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Personal Voice Assistant Robot

Shwethaa.A.R, Ashwini GV, Samarth R Biradar, Shrikant Ravi Rathod, Sowmya G, Yamanur

Dept. of Electronics And Communication Engineering, AMC Engineering College, Bengaluru, Karnataka-83,India

Abstract - This project focuses on the development of a multifunctional Personal Assistant Robot designed to perform autonomous floor cleaning and home automation tasks. The system integrates various sensors, actuators, and controllers to navigate indoor environments, detect obstacles, and execute tasks such as vacuuming, mopping, and controlling lights or appliances. The robot can be operated using voice commands or a mobile application, enhancing user convenience and supporting smart home integration. By combining real-time decision-making with automation, this robot serves as a cost-effective and efficient solution for modern households, particularly aiding elderly or physically challenged individuals.

Keywords - Personal Assistant Robot, Autonomous Navigation, Obstacle Detection, Floor Cleaning Robot,

I. INTRODUCTION

In recent decades, the relentless advancement of robotic technology has paved the way for autonomous cleaning robots, which have been developed to supplant human labor in a variety of structured environments [4]. Among these inno- vations, robotic vacuum cleaners have achieved widespread adoption and recognition for their remarkable efficiency in cleaning indoor household floors [4]. However, the application and development of autonomous cleaning robots for large- scale, semi-structured environments—such as the sidewalks found in parks, university campuses, and residential commu- nities—remain in a nascent stage of development [4]. Despite the considerable progress made in the field of indoor cleaning robotics, extending these technologies to outdoor settings presents a host of substantial and unique challenges [4].

The primary objective for any cleaning robot, especially in large and complex outdoor spaces, is to ensure high efficiency and quality of cleaning [4]. To meet this standard, a cleaning robot must fulfill two primary objectives: maximizing its cov- erage of the designated area and minimizing the time required to complete the task [4]. Maximizing coverage necessitates optimizing the robot's path to ensure every part of the cleaning area is traversed, while minimizing task time involves reducing both the total travel distance and the number of turns in the planned path [4].

This paper proposes a comprehensive review of the tech- nologies required to create a "Personal Voice Assistant Robot." We will review the state-of-the-art in several key areas:

- Human-Robot Interaction: Exploring how design choices, from expressive lights to zoomorphic forms, can make robots more approachable and accepted.
- Robotic Design and Locomotion: Examining how in- novative hardware, such as reconfigurable bodies and advanced driving mechanisms, can enhance a robot's ability to navigate complex environments.
- Voice Assistant Technology: Analyzing the architectures of both cloud-based and embedded VAs to determine the best approach for a personal robot.

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- AI and Navigation Algorithms: Investigating the soft- ware intelligence, from CPP algorithms to deep learning models for speech recognition, that underpins the robot's autonomy.

II. LITERATURE REVIEW AND RELATED WORK

The development of a personal voice assistant robot is a multidisciplinary endeavor that builds upon decades of re- search in robotics, artificial intelligence, and human-computer interaction. This section provides a review of the foundational and recent works that inform the design of such a system. We categorize the literature into three primary areas: Human- Robot Interaction (HRI) specifically for cleaning robots, the technology behind Voice Assistants, and the mechanical and algorithmic aspects of Robot Design, Locomotion, and Navi- gation.

Human-Robot Interaction in Cleaning Robots

Early generations of cleaning robots were designed with a singular focus on functional efficiency, often neglecting the user experience. However, as these robots have moved into homes and other human-occupied spaces, the importance of HRI has become increasingly apparent [1]. Research now shows that human-friendly features are not just desirable but essential for the long-term adoption of these technologies [1]. Two key areas of HRI research are particularly relevant: robot expressiveness and the physical form of the robot.

- Robot Expressiveness: A robot's inability to communi- cate its internal state is a major barrier to effective HRI [1]. When a robot gets stuck or encounters a problem, a non- expert user may not be able to diagnose the issue, leading to frustration [1].
- Zoomorphic and Playful Design: The physical appear- ance of a robot profoundly influences how it is perceived by humans. This is especially critical in environments with vulnerable populations, such as care homes for the elderly. A study by Grimme et al. (2023) documented how a stan- dard, commercially available robotic vacuum cleaner was counterproductive to residents' well-being, as its dark color, unpredictable movements, and noise level were perceived as unsettling and frightening by people with dementia [2].

Voice Assistant Technology

The integration of a voice assistant is the core feature of the proposed robot. The technology behind VAs has evolved rapidly, branching into two main architectural paradigms: cloud-based and embedded systems.

- Cloud-Based and IoT-Enabled VAs: Most commercial VAs, such as those used in smart home systems, are cloud- based [8]. These systems capture a user's voice command, send it to a powerful cloud server for ASR and NLU pro- cessing, and then route the command to the appropriate IoT service to execute the action [8]. Platforms like IFTTT (If This Then That) and Adafruit IO act as intermediaries, connecting various devices and services to create a cohesive smart home ecosystem [8].
- Embedded and Offline VAs: To overcome the limita- tions of cloud-based systems, recent research has focused on developing end-to-end VAs that operate entirely offline on embedded hardware [7]. Lazzaroni et al. (2024) demonstrated the feasibility of such a system by creating a fully offline VA
- for the Italian language running on an NVIDIA Jetson AGX Xavier board [7].

Robot Design, Locomotion, and Navigation

The robot's physical capabilities are just as important as its interactive ones. Research in this area focuses on improving how robots move through and cover complex spaces.

- Reconfigurable Morphology: Fixed-morphology clean- ing robots often fail to clean tight spaces and corners ef- ficiently [3]. Reconfigurable robots, which can change their shape, offer a viable

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solution. Tun et al. (2019) developed the hTetro robot, a platform composed of four modules that can rearrange themselves into any of the seven tetromino shapes (I, L, Z, etc.) [3].

- Advanced Locomotion and Path Planning: Reconfig- urable robots present unique locomotion challenges. To ad- dress this, the hTetro robot was equipped with a Four-Wheel Independently-controlled Steering and Driving (4WISD) mechanism [3]. In this system, each wheel's steering and driving motors are decoupled and controlled independently, allowing for omnidirectional movement and a high degree of maneuverability essential for both path following and the reconfiguration process [3].

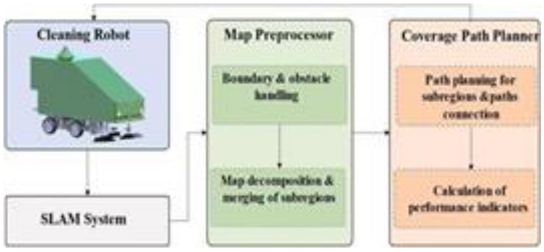

Fig. 1.. Cleaning robot coverage path planning framework.

III. HARDWARE SPECIFICATIONS

The physical implementation of a Personal Voice Assistant Robot requires a carefully selected set of hardware compo- nents capable of handling complex tasks such as autonomous navigation, real-time AI inference, and robust physical interac- tion. This section details the proposed hardware specifications for such a robot, drawing upon the components and systems described in the reviewed literature.

Central Processing Unit (CPU)

The "brain" of the robot must be a powerful embedded computing platform capable of running multiple processes in parallel, including the SLAM algorithm, the path planner, and the entire voice assistant

High-Performance Embedded Board: The reviewed literature points to two main classes of devices. For high- end applications requiring significant AI processing power, a board like the NVIDIA Jetson AGX Xavier is ideal. It features a 512-core NVIDIA Volta GPU with Tensor Cores, an 8-core ARM v8.2 CPU, and 32 GB of memory, making it well-suited for running complex deep learning models for ASR, NLU, and TTS completely of- fline [7]. For more cost-effective or less computationally demanding systems, a Raspberry Pi (e.g., Model 3 or 4) can be used. It is a low-cost, small-size computer that can handle basic home automation tasks and run lightweight AI models for voice control [8].

Sensory System

To perceive its environment and interact with users, the robot requires a comprehensive sensor suite.

Navigation Sensors: For robust autonomous navigation, a multi-sensor fusion approach is necessary. This in- cludes:

LIDAR: A 360-degree laser scanner is essential for generating accurate maps of the environment and for real-time obstacle detection, forming the backbone of the SLAM system [4].

IMU (Inertial Measurement Unit): Provides data on the robot's orientation and angular velocity, which is fused with LiDAR data in advanced SLAM algo- rithms like LIO-SAM to create more accurate 3D point cloud maps [4].

Cameras: Can be used for visual SLAM, object recognition, and potentially for gesture-based HRI in future implementations [4].

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Voice and State Sensors:
Microphone Array: A high-quality microphone is needed to capture user voice commands clearly, even in noisy environments [5]. An array can help with noise cancellation and determining the direction of the speaker.
Bump Sensors: These are simple but effective sen- sors that detect physical collisions. The data from these sensors can be used by an intelligent system to infer when the robot is trapped or struggling, triggering an "attention requirement" state [1].
Cliff and Dirt Sensors: Standard on many commer- cial cleaning robots, these sensors prevent the robot from falling down stairs and can detect heavily soiled areas for more focused cleaning [1].

Mobility and Actuation System
This system comprises the hardware responsible for the robot's movement and physical tasks.

Locomotion Mechanism: The 4WISD (Four-Wheel Independently-controlled Steering and Driving) mech- anism is proposed for its high maneuverability [3]. Each of the four wheels is equipped with:
A Steering Servo (e.g., Herkulex Servos) to control the orientation of the wheel independently [3].
A Micro-DC Motor with an Encoder to control the driving speed and direction of the wheel [3]. This decoupling of steering and driving allows for omnidirectional movement.
Reconfigurable Chassis: The body of the robot is modu- lar, consisting of multiple interconnected units. The con- nections are made via spring-loaded hinges which allow for compliance on uneven surfaces [3]. Electromagnets and limit switches are used to lock the modules into specific configurations (e.g., I, L, T shapes) during the transformation process [3].
Support and Stability: To ensure balance across differ- ent configurations and on uneven terrain, each module is supported by spring-loaded caster balls at its corners [3].

Interaction Hardware
These components are dedicated to communicating with the user.
Visual Feedback: An Adafruit NeoPixel Digital RGB LED strip or a similar component is attached around the robot's body. This strip is controlled by the main processor to change color based on the robot's state (e.g., cleaning, listening, trapped) [1].
Auditory Feedback: An onboard speaker is required for the Text-to-Speech (TTS) engine to output the robot's voice responses [8].

Power System
A distributed power system is necessary to supply the various components. This includes a main power source, such as a LiPo battery [1], and power relays controlled by the main CPU to manage power distribution to the motor controllers and other high-drain components, ensuring safety and efficient power management [3].

IV. SOFTWARE SPECIFICATIONS

The software architecture of the Personal Voice Assistant Robot is as critical as its hardware. It orchestrates the robot's autonomous behavior, processes user commands, and enables intelligent interaction. The proposed software stack is built upon open-source frameworks and a pipeline of specialized AI models.

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Core Frameworks and Operating System

Robot Operating System (ROS): ROS is the de facto standard for robotics research and development. It pro- vides a flexible framework of tools, libraries, and con- ventions to simplify the task of creating complex and robust robot behavior across a wide variety of platforms.

It would be used to manage communication between all the different hardware drivers and software modules, such as the SLAM system, the path planner, and the motor controllers.

Programming Language: Python is the primary lan- guage for implementation due to its extensive support for AI and machine learning libraries, as well as its ease of use for scripting complex behaviors [9]. Libraries like PyAudio would be used to manage real-time audio streams for the voice assistant [7].

Artificial Intelligence and Machine Learning Modules

The intelligence of the robot is driven by a series of AI and ML models that run on the embedded processor.

Voice Assistant Pipeline: This pipeline processes raw audio input into actionable commands and generates spoken responses. It is designed to run entirely offline.

Voice Activity Detection (VAD) and Keyword Spotting (KWS): A lightweight neural network like MarbleNet is used for the combined task of detecting human speech and listening for a specific wake-word. This model runs continuously but has a very small footprint (88K param- eters), making it efficient for an always-on task [7].

Automatic Speech Recognition (ASR): Once the wake- word is detected, a more powerful ASR model is activated to transcribe speech to text. The NVIDIA QuartzNet 15x5 model, available through the NeMo toolkit, is an excellent choice. It is a deep, time-channel separable con- volutional network that provides high accuracy. Through transfer learning, a model pre-trained on English can be fine-tuned on a smaller dataset for another target language, like Italian, achieving a low Word Error Rate (WER) [7].

Natural Language Understanding (NLU): The tran- scribed text is passed to an NLU engine to extract the user’s intent and any associated entities. The open-source Rasa framework, with its DIET (Dual Intent and Entity Transformer) classifier, is highly suitable for this task. It allows for the creation of a custom NLU model trained specifically on the commands relevant to the robot’s functions (e.g., cleaning, navigation) [7].

Text-to-Speech (TTS): To provide a voice response, a two-stage TTS system is used. First, a model like Tacotron2 generates a mel spectrogram from the re- sponse text. Then, a vocoder model like MelGAN syn- thesizes a human-like speech waveform from the spectro- gram. Both models are available in the NeMo toolkit and can be trained on single-speaker datasets like M-AILABS to create a unique voice for the robot [7].

Navigation and Control Intelligence:

SLAM System: An advanced SLAM algorithm like LIO- SAM is used to process data from the LiDAR and IMU to build a 3D point cloud map of the environment and continuously track the robot’s position within it [4].

Coverage Path Planner (CPP): The software proposed by Wu et al. (2025) provides a complete framework. It includes a Map Preprocessor that refines the SLAM map into optimized subregions and a Path Planner that uses an STC-based algorithm to generate a path minimizing turns and maximizing coverage [4].

Expressive State Controller: A Mamdani-type fuzzy inference system is used to determine the robot’s need for attention. It takes inputs like the recent bumping count and the robot’s past experience (stored in an ”Attention Memory”) to output an ”attention requirement” level. This numerical output is then mapped to a specific color on the RGB LED strip [1].

Software Comparison

The choice of ASR model is one of the most critical software decisions, as it directly impacts the core functionality of the voice assistant. The work by Lazzaroni et al. (2024) provides a direct comparison of several offline models on the Italian Common Voice dataset, which serves as an excellent benchmark.

Table I
Comparison of Offline Asr Model Performance

Model	WER (%)	CER (%)	Transcription Time (s)
Ours (NeMo-based)	11.7	3.12	0.215
Vosk	29.8	12.5	0.464
DeepSpeech	45.8	13.24	1.778

Results from Lazzaroni et al. (2024) on the Common Voice Italian test set for a 5.269s audio file [7].

As shown in Table I, the NeMo-based model achieved a significantly lower Word Error Rate (WER) and Character Error Rate (CER) compared to other popular offline solutions like Vosk and DeepSpeech. Furthermore, its transcription time was substantially faster, making it far more suitable for a real- time, interactive application [7]. This data strongly supports the selection of the NeMo toolkit and the QuartzNet architec- ture for the ASR component of the system.

V. SYSTEM METHODOLOGY AND DESIGN

The design of the Personal Voice Assistant Robot is guided by a methodology that prioritizes modularity, user-centric interaction, and robust autonomy. The system's operation can be conceptualized as a continuous loop of perception, reasoning, and action, orchestrated by the integrated software and hardware components. This section details the overall system workflow and the design of its key intelligent modules.

Overall System Workflow

The robot's operation follows a structured, event-driven workflow, as illustrated in the conceptual diagram (Fig. ??).

Initialization: Upon startup, the robot loads its envi- ronmental map (if previously generated) or initiates the SLAM process to build a new one. All software mod- ules, including the voice assistant pipeline, are initial- ized. The robot enters an idle state, with the lightweight Speech Classification (SC) module actively listening for the wake-word [7]. The LED strip displays a calm color, such as green, to indicate it is ready [1].

Voice-based Task Initiation: The user speaks the wake- word. The SC module detects it and activates the main ASR module to start transcribing the user's command (e.g., "Clean the living room") [7].

Path Planning and Execution: Based on the user's command, the Coverage Path Planner (CPP) generates an optimal cleaning path for the specified area using the preprocessed map [4]. The plan, a sequence of way- points and actions, is sent to the mobility controller. The controller translates these actions into specific steering angles and wheel velocities using the 4WISD kinematic model and sends the commands to the motors [3].

Continuous Interaction and Feedback: As the robot executes its task, it provides continuous feedback. The TTS module generates spoken updates (e.g., "Okay, starting to clean the living room") [7].

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State Monitoring and Exception Handling: Through- out its operation, the robot monitors its internal state. The fuzzy inference system continuously analyzes data from the bump sensors. If the robot enters an unde- sirable state, such as becoming trapped, the ”attention requirement” level increases [1]. This triggers a change in the LED color to red and a spoken alert (e.g., ”I seem to be stuck. Can you help me?”), actively seeking user intervention [1].

Design of Intelligent Modules

Voice Interaction Module: The core of the user experi- ence is the voice interaction module. Its design is based on the robust, offline pipeline proposed by Lazzaroni et al. [7]. A key design choice is the separation of the always-on, low- power SC module from the main ASR module. This ensures privacy and efficiency, as the system only processes and transcribes speech after being explicitly activated by the wake- word [7]. For personalization, the system can incorporate a speaker verification model. After wake-word detection, a short voice sample can be used to verify the user's identity before proceeding, ensuring that the robot responds only to authorized household members and can load user-specific preferences [5].

Navigation and Reconfiguration Module: This module is responsible for the robot's intelligent movement and physical adaptation.

Hierarchical Planning: The CPP framework operates hierarchically. The Map Preprocessor first performs a high-level decomposition of the environment into opti- mal, coverable subregions [4]. The Path Planner then generates detailed, low-turn paths within these subregions [4]. This two-step process makes the planning problem more tractable and efficient, especially in large, complex environments.
Adaptive Grid Discretization: A key innovation in the Map Preprocessor is the dynamic adjustment of the grid cell size (D) based on the geometric width of each subregion [4]. This allows the robot to adapt its path to the specific characteristics of different areas which is crucial for maximizing the coverage rate [4].

Unified Locomotion and Transformation Control: The 4WISD mechanism is controlled by a single kinematic model that can manage both standard locomotion (fol- lowing a path) and complex transformation maneuvers (reconfiguring the robot's shape). The general transfor- mation algorithm provides a lookup table of motion se- quences for changing between any of the seven tetromino configurations, simplifying the control logic [3].

VI. RESULT AND DISCUSSION

While this paper presents a conceptual review and system design rather than a novel implementation, we can project the expected results and discuss their implications based on the strong empirical evidence from the cited literature. The performance of the integrated Personal Voice Assistant Robot is anticipated to show significant improvements over existing commercial systems in key areas of efficiency, user interaction, and adaptability.

- Expected Performance Gains: The primary outcome of the proposed system is a marked enhancement in both cleaning efficiency and user satisfaction. The CPP framework proposed by Wu et al. (2025) demonstrated a coverage rate of 97.5% in real-world experiments, a substantial improvement over other methods which hovered around 70% [4]. This is largely attributed to the adaptive map preprocessing that tailors the path to the environment's geometry. While this focus on coverage leads to a longer path length and completion time in absolute terms, the value gained from a near-complete cleaning is significant [4].

- Discussion of Trade-offs and Challenges: The design of such a complex system inevitably involves trade-offs. The decision to prioritize coverage rate in the CPP algorithm, for instance, results in a longer task completion time compared to methods that cover less area [4].

Future Scope

The conceptual framework for the Personal Voice Assistant Robot, while comprehensive, represents a starting point. The reviewed literature itself points toward numerous avenues for future research and development that could further enhance the capabilities and user experience of such a system. This section outlines the most promising directions for future work, categorized into enhancements for autonomy, interaction, and broader applications.

Enhancing Autonomy and Intelligence

While the proposed system is highly autonomous in static environments, real-world homes are dynamic and ever- changing.

Dynamic Environment Handling: The current CPP framework is designed for static, a priori maps [4]. A critical area for future work is the integration of local trajectory planning and replanning capabilities. This would allow the robot to react in real-time to dynamic obstacles, such as people walking by, pets, or newly placed furniture, without halting its entire cleaning task [4].

- Long-Term Learning and Adaptation: The robot could be enhanced with long-term learning capabilities. By stor- ing and analyzing data over time, it could learn patterns in the environment, such as which areas accumulate dirt most quickly, and adapt its cleaning schedule accordingly.
- Terrain-Aware Locomotion: Future research could focus on developing terrain-aware locomotion paradigms. By using its onboard sensors to identify different floor types (e.g., carpet, hardwood, tile), the robot could automati- cally adjust its cleaning mechanism (e.g., brush height, suction power) and even its locomotion parameters for optimal performance on each surface [3].

Improving Human-Robot Interaction

The quality of the interaction can always be refined and deepened to create a more natural and engaging experience.

- Multi-Modal Interaction: The current design relies on voice and simple lights. Future iterations could incorpo- rate vision-based interaction. The robot could be trained to recognize gestures, allowing a user to simply point to an area and say, "Clean over there."
- Proactive and Mixed-Initiative Interaction: The current model is purely reactive, only acting upon a user's com- mand. A more advanced system could exhibit proactive behavior. For example, it might notice a spill using its camera and ask, "I see a mess on the floor. Would you like me to clean it up?" Exploring these mixed-initiative interactions, where the robot can initiate conversations, is a key area for future HRI research [6].
- Enhanced Conversational Resilience: While LLMs can absorb many errors, conversational breakdowns will still occur. Future work should focus on designing more sophisticated, multi-step recovery strategies. For instance, instead of just apologizing and asking for clarification, the VA could offer corrective options based on its inter- pretation of the flawed command, making the recovery process faster and more intuitive for the user [6].

VII. CONCLUSION AND REMARKS

This paper has presented a comprehensive review of the key research areas converging toward the creation of an advanced Personal Voice Assistant Robot for autonomous cleaning. By synthesizing the findings from the literature on Human-Robot Interaction (HRI), embedded voice assistant technologies, and reconfigurable robotic systems, we have outlined a conceptual framework for a robot that is not only highly efficient but also intuitive, user-friendly, and personalized.

The core conclusion of this review is that the limitations of current cleaning robots—namely their poor adaptability to complex environments and their lack of effective communica- tion with users—can be systematically addressed through the integration of modern hardware and software innovations. The mechanical challenges of navigating cluttered, semi-structured spaces can be overcome with reconfigurable morphologies and highly maneuverable locomotion systems like the 4WISD platform [3]. The algorithmic challenges of efficient navigation can be solved with sophisticated Coverage Path Planning (CPP) frameworks that maximize coverage while minimizing time and energy consumption [4].

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