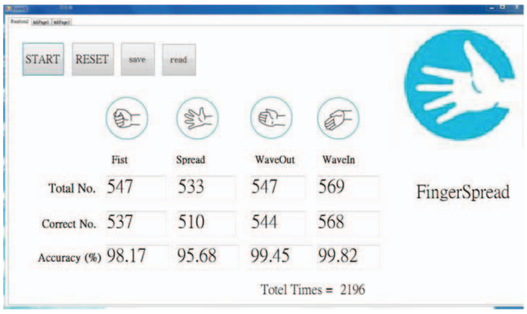

FIGURE 5 Simulation window for recognition rate test

This paper presents two MGCIs for robot navigation control. The first one maps the four gestures “fist”, “spread fingers”, “wave left” and “wave right” to the robot commands “stop”, “go forward”, “rotate counterclockwise”, and “rotate clockwise”, respectively. Figure 6 shows the simulation window of the first MGCI system. Obviously four gestures were not enough for us to exert the fully functional omni-directional platform. To solve this problem the second approach fuses the spatial and gesture data (IMU+ EMG) to generate two more gestures – fist gesture turn ±90° in the direction of roll-axis. In such situation, the mobile robot can move simultaneously and independently in translation and clockwise/counterclockwise rotation. The simulation window of the second approach is depicted in Figure7. Note that, the raw data of the 8-channel EMG were shown in the right side concurrently in real-time.

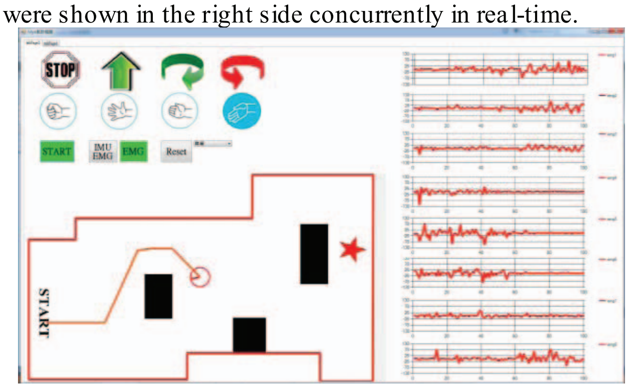

FIGURE 6 Simulation window for the first mgci

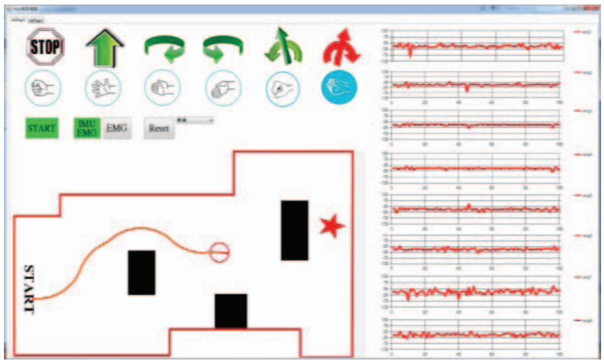

FIGURE 7 Simulation window for the second mgci

5. Results and Discussions

5.1. Simulation Results

We conduct four simulations using the proposed two MGCI systems. The first one is to navigate a virtual omni-directional mobile robot in an 8-type passage while the last one is to navigate the robot to a goal position in virtual environment with 3 fixed obstacles. The other two cases are to navigate the robot to pass two maze type corridors of which width is about 1.5 times the diameter of mobile platform. In order to evaluate the proposed MGCI systems, the same subject performs three trials for each case with two kinds of MGCIs. The simulation results for the first and second MGCI system are shown in Figures 8 and 9, respectively.

Clearly the mobile robot trajectories for the second MGCI system are much smoother than those of the first MGCI system for all 4 environments. Furthermore the elapse time for the second MGCI system is less than the first approach.

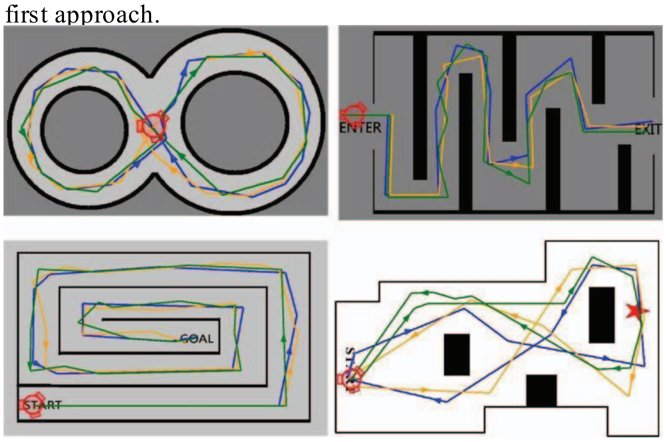

FIGURE 8 The simulation results for the first mgci system

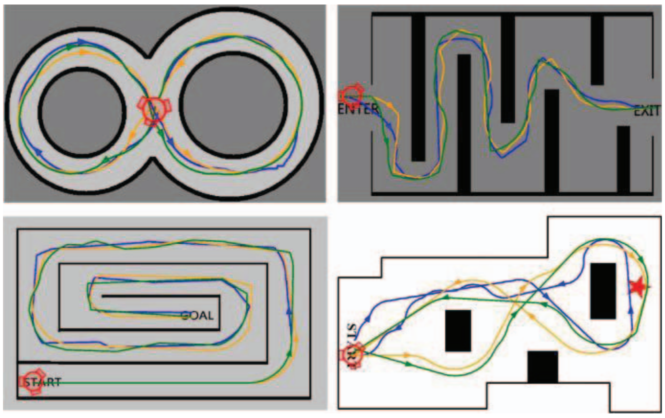

FIGURE 9 The simulation results for the second mgci system

5.2. Experiments

The proposed second MGCI system was applied to control a three-wheeled omni-directional mobile robot for the first and the last cases due to its smoother trajectories and less elapse time required. Figure 10 shows the user navigating the mobile robot in these two indoor environments. The computer used in this study is Surface Pro 3 with Intel i5 and 256 GB RAM. The user performs three trials for each case to evaluate the performance of the proposed MGCI system.

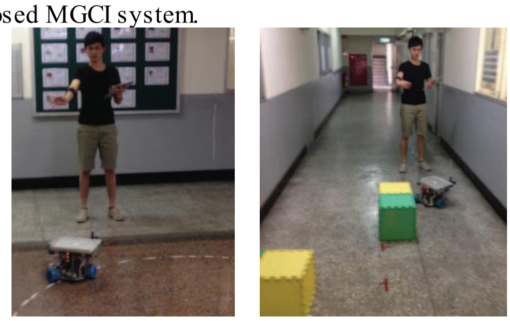

FIGURE 10 The user navigate a mobile robot in two environments

Figure 11 shows a series of navigation sequences along the 8-type trajectory. The number under each picture denotes the sequence number. The initial state stop as shown in sequence '1'. Figure 12 illustrates the three trajectories (dash lines with blue, green and red colors) of the geometry center of the mobile robot. Compared with the reference 8-type trajectory (white color line), the performance seems quite well and can be improved further for more practice.

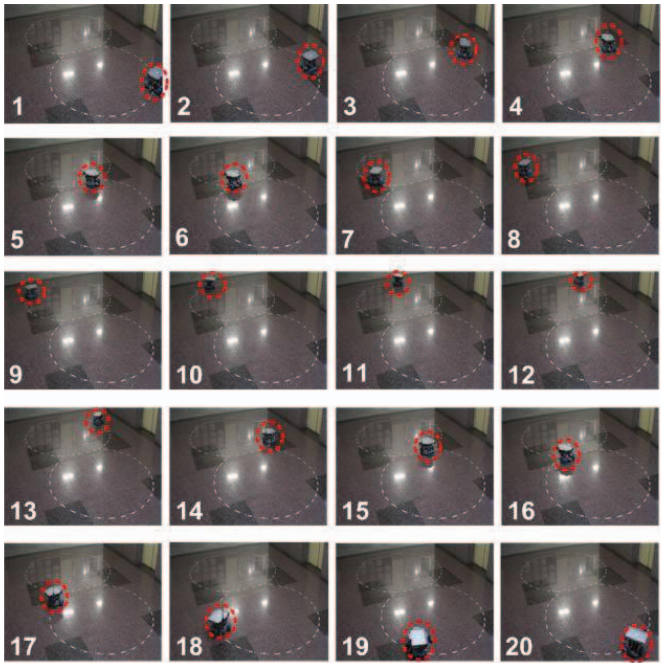

FIGURE 11 Omni-directional mobile robot navigation sequences

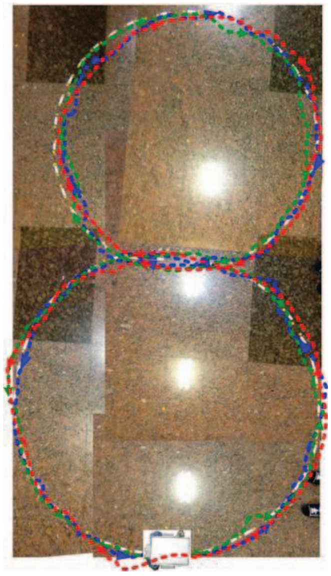

FIGURE 12 Navigation trajectories in 8-type character environment

Figure 13 demonstrates the mobile robot trajectories (dash lines with blue, green and red colors) for corridor navigation. Moreover, three fixed obstacles were placed in the alleyway. It shows that the user can intuitively navigate the robot and avoid obstacles effectively.

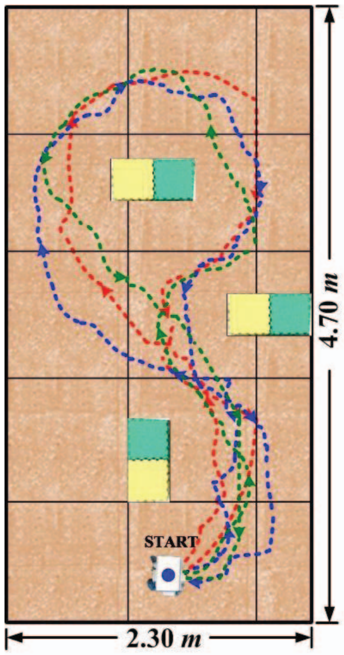

FIGURE 13 Navigation trajectories in fixed-obstacle corridor

6. Conclusions

In this paper, two approaches of MGCI systems were proposed for intuitive and natural robot navigation control utilizing MYO gesture armband. The first one acquired only the gesture data while the second one fuse spatial and gesture data. The simulation results show that the user can successfully navigate a virtual omni-directional mobile robot in four different virtual environments employing both MGCI approaches. However, the second approach seems to have the advantage of smoother trajectories and less elapse time.

Eventually two experiments were implemented to evaluate the performance of real robot navigation. The experimental results show the feasibility and accomplishment of real-time robot navigation control.

Acknowledgements

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