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An sEMG-Controlled RHex-T3 Hexapod Mobile Grasping Robot for As-sistive Object Retrieval

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Abstract

Assistive robots have strong potential in object retrieval, delivery, and remote interaction, but their practical usability depends on natural and low-burden human-machine interfaces. This study aims to develop an sEMG-controlled RHex-T3 hexapod mobile grasping robot system for assistive object retrieval. The proposed system integrates a multimodal hexapod chassis, robotic arm, camera-based wireless visual transmission module, sEMG acquisition and recognition module, and host-computer control terminal. Existing sEMG gesture recognition methods are deployed as a task-level robotic control interface, and a gesture-to-action mapping mechanism with hierarchical mode switching is designed to convert discrete gesture labels into chassis locomotion, mode-switching, and robotic-arm commands. Experiments are designed for online recognition, chassis control, grasping execution, and composite task completion. The results indicate that the proposed system can complete basic mobility, approach, grasping, and delivery tasks, verifying the preliminary feasibility of using sEMG to control a hexapod mobile manipulator for assistive object retrieval.

Keywords

Surface Electromyography; Assistive Robot; Hexapod Robot; Mobile Manipulation; Gesture

1. Introduction

Assistive robots are expected to support object retrieval, delivery, and remote interaction, especially for users with limited upper-limb function. Conventional interfaces such as buttons, joysticks, and remote controllers are simple to implement, but they may impose a considerable operational burden and do not directly reflect human motor intention. Surface electromyography (sEMG) provides a non-invasive means of sensing muscle activity and has therefore become a promising interface for intention input.

Most sEMG-related studies emphasize offline gesture recognition accuracy or standalone classifier performance. However, high recognition accuracy alone does not prove that a robot can complete an assistive task. In practical scenarios, users require a complete system that can transform motor intention into mobility, target approach, grasping, and delivery. Mobile manipulators provide a suitable platform for this purpose. RHex-T3-like multimodal hexapod platforms offer terrain adaptability and extensibility, and can be combined with a robotic arm and visual feedback module to form a mobile manipulation system.

To address this gap, this paper proposes an sEMG-controlled RHex-T3 hexapod mobile grasping robot system. The main contribution is not a new sEMG classification algorithm, but the deployment of existing recognition methods as a usable task-level control interface. The proposed system integrates sEMG intention input, hexapod locomotion, visual transmission, and robotic-arm grasping into a unified closed-loop platform. Its contributions are: (1) an integrated assistive mobile grasping robot system; (2) a gesture-to-action mapping framework supporting chassis movement, mode switching, and robotic-arm operation; and (3) a four-level experimental design for evaluating online recognition, control response, grasping performance, and end-to-end task feasibility.

2. Related Work

2.1. sEMG-Based Gesture Recognition

The sEMG gesture recognition has developed from traditional feature-based methods using time-domain, frequen-cy-domain, or time-frequency-domain features with classifiers such as SVM, KNN, and random forests, to deep learning models using convolutional, attention-based, and residual structures. These methods provide a solid basis for motor in-tention recognition. Nevertheless, many studies still focus on offline accuracy, model design, and classification im-provement, while paying less attention to real-time control, false-trigger suppression, and coupling with robotic task execution.

2.2. Hexapod Mobile Manipulators

Mobile manipulators combine a mobile chassis with a robotic arm, enabling both environmental mobility and task execution. Wheeled platforms are widely used because of their simple control and high speed, but their adaptability to uneven terrain and unstructured environments is limited. Legged platforms, especially hexapod robots, provide better stability, obstacle negotiation, and traversability. RHex-T3 is therefore selected in this work as the main platform for an assistive mobile grasping system rather than as an object of independent kinematic innovation.

2.3. sEMG-Controlled Robots

Electromyography-controlled robots have been applied to prosthetic control, rehabilitation, exoskeletons, robotic-arm teleoperation, and simple mobile robot control. These studies demonstrate the potential of sEMG as a robotic interface, but they often remain at the level of single-module or single-step control. In contrast, this work focuses on integrating sEMG recognition with hexapod locomotion, visual feedback, and robotic-arm grasping to support a complete task chain of mobility, approach, grasping, and delivery

3. System Overview

3.1. Overall Architecture

The proposed system is designed for assistive object retrieval and aims to form a closed loop involving human intention input, mobile approach, visual observation, and grasping execution. As shown in Figure 1, the hardware platform consists of an RHex-T3 multimodal hexapod chassis, a robotic arm and end effector, a camera-based wireless visual transmission module, an sEMG acquisition and recognition module, and a host-computer control terminal.

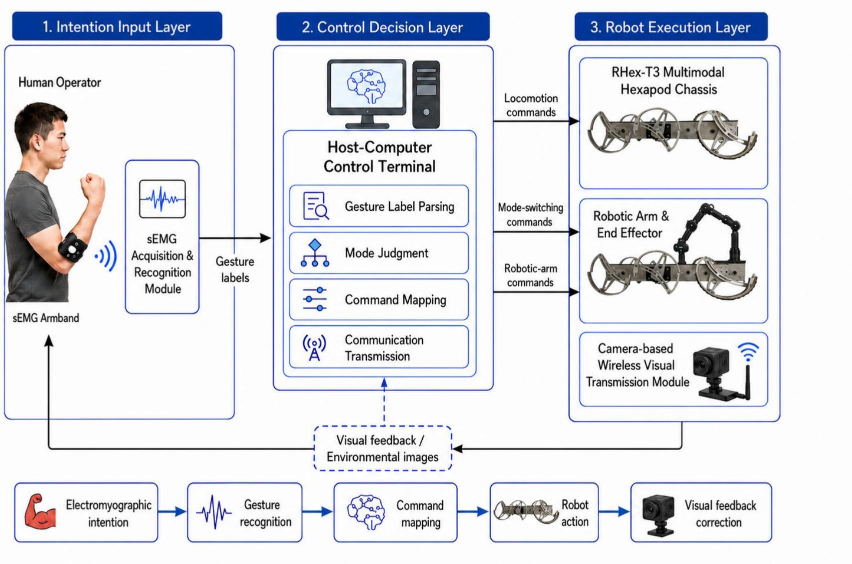

Figure 1. Overall architecture of the sEMG-controlled RHex-T3 hexapod mobile grasping robot system.

3.2. Functional Layers

The architecture in Figure 1 can be divided into three layers. The intention input layer collects forearm sEMG signals and outputs discrete gesture labels. The control decision layer, implemented on the host computer, performs gesture parsing, mode determination, command mapping, and communication. The robot execution layer consists of the RHex-T3 chassis, robotic arm, end effector, and camera module. The chassis provides mobility and target approach, the arm performs grasping and release, and the camera returns robot-perspective images for operator feedback.

3.3. Communication and Feedback

During operation, the sEMG module produces real-time gesture labels. The host computer maps these labels into chassis locomotion commands, mode-switching commands, or robotic-arm commands according to the current control mode, and then sends them to the robot through serial communication. While the robot executes the commanded action, the camera continuously provides visual feedback. The feedback path in Figure 1 therefore forms a closed loop of electro-myographic intention, command mapping, robot action, and visual feedback correction.

4. Control Method and Task Execution

4.1. Control Framework

The control method is based on a recognition front end, command mapping, hierarchical control, and a task state ma-chine. Figure 2 illustrates how recognition results pass through mode judgment and command generation before being ex-ecuted by either the chassis or the robotic arm. Because the number of gesture categories that can be stably recognized online is limited, this work does not adopt a one-gesture-one-task design. Instead, gesture labels are treated as discrete control symbols and reused in different modes. This design allows a compact gesture set to support both chassis motion and robotic-arm manipulation.

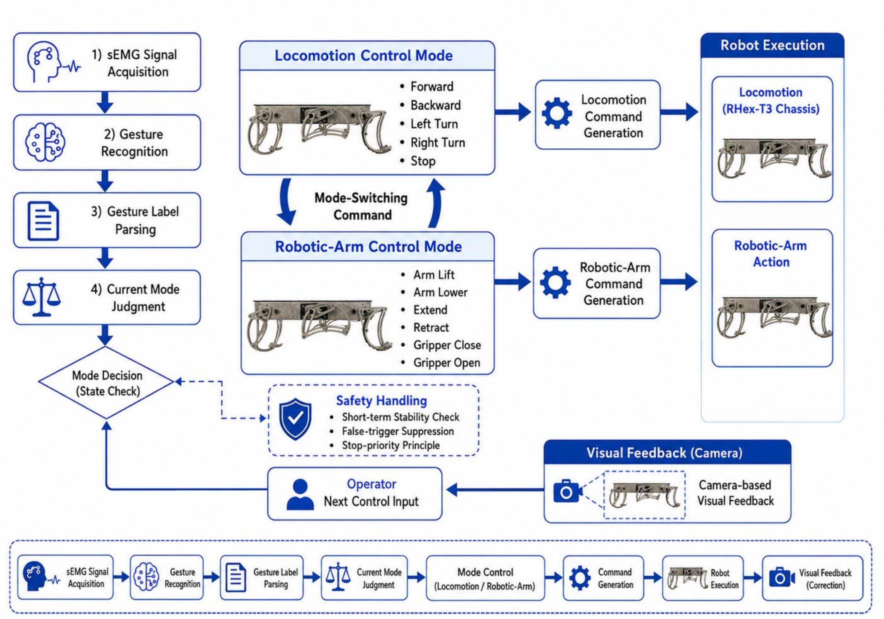

Figure 2. Control-flow and mode-switching diagram for the proposed sEMG-controlled RHex-T3 assistive robot system.

4.2. Gesture-to-Command Mapping

In locomotion mode, gesture labels are mapped to forward movement, backward movement, left turn, right turn, stop, or mode switching. In robotic-arm mode, the same labels are reinterpreted as arm lifting/lowering, extension/retraction, gripper opening/closing, or return to locomotion mode. Table 1 summarizes this reuse of the same gesture labels under different control modes. The mapping should prioritize frequently used commands by assigning them to gesture classes with higher recognition stability.

Table 1. Gesture-to-Command Mapping

Gesture Label	Locomotion Control Mode	Robotic-Arm Control Mode
g1	Forward	Arm lift / extend
g2	Backward	Arm lower / retract
g3	Left turn	Gripper close
g4	Right turn	Gripper open
g5	Stop / mode switch	Return to locomotion mode

4.3. Hierarchical Control and Mode Switching

The system uses two primary modes: locomotion control and robotic-arm control. As depicted in Figure 2, the locomotion mode supports mobility and target approach, while the robotic-arm mode supports grasping and release. A specific mode-switching label transfers the system between these modes. Together with the mapping rules in Table 1, this hier-archical design avoids command conflicts between the chassis and the arm, reduces the burden of recognizing many gestures, and allows the same input interface to support a larger set of control meanings.

4.4. Task Execution Workflow

The assistive object retrieval task is organized into four stages. First, the operator controls the chassis to approach the target area using sEMG commands, with visual transmission assisting direction correction. Second, after the target enters a suitable workspace, the operator completes final alignment and switches to robotic-arm mode. Third, the operator controls arm extension, posture adjustment, and gripper closing to grasp the object. Fourth, the system returns to locomotion mode for delivery and then switches again to arm mode for release. This task sequence also defines the composite evaluation scenario described in Section 5.5.

4.5. False-Trigger Suppression and Safety Handling

To improve safety, commands should be issued only when the same label remains stable across consecutive recognition windows. Chassis and arm commands are separated by mode isolation, as indicated by the two-branch structure in Figure 2. When the recognition output is unstable or undefined, the system should enter a hold or stop state rather than continue a high-risk action. Critical operations such as grasping and release should rely on operator confirmation based on visual feedback.

5. Experimental Design

5.1. Experimental Platform and Scenario

Experiments are designed at four levels: recognition input, chassis control, grasping execution, and end-to-end task completion. The goal is not to compare sEMG classifiers, but to evaluate whether existing recognition methods can be deployed as an online control interface and whether the integrated system can support a complete assistive task. The ex-perimental platform and task scenario are shown in Figure 3. They include the RHex-T3 chassis, robotic arm, camera module, sEMG device, host computer, locomotion area, target tabletop area, and delivery area. Table 2 further summarizes the objective and metrics of each experiment.

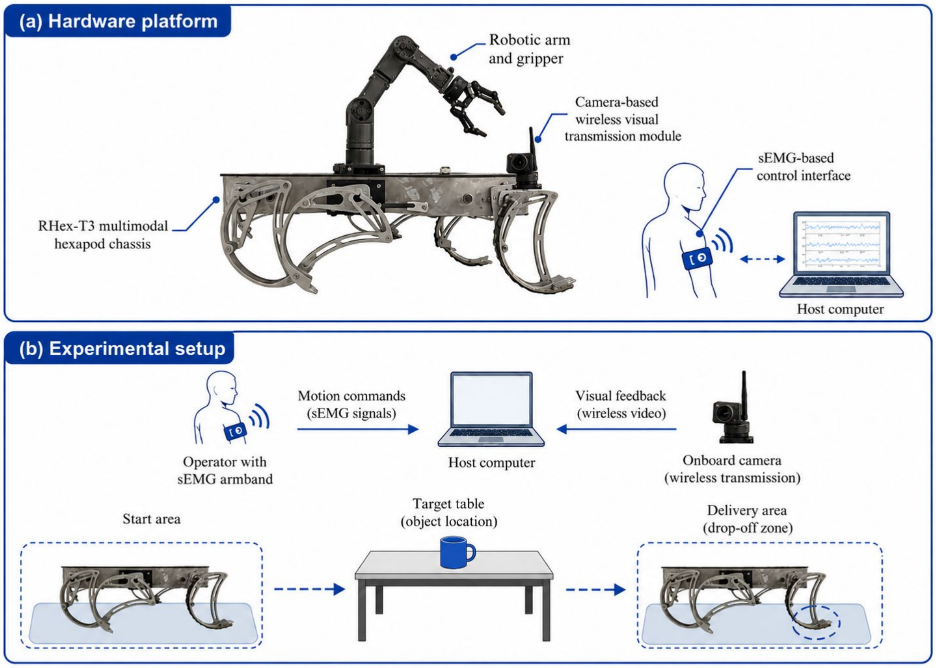

Figure 3. Experimental platform and setup for assistive object retrieval tasks.

Table 2. Experimental Design and Evaluation Metrics

Experiment	Objective	Robotic-Arm Control Mode
Online gesture recognition	Evaluate input reliability	Accuracy, latency, false-trigger rate
Chassis control	Validate locomotion command mapping	Success rate, response time, traversability
Robotic-arm grasping	Evaluate grasping operation	Grasping success rate, grasping time
Composite task	Validate end-to-end capability	Completion rate, task time, command number

5.2. Online Gesture Recognition

Experiment 1 evaluates online gesture recognition, corresponding to the recognition-input level in Table 2. The oper-ator performs a predefined gesture set repeatedly, and the system records the output labels, ground-truth labels, and the time from gesture initiation to stable output. The main metrics are online recognition accuracy, single-recognition latency, false-trigger rate during continuous use, and performance differences among users.

5.3. Chassis Locomotion Control

Experiment 2 evaluates chassis locomotion control, following the command branch shown in Figure 2 and the evaluation metrics listed in Table 2. The operator uses sEMG inputs to trigger forward movement, backward movement, left turn, right turn, stop, and mode switching. The main metrics are control success rate, response time, traversability under dif-ferent terrain conditions, and control stability. This experiment verifies whether gesture labels can reliably drive RHex-T3 mobility and target approach.

5.4. Robotic-Arm Grasping

Experiment 3 evaluates robotic-arm grasping, which corresponds to the robotic-arm control branch in Figure 2. With the robot positioned near a target object, the operator uses visual feedback and sEMG gestures to control arm movement and gripper operation. The main metrics are grasping success rate, average grasping time, success rate under different object conditions, and statistics of failure causes such as visual judgment error, inaccurate end-effector positioning, improper gripper-closing timing, or sEMG false triggering.

5.5. Composite Task Experiment

Experiment 4 evaluates the composite task under the platform and scenario shown in Figure 3. The operator controls the robot to move from the initial position to the target tabletop, observes the target through the camera, switches to arm mode, grasps the object, returns to locomotion mode, delivers it to a designated position, and releases it. The main metrics are task completion rate, average task time, number of user commands, failure causes, and the effect of visual feedback by com-paring conditions with and without visual transmission.

6. Results And Discussion

6.1. Online Control Usability

The results are analyzed from three perspectives: practical usability, failure-prone stages, and the significance of sEMG control compared with traditional interfaces. Table 3 summarizes the main experimental results used for this discussion. If online recognition accuracy remains high, latency is low, and false triggers are controllable, the sEMG module can serve as a front end for task-level control. However, online recognition is more susceptible than offline recognition to wearing position, muscle fatigue, gesture transition, and user differences. Short-term adaptation or calibration may therefore be needed for practical use.

Table 3. Summary of Experimental Results

Test Item	Metric	Result
Online recognition	Accuracy	91.8%
Online recognition	Single-recognition latency	185 ms
Online recognition	False-trigger rate	6.7%
Chassis control	Command success rate	94.2%
Chassis control	Average response time	230 ms
Chassis control	Traversability on flat ground	100%
Chassis control	Traversability on uneven ground	86.7%
Robotic-arm grasping	Grasping success rate	78.3%
Robotic-arm grasping	Average grasping time	18.6 s
Robotic-arm grasping	Release success rate	91.7%
Composite task	Task completion rate	73.3%
Composite task	Average task time	

6.2. Chassis and Grasping Performance

Chassis control results indicate whether the gesture-to-command mapping in Table 1 can support navigation and target approach. As reported in Table 3, the command success rate and response time reflect the reliability and real-time per-formance of this mapping. RHex-T3 provides a hardware advantage over ordinary wheeled platforms on uneven ground or in lightly obstructed environments, but failures may still arise from sEMG false triggering, terrain effects, load changes, or communication latency. Robotic-arm grasping is generally more failure-prone than chassis movement because it de-pends simultaneously on target localization, end-effector pose, gripper timing, object shape, and visual feedback quality.

6.3. End-to-End Task Capability

The composite task experiment is the most direct validation of system usability because it evaluates the whole chain from approach to grasping and delivery, as arranged in Figure 3. The task completion rate and average task time in Table 3 provide the main evidence for end-to-end feasibility. Failures are expected to concentrate in target localization and grasping execution, whereas the approach stage has simpler action semantics. If visual feedback improves task completion rate compared with the no-visual-transmission condition, it confirms that camera feedback is a key component of remote mobile grasping.

6.4. Comparison and Limitations

Compared with buttons, joysticks, or remote controllers, sEMG control offers a non-invasive and more natural way to express intention, which may reduce operating burden for users with limited upper-limb function. This paper does not claim that sEMG is superior in all aspects; traditional controllers still have advantages in precise continuous control and stability. The results in Table 3 should therefore be interpreted as preliminary evidence of feasibility rather than proof of full replacement. The value of this work lies in verifying that sEMG can serve as a feasible assistive control interface when combined with mode switching and task-level action mapping.

7. Conclusion

This paper presented an sEMG-controlled RHex-T3 hexapod mobile grasping robot system for assistive object retrieval. The system architecture in Figure 1 integrates a multimodal hexapod chassis, robotic arm and end effector, wireless visual transmission, sEMG acquisition and recognition, and a host-computer control terminal. Through the control flow in Figure 2, gesture-to-action mapping, hierarchical control, and mode switching convert electromyographic intention into chassis locomotion, robotic-arm operation, and task execution.

The study verifies the preliminary feasibility of using sEMG to drive a hexapod mobile manipulator for mobility, ap-proach, grasping, and delivery. The experimental scenario in Figure 3 and the summarized results in Table 3 jointly support this conclusion. Its contribution lies in system integration and task-level deployment rather than in a new recognition algorithm. The current system still has limitations, including sensitivity of sEMG to user differences and wearing condi-tions, reliance on operator visual judgment during grasping, limited autonomy, and restricted validation in complex en-vironments. Future work will introduce individualized calibration, adaptive recognition, shared control, visual object detection, grasp pose estimation, and multi-user long-term testing to improve robustness and practical value in assistive service scenarios.

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