Akshaya E, 2025, 13:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Towards a substantially autonomous robot as a personal assistant: An overview

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Abstract- An autonomous robot is a of machine equipped with sensors, actuators and processors, that empower it to detect its surroundings, handle information, and undertake tasks without human involvement. These robots are a demonstration of AI technology, as they depend on machine learning and deep learning algorithms to carry out tasks. Personal assistant robots are robots formulated to guide individuals with assorted tasks and activities. From automating household activities and repetitive tasks, robots rise above their traditional roles, by serving as companions and support systems. In essence, Autonomous robots beckon us forward to be used as personal assistant due to their potential to solve daily tasks and enhance productivity with human capabilities. These robots aim to strengthen the quality of life by automating regular duties and delivering personalized guidance. By closing the divide between humans and machines, this advancement opens up a world of eternal avenues.

Keywords: Personal Assistants, human capabilities, Companions.

I. INTRODUCTION

In the field of quality-of-life technology, we envision service robots playing an important role in our daily lives. Among the multifaceted roles of autonomous robots, one of the most captivating potentials is their ability to serve as personal assistants. They have been major contributors to enhancing personal care assistant tasks. These robots will operate in close proximity to human operators, so they must be safe and trustworthy. Let us delve into the world of autonomous robots as personal assistants and explore how they efficiently function in our homes and workplaces.

In the modernization of technology, current robots equipped with a variety of refined sensors are capable of navigation and operation. Robots must be capable of making decisions and they learn to recognize changes by fixing themselves. Robotic systems designed for structured environments, including those mounted on wheelchairs and mobile companions, are used for personal assistance and caregiving tasks, closely interacting with the user [21].

The Swiss F&P Robot Company has revolutionized the nursing industry with the development of Lio, a highly advanced artificial intelligence nursing robot that emulates various human capabilities. Amid the COVID-19 pandemic, Lio was swiftly modified to offer extra features like disinfection and monitoring body temperature remotely. Lio is fully compliant with ISO13482 safety standards, ensuring confidently tested and utilized in care facilities [38].

In 2007, Waseda University in Japan introduced 'TWENDYONE,' a high-tech nursing robot with 13 sensors in its hand. These sensors include one on its fingertips to detect force and others on its palm to sense pressure, helping it move precisely and offer a more natural, gentle touch with its soft palm. Equipped with a high-powered motor in its arm, "TWENDYONE" boasts exceptional power and versatility [16].

The burgeoning field of personal assistant robots has indeed seen a significant increase in survey papers, yet there remains a gap in comprehensive analysis and practical demonstrations of the methodologies employed. Recent literature indicates a trend towards integrating advanced machine learning techniques, such as reinforcement learning and artificial neural networks, to enhance the capabilities of these robots. Moreover, the development of virtual personal assistants (VPAs) has been propelled by advancements in computer vision, deep learning, speech generation, and recognition, aiming to create more natural and intuitive user experiences.

Robotics technology has evolved concentrated focused on three key areas of development generalities stable systems that function in structured surroundings, robotic systems mounted on wheelchairs, along with mobile companion robots able to follow its stoner for particular and care operations [21].

The initial category of robotic systems includes veritably beneficial for individuals requiring backing in a confined living space and for a specific range of tasks, similar to eating/drinking. The Handy 1 Robot Arm serves as a great example of a stationary robotic system. It offers an affordable solution for personal care and assistance. However, a significant drawback of static robotic systems is their limited mobility, making it difficult, and sometimes nearly impossible, to change their position. Using the robot for tasks like eating on a different floor might require frequently carrying it up and down stairs and manually attaching and detaching it repeatedly! [58].

The next category of robotic systems is the wheelchairmounted type, with the MANUS system being a leading example. The robotic arm is permanently attached to either the left or right side of the wheelchair, which can be inconvenient for performing certain tasks. Additionally, this design can cause mobility challenges, particularly when navigating through doors or stairs. Moreover, the cost of these systems is typically quite high.

The third concept proposes a mobile manipulator that trails behind the user's wheelchair in a structured environment. While it shares some of the same drawbacks as previous designs, it offers one significant benefit: the robot can navigate the area independently of both the wheelchair and the user. A well-known example of this type of robotic system is the KARES II mobile manipulator [2].

These studies underscore the importance of not only presenting theoretical frameworks but also providing empirical evidence and detailed illustrations of how these state-ofthe-art techniques can address the key challenges faced by personal assistant robots. As the technology progresses, future survey papers could benefit from a more hands-on approach, showcasing real-world applications and user evaluations to bridge the gap between theory and practice.

In this paper, we embark on the intricate realms of Computer Vision, Voice recognition and generator, Gesture Movements, Information retrieval and processing, Sensors, autonomous navigation, and Interconnectivity or Interoperability with other autonomous devices.

II. SYSTEM OVERVIEW

The paper discusses the path planning for personal assistant robots which includes Navigation, human-robot collaboration as gesture recognition techniques, Voice recognition to issue commands, Sensors that are used to implement and techniques behind them and methods of providing data essential data to autonomous robots. First, we discuss about the navigational framework for autonomous personal assistant robots revolves around employing Simultaneous Localization and Mapping (SLAM) techniques, including LiDAR-based SLAM, Visual SLAM (VSLAM), and sensor data fusion, to facilitate accurate and efficient navigation to avoid obstacles. Through comparison of SLAM methods, such as utilizing LiDAR sensors, stereo cameras, and inertial measurement units (IMUs), developers can ensure optimal performance in various environments. Leveraging frameworks like the Robotic Operating System (ROS) and algorithms like ORB SLAM and RTABMap, these robots can effectively navigate and interact with their environment, enhancing their ability to assist users in daily tasks. The next section addresses challenges such as the communication gap between humans and robots and ambiguity in gestures by employing vision-based sensors like depth cameras, particularly Kinect depth sensors, which offer accuracy and robustness in cluttered environments. These sensors capture gestures in real time, which are then processed using some machine learning algorithms such as Hidden Markov Models (HMMs) or Convolutional Neural Networks (CNNs).

Next, part of this paper provides a comprehensive overview of the sensors and techniques employed in autonomous personal assistant robots, focusing on their role in navigation, obstacle detection, and interaction with the environment. Sensors, including LiDAR, RADAR, IMU, Ultrasonic, Camera, Infrared, Depth, and Voice Recognition sensors, serve as the robot's sensory apparatus, enabling it to perceive and understand its surroundings. Through advanced signal processing algorithms and machine learning, these sensors contribute to the development of autonomous personal assistant robots, enhancing their functionality, adaptability, and user interaction in various environments. Next, we described about the microphone sensors for voice recognition, which are used for issuing commands to the robots. Methodologically, a dedicated Voice Recognition Processor (VRP) combined with a low-power microcontroller is employed, allowing recognition of a limited number of voices organized under directories for efficient control of multiple robots.

The next section explores data loading strategies for enhancing the autonomy, accuracy, and performance of autonomous robots, with a focus on the Reinforcement Learning (RL) framework. RL stands for its ability to enable robots to learn and interact with their environment without requiring extensive labelled data, thus improving time efficiency in task accomplishment and decision-making. Its capability to handle delayed rewards and transfer knowledge between related tasks ensures sustained benefits and high performance in diverse scenarios, such as route planning for personal assistant robots. Finally, we conclude this paper by providing the techniques which are higher in accuracy and efficiency.

III. NAVIGATIONAL FRAMEWORK

Overview

An autonomous robot can observe its surroundings, make judgments, and act accordingly. Autonomous personal assistant robots are capable of independent decision-making and autonomously correcting themselves by taking action. The objective of navigation is to guide the rover from a starting point to its destination while steering clear of any obstacles along the way. In robotics, various techniques are used for robot localization and navigation. These techniques vary in terms of their accuracy, cost, and complexity. The table below will compare and contrast several different robot localization and navigation techniques.

SLAM Approaches in Navigation

Using ROS the simulation results of plan generation and navigation in an office-like environment can be done.

TABLE I NAVIGATION TECHNIQUES FROM VARIOUS ARTICLES

S.No	Method	Description	Battery Consumption	Accuracy Rate	Cost	Execution Time	Environment
1	Odometry	Uses encoders on wheels to track robot movement.	Low	Low (Drift Errors)	Low	Fast	Indoor, Flat Surfaces
2	LiDAR SLAM [18]	Builds a map and localizes the robot using a LiDAR sensor (laser radar).	High	High (Excellent Obstacle Detection)	High	Moderate	Indoor / Outdoor (Lighting Dependent)
3	Camera SLAM [62]	Builds a map and localizes the robot using a camera.	Moderate	Moderate (Less accurate outdoors / low light)	Moderate	Moderate	Indoor (Well-lit)
4	Ultrasonic SLAM [9]	Builds a map and localizes the robot using ultrasonic sensors.	Low	Moderate (Shorter range, less complex environments)	Low-Moderate	Fast	Indoor (Limited Outdoor Use)

5	WiFi / Radio Fingerprint [20]	Locates robot in a premapped environment using signal strength.	Low	Moderate (Reliant on PreExisting Map)	Low	Fast	Indoor (Pre-mapped Loca-tions)
6	Visual SLAM [34]	Builds map and localizes using cameras (monocular, stereo).	Moderate-High (depends on processing)	Moderate-High (Lighting dependent)	Moderate	Moderate	Indoor / Outdoor (Lighting Dependent)
7	MiR Mapping [39].	Pre-built map loaded on the robot for navigation (Not suitable for real-time environments)	Moderate on (Reliant Pre-Existing Map)	Varies (can be expensive)	Low	Known	Static Environment
8	Dijkstra's Algorithm [40]	Finds the shortest path between two points.	Moderate	High (Guaranteed Optimal Path)	Low	Slow (Large Maps)	Static environments (Precomputed)
9	A* Search Algorithm [51]	Similar to Dijkstra's with heuristic prioritization.	Moderate	High (Faster for Large Maps)	Low	Moderate	Static / Dynamic environments
10	Artificial Potential Fields (APF)	Create a virtual force field around obstacles to guide the robot.	Low	Moderate (Can get stuck in local minima)	Low	Fast	Dynamic environments (obstacle avoidance)
11	Reactive Control	Relies on sensors to react to immediate surroundings.	High	Moderate (Limited Planning Ability)	Low	Very Fast	Dynamic environments (simple navigation)
12	Kalman Filter [62]	Combines data from multiple sensors for accuracy/robustness.	Moderate (Dependent on sensor usage)	High (Reduces Sensor Noise)	Moderate	Moderate	Varied (Depends on sensors used)
13	Particle Filter [62]	Represents the robot's location with a set of particles (samples) and updates them based on sensor data.	High	High (Handles non-Gaussian noise well)	Moderate	Slow	Dynamic/Uncertain environments

This paper [32] covers the introduction of LiDAR-based SLAM, Visual-based SLAM, and the combined approach. The focus is on achieving three main objectives and contributions: 1) creating a 3D reconstructed map point cloud using LiDAR sensor and RGB-D camera, 2) streamlining the point cloud data collection and registration process to enhance construction quality and safety while saving time and effort, and 3) delivering a high-resolution registered RGB-mapped point cloud.

Evaluating Optimal Navigation Approaches (Literature Review)

Simultaneous Localization and Mapping (SLAM) is considered the most efficient navigation technique due to its ability to seamlessly integrate hardware and software components, resulting in superior accuracy and ease of implementation. Before opting for SLAM, thorough research is conducted on the different methods proposed by technical, surveys, and empirical evidence presented in various articles and papers. By carefully analyzing and comparing the benefits and drawbacks of each technique, the decision to choose SLAM is made with confidence, knowing that it offers the best solution for achieving accurate and efficient navigation in various environments.

This paper [18] describes the autonomous navigation of robots in factory settings using minimal sensors and advanced technologies for efficient and safe movement. The sensors used in this paper are

- Internal Sensors: Inertial Measurement Units (IMU) and motor encoders are commonly used for internal sensing.
- External Sensors: Global Navigation Satellite System (GNSS) sensors are mentioned as external sensors for localization.
- Camera: Stereo cameras are utilized for visual SLAM onboard.
- LIDAR: 2D LIDAR sensors are evaluated for SLAM, but limitations in object detection are highlighted.
- Industry Adaptor: Object recognition and augmentation modules are introduced to enhance sensor data for SLAM.

The tools used for this technique are the Robotic Operating System (ROS) framework and the packages are ORB SLAM and Intel tracking camera T265.

This paper [62] analyzes various LiDAR SLAM methods for indoor navigation of autonomous vehicles, comparing seven representative methods and evaluating them on the same dataset. The techniques are Gaussian Filter-Based Solution,

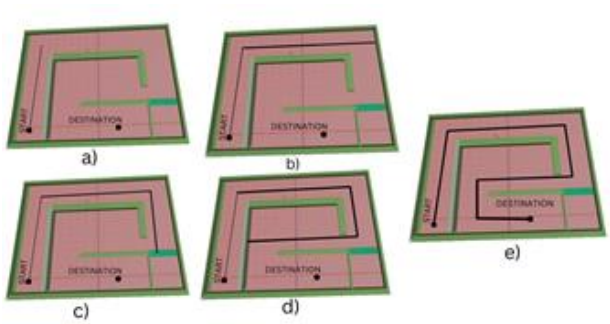


Figure 1. Navigation using Slam

Particle Filter-Based Solution, Graph Optimization-Based Solution, Sparse Pose Adjustment Algorithm, CoreSLAM Algorithm, Iterative Closest Point Algorithm (ICP), Loop-Closure Mechanism, Bayesian Filter.

This paper [34] explained the OpenVSLAM which is most suitable for general-purpose service robots, ORB-SLAM3 with inertial fusion is also viable, RTABMap stable but less accurate. The techniques are about to be described here are ORB-SLAM3, OpenVSLAM, RTABMap, Kimera and VINS-Fusionsupport.

The Simulation and experimental evaluation is done and explained in [52]. The Slam technique or method is used here for the navigation of the autonomous robot. It helps you to experience how to train the robot in an unknown environment.

This paper [32] explains the integration of LiDAR Visualbased SLAM for 3D construction navigation which gives better accuracy than the others. Collaboration of multiple mobile robots and real-life applications is suggested for further development. Self-tuning Fuzzy-PID controller enhances robot navigation accuracy.

Object detection and obstacle avoidance are illustrated clearly in [41]. It implements a landmark-based V-SLAM algorithm using object detection for loop closure in industrial environments. This paper uses the Utilize YOLOv5 for object detection, Bag-of-Visual-Words for loop closure, and SURF features for frame comparison.

In summary, SLAM techniques, including LiDAR SLAM, VSLAM, and sensor data fusion, play a crucial role in enabling autonomous robotic personal assistants to navigate and interact with their environment effectively. By combining different sensing modalities and advanced algorithms, SLAM enhances localization accuracy, adaptability, and overall performance, making it a fundamental technology in robotics applications.

IV. GESTURE RECOGNITION SYSTEM

In the human-robot collaboration, It has been noted that the increasing popularity of personal assistant robots presents several challenges, one of which is security. Another challenge relevant to this paper is the communication barrier between robots and humans. For robots to effectively work alongside people, they need to understand spoken language or use gestures to facilitate natural interactions. Their reliability has improved thanks to continuous progress in programming frameworks, algorithms, and the extensive datasets required for these models. When it comes to gesture recognition and tracking, it's crucial to select the right combination of sensors that can accurately track gestures even in challenging conditions like occlusion, low light, and ensuring user comfort while using the sensors. Gestures can be unclear and not always welldefined. For instance, to signal "stop," a person might raise a hand with the palm facing forward. Like spoken language and handwriting, gestures can differ from one person to another, and even the same person may use different gestures in different situations. The interpretation of a gesture can be influenced by various factors.

- spatial information: where it occurs;
- pathic information: the path it takes;
- symbolic information: the sign it makes;
- affective information: its emotional quality;

Moreover, gestures can be the following types: hand and arm gestures, head and face gestures and body gestures [36].

A. RELATED WORKS

Recently, several surveys have primarily concentrated on general hand gesture recognition [10], [36]. Unlike these broader reports on gesture recognition, our focus is specifically on some of the most significant gesture recognition systems and datasets within this field.

The authors of the paper [31] introduced a hand gesture recognition system that was specifically developed to function effectively in crowded and noisy environments. The important feature of their system is to modify its height by changing the alignment of the torso to enhance its ability to interact. They introduced a AI-based gesture recognition system which is able to follow human commands accurately.

The authors of the paper [7] describe 3D hand gesture recognition approaches. The 3-D depth recognition can be employed to obtain hand contours for reliable hand gesture recognition comfortably and efficiently by easily applying thresholding to a depth map to separate the hands.

The authors of the paper [14] developed a a multi-modal system that integrates inertial and visual data to provide Accurate identification of human gestures in a typical daily life setting. In this method, data regarding movements was gathered using a wearable device, even when the individual was outside the robot's optimal field of view.

The authors of the paper [46] discuss the role of gestures in sign language. Signers employ gestures to produce signs, which consist of movements, shapes, and locations.

Vision Based Gesture recognition

Vision-based sensors provide a much larger working distance when compared to other sensors. Vision-based gesture recognition systems can be divided into two categories.

- The first category is machine learning approaches. For a dynamic gesture, by treating it as the output of a stochastic sequence, hand gesture recognition can be

TABLE II
GESTURE RECOGNITION TECHNIQUES FROM VARIOUS SOURCES

S.No	Dataset used	Tools / Techniques	Accuracy	Description	Applications	Limitations
1	Camera Sensor [14]	Support vector machine (SVM), Random forest (RF), K-Nearest Neighbours (KNN)	High	Basic gesture: walking	photography, surveillance and security, Medical Imaging	Limited Dynamic Range
2	Hidden Markov model [28]	Baum-welch reestimation algorithm	high	Spatio-temporal variability of gestures	Gesture recognition, Environmental monitoring	limited memory, overfitting
3	Depth cameras [48]	Finger-earth Mover's distance (FEMD)	High	hand gesture recognition using Kinect sensors	gaming, Entertainment, Gesture-controlled interfaces	Resolution and Precision, Limited field of view
4	Inertial S ensor Fusion [5]	Depth motion maps(DMM), RGB-Depth camera sensor	High	Wearable device	Motion tracking and analysis, wearable devices	Integration errors, Limited dynamic range
5	HaGRID dataset [31]	convolutional neural network(CNN)	High	Hand recognition	Assistive technology, automatic transcription services	limited variability, size and coverage
6	Multisensor Data Fusion [29]	Ensemble classifiers with multisensors	high	basic gesture	Gesture, Speech recogniton	Sensor heterogeneity, privacy and security

approached using statistical modeling techniques, such as Hidden Markov Models (HMMs) and Principal Component Analysis (PCA) [28].

- **The second category is rule-based methods:** These approaches involve a collection of predefined rules that connect feature inputs, making them suitable for both dynamic and static gestures [54].

As we see, the hand gesture recognition methods apply restrictions to the user/surroundings because of the constraints of optical sensors due to their environmental sensitivity and limited range. To enhance hand gesture recognition techniques, a practical approach is to utilize additional sensors to detect hand gestures and movements. By analyzing various papers, we conclude that human gesture recognition involves focusing on depth sensors.

TABLE III
VARIOUS TYPES OF DEPTH SENSORS

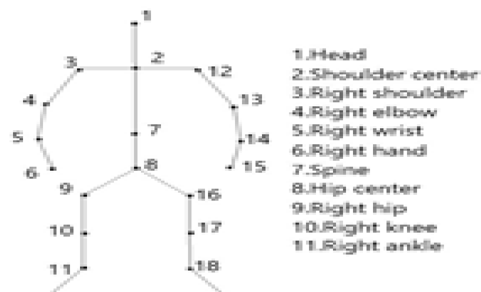
Depth Sensor	Accuracy	Resolution	Range
Microsoft KinectV1 [7]	High	640 x 480 pixels	0.5 to 4metres
Microsoft Kinect V2 [7]	High	512 x 424 pixels	0.5 to 4.5 metres
Azure kinect [7]	High	1024 x 1024 pixels	0.5 to 10 metres

In the table above, we summarized the implementation of Kinect depth sensors in personal assistant robots which is stated to be accurate, efficient and robust to cluttered backgrounds [48].

To implement Kinect depth sensors in autonomous personal assistant robots, developers would typically incorporate the sensors into the robot's hardware architecture and develop software algorithms to process the depth data, such as Hidden Markov Models (HMMs) or Convolutional Neural Networks (CNNs), to perceive and understand the environment accu-

Depth sensor	Field ofView	Technology
Microsoft Kinect V1	57∘ H & 43 ∘ V	structured light(prime sense)RGB camera
Microsoft Kinect V2	70∘ H & 60 ∘ V	Time-ofFlight(ToF)RGB camera
Azure Kinect	75∘ H & 65∘ V	Time-ofFlight(ToF)RGB camera

Figure. 2. SKELETAL JOINTS CAPTURED BY KINECT DEPTH SENSORS



rately and interact intelligently with the users. Additionally, machine learning techniques may be employed to enhance the accuracy and robustness of these algorithms over time through training with real-world data.

V. DATA LOADING STRATEGIES

Data feeding techniques embrace the methods of providing essential data to autonomous robots, enabling them to perceive, navigate, and interact with their environment effectively. Personal Assistant robots should have limited cognizance of human actions and their appropriate verbal and non-verbal behaviours. Interactive Robot Learning deals with paradigms allowing a human to enlighten the learning process of the robot by providing the signals [27].

TABLE IV DATA FEEDING TECHNIQUES

S.No	Learning Technique	Description	Data Requirement	Scalability	Accuracy Rate	Memory Usage	Implementation	Complexity
1	Supervised Learning [15]	Learns from labelled training data, mapping inputs to outputs based on example input-output pairs.	Large	Limited	High	High	Moderate	High

2	Unsupervised Learning [61]	Learns from unlabeled data to find hidden patterns or structures within the data	Varies	Scalable	Varies	Moderate	Moderate	Moderate
3	Reinforcement Learning [27]	Learns through trial and error by interacting with an environment to maximize cumulative rewards	Varies	Challenging	Varies	Moderate to high	Moderate to high	High
4	Transfer Learning [1]	Utilizes knowledge gained from one task to improve performance on a related task	Transferable	Scalable	Varies	Moderate	Moderate	Moderate
5	Deep Learning [43]	Learns intricate patterns from raw data through neural networks with multiple layers	Large	Scalable	High	High	Moderate to High	High
6	Imitation Learning [6]	Learns by mimicking expert behaviour, often from demonstrations or expert guidance.	Demonstration	Scalable	Varies	Moderate	Moderate	Moderate

Innovative robot behavior is achieved by

- assessing the current status of the human collaborator and the environment through real-time observations,
- human action estimation given the task framework and the sightings,
- producing robot actions that align with the predictions.

To competently engage humans in refined learning methodologies, robots should be granted the ability to analyze, model and predict human actions [15].

In the table below, the various data-feeding techniques utilized in autonomous robots will be discussed by highlighting their significance in augmenting robot autonomy, accuracy and performance.

The diverse set of humans daily actions can be understood and categorized by the robotic systems through ML procedures that control the robot's behaviours.

REINFORCEMENT LEARNING FRAMEWORK

Reinforcement learning does not need tremendous, labelled data for learning and learns to engage with the environment and the opaque environment. This approach does not need tremendous, labelled data for learning. RL agent learns to avoid all the static obstacles and plan the path efficiently using prevalent RL algorithms, Q-learning (QL) and Deep QLearning (DQL) for path planning [27].

RL agents can be made dynamic systematically with persistent learning ability by the Transfer Learning algorithm. In a league of its own, a reinforcement learning agent can be trained with a minimal

dataset. This algorithm uses an agent to learn a task by interacting with the environment through its actions. Reinforcement learning is based on hit-and-miss that requires a large amount of engaging data [15].

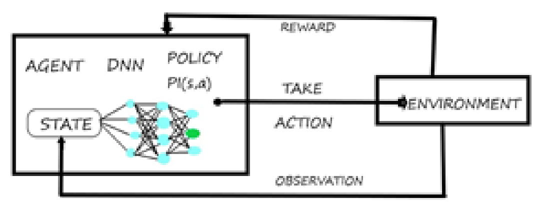


Figure. 3. DATA LOADING FRAMEWORK

EVALUATING THE OPTIMAL APPROACH

In [15], deep reinforcement learning is used to detect the current state of the associate and the environment based on current insights and the current state of the companion, predicting human actions based on the model and the perception, and fabricating the appropriate robot actions. This paper contributes to enhancing the time efficiency of tasks accomplishment in collaboration between the human-robot partners. The benefits of this approach are enhancing robot action decision-making through effective management of the instabilities in human action identification, enabling the robot to distinguish whether it is ideal or not to take an immediate action, and eradicating the need of monotonous manual tagging of human activities by directly learning from unprocessed data.

Reinforcement learning learns by interacting with their environment and takes in the feedback in the guise of returns and reparations whereas the other approaches don't have direct interaction with their environment and learn from the labelled and the unlabeled data. RL can harness the knowledge gained in a particular task to improve performance in other related tasks. RL can deal with agents who don't have a sufficient understanding of the environmental state. This technique upgrades sustained advantages even if the returns are delayed. Based on the topological map of different market ambiences, the reinforcement learning approach learns all the routes for the personal assistant robots with an accuracy of over 98%
[27].

VI. SENSOR TECHNOLOGIES

This section explores the sensors and techniques used in the personal assistant autonomous robot. This paper illustrates the various sensors that an autonomous robot uses and the techniques behind them and also tells about how these technologies work and their importance in making personal assistant robots by providing insights into their applications, functionalities, and advancements.
A sensor is a device that detects and makes a change in the environment which converts them into signals or data that are processed by a computer or device to gather information about the surroundings. Sensors are used everywhere in our daily lives, personal assistant robots play a crucial role in helping the robots understand the world around them. The various sensors used in personal assistant robots include LIDAR, RADAR, Camera, Ultrasonic, Infrared, IMU sensors etc... [25].

One of the major challenges in autonomous robots is obstacle detection and avoidance. This challenge can be overcome through many sensors as mentioned above through algorithms. This paper [44] provides the future directions in sensor Technology for personal assistant autonomous robots.

Navigating the Future: Breakthroughs in Sensor Technology

Navigation in the autonomous robot is the most challenging task that enables the robot to move from one place to another place in its surroundings without any human control. To achieve this, robots use suitable sensors which act as their eyes and ears in the environment. The Sensors include LiDAR, RADAR, IMU, Ultrasonic, GPS etc... [18]. The objective of navigation is to guide the rover from a starting point to its destination while steering clear of any obstacles along the way.

- LiDAR (Light Detection And Ranging): The LiDAR sensor is a crucial tool for creating detailed 3D maps for navigation. Operating within a frequency range of 200THz to 600THz, it offers high accuracy and precision. However, its cost is relatively high, and it requires moderate power. Using Time of Flight (TOF) technology, it accurately measures distances to obstacles, employing the formula distance.

Distance= (speed of sound * TOF) / 2 [57].
The RPLIDAR 360°, for instance, can detect obstacles within a 12-meter range with less than 1% error and 1°accuracy in both distance and angle measurements [44]. It's essential to note that sunlight and dust can affect its functionality due to sensitivity. The sensor covers a 360°clockwise direction and is commonly found in devices like Velodyne and Ouster [25]. With a weight ranging from 400g to 1kg and dimensions of 19.6mm in height and 98.5mm in diameter, it consumes between 8 to 30 watts of power [47].

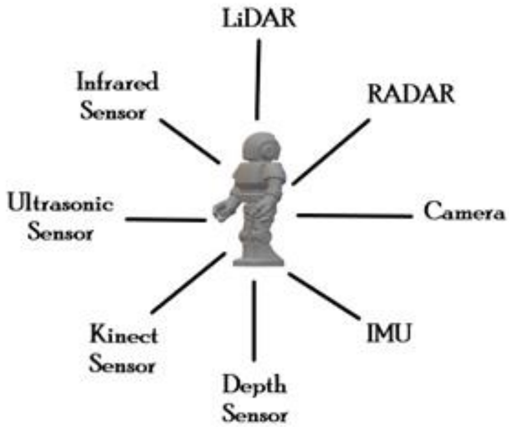


Figure 4. Sensors

- RADAR (Radio Detection And Ranging): Radar, which measures distances using radio waves and can operate over both short and long ranges. A Long-range radar has a low resolution but it can measure speed and detect vehicles and obstacles to 200 m away. Example: microwave radar at 77 GHz. Short/medium range radar can detect velocity and distance with limited resolution and long wavelength.

It is more expensive than some other sensors but offers high accuracy and operates within a frequency range of 30GHz to 300GHz. Radar is less affected by adverse weather conditions such as fog, rain, dust, and poor lighting, making it effective even in low light or darkness. For example, the TI AWR1843 radar sensor has dimensions of 10.4mm by 10.4mm and consumes between 1 to 3 watts of power, with a maximum consumption of less than 5 watts [25], [47].

- **Inertial Measurement Unit (IMU):** An Inertial Measurement Unit (IMU) is a sensor that tracks motion and orientation. It can measure how something is oriented, how fast it's moving, and the magnetic field in its environment. IMUs are commonly used in navigation systems and for controlling movement in various devices. While they aren't always highly accurate, their affordability makes them widely used in many applications where precise measurements are less critical [50].
- **Ultrasonic Sensor:** Ultrasonic sensors which is used for navigation operate at high frequencies, typically between 40kHz and 70kHz, providing high accuracy in measuring distances. They are cost-effective and consume low power, making them popular for various applications.

Emitting sound waves above 20kHz, they are employed to detect obstacles and prevent collisions. While less precise compared to some other sensors, ultrasonic sensors are commonly used by brands like Bosch and Maxbotix. They are compact, weighing up to 14g (occasionally up to 50g), with dimensions around 44mm in length, 26mm in width, and

TABLE V TYPES OF SENSORS: PROS AND CONS

S.No	Sensor	Description	Pros	Cons	frequency Range	Weight (g)	Dimensions (mm)	Power consumption (W)	Example
1	LiDAR [25]	Uses time-of-flight to measure distance and create 3D maps	High accuracy and precision	Expensive, moderate power consumption, affected by sunlight and dust	200-600 THz	400 - 1000	19.6(h)*98.5	8 - 30	Velodyne, Ouster
2	Camera [44]	Captures visual information about obstacles (colour, shape, texture)	Low cost, medium power consumption	Low light and bright sunlight performance	300-430 THz	SoC	Varies	0.8 - 1	Omron, Omnivision
3	Depth Sensing Sensor [57]	Captures depth using ToF, structured light, or Stereo vision sensor	Accurate depth estimation	more power and storage capacity needed	-	SoC	Varies	-	Microsoft Kinect, Intel, Orbbec

4	Ultrasonic Sensor [47]	Uses time-of-flight to measure distance	Low cost, low power consumption	Less precise	40 - 70 THz	Upto 50	44(l)x26(w) x23(d)	<1	Bosch, Maxbotix
5	RADAR Sensor [50]	Measures distances using radio waves	Works well in low light, less affected by weather	more expensive	30 - 300 THz	SoC	10.4x10.4	1 - 3	TI (AWR1843)
6	Infrared (IR) sensor [26]	Detects infrared radiation obstacles	short range detection, low cost	Limited accuracy affected by sunlight	-	Upto 14	44(l)x26(w) x23(d)	Low	Infrared Thermometer
7	IMU [17]	Measures orientation, acceleration, and magnetic field	Low cost	Limited accuracy	-	SoC	Varies	Low	Gyroscope, Acceleration

Smart Vision Sensor for Autonomous Robot:
Vision Sensor is the advanced computer vision technology in personal assistant robots to enhance their ability to see, understand, and interact with their surroundings.

Voice Recognition Sensor:

- **Microphone Sensor :**
- Camera Sensor: Camera sensors, essential for capturing detailed visual information about obstacles, operate in the 300 GHz to 430 THz range (logarithmic values 11.48 to 14.63) and convert light into electrical signals using an array of photodetectors. They include monochrome, colour, RGB and Stereo vision sensor types: monochrome sensors capture light intensity with high sensitivity and low cost but no colour information; colour sensors provide detailed colour accuracy but are more expensive and power-intensive.

These sensors face challenges in low light and bright sunlight conditions, with typical power consumption ranging from 0.8W to 1W and dimensions of 14mm x 18mm x 8.93mm (or 7.3mm x 7.8mm). Examples include the Omron thermal sensor and Omnivision OV10625, demonstrating their critical role in recognition, tracking, and navigation applications [25], [47].

- **Infrared Sensor (IR) :** Infrared sensors are used to detect obstacles by sensing infrared radiation. They are suitable for short-range detection and are known for being low-cost. However, their accuracy is limited and can be significantly affected by infrared radiation from sunlight, which can interfere with their readings and reduce their effectiveness.
- **Depth Sensor :** Depth sensing sensors use technologies like time-of-flight (ToF), structured light, or stereo vision to capture precise depth information, often accurate to the millimetre. These sensors are crucial for applications like mapping, object recognition, obstacle detection, and gesture recognition.

An example is the Microsoft Kinect, which uses structured light technology for depth sensing and skeletal tracking, enabling gesture-based interactions such as control and command activation. ToF cameras, produced by manufacturers like Intel, Orbbec, and Occipital, are also widely used for their accurate depth estimation capabilities [8], [17], [26], [55].

Microphone sensors play a pivotal role in voice recognition systems, converting sound waves into electrical signals for processing. They are integral components in various applications such as virtual assistants, speech-to-text software, and smart home devices. These sensors are optimized for clear and accurate audio capture, often featuring noise cancellation and directionality to enhance performance.

Knowles microphone solutions tailored for voice recognition. With advanced signal processing algorithms and machine learning, these sensors deliver high accuracy in voice recognition tasks, even in noisy environments. Their compact size and low power consumption make them ideal for integration into consumer electronics and IoT devices, driving the adoption of voice-controlled technologies [60].

VII. VOICE-CONTROLLED ROBOTIC SYSTEMS

This method allows for more intuitive and natural control over the robot's movements, making it easier for users to manipulate the robot to perform specific tasks. In addition to verbal interaction, other methods such as gesture control, brain-computer interfaces, and haptic feedback have also been developed to enhance the control of robots. These advancements in robotics control have opened up new possibilities for applications in various industries, such as manufacturing, healthcare, and entertainment.

As technology continues to evolve, we can expect even more innovative and effective methods of controlling robots to be introduced in the future. The voice-activated robot featured in this paper marks a notable technological progression, as it not only obeys voice instructions but also engages with the user through a variety of outlined methods in this section.

This paper [12] illustrates the document mentions successful tests but does not provide detailed results in the excerpt provided. The system is designed to control multiple autonomous robots using voice commands. A voice command system for three autonomous robots was implemented. Commands were selected from French words.

Components and Technical
Details

Sensors	Navigation	Vision	Gesture Recognition	Voice Recognition
LiDAR	✓			
RADAR	✓			
IMU	✓			
Camera (RGB)		✓	✓	
Camera (Stereo)	✓	✓	✓	
Camera (Infrared)		✓	✓	
Ultrasonic	✓			
Infrared (IR) Sensor		✓	✓	
Depth Sensor		✓	✓	
Microphone Sensor				✓
GPS	✓			
Sonar Sensor	✓			
Thermal Camera		✓	✓	
Time of Light	✓	✓	✓	
Touch Sensor			✓	
Proximity Sensor	✓		✓	

Fig. 5. Sensors for Navigation, Vision, and Gesture Recognition

Voice Recognition Processor: RSC-364, capable of recog nizing up to 60 words/phrases in slave mode.

Microcontroller: PIC16F876, an 8-bit microcontroller usec for handling the command interface and controlling the robots.

RF Communication: Used to send commands to the robots. The RF modules operate at 433.92 MHz.

The development of a voice-controlled robot that can follow voice commands and interact with users by speaking pre-recorded phrases was outlined by [45]. The robot is controllec via voice commands through a smartphone and responds with human-like voice feedback and uses pre-recorded voice files stored on an SD card to communicate with the use during operations. The core of the robot's system is the Arduino Uno microcontroller. Utilizes Bluetooth to receive voice commands from an Android smartphone. An app on the smartphone converts voice commands to text, which is ther sent to the microcontroller. The robot responds to commands by moving in specified directions and speaking pre-recordec phrases stored on an SD card [45].

Figure. 6. VOICE RECOGNITION SYSTEM

An Intelligent Personal Assistant (IPA) capable of performing various tasks, such as moving objects and providing information from the internet proposed by the paper [23]. This document reviews prior research on face, object, and speech recognition technologies used in robotics. It mentions various approaches and methods, including the AdaBoost algorithm for face detection and the use of Mel Frequency Cepstrum Coefficient (MFCC) and Dynamic Time Warping (DTW) for voice recognition. The hardware section describes the components used in the robot including: Raspberry Pi and Pi CameraMotor Driver (L298N). The architecture involves using Raspberry Pi to process images and voice commands, controlling the motors, and providing output. It integrates various technologies like speech recognition, text detection, and motor control to create an interactive and functional robotic assistant.

VIII. A RISE OF VISION-BASED ROBOTICS

The field of robotics is undergoing a dramatic transformation fueled by advancements in computer vision. This technology, which equips robots with the ability to ”see” and interpret their surroundings, is unlocking a new era of automation and efficiency across various sectors. One of the most exciting applications lies in autonomous manufacturing.

A novel vision-based robotic recognition method has been developed, merging image processing with scene text recognition. This approach goes beyond simply identifying objects; it can decipher text displayed on machinery, such as a CNC machine’s status message. This breakthrough has the potential to revolutionize factory floors by enabling robots to not only locate equipment but also understand its real-time operational state. The implications are significant: improved accuracy, enhanced efficiency, and the potential for truly autonomous operations [22].

Beyond manufacturing, vision-based technology is transforming agriculture. The Autonomous AGRIBOT exemplifies this shift. Equipped with low-cost sensors and powerful processors, this innovation navigates fields with precision, autonomously sowing seeds. By leveraging advanced techniques like edge detection and coordinate conversion, the AGRIBOT ensures seamless seed placement, marking a significant leap forward in agricultural efficiency [49].

Similar advancements are taking place in the realm of quadruped robots. Computer vision-based navigation is empowering these agile machines, as seen with the HyQReal robot. This innovation facilitates precise waypoint generation, enabling robots to perform automated tasks with remarkable accuracy. The future holds promise for even greater refinement, with efforts underway to improve grapevine detection and integrate navigation with manipulation arms for tasks like autonomous winter pruning [35].

The impact of vision-based technology extends beyond specific applications. It represents a fundamental shift in how robots perceive and interact with the world. Take face recognition, a key application of computer vision. This technology finds use in everything from surveillance systems to user interaction, as exemplified by systems like Hobbit and SyPEHUL. These systems showcase the versatility of vision-based solutions in driving the development of intelligent robotic technologies [60].

Finally, the importance of vision and perception cannot be overstated for effective industrial robot utilization. Studies have confirmed the exceptional navigation capabilities of vision-equipped Automated Guided Vehicles (AGVs) within industrial settings. Omnidirectional mobility is crucial for navigating tight spaces, while robust vision systems are essential for adapting to dynamic environments and overcoming challenges like low-textured surfaces [42].

In conclusion, the integration of vision technology marks a turning point in robotics. From revolutionizing manufacturing and agriculture to enabling advanced navigation and interaction capabilities, this technology is paving the way for a future where robots seamlessly integrate into our world, performing tasks with ever-increasing autonomy and intelligence.

IX. AUTONOMOUS DEVICE INTERACTION

IoT applications heavily rely on sensing-enabled devices for data collection, communication, and decision-making, facilitated by wireless networks ensuring robust operations and wide coverage with high energy efficiency. Cellular networks have adapted to the demands of autonomous devices through multi-connectivity frameworks, enabling customized aggregation [24].

Emerging techniques like Device-to-Device (D2D) communication address rising mobile traffic, leveraging deep learning for optimization. D2D networks promise enhanced spectral efficiency and increased mobile network capacity within limited radio frequencies. Cooperative localization enhances robot performance by sharing observations and improving spatial awareness collectively. Radio waves remain the primary medium for seamless data transmission among IoT devices and vehicles. These advancements in wireless technology promise solutions for connectivity and data traffic challenges in IoT and mobile communication [53].

SATELLITE BASED CONNECTIVITY SYSTEM

Satellite communication empowers off-site control, allowing operators to manage robots from afar, vital for space exploration, deep-sea expeditions, and disaster response. Secondly, real-time data transmission from the robot's sensors and cameras facilitates immediate analysis and informed decision-making by operators. Satellite communication offers global coverage, ensuring robots can operate anywhere without relying on ground infrastructure, and its endurance proves invaluable in disaster-prone regions. Advanced robots utilize satellite data like GPS for autonomous navigation, which is crucial in navigating unreliable or challenging environments. Moreover, interoperability facilitated by satellite communication fosters collaboration between different robots, enhancing overall efficiency and effectiveness. This communication backbone extends the robot's reach to remote and inaccessible areas, ensuring continuous communication even in adverse conditions. Overall, satellite communication significantly amplifies robots effectiveness in various applications, enabling them to tackle missions that would otherwise be impractical or impossible [4].

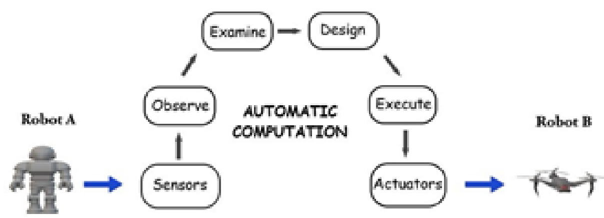


Figure. 7. INTER ROBOT COMMUNICATION

OPTIMIZATION ANALYSIS

Satellite communication offers robots incomparable advantages, ensuring connectivity even in remote areas and hazardous environments. Reliability is reinforced by redundant infrastructure and error correction techniques. Scalability allows numerous robots to be integrated simultaneously. Realtime communication empowers swift decision-making and dynamic monitoring. Autonomous navigation benefits from

TABLE VI INTER-ROBOT COMMUNICATION TECHNIQUES

S.No	Technique	Description	Accuracy	Range	Environment	Complexity	Tools required
1	Acoustic Communication [3]	Relies on sound waves to transmit data between robots, suitable for underwater or noisy environments	Moderate to High	Short to Medium	Ideal for underwater communication and noisy environments where other methods may fail	Moderate	Hydrophones, transducers, acoustic modems
2	Infrared Communication [56]	Utilizes infrared light to transmit data between robots, often in shortrange applications	Moderate	Short	Suitable for short-range applications and indoor environments with clear line-of-sight communication	Low to Moderate	Infrared transceivers, line-of-sight alignment
3	Optical Communication [19]	Uses light signals, such as lasers or LEDs, for high-speed data transmission between robots	High	Short to Medium	Suitable for short-range applications where lineof-sight communication is feasible	Moderate to high	Optical transceivers, lasers, photodiodes

4	RFID Communication [30]	Utilizes radio frequency identification tags and readers to exchange data between robots	Moderate	Short to Medium	Ideal for short-range identification and tracking applications within controlled environments	Low to Moderate	RFID tags, readers, protocols
5	Satellite Communication [11]	Utilizes satellite networks to enable communication between robots across large distances	High	Long to Global	Suitable for long-distance communication where terrestrial infrastructure is unavailable or impractical	High	Satellite terminals, ground stations, antennas
6	Ultrasonic Communication [13]	Utilizes ultrasonic waves for communication, often used in localization and navigation systems for robots	Low to Moder-ate	Short to Medium	Ideal for indoor environments where other methods may suffer from interference or signal degradation	Low to Moderate	Ultrasonic transducers, signal processing tools
7	Wired Communication [37]	Employs cables or wires to establish connections between robots, ensuring reliable and secure data transmission	High	Short to Medium	Ideal for controlled environments where mobility is not a primary concern	Moderate	Cables, connectors, networking hardware
8	Wireless Communication [33]	Utilizes radio frequencies, Bluetooth, or Wi-Fi to transmit data between robots	Moderate to High	Short to Medium	Suitable for indoor and open environments. Not ideal for highly congested or noisy environments	Moderate	RF modu les, antennas, network protocol

precise GPS-based positioning, enabling accurate movement. Security features, including encryption, safeguard sensitive data transmission. Long-range communication facilitates connectivity with distant bases for extensive missions. The Satellite system's endurance to impediment ensures reliable communication in challenging environments. These advantages establish satellite communication as indispensable for robots across diverse domains, enhancing their effectiveness and robustness [59].

X. CONCLUSION

In conclusion, this survey paper has explored the overview of personal assistant robots by analysing various articles that were published within the last ten years has been reviewed. It compares and contrasts various tools and techniques by analysing various data sources and data acquisition systems for the implementation of personal assistant robots by demonstrating the accuracy, efficiency and effectiveness of the technique. Autonomous personal assistant robots represent a promising frontier in technology, poised to revolutionize daily life by flawlessly combining into households and workplaces. The advancement in this technology presents a promising future where technology seamlessly integrates into daily life to enhance productivity, convenience, and accessibility. From managing our schedules and tasks to providing companionship and entertainment, autonomous personal assistant robots have the potential to become necessary allies in navigating the complexities of modern life. As we continue to refine their capabilities and address challenges, we clear the path for a future where autonomous personal assistant robots become trusted

companions, enhancing our lives in ways we've only begun to imagine

ACKNOWLEDGEMENT
We are deeply expressing our sincere gratitude to our project guide Dr. Damodar Reddy Edla who has always supported and guided us with valuable
comments. We express our immense pleasure and thankfulness to our project mentor Annu Kumari Department of Computer Science and Engineering, National Institute of Technology Goa. We would like to express our deepest gratitude to Dr. N. Marie Wilson, Managing Director of Jeppiaar Institute of Technology, for providing us with the financial support that made this research possible. We are also immensely grateful to Dr. S. Shenbaga Ezhil, Professor at Jeppiaar Institute of Technology, Email id: iqac@jeppiaarinstitute.org, for her invaluable guidance. Your support has been invaluable in helping us achieve our goals and complete this project successfully.

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