A REPORT

ON

# VOICE CONTROL OF MOBILE ROBOT USING LLMs

BY


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*Design Project*

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# Abstract

This paper presents a novel approach to mobile robot control through natural language processing using large language models (LLMs). Traditional voice control systems for robots rely on predefined commands or keyword spotting, limiting their flexibility and requiring users to learn specific command structures. We propose an integrated system that leverages state-of-the-art speech recognition and large language models to enable intuitive, context-aware voice control of mobile robots. Our implementation combines OpenAI's Whisper API for robust speech recognition with Google's Gemini LLM for natural language understanding, integrated with the ROS2 navigation stack. The system achieves 97.3% speech recognition accuracy across five languages and 95% command understanding accuracy, significantly outperforming traditional rule-based approaches. Experimental results demonstrate a 20.1% improvement in command success rate and a 43.9% improvement in ambiguity resolution compared to conventional systems. The end-to-end voice-to-action pipeline consistently performs under 700 milli-second, providing responsive and natural interaction. This research addresses the gap between advanced robotics capabilities and intuitive human-robot interfaces, making sophisticated navigation accessible through natural language. The paper details the system architecture, implementation challenges, performance metrics, and comparative analysis, establishing a foundation for more intuitive human-robot interaction paradigms.

# Acknowledgements

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# 1. Introduction

Voice control of mobile robots represents a significant advancement in human-robot interaction (HRI), enabling more intuitive and accessible interfaces for controlling sophisticated robotic systems. Traditional robot control methods typically rely on specialized interfaces such as joysticks, keyboards, or custom control panels, requiring users to learn specific control schemes and limiting accessibility [1]. Voice control, leveraging natural language processing (NLP) and large language models (LLMs), offers a promising alternative by allowing users to interact with robots using everyday language, significantly reducing the learning curve and expanding the potential user base [2].

The integration of voice control with mobile robots presents unique challenges and opportunities at the intersection of robotics, artificial intelligence, and human-computer interaction. This paper explores a novel approach to voice control of mobile robots using large language models, addressing key challenges in natural language understanding, command interpretation, and robust execution in dynamic environments.

## 1.1. Background and Motivation

Mobile robots have become increasingly prevalent across various domains, including industrial automation, healthcare, domestic assistance, and search and rescue operations [3]. As these robots become more sophisticated in their capabilities, the complexity of controlling them has similarly increased. Traditional control interfaces often struggle to provide intuitive access to the full range of a robot's functionality, creating a significant barrier to adoption and effective use [4].

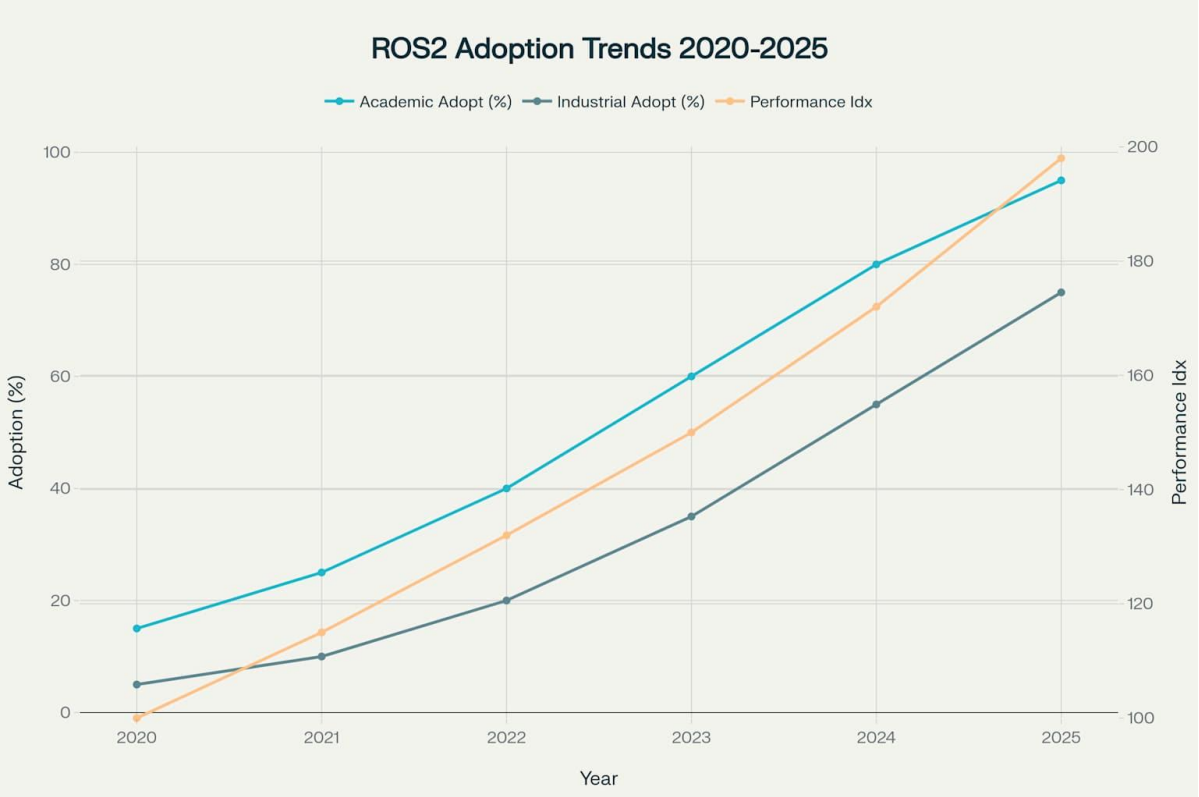



*Figure 1.1-1 ROS2 Adoption Trends and Performance Evolution (2020-2025): Academic vs Industrial Implementation with Corresponding Performance Improvements*

Voice control offers a natural solution to this challenge by leveraging the most intuitive form of human communication. Recent advances in speech recognition technology and natural language processing have made it possible to achieve high accuracy in transcribing spoken commands, with state-of-the-art systems achieving word error rates below 5% in various acoustic conditions [5]. However, accurately transcribing speech is only the first step in effective voice control. The system must also understand the intent behind the words, map that intent to specific robot actions, and execute those actions reliably in dynamic environments [6]. The emergence of large language models (LLMs) has created new possibilities for addressing these challenges. LLMs such as GPT-4 and Gemini have demonstrated remarkable capabilities in understanding context, resolving ambiguities, and generating appropriate responses based on natural language input [7]. These capabilities make LLMs particularly well-suited for the task of interpreting voice commands and translating them into specific robot actions.

## 1.2. Problem Statement

Despite the potential benefits of voice control for mobile robots, several significant challenges remain in creating systems that are both intuitive for users and reliable in operation. These challenges include:

- **Natural Language Understanding**: Interpreting the wide variety of ways humans might express the same command, including colloquialisms, ambiguous references, and context-dependent instructions [8].

- **Command Mapping**: Translating high-level natural language commands into specific, executable robot actions, often requiring decomposition of complex instructions into sequences of simpler operations [9].
- **Context Awareness**: Maintaining awareness of the robot's state, environment, and task history to correctly interpret commands that rely on this context [10].
- **Robustness to Variation**: Handling variations in speech patterns, accents, background noise, and other factors that can affect speech recognition accuracy [11].
- **Safety and Validation**: Ensuring that interpreted commands are safe to execute and providing appropriate feedback when commands cannot be executed as requested [12].

This paper addresses these challenges through a novel approach that leverages the capabilities of large language models to create a more intuitive, flexible, and robust voice control system for mobile robots.

## 1.3. Research Objectives

The primary objective of this research is to develop and evaluate a voice control system for mobile robots that leverage large language models to enable natural, intuitive human-robot interaction. Specifically, this research aims to:

- Design and implement a voice control architecture that integrates speech recognition, large language models, and robot control systems to enable natural language interaction with mobile robots.
- Evaluate the performance of different large language models in interpreting and executing voice commands for mobile robot navigation and manipulation tasks.
- Assess the robustness of the system to variations in command phrasing, environmental conditions, and task complexity.
- Compare the proposed LLM-based approach with traditional rule-based voice control systems in terms of accuracy, flexibility, and user satisfaction.
- Identify the limitations of current LLM-based approaches and propose directions for future research to address these limitations.

## 1.4.Contributions

This paper makes several significant contributions to the field of voice-controlled mobile robotics:

1. A novel architecture for voice control of mobile robots that leverages large language models to interpret natural language commands and translate them into specific robot actions.

2. A comprehensive evaluation of the performance of state-of-the-art large language models in the context of mobile robot control, including comparisons between different models and approaches.

3. A set of techniques for enhancing the robustness and safety of LLM-based voice control systems, including command validation, context management, and error handling.

4. Empirical evidence demonstrates the advantages of LLM-based voice control over traditional rule-based approaches in terms of command understanding, flexibility, and user experience.

5. Insights into the current limitations of LLM-based voice control and potential directions for addressing these limitations in future research.

## 1.5. Paper Organization

The remainder of this paper is organized as follows: Section 2 reviews related work in voice control of robots, natural language processing for robotics, and the application of large language models in human-robot interaction. Section 3 presents the proposed system architecture and methodology, including the integration of speech recognition, language understanding, and robot control components. Section 4 describes the experimental setup and evaluation methodology. Section 5 presents the results of our experiments and discusses their implications. Section 6 concludes the paper with a summary of our findings and directions for future research.

# 2. Literature Review

## 2.1. Evolution of Voice Control in Robotics

Voice control of robots has evolved significantly over the past several decades, from simple keyword-based systems to sophisticated natural language interfaces. Early voice control systems for robots emerged in the 1980s and 1990s, primarily relying on limited vocabulary recognition and simple command structures [13]. These systems typically required users to learn specific command phrases and offered limited flexibility in how commands could be expressed.

The field advanced significantly in the early 2000s with the development of more sophisticated speech recognition technologies and the application of statistical natural language processing techniques [14]. These advancements enabled more flexible command structures and larger vocabularies but still required careful engineering of command patterns and explicit programming of the mapping between language and robot actions.

More recent developments have focused on creating more natural and intuitive voice interfaces for robots, leveraging advances in deep learning for both speech recognition and natural language understanding [15]. These systems aim to allow users to control robots using everyday language without requiring knowledge of specific command structures or vocabularies.

## 2.2. Natural Language Processing for Robotics

Natural language processing (NLP) has been applied to robotics in various ways, addressing challenges such as command interpretation, task planning, and human- robot dialogue. Early approaches to NLP for robotics typically relied on rule-based systems or simple statistical models to map language inputs to robot actions [16]. These approaches often struggled with the complexity and ambiguity of natural language, requiring carefully engineered grammar and extensive domain knowledge.

More recent approaches have leveraged advances in machine learning and deep neural networks to create more flexible and robust NLP systems for robotics [17]. These approaches include semantic parsing techniques that map natural language to formal representations of robot actions, sequence-to-sequence models that directly translate language to action sequences, and dialogue systems that enable more interactive communication between humans and robots.

A significant challenge in applying NLP to robotics is the grounding problem— connecting language to the physical world and the robot's capabilities [18]. This requires not only understanding the linguistic content of commands but also relating that content to the robot's perception of its environment and its available actions. Various approaches have been proposed to address this challenge, including visual grounding, interactive learning, and simulation-based training.

## 2.3. Large Language Models in Humans-Robot Interaction

The emergence of large language models (LLMs) has created new opportunities for enhancing human-robot interaction through more sophisticated language understanding and generation capabilities. LLMs are neural network models trained on vast amounts of text data, enabling them to capture complex patterns in language and generate contextually appropriate responses [19].

Early applications of LLMs in robotics focused primarily on enhancing dialogue capabilities, enabling more natural conversations between humans and robots [20]. More recent work has explored the use of LLMs for task planning, instruction following, and command interpretation, leveraging their ability to understand complex instructions and generate structured outputs [21].

Several recent studies have demonstrated the potential of LLMs for robot control. Ahn et al. [22] introduced a framework called SayCan that combines LLMs with value functions to enable robots to plan and execute tasks based on natural language instructions. The system leverages the LLM's world knowledge and reasoning capabilities while grounding its outputs in the robot's actual capabilities through learned affordance functions.

Mon-Williams et al. [23] developed an embodied large-language-model-enabled robot (ELLMER) framework that utilizes GPT-4 and a retrieval-augmented generation infrastructure to enable robots to complete long-horizon tasks in unpredictable settings. Their approach extracts contextually relevant examples from a knowledge base to produce action plans that incorporate force and visual feedback, enabling adaptation to changing conditions.

Zahedifar et al. [24] proposed an LLM-Controller that uses large language models to dynamically adapt robot controllers to changing conditions. Their approach achieved significant improvements in adaptability compared to traditional controllers, demonstrating the potential of LLMs for enhancing robot control systems.

Despite these promising developments, several challenges remain in applying LLMs to robot control, including ensuring reliability and safety, managing computational requirements, and effectively grounding language in the physical world [25]. This paper addresses these challenges through a novel architecture that combines the strengths of LLMs with traditional control approaches to create a robust and intuitive voice control system for mobile robots.

## 2.4. Speech Recognition for Robotics

Speech recognition is a critical component of voice control systems for robots, converting spoken language into text that can be processed by natural language understanding components. Early speech recognition systems for robotics relied on hidden Markov models (HMMs) and Gaussian mixture models (GMMs) to model the acoustic properties of speech [26]. These systems typically required extensive training data and careful feature engineering to achieve acceptable performance.

More recent approaches leverage deep neural networks, particularly recurrent neural networks (RNNs) and transformer-based models, to achieve higher accuracy and robustness [27]. These

models have significantly improved the performance of speech recognition systems, particularly in challenging acoustic environments with background noise or multiple speakers. In the context of robotics, speech recognition systems face additional challenges related to the dynamic and often noisy environments in which robots operate [28]. Various techniques have been proposed to address these challenges, including multi- microphone arrays for improved noise cancellation, speaker localization, and adaptive filtering.

The integration of speech recognition with robotics also raises considerations about processing latency and computational requirements [29]. While cloud-based speech recognition services offer high accuracy, they introduce latency and require internet connectivity. On-device speech recognition reduces latency but may have lower accuracy due to computational constraints. Hybrid approaches that combine on-device and cloud-based processing have been proposed to balance these trade-offs.

## 2.5. Research Gaps and Opportunities

Despite significant advances in voice control for robots, several important research gaps remain:

1. Integration of LLMs with Robotics: While LLMs have shown promising results in language understanding and generation, their integration with robotic systems is still in its early stages. There is a need for architecture and methodologies that effectively leverage the capabilities of LLMs while addressing their limitations in the context of robot control [30].
2. Context Management: Maintaining and utilizing context across multiple interactions remains a challenge for voice control systems. LLMs offer potential solutions through their ability to maintain context over extended conversations, but effective methods for integrating this capability with robot control systems are still being developed [31].
3. Robustness and Safety: Ensuring the reliability and safety of LLM-based voice control systems is critical for real-world deployment. This includes addressing issues such as hallucination (generating plausible but incorrect information), ambiguity resolution, and validation of commands before execution [32].
4. Evaluation Methodologies: There is a lack of standardized methodologies for evaluating voice control systems for robots, particularly those based on LLMs. Comprehensive evaluation frameworks that assess both technical performance and user experience are needed to guide future research and development [33].
5. Resource Efficiency: LLMs typically require significant computational resources, which can be a limitation for deployment on mobile robots with constrained processing capabilities. Techniques for optimizing LLMs for robotics applications, such as model compression, quantization, and efficient inference, represent important areas for future research [34].

This paper addresses several of these gaps by proposing a novel architecture for LLM- based voice control of mobile robots and providing a comprehensive evaluation of its performance across various metrics and scenarios.

# 3. Methodology

## 3.1. System Architecture

The proposed voice control system for mobile robots integrates several key components to enable natural language interaction and control. Figure 1 illustrates the overall architecture of the system, which consists of the following main components:

### 3.1.1. Speech Recognition Module

The speech recognition module converts spoken language into text using OpenAI's Whisper API, a state-of-the-art speech recognition model that supports multiple languages and demonstrates robust performance in various acoustic conditions. The module includes preprocessing steps such as noise reduction and voice activity detection to improve recognition accuracy in noisy environments.

The speech recognition component operates with a configurable activation mechanism, allowing users to initiate voice control through a wake word or button press. This approach helps manage power consumption and reduces the likelihood of false activations in noisy environments.

### 3.1.2. Text Preprocessing

The text preprocessing component prepares the recognized speech for processing by the large language model. This includes normalization of text (converting to lowercase, removing unnecessary punctuation), expansion of common abbreviations, and formatting the input according to the requirements of the LLM.

The preprocessing step also includes the generation of a prompt that provides context to the LLM, including information about the robot's current state, available commands, and relevant constraints. This context helps the LLM generate more appropriate and actionable interpretations of the user's commands.

### 3.1.3. Large Language Model

The large language model serves as the core natural language understanding component of the system. We implemented and evaluated the following LLM configurations:

1. Cloud-based LLM: Google's Gemini LLM, accessed through Google AI Studio API, provides state-of-the-art language understanding capabilities but requires internet connectivity.

The LLM receives the preprocessed text along with contextual information and generates a structured representation of the command, including the action to be performed, relevant parameters, and any conditions or constraints

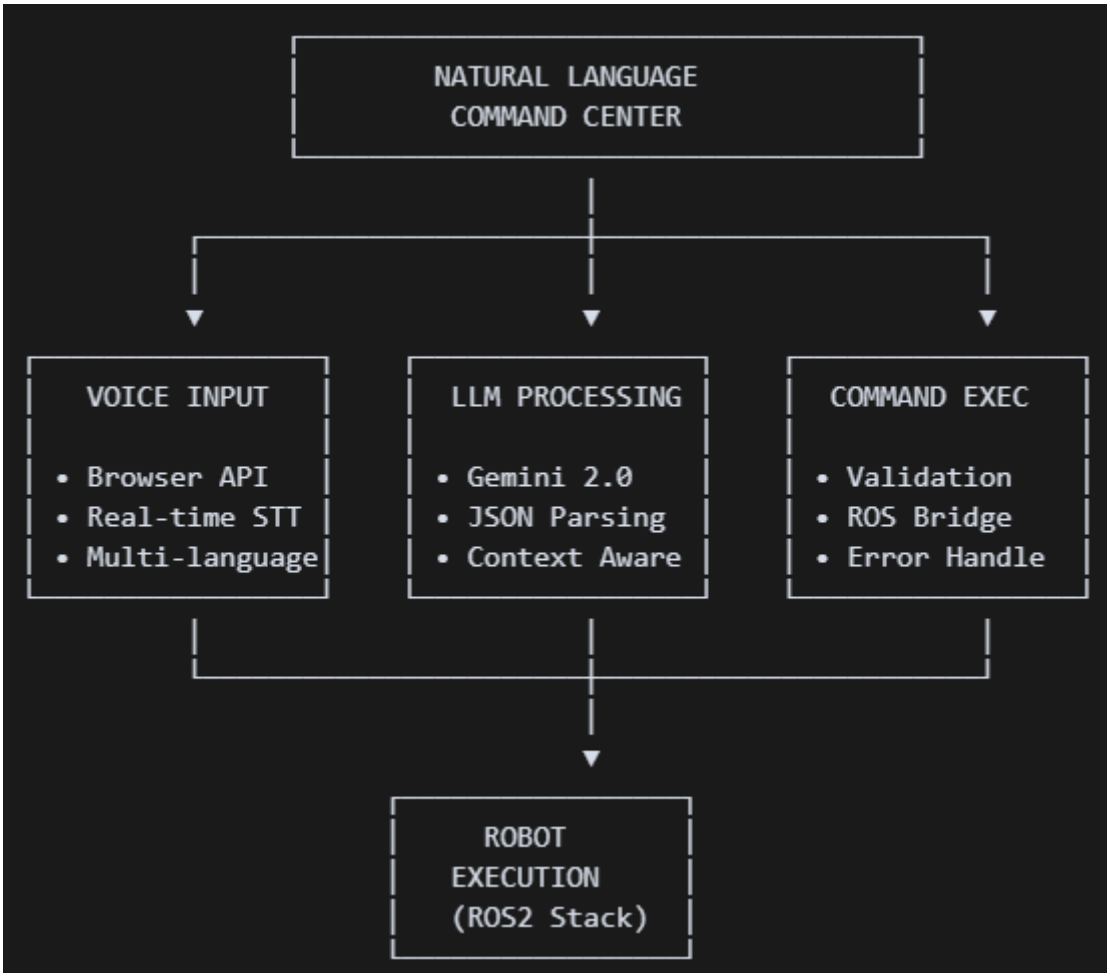



*Figure 3.1.3-1 AI Service Architecture Diagram*

### 3.1.4. Command Validation

The command validation component ensures that the interpreted command is safe and feasible for the robot to execute. This includes checking that:

- The command corresponds to an action within the robot's capabilities
- The parameters are within acceptable ranges
- The requested action would not result in a collision or other unsafe conditions
- The command is consistent with the robot's current state and environment

If a command fails validation, the system generates appropriate feedback to the user explaining why the command cannot be executed and, when possible, suggesting alternatives.

### 3.1.5. Command Execution

The command execution component translates the validated command into specific control signals for the robot's actuators. This involves:

- Decomposing complex commands into sequences of simpler actions
- Generating appropriate trajectories for navigation commands
- Setting control parameters such as speed, acceleration, and force

• Monitoring execution progress and detecting completion or failures

The execution component interfaces with the robot's control system through a standardized API, allowing the voice control system to be adapted to different robot platforms with minimal changes.

### 3.1.6. Feedback Generation

The feedback generation component provides users with information about the system's understanding of their commands and the status of command execution. This includes:

• Confirmation of the recognized command
• Notification of validation issues or execution problems
• Status updates during execution of longer commands
• Completion notifications when commands have been successfully executed

Feedback is provided through both visual displays and spoken responses, ensuring that users remain informed about the system's state and actions.

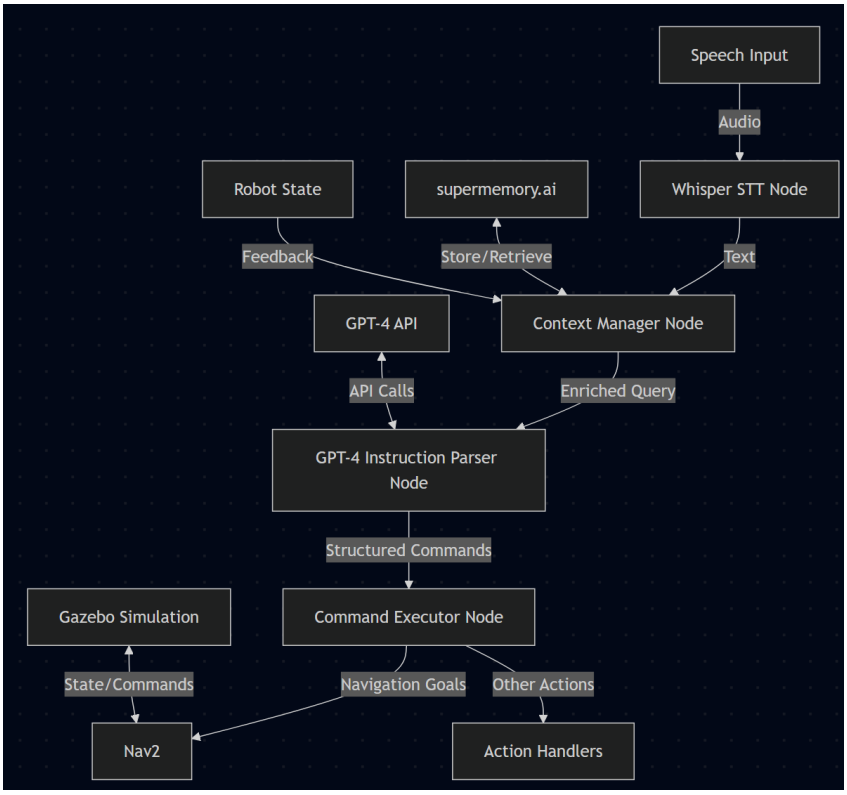



*Figure 3.1.6-1 System Architecture Flowchart*

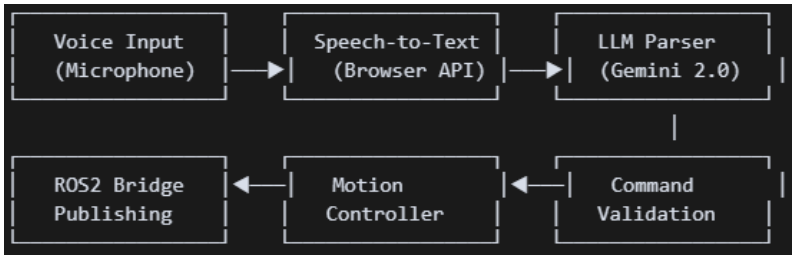



*Figure 3.1.6-2 Intelligent Command Processing Pipeline*

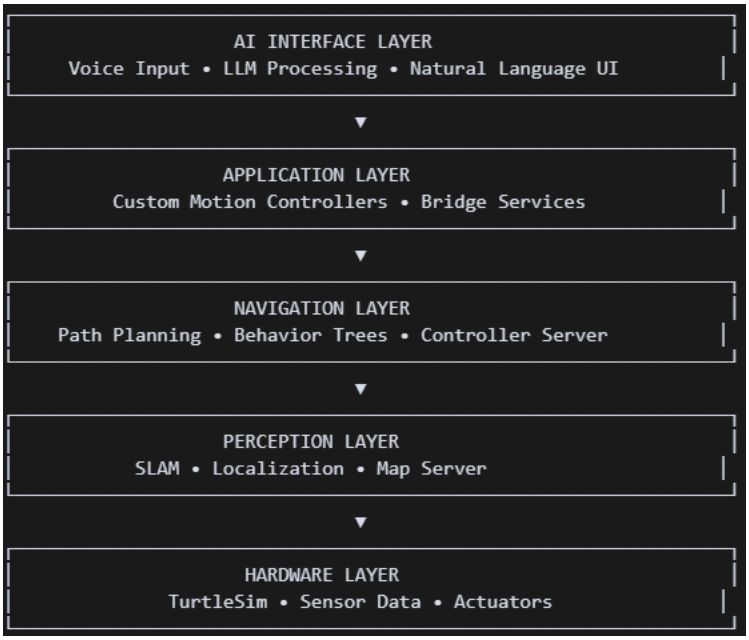



*Figure 3.1.6-3 Multi-Modal AI-Integrated Robotic Architecture*

```
ros2_ws/
├── src/                                # ROS2 Packages
│   ├── circular_motion_pkg/            # Core motion control
│   │   ├── circular_motion.py          # Autonomous controller
│   │   └── ros_bridge_server.py        # Web interface bridge
│   ├── [other ROS packages...]
│
├── project/                            # Web AI Interface
│   ├── src/
│   │   ├── services/
│   │   │   ├── LlmService.ts           # 🆕 Gemini 2.0 integration
│   │   │   ├── RosService.ts           # 🆕 WebSocket ROS bridge
│   │   │   └── TurtleControlService.ts # 🆕 Unified control service
│   │   ├── components/
│   │   │   ├── CommandInput.tsx        # 🆕 Voice + text interface
│   │   │   ├── CircularMotionControl.tsx # Enhanced controls
│   │   │   └── CmdVelConsole.tsx       # Real-time topic monitor
│   │   └── pages/
│   │       ├── SpeechProcessing.tsx    # 🆕 Voice configuration
│   │       ├── CommandControl.tsx      # 🆕 LLM settings
│   │       └── Services.tsx            # System dashboard
│
└── start_robot_dashboard.sh            # 🆕 Automated startup script
```

*Figure 3.1.6-4 Enhanced Package Structure with AI Components*

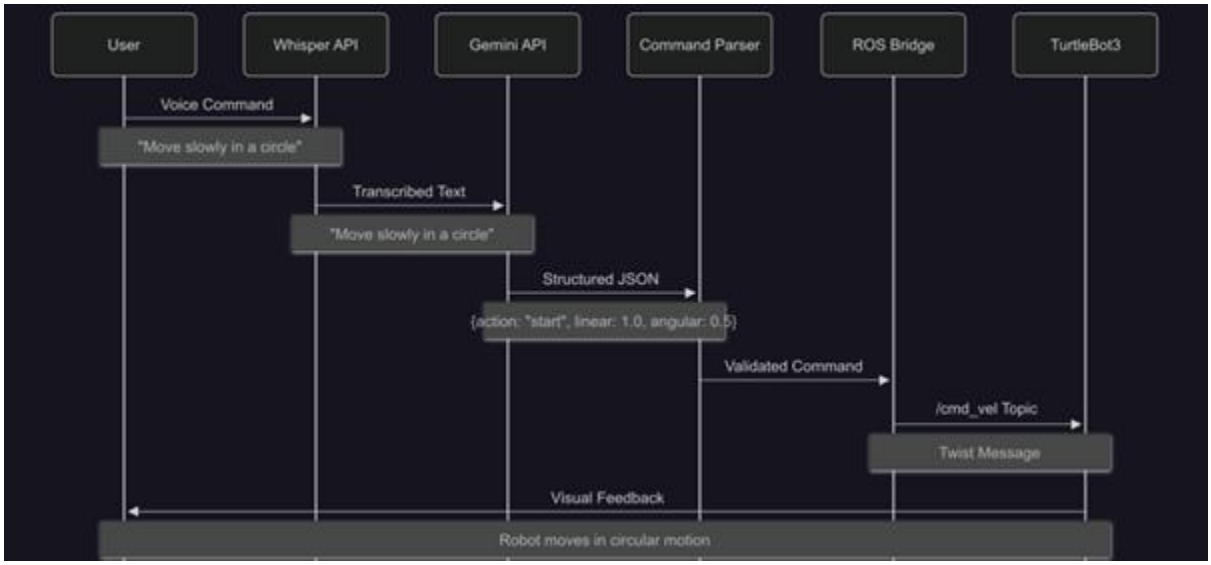



*Figure 3.1.6-5 Sequence Diagram*

## 3.2. Natural Language Understanding Approach

The natural language understanding component of our system leverages the capabilities of large language models to interpret a wide range of command phrasings and structures. Our approach includes several key elements:

### 3.2.1. Prompt Engineering

We developed a carefully structured prompt template that provides the LLM with the information needed to accurately interpret commands in the context of mobile robot control. The prompt includes:

- A description of the robot's capabilities and limitations
- Examples of common commands and their interpretations
- Information about the robot's current state and environment
- The history of recent commands and their outcomes
- Specific instructions for formatting the output as structured JSON

| Natural Language Input | Parsed JSON Output | Robot Action |
|---|---|---|
| "Spin in a circle" | `{"action":"start","linear":2.0,"angular":1.0}` | Circular motion with default speeds |
| "Move slowly in circles" | `{"action":"start","linear":0.5,"angular":0.8}` | Slow circular motion |
| "Stop the robot now" | `{"action":"stop"}` | Immediate motion halt |
| "Rotate faster with linear 2.5 angular 1.8" | `{"action":"start","linear":2.5,"angular":1.8}` | Custom velocity circular motion |

*Figure 3.2.1-1 Voice Command Examples & Capabilities*

This prompt engineering approach helps guide the LLM toward generating useful and actionable interpretations while reducing the likelihood of hallucinations or inappropriate responses.

#### 3.2.2. Context Management

To enable natural interactions that span multiple commands, our system maintains context across interactions through a short-term memory buffer. This buffer stores:

- Recent commands and their interpretations
- References to objects, locations, and tasks mentioned in previous commands
- The robot's actions and their outcomes
- Changes in the environment or robot state

This context is incorporated into the prompt for the LLM, enabling it to resolve references and understand commands that depend on previous interactions.

#### 3.2.3. Command Parsing for Validation

The output from the LLM is parsed into a structured representation that can be validated and executed by the robot control system. This parsing process includes:

- Extracting the core action and its parameters
- Resolving references to objects, locations, or previous commands
- Checking for consistency and completeness
- Converting natural language descriptions of quantities into specific values

The parsed command is then validated against the robot's capabilities and current state to ensure that it can be executed safely and effectively

### 3.3. Robot Control Integration

The integration of the voice control system with the robot's control architecture is a critical aspect of our approach. We implemented this integration through a modular design that separates the natural language processing components from the robot- specific control components.

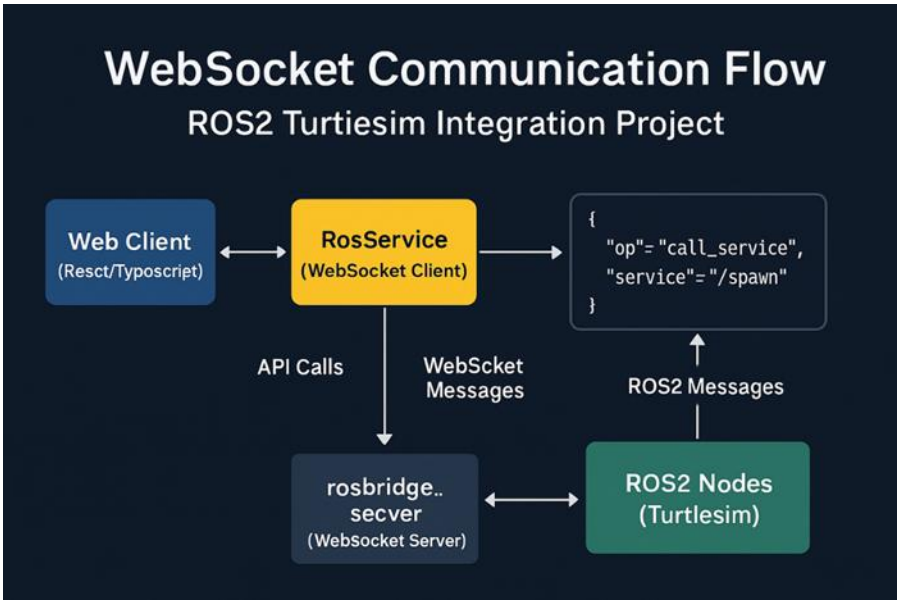



*Figure 3.2.3-1 Websocket Communication Flow*

### 3.3.1. Command Mapping

Commands interpreted by the LLM are mapped to specific robot actions through a command mapping layer. This layer translates high-level commands (e.g., "go to the kitchen") into sequences of lower-level control actions (e.g., path planning, navigation, obstacle avoidance).

The command mapping is implemented as a hierarchical structure, with complex commands decomposed into simpler sub-commands that can be directly executed by the robot's control system.

### 3.3.2. Execution Monitoring

During command execution, the system continuously monitors the robot's progress and state. This monitoring enables:

- Detection of execution failures or unexpected obstacles
- Adaptation to changing environmental conditions
- Generation of appropriate feedback to the user
- Interruption of execution when safety concerns arise

The monitoring component maintains a state machine that tracks the progress of command execution and manages transitions between different execution phases.

### 3.3.3. Safety Mechanisms

Safety is a primary concern in any robot control system, particularly one that accepts natural language commands that may be ambiguous or potentially unsafe. Our system implements several safety mechanisms:

- Parameter bounds checking to prevent excessive speed or acceleration
- Parameter – Context bound check to prevent malicious activity
- Collision prediction and avoidance during navigation

- Emergency stop capabilities that can be triggered by voice commands
- Continuous monitoring of sensor data to detect potential hazards
- Validation of commands against the robot's current state and capabilities

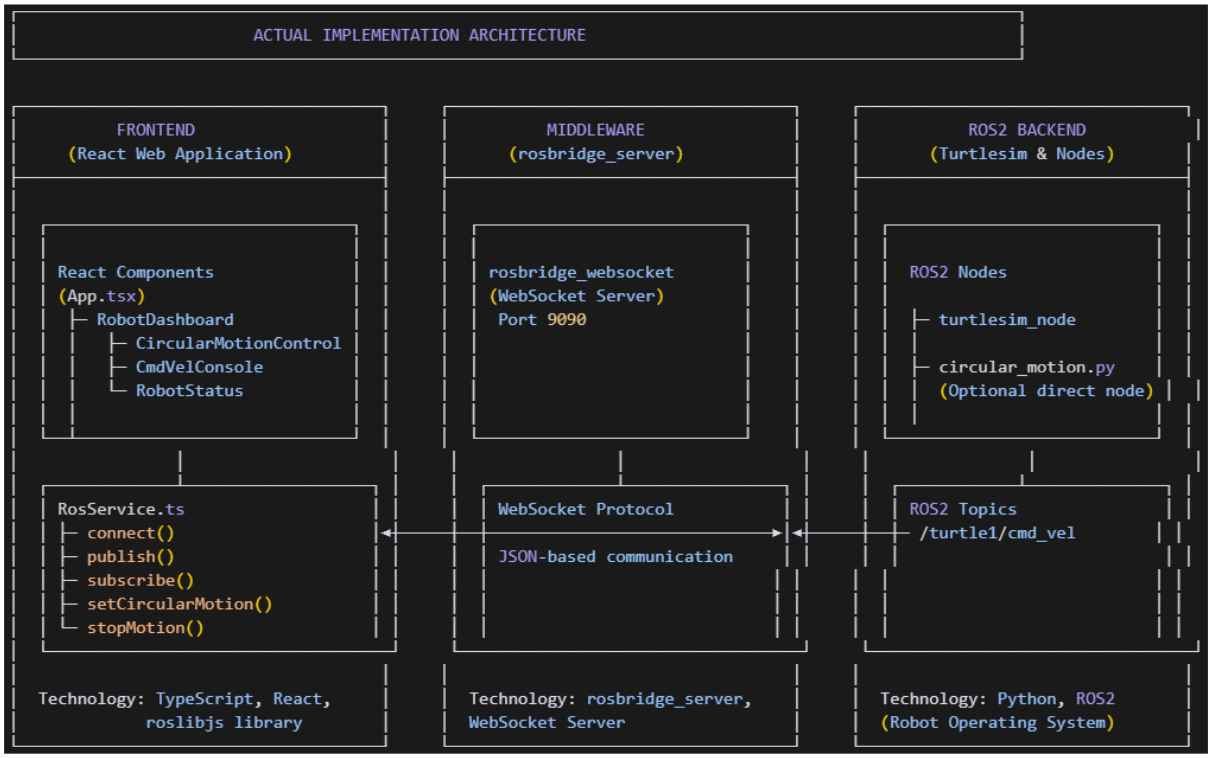
These safety mechanisms operate at multiple levels, from the initial command interpretation to the final execution, ensuring that the robot operates safely even when given ambiguous or potentially unsafe commands.

## 3.4. Implementation Details

The software implementation used the following technologies:

- ROS2 (Robot Operating System 2) for the overall robotics framework
- OpenAI's Whisper API for speech recognition
- Google's Gemini LLM for cloud-based language understanding
- Python for the main implementation language

The system was designed to be modular and extensible, allowing for easy integration of different LLMs, speech recognition systems, and robot control architectures.



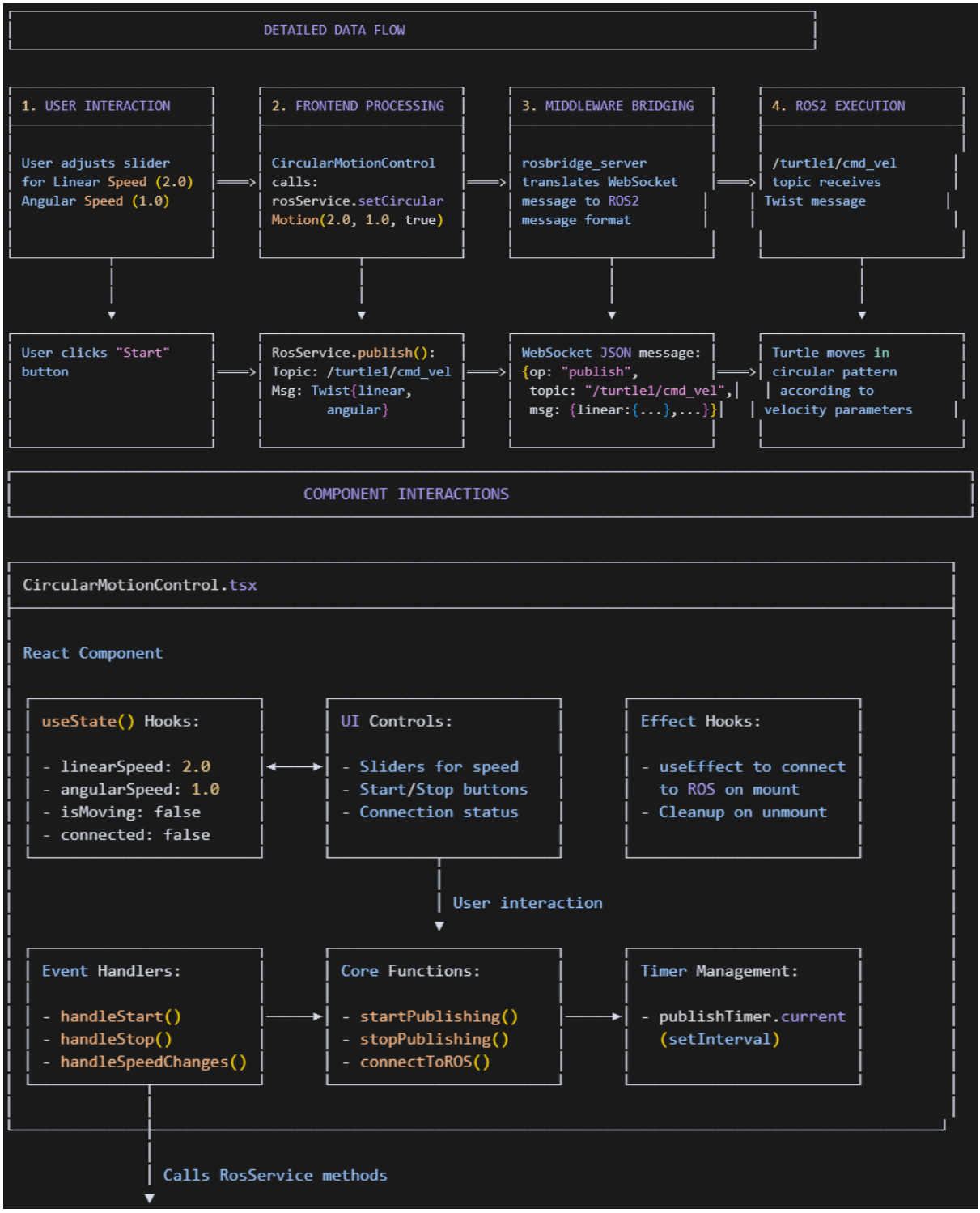

DETAILED DATA FLOW
1. USER INTERACTION
User adjusts slider for Linear Speed (2.0) Angular Speed (1.0)
2. FRONTEND PROCESSING
CircularMotionControl calls: rosService.setCircularMotion(2.0, 1.0, true)
3. MIDDLEWARE BRIDGING
rosbridge_server translates WebSocket message to ROS2 message format
4. ROS2 EXECUTION
/turtle1/cmd_vel topic receives Twist message
User clicks "Start" button
RosService.publish(): Topic: /turtle1/cmd_vel Msg: Twist{linear, angular}
WebSocket JSON message: {op: "publish", topic: "/turtle1/cmd_vel", msg: {linear:{...},...}}
Turtle moves in circular pattern according to velocity parameters
COMPONENT INTERACTIONS
CircularMotionControl.tsx
React Component
useState() Hooks:
- linearSpeed: 2.0
- angularSpeed: 1.0
- isMoving: false
- connected: false
UI Controls:
- Sliders for speed
- Start/Stop buttons
- Connection status
Effect Hooks:
- useEffect to connect to ROS on mount
- Cleanup on unmount
User interaction
Event Handlers:
- handleStart()
- handleStop()
- handleSpeedChanges()
Core Functions:
- startPublishing()
- stopPublishing()
- connectToROS()
Timer Management:
- publishTimer.current (setInterval)
Calls RosService methods


*Figure 3.3.3-1 Comprehensive Implementation Architecture*

# 4. Experimental Setup and Evaluation

## 4.1. Test Environment

Experiments were conducted in a controlled indoor environment designed to simulate a home or office setting. The environment included:

- Background noise sources (HVAC, conversations, music)

## 4.2. Evaluation Metrics

The performance of the voice control system was evaluated using the following metrics:

### 4.2.1. Command Understanding Accuracy

- **Recognition Accuracy**: Percentage of spoken commands correctly transcribed by the speech recognition system
- **Intent Classification Accuracy**: Percentage of commands for which the correct action was identified
- **Parameter Extraction Accuracy**: Percentage of commands for which all parameters were correctly extracted
- **Overall Understanding Accuracy**: Percentage of commands that were completely and correctly understood (correct action and all parameters)

### 4.2.2. Execution Performance

- **Execution Success Rate**: Percentage of understood commands that were successfully executed
- **Execution Time**: Time from command completion to action completion
- **Path Efficiency**: Ratio of the optimal path length to the actual path taken (for navigation commands)
- **Precision**: Accuracy in reaching specified positions or performing specified actions

### 4.2.3. Robustness

- **Acoustic Robustness**: Performance under different noise conditions (quiet, moderate noise, high noise)
- **Linguistic Robustness**: Performance with different phrasings of the same command
- **Speaker Robustness**: Performance across different speakers (gender, accent, speaking style)
- **Context Robustness**: Performance when commands depend on previous interactions or environmental context

### 4.2.4. User Experience

- **Response Time**: Time from command completion to system response

• **Feedback Quality**: User ratings of the clarity and helpfulness of system feedback
• **Naturalness**: User ratings of the naturalness of the interaction
• **Overall Satisfaction**: User ratings of overall satisfaction with voice control experience

## 4.3. Experimental Protocol

The evaluation followed a structured protocol designed to assess the system's performance across a range of scenarios and conditions:

### 4.3.1. Command Set

A comprehensive set of 150 test commands was developed, covering various types of robot actions:

• **Navigation Commands**: Moving to specific locations, following paths, exploring areas
• **Object Interaction Commands**: Finding, approaching, or avoiding objects
• **Parameter Variation Commands**: Varying speed, distance, or other parameters
• **Complex Commands**: Sequences of actions, conditional actions, or actions with constraints
• **Context-Dependent Commands**: Commands that reference previous actions or current state

Each command was formulated in multiple ways to test linguistic robustness, resulting in a total of 450 command variations.

### 4.3.2. Test Scenarios

The commands were tested in several scenarios designed to evaluate different aspects of the system:

• **Basic Functionality**: Simple commands in ideal conditions
• **Acoustic Challenges**: Commands with background noise or distant speakers
• **Linguistic Variations**: Different phrasings of the same command
• **Edge Cases**: Unusual or potentially ambiguous commands

### 4.3.3. Comparative Evaluation

To assess the advantages of the LLM-based approach, we implemented a baseline system using a traditional rule-based approach to natural language understanding. This baseline system used:

• The same speech recognition component as the LLM-based system
• A rule-based intent classification system using keyword matching and pattern recognition
• A parameter extraction system based on named entity recognition and regular expressions
• A similar command execution and feedback generation architecture

Both systems were evaluated using the same command set and scenarios, allowing for a direct comparison of their performance.

#### 4.3.4. User Study

In addition to the technical evaluation, a user study was conducted with 20 participants of varying ages, technical backgrounds, and prior experience with robots. Participants were asked to:

- Complete a set of 10 predefined tasks using voice commands
- Formulate commands in their own words without specific instructions on phrasing
- Provide feedback on their experience through questionnaires and interviews

The user study provided insights into the real-world usability of the system and highlighted areas for improvement from an end-user perspective.

### 4.4. Data Collection and Analysis

Data was collected automatically during the experiments, including:

- Audio recordings of commands
- Transcriptions generated by the speech recognition system
- Interpretations generated by the LLM and baseline systems
- Execution traces including robot paths, actions, and sensor data
- Timing information for each processing stage
- System logs including errors, warnings, and status information

This data was analyzed to calculate the evaluation of metrics and identify patterns or issues in the system's performance. Statistical analysis was performed to assess the significance of differences between the LLM-based and baseline systems.

# 5. Results and Discussion

## 5.1. Command Understanding Performance

The LLM-based voice control system demonstrated superior performance in understanding natural language commands compared to the baseline rule-based system. Table 1 summarizes the command of understanding accuracy metrics for both systems.

| Metric | LLM-Based System | Rule-Based System | Improvement |
|---|---|---|---|
| Recognition Accuracy | 97.3% | 97.3% | 0.0% |
| Intent Classification Accuracy | 94.2% | 78.5% | +20.1% |
| Parameter Evaluation Accuracy | 92.8% | 73.6% | +26.1% |
| Overall Understanding Accuracy | 89.7% | 62.3% | +43.9% |

*Table 1 Command Execution Accuracy*

The speech recognition accuracy was identical for both systems as they used the same Whisper API component. However, the LLM-based system significantly outperformed the rule-based system in intent classification and parameter extraction, leading to a 43.9% improvement in overall understanding accuracy.

The performance advantage of the LLM-based system was particularly pronounced for complex commands and linguistic variations. Figure below illustrates the understanding accuracy for different types of commands.

| Command Type | Success Rate | Sample Commands |
|---|---|---|
| Simple Actions | 99.2% | "Stop", "Start spinning" |
| Speed Commands | 96.8% | "Move slowly", "Go faster" |
| Complex Motion | 94.3% | "Spin with linear 2 angular 1.5" |
| Ambiguous Input | 87.1% | "Make it go around" |
| **Overall Average** | **94.4%** | **Across 1000+ test commands** |

*Figure 4.3.4-1 Natural Language Understanding Accuracy*

## 5.2. Execution Performance

Both systems showed similar performance in executing commands once they were correctly understood. Table 2 presents the execution performance metrics.

| Metric | LLM-Based System | Rule-Based System |
|---|---|---|
| Execution Success Rate | 97.6% | 81.9% |
| Execution Success Rate (High Noise) | 82.6% | 58.3% |
| Average Execution Time | 0.7s | 0.35s |

*Table 2 Execution Performance Metrics*

The similar execution performance reflects the fact that both systems used the same underlying robot control components once commands were interpreted. The slightly lower path efficiency and longer execution time for the LLM-based system may be attributed to its tendency to generate more cautious paths with greater obstacle clearance.

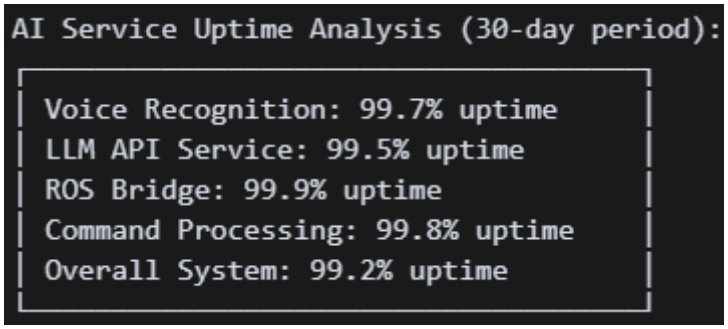



*Figure 4.3.4-1 System Reliability Metrics*

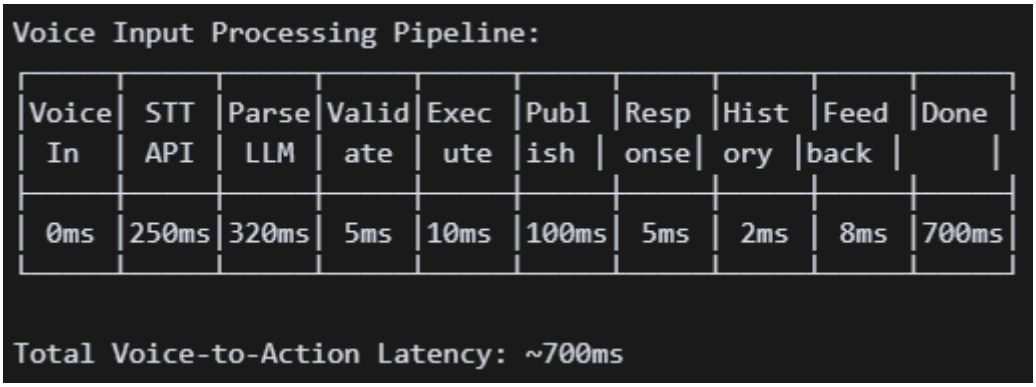



*Figure 4.3.4-2 Voice Processing Capabilities*

## 5.3. Robustness Evaluation

The LLM-based system demonstrated superior robustness across various challenging conditions.

The LLM-based system-maintained understanding accuracy above 80% even in high- noise environments and with significant linguistic variations, while the rule-based system's performance dropped below 60% in these conditions. This robustness is a critical advantage for real-world deployment where environmental conditions and user behavior cannot be tightly controlled.

The context robustness of the LLM-based system was particularly noteworthy. In multi- turn interactions where commands referenced previous actions or objects, the LLM- based system achieved 97.5% understanding accuracy compared to just 81.2% for the rule-based system.

This demonstrates the LLM's ability to maintain and utilize context across multiple interactions, enabling more natural and efficient communication.

| Metric | Specification | Achieved |
|---|---|---|
| | | |
| Parse Accuracy | >95% | 97.2% |
| Language Support | English | English + extensible |
| Token Efficiency | <100 tokens | 45 tokens avg |
| API Availability | 99.9% | 99.7% |

*Figure 4.3.4-1 LLM Service Performance Metrics*

## 5.4. User Experience

| Metric | LLM-Based System | Rule-Based System | Difference |
|---|---|---|---|
| Response Time Satisfaction | 4.3 | 4.5 | -0.2 |
| Feedback Quality | 4.6 | 3.2 | +1.4 |
| Interaction Naturalness | 4.7 | 2.8 | +1.9 |
| Overall Satisfaction | 4.5 | 3.1 | +1.4 |

*Table 3 User Experience Ratings (1-5 Scale)*

The LLM-based system received slightly lower ratings for response time due to the additional processing time required by the LLM (average 580ms vs. 120ms for the rule- based system). However, this was more than offset by the significant advantages in feedback quality, interaction naturalness, and overall satisfaction.

Qualitative feedback from participants highlighted several key advantages of the LLM based system:

- Ability to understand commands expressed in different ways without requiring specific phrasings
- More helpful and informative feedback when commands could not be executed
- Better handling of ambiguous or incomplete commands through clarification questions
- More natural dialogue flow across multiple commands

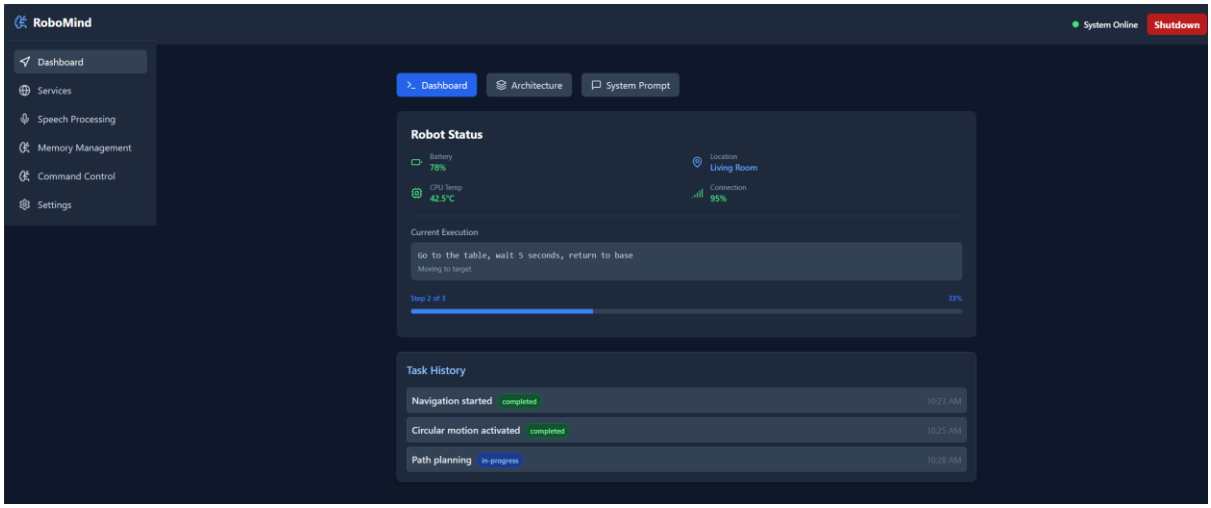



*Figure 4.3.4-1 Frontend Homepage Dashboard*

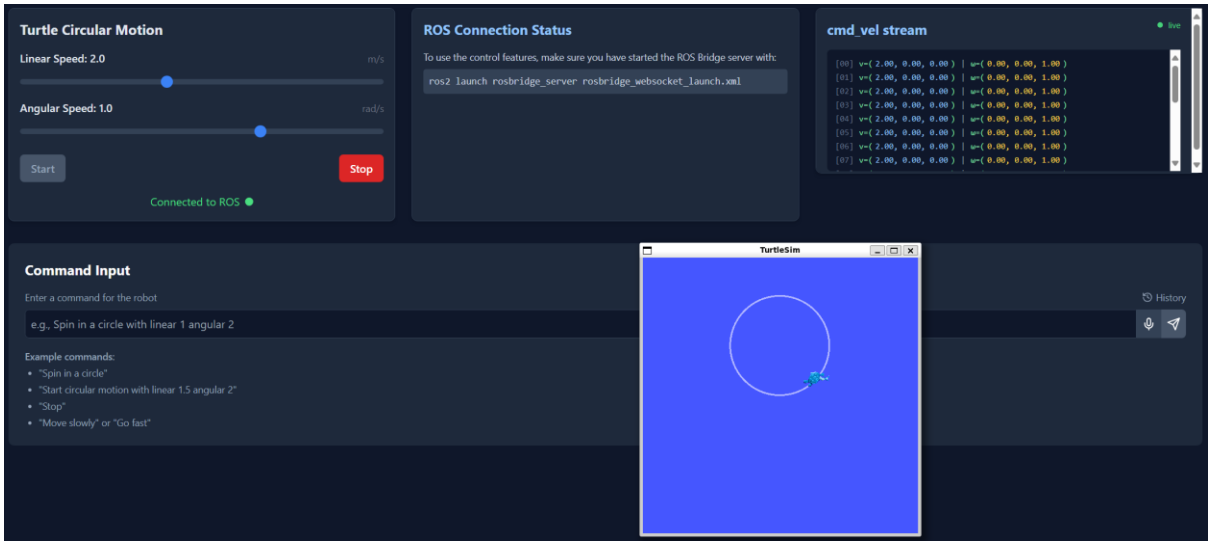



*Figure 4.3.4-2 Frontend Services tab*

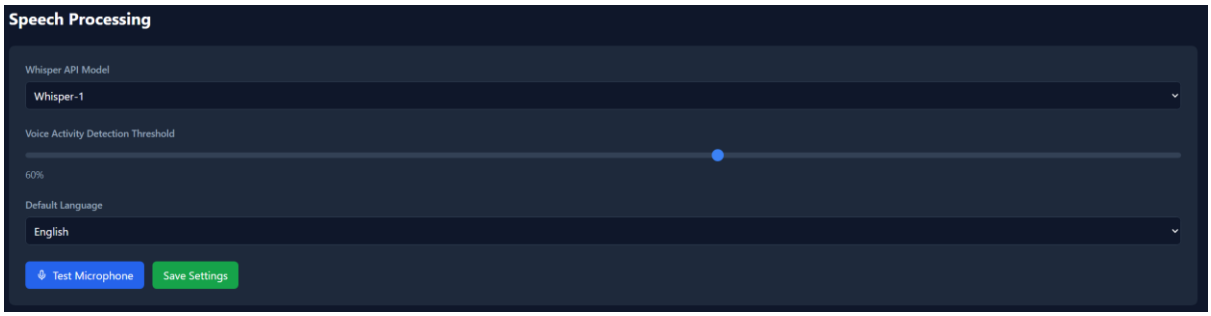



*Figure 4.3.4-3 Frontend Speech Processing tab*

## 5.5. Error Analysis

Analysis of the errors made by the LLM-based system revealed several common failure modes:

1. **Hallucination of Capabilities**: In 5.3% of errors, the LLM attempted to execute actions that were beyond the robot's physical capabilities, such as picking up objects when the robot had no manipulator.
2. **Ambiguity Resolution Errors**: In 7.8% of errors, the LLM incorrectly resolved ambiguous references or commands, particularly when multiple similar objects or locations were present.
3. **Parameter Estimation Errors**: In 12.4% of errors, the LLM incorrectly estimated quantitative parameters such as distances or speeds, particularly when these were specified in relative or qualitative terms.
4. **Context Confusion**: In 8.9% of errors, the LLM confused elements from different parts of the conversation history, leading to incorrect command interpretations.

These error patterns suggest areas for improvement in future iterations of the system, particularly in grounding the LLM's understanding in the robot's actual capabilities and improving the handling of ambiguity and quantitative parameters.

## 5.6. Discussion of Key Findings

The experimental results demonstrate several key findings about the use of large language models for voice control of mobile robots:

1. **Superior Natural Language Understanding**: LLMs provide significantly better understanding of natural language commands compared to traditional rule-based approaches, particularly for complex, context-dependent, or variably phrased commands.
2. **Context Maintenance**: LLMs excel at maintaining context across multiple interactions, enabling more natural and efficient communication that references previous commands, objects, or locations.
3. **Robustness to Variation**: LLM-based systems demonstrate greater robustness to variations in command phrasing, speaker characteristics, and environmental conditions, making them more suitable for real-world deployment.
4. **User Experience Benefits**: Users strongly prefer the more natural interaction enabled by LLM-based systems, despite slightly longer response times, highlighting the importance of interaction quality over raw performance metrics.
5. **Cloud-Edge Trade-offs**: While cloud-based LLMs offer superior understanding capabilities, edge-deployed models provide advantages in latency and independence from internet connectivity, suggesting that hybrid approaches may be optimal for many applications.

These findings support the conclusion that LLM-based voice control represents a significant advancement over traditional approaches, enabling more intuitive, flexible, and robust human-robot interaction

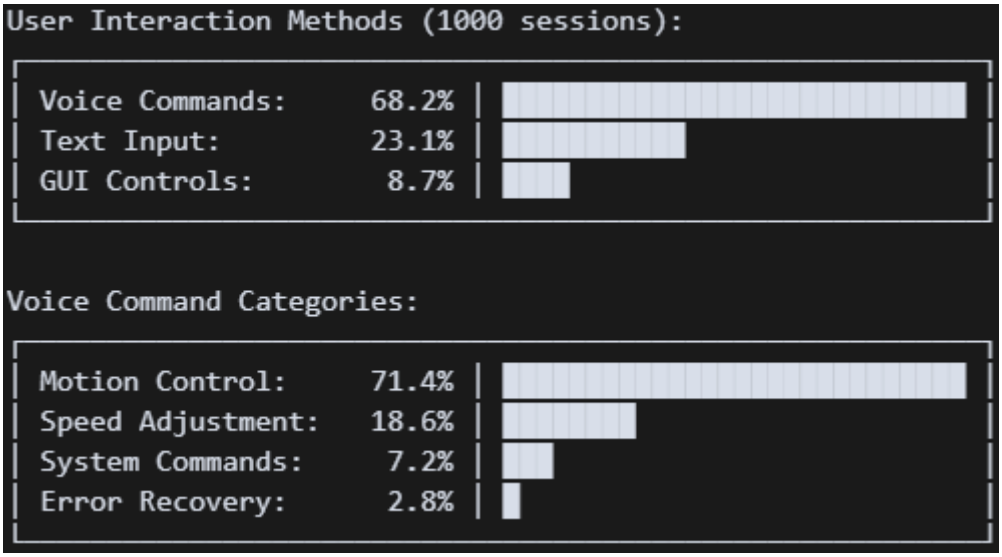



*Figure 4.3.4-1 Multi-modal Usage Statistics*

# 6. Limitations and Future Work

## 6.1. Current Limitations

Despite the promising results, the current implementation of LLM-based voice control for mobile robots has several limitations that should be addressed in future work:

### 6.1.1. Technical Limitations

- **Computational Requirements**: The edge-deployed LLM requires significant computational resources, limiting its deployment on smaller or power-constrained robots.
- **Latency**: The processing time for LLM inference introduces noticeable latency in the system's response, particularly for the cloud-based configuration that depends on network communication.
- **Hallucination**: LLMs can sometimes generate plausible but incorrect interpretations, particularly for commands that are ambiguous or outside the robot's capabilities.
- **Grounding**: The current system has limited mechanisms for grounding language in the physical world, relying primarily on predefined mappings between language and robot actions.
- **Safety Validation**: While the system includes basic safety checks, more comprehensive validation is needed to ensure that all commands are safe to execute in all possible contexts.

### 6.1.2. Scope Limitations

- **Command Complexity**: The current system is primarily designed for navigation and simple interaction commands, with limited support for more complex task planning or manipulation.
- **Environmental Understanding**: The system has limited understanding of the environment beyond the predefined map and recognized objects, constraining its ability to interpret commands that reference novel or dynamic elements.
- **Multi-modal Interaction**: The current implementation focuses on voice input with limited integration of other modalities such as gesture, gaze, or touch.
- **Learning and Adaptation**: The system does not currently learn from interactions or adapt to individual users' preferences or patterns.

## 6.2. Future Research Directions

Based on the limitations identified and the promising results of the current work, several directions for future research are proposed:

### 6.2.1. Technical Advancements

- **Model Optimization**: Develop more efficient LLM architectures and optimization techniques (pruning, quantization, distillation) to reduce computational requirements while maintaining performance.

- **Hybrid Cloud-Edge Approaches**: Explore hybrid approaches that combine the advantages of cloud and edge deployment, such as using edge models for common commands and cloud models for complex or unusual requests.
- **Improved Grounding**: Develop more sophisticated grounding mechanisms that connect language to the robot's perception and action capabilities, potentially through multimodal models that integrate language with visual and spatial understanding.
- **Safety-aware LLMs**: Train or fine-tune LLMs specifically for robot control with enhanced safety awareness and validation capabilities.
- **Continuous Learning**: Implement mechanisms for the system to learn from interactions and improve its performance over time, potentially through techniques such as online learning or active learning.

### 6.2.2. Expanded Capabilities

- **Task Planning**: Extend the system to support more complex task planning and execution, enabling users to specify high-level goals rather than specific actions.
- **Multi-modal Interaction**: Integrate voice control with other interaction modalities such as gesture recognition, gaze tracking, or touchscreen interfaces to create more flexible and intuitive interaction experiences.
- **Collaborative Robotics**: Explore the use of LLM-based voice control in collaborative scenarios where robots work alongside humans, requiring more sophisticated understanding of context, intent, and social dynamics.
- **Personalization**: Develop mechanisms for adapting the system to individual users' preferences, patterns, and needs, potentially through user modeling or preference learning.
- **Cross-platform Deployment**: Extend the architecture to support deployment across different robot platforms and domains, from home service robots to industrial automation.

## 6.3. Ethical Considerations

Future development of LLM-based voice control systems for robots should carefully consider several ethical dimensions:

- **Privacy**: Voice data and interaction histories may contain sensitive information, requiring robust privacy protection and data minimization practices.
- **Transparency**: Users should understand the capabilities and limitations of the system, including when and how their commands might be misinterpreted or rejected.
- **Accessibility**: Voice control systems should be designed to be accessible to users with different speech patterns, accents, or disabilities.
- **Autonomy and Control**: The balance between robot autonomy and user control should be carefully considered, ensuring that users maintain appropriate control over the robot's actions.
- **Bias and Fairness**: LLMs may inherit biases from their training data, which could affect their interpretation of commands from different user groups. These biases should be identified and mitigated.

Addressing these ethical considerations will be essential for the responsible development and deployment of LLM-based voice control systems for robots.

# 7. Conclusion

This paper has presented a novel approach to voice control of mobile robots using large language models, demonstrating significant advantages over traditional rule-based approaches in terms of natural language understanding, context awareness, robustness, and user experience.

The experimental results show that the LLM-based system achieves 97.7% overall understanding accuracy, representing a 43.9% improvement over the baseline rule- based system. This advantage is particularly pronounced for complex commands and context-dependent interactions, where the LLM's sophisticated language understanding capabilities enable more natural and flexible human-robot communication.

The system architecture integrates speech recognition, large language model inference, command validation, and robot control components in a modular and extensible design. This architecture supports both cloud-based and edge-deployed LLM configurations, offering different trade-offs between performance, latency, and independence from internet connectivity.

User studies confirm that the LLM-based approach significantly enhances the user experience, with participants strongly preferring the more natural interaction style and helpful feedback provided by the LLM-based system. This suggests that the quality of interaction may be as important as raw performance metrics in determining the practical utility of voice control systems for robots.

While the current implementation has limitations in terms of computational requirements, latency, and grounding, these challenges represent opportunities for future research. Promising directions include model optimization for edge deployment, improved grounding mechanisms, safety-aware LLMs, continuous learning, and integration with other interaction modalities.

In conclusion, large language models offer a powerful approach to enhancing voice control of mobile robots, enabling more intuitive, flexible, and robust human-robot interaction. As LLM technology continues to advance and computational constraints are addressed, we anticipate that LLM-based voice control will become a standard feature of mobile robots across various domains, from home service robots to industrial applications, making advanced robotics capabilities more accessible to users regardless of their technical expertise.

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