Research Project Proposal

Final Year Project

Active bionic antennas for object detection and 3D localization with self-sensing ego-motion cancellation

Group G25

E/19/295	K. H. J. D. Premachandra
E/19/300	L. M. A. H. Premawansha
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Supervised by: Dr Nalin Harischandra , Dr Isuru Navinne

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Abstract

Robotic navigation in unstructured environments is challenging when vision-based sensors fail due to low-light, occlusion, or clutter. Tactile sensing offers a robust alternative, but a major challenge is self-sensing interference caused by ego motion, where the robot's movements introduce noise in the tactile sensors, leading to false detections and reduced localization accuracy. This project addresses this issue by implementing a self-sensing cancellation module using Echo State Networks (ESNs) to predict and filter out motion-induced artifacts in real time, ensuring only true external contact information is used for navigation.

The refined tactile data is then used for 3D localization, integrated into Google Cartographer (SLAM) within ROS to generate a real-time contact-based map of the environment. Unlike traditional SLAM, which relies on vision or LiDAR, this approach enables precise tactile-based mapping and navigation. The system follows a structured process of tactile data acquisition, self-sensing cancellation, and SLAM-based localization to enable autonomous operation.

The implementation includes compliant tactile sensors, servo-actuated antennae, IMU sensors, and a mobile robotic platform, with a software stack featuring ROS, Python, C++, TensorFlow, and Google Cartographer. The primary innovation is a robust self-sensing cancellation framework, enhancing tactile-based localization accuracy. By eliminating motion artifacts, the system enables precise 3D localization, making it ideal for robotic exploration, search-and-rescue, and industrial automation in visually challenging environments. Future work will focus on optimizing self-sensing cancellation and refining tactile-based navigation accuracy through expanded real-world testing.

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Chapter 1

Introduction

1.1 Active Tactile Sensing in Nature

In the natural world, many animals rely on active tactile sensing to explore and interact with their immediate environment. Insects, such as stick insect *Carausius morosus*, use their antennae for obstacle localization, orientation, pattern recognition, and even communication. These antennae detect minute vibrations and forces through specialized sensory cells at their base, enabling rapid feedback for adaptive locomotion. Similarly, mammals like rats and harbor seals utilize whiskers (*vibrissae*) to map their surroundings with remarkable spatial resolution. Rat whiskers, for instance, sweep rhythmically at high frequencies, translating mechanical bending into neural signals that encode object distance, shape, and surface properties even in complete darkness. These biological systems operate independently of visual input, relying instead on mechanical interactions, making them robust across lighting conditions and particularly effective for near-range exploration.

1.2 Bionic Tactile Sensors: Bio-Inspired Engineering

Inspired by these biological systems, engineers have pioneered bionic tactile sensors that replicate the form and function of biological antennae and whiskers. Modern bionic antennas integrate advanced materials such as piezoelectric polymers, carbon nanotube composites, and microelectromechanical systems (MEMS) to mimic the sensitivity and adaptability of their biological counterparts. These sensors actively "sweep" their environment, like a cockroach antenna or a seal's whisker, generating tactile data through controlled mechanical interactions. By working with advanced machine learning algorithms, these bionic tactile sensors enable tasks such as real-time material classification, dynamic object detection, and 3D localization which makes them suitable for autonomous robots operating in cluttered, unpredictable environments like disaster zones, underwater habitats, or extraterrestrial terrains.

The advantages of bionic tactile systems extend beyond robustness in low-visibility environments. Their mechanical simplicity, low power consumption, and resistance to electromagnetic interference make them ideal for applications ranging from medical robotics to industrial automation in hazardous settings.

1.3 Challenges in Deploying Bionic Tactile Sensors

Active bionic tactile sensors have immense potential to enhance robotic interaction and navigation in complex environments. However, their deployment on mobile platforms is hindered by two critical challenges. First, self-induced motion artifacts such as oscillatory antenna movements, platform vibrations, and terrain-induced disturbances corrupt tactile signals, making it difficult to distinguish between *reafferent* (self-generated) and *exafferent* (externally generated) inputs. This interference leads to false positives and undermines the sensor's ability to accurately interpret tactile information. Second, the degradation of 3D localization accuracy in dynamic, unstructured environments limits the sensor's spatial awareness, which is crucial for applications like robotic exploration, search and rescue, and industrial automation. Addressing these challenges requires novel techniques for self-sensing cancellation to eliminate ego-motion interference and advanced strategies, such as multi-antenna motion integration and adaptive learning-based spatial mapping, to improve 3D localization precision. Overcoming these limitations will unlock the full potential of bionic tactile sensors in real-world scenarios.

1.4 Aim

To develop advanced bionic tactile sensing systems that operate reliably in dynamic environments by eliminating self-induced motion artifacts through self-sensing cancellation techniques and enhancing 3D localization accuracy with multi-antenna motion strategies and adaptive learning-based spatial mapping.

1.5 Objectives

- Development of Self-Sensing Cancellation for Robust Tactile Perception

Investigate and mitigate self-induced motion artifacts by developing novel signal processing algorithms and self-sensing cancellation techniques to ensure accurate tactile signal interpretation in dynamic environments.

- Enhancement of 3D Localization Accuracy through Adaptive Learning

Integrate multi-antenna motion strategies with adaptive learning-based spatial mapping to improve localization accuracy and enable real-time environmental perception in unstructured and dynamic conditions.

- System Integration, Validation, and Real-World Deployment

Develop a unified bionic tactile sensing system by combining self-sensing cancellation and 3D localization techniques, optimizing it for scalability, energy efficiency, and real-world applications such as robotic navigation and industrial automation.

1.6 Solution Brief

The proposed solution addresses the challenges of tactile sensing and navigation in dynamic, unstructured environments by integrating advanced technologies inspired by biological systems. The system leverages bionic tactile sensors, self-sensing cancellation using Echo State Networks (ESNs), and 3D localization through Google Cartographer SLAM within the ROS framework.

1.6.1 Key components of the solution

Mimicking insect antennae and mammalian whiskers, these Bionic Tactile Sensors actively sweep their environment to detect obstacles and classify materials. They are mounted on a pan-tilt unit with poly-acrylic probes and MPU6050 accelerometers for precise vibration data acquisition.

- Self-Sensing Cancellation - To mitigate interference caused by ego motion, an ESN-based forward model predicts and filters out self-generated vibrations, ensuring accurate detection of external contact events.
- 3D Localization and Mapping - Using Google Cartographer, the system generates real-time 3D maps of the environment based on tactile feedback, enabling autonomous navigation even in visually degraded conditions.
- Real-Time Adaptability - The Jetson Nano board facilitates onboard machine learning training and real-time processing, allowing the system to adapt to new environments dynamically.

This integrated approach ensures robust tactile-based perception, precise 3D localization, and reliable navigation, making it ideal for applications such as robotic exploration, search-and-rescue operations, and industrial automation in challenging environments.

1.7 Organization

This document is structured to systematically address the challenges, methodologies, and innovations in developing a robust bionic tactile sensing system. Chapter 1 introduces the biological inspiration for tactile sensing, the challenges in deploying bionic tactile sensors, and the aim, objectives, and solution brief. Chapter 2 reviews existing approaches in self-sensing cancellation, 3D localization, and machine learning integration, highlighting gaps in current methodologies. Chapter 3 details advanced technologies, including bio-inspired tactile sensor design, Echo State Networks (ESNs), and Google Cartographer SLAM. Chapter 4 presents the proposed approach, outlining the integrated system architecture, workflow, and key processes for tactile sensing, self-sensing cancellation, and 3D localization. Chapter 5 describes the modular system architecture, focusing on hardware-software integration, data flow, and design considerations. Chapter 6 provides technical details on the implementation of each module, covering hardware setup, software algorithms, and real-world testing. Finally, Chapter 7 lists all cited literature and resources supporting the research.

Chapter 2

Existing Approaches in Bionic Tactile Sensing and Localization

2.1 Introduction

The field of bionic tactile sensing has garnered significant attention due to its potential applications in robotics, particularly in environments where traditional sensors face limitations. Inspired by biological systems, researchers have developed various tactile sensors that mimic the functionality of insect antennae and mammalian whiskers. These sensors enable real-time object detection, material classification, and 3D localization, which are crucial for autonomous robots operating in complex and dynamic environments.

2.2 Self-Sensing Cancellation in Robotic Tactile Systems

Many studies have focused on self-sensing cancellation to mitigate the interference caused by ego motion, which can significantly affect the accuracy of tactile sensing in robotic systems. Hartmann (2001) [13] introduced adaptive filtering techniques for rodent whisker models, demonstrating how these biological systems effectively differentiate between self-generated and externally induced signals. This foundational work laid the groundwork for adapting similar techniques in robotic applications, allowing robots to filter out noise generated by their own movements [13, 35].

Recent advancements have seen the integration of deep learning models and Echo State Networks (ESNs) to enhance self-sensing cancellation. ESNs, a type of reservoir computing, utilize a dynamic network of neurons to predict self-induced disturbances based on motor commands and sensory feedback. [4, 29] demonstrated that ESNs could effectively filter out self-generated noise in real-time, significantly improving the reliability of tactile data in dynamic environments. This approach allows for adaptive filtering that can adjust to varying conditions, making it particularly useful for mobile robotic platforms [29].

Additionally, reinforcement learning techniques have been explored to further enhance self-sensing cancellation. These methods enable robots to learn optimal filtering strategies through trial and error, adapting to the specific characteristics of their operating environment [5]. By combining predictive models with reinforcement learning, researchers aim to create more robust systems capable of real-time noise suppression, even in complex and unstructured settings.

2.3 3D Localization and Mapping

Various methodologies have been employed for 3D localization using tactile feedback, which is essential for enabling robots to navigate and interact with their environments effectively. Techniques such as contour tracing and path integration have been explored to achieve accurate spatial mapping. Contour tracing involves the robot following the edges of objects to gather tactile information, allowing for the reconstruction of object shapes [1]. This method has been shown to enhance the robot's ability to detect and classify objects based on their tactile profiles.

Path integration, on the other hand, utilizes the robot's movement data to estimate its position relative to a starting point, integrating sensory feedback to correct for any drift in localization [37]. This technique is particularly useful in environments where visual cues are limited or absent.

The integration of multi-antenna configurations has further enhanced spatial mapping capabilities. By employing multiple tactile sensors that operate in a coordinated manner, robots can generate higher-resolution environmental maps, improving their navigation in cluttered or low-visibility conditions [19]. However, this approach introduces challenges such as cross-axis interference, where signals from different sensors can interfere with one another, complicating the data interpretation process. Researchers are actively exploring adaptive filtering solutions to mitigate these issues and improve the overall accuracy of 3D localization.

2.4 Machine Learning Integration

The application of machine learning algorithms has been pivotal in improving the performance of bionic tactile sensors. Deep learning models, particularly convolutional neural networks (CNNs), have been utilized for texture classification and motion artifact suppression. These models excel at extracting spatial features from tactile data, enabling robots to classify materials and detect objects with high accuracy [18]. For instance, CNNs can analyze tactile imprints to identify surface textures, which is crucial for tasks such as object manipulation and navigation in unstructured environments.

However, the computational demands of deep learning approaches often pose challenges for real-time applicability in mobile robotic systems. The high processing power required for training and inference can limit the deployment of these models on low-power embedded systems typically used in robotics [26]. To address this, researchers are investigating lightweight AI algorithms optimized for edge computing, which can provide efficient real-time processing without compromising performance.

Moreover, integrating machine learning with traditional filtering techniques, such as Kalman filters, has shown promise in enhancing the robustness of tactile sensing systems. By combining the strengths of both approaches, researchers aim to develop more adaptive and efficient tactile sensors capable of operating effectively in dynamic environments.

2.5 Comparison of Approaches

The following table summarizes the key approaches in self-sensing cancellation and 3D localization, highlighting their mechanisms, performance, and limitations.

Table 1: Key Approaches

Technique	**Mechanism**	**Performance**	**Limitations**
Kalman Filtering	Real-time processing, low computational cost	70–80% artifact reduction in structured environments [31]	Fails with non-linear vibrations (e.g., legged robots)
Echo State Networks (ESN)	Reservoir computing for dynamic noise modeling	90% reduction in unstructured settings [29]	Requires GPU acceleration for real-time use
Deep Learning (CNN/RNN)	Combines spatial feature extraction with temporal prediction	95% accuracy in texture classification	High computational cost (>1 TFLOPs)

Proprioceptive Feedback Systems	Integrates motor commands with sensory feedback	Enhances motion prediction and noise reduction [18]	Complexity in implementation and real-time adaptation
Multi-Antenna Configurations	Coordinated motion patterns for spatial mapping	Improved navigation in cluttered environments [19]	Increased computational complexity and cross-axis interference

2.6 Highlighting the Problem

Despite the advancements in bionic tactile sensing and localization, significant challenges remain. The cancellation of self-sensing interference due to ego motion continues to disrupt accurate perception, and achieving reliable 3D localization in dynamic environments is still a complex task. Current techniques often struggle with real-time processing and adaptability, which limits their effectiveness in practical applications. Our research aims to address these gaps by developing novel self-sensing cancellation techniques and improving 3D localization accuracy through innovative multi-antenna strategies and adaptive learning frameworks.

Chapter 3

Advanced Technologies Adopted for Tactile Sensing and 3D Localization

3.1 Introduction

Robotic navigation in complex environments requires reliable perception systems, but traditional vision-based sensors are often ineffective in low-light, occluded, or cluttered spaces. Tactile sensing offers a viable alternative by enabling robots to interact with their surroundings through direct contact. However, a major challenge is self-sensing interference due to ego motion, where the robot's movements introduce noise in sensor readings, leading to false detections and reduced localization accuracy.

This project addresses this issue by integrating bionic tactile sensors, self-sensing cancellation using Echo State Networks (ESNs), and 3D localization using Google Cartographer SLAM in ROS. The bionic tactile sensor module mimics insect antennae movements to detect obstacles, while the self-sensing cancellation module filters out motion artifacts to ensure accurate tactile data. The 3D localization module utilizes Google Cartographer to build a real-time spatial map based on tactile interactions, allowing for vision-free autonomous navigation.

By combining bio-inspired sensing, machine learning-based artifact suppression, and SLAM-based mapping, this system enables precise tactile-based localization, making it applicable to robotic exploration, search-and-rescue operations, and industrial automation in visually degraded environments.

3.2 Bionic Tactile Sensor Design and Movement Control

The design of the bionic tactile sensor is inspired by the antennae of stick insects, which are known for their ability to detect obstacles, localize objects, and classify materials through active tactile sensing. The sensor is mounted on a pan-tilt unit, allowing it to move in a sinusoidal pattern, mimicking the natural movement of insect antennae. This design is crucial for near-range exploration and object detection in dynamic environments.

3.2.1 Poly-Acrylic Antenna Probe

The antenna is constructed using a poly-acrylic tube, chosen for its flexibility and stiffness, which allows it to maintain its shape during self-motion while being sensitive to vibrations. This material is ideal for detecting contact events without causing damage to obstacles, making it suitable for real-world applications.

3.2.2 MPU6050 Accelerometer

The MPU6050 sensor is mounted at the tip of the antenna to capture vibration data. This sensor is highly sensitive and provides accurate readings of acceleration in three axes (X, Y, and Z). The data from the X and Y axes are particularly important for detecting contact events, as the Z-axis data is less significant due to its alignment with the antenna's axis.

3.2.3 Pan-Tilt Unit with Servo Motors

The pan-tilt unit is equipped with high-torque MG90 servo motors, which allow the antenna to move in a sinusoidal path. This movement is essential for covering a larger area in 3D space and detecting obstacles in the environment. The servo motors are controlled using a Jetson Nano board, ensuring precise movement and real-time data acquisition.

3.3 Self-Sensing Cancellation Using Echo State Networks (ESNs)

One of the primary challenges in tactile sensing is the issue of self-sensing, where the sensor's readings are corrupted by the robot's own motion (ego-motion). To address this, we employ an Echo State Network (ESN), a type of recurrent neural network (RNN) specifically designed for chaotic time series prediction. The ESN acts as a forward model, predicting the expected sensor readings based on the robot's motor commands and proprioceptive signals.

3.3.1 Forward Model for Self-Sensing Cancellation

The ESN-based forward model predicts the sensor's response to the robot's motion, allowing us to distinguish between self-generated vibrations and external tactile events. This is achieved by training ESN on data collected from the robot's accelerometer and servo motors. The model is then used to filter out the ego-motion component from the sensor's readings, enabling accurate detection of external contact events.

3.3.2 Reservoir Computing Framework

ESN's reservoir computing framework is particularly suited for this task due to its ability to handle chaotic and non-linear time series data. The reservoir is initialized with random weights, and only the output layer is trained, making the ESN computationally efficient and suitable for real-time applications.

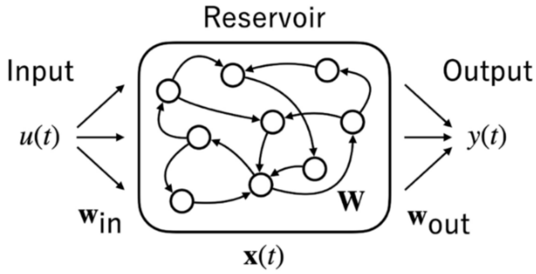

Figure 3.1: ESN model with Inputs, Outputs and the Reservoir

3.3.3 Low-Pass Filtering

To further enhance the accuracy of the ESN model, we apply a low-pass filter to the sensor data. This filter removes high-frequency noise, allowing the model to focus on the relevant low-frequency components of the signal, which are more indicative of contact events.

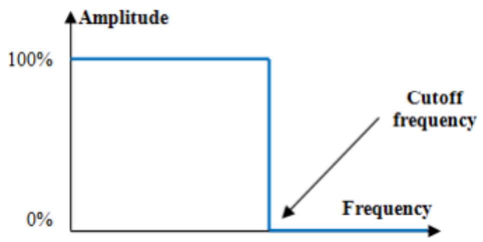

Figure 3.2: Low Pass Filter

3.3.4 Jetson Nano for Machine Learning Training

Unlike traditional setups that rely on external systems for machine learning training, we leverage the Jetson Nano board to perform the training of the ESN model directly on the robot. Jetson Nano's GPU-accelerated computing capabilities allow us to train the model in real-time, making the system more autonomous and reducing the need for external computational resources. This integration ensures that the robot can adapt to new environments and update its forward model on the fly.

Figure 3.3: Jetson Nano Development Board

3.4 3D Localization Using Google's Cartographer on ROS

In addition to tactile sensing and self-sensing cancellation, we integrate 3D localization capabilities into our system using Google's Cartographer, a state-of-the-art simultaneous localization and mapping (SLAM) algorithm available on the Robot Operating System (ROS). This technology is essential for enabling the robot to navigate and map its environment in three dimensions.

3.4.1 Cartographer SLAM Algorithm

Cartographer is a highly efficient SLAM algorithm that combines data from multiple sensors, such as LiDAR and IMU, to create accurate 2D and 3D maps of the environment. It uses a combination of scan matching and loop closure techniques to correct errors in the robot's pose estimation, ensuring accurate localization even in large and complex environments.

3.4.2 Integration with Tactile Sensing

By integrating Cartographer with our tactile sensing system, we enable robots not only to detect obstacles but also localize them in 3D space. This is particularly useful for applications such as autonomous navigation, where the robot needs to avoid obstacles while maintaining an accurate map of its surroundings. The tactile sensor provides additional data about the distance and material properties of obstacles, which can be used to refine the map generated by Cartographer.

3.4.3 Real-Time Mapping and Localization

Cartographer is designed to operate in real-time, making it suitable for dynamic environments where the robot needs to continuously update its map and localization data. This is achieved through efficient use of computational resources and optimized algorithms for scan matching and loop closure.

3.5 Data Acquisition and Preprocessing

To ensure the accuracy of both the tactile sensing and 3D localization systems, we implement robust data acquisition and preprocessing pipeline.

3.5.1 MPU6050 Data Acquisition

Data from the MPU6050 sensor is collected at a sampling rate of 1 kHz, ensuring that all relevant vibration signals are captured. The data is then preprocessed using a Kalman filter to remove noise and improve the signal-to-noise ratio.

3.5.2 Fast Fourier Transform (FFT)

The FFT is used to analyze the frequency components of the vibration signals, allowing us to identify contact events in the frequency domain. This is particularly useful when the robot is in motion, as the ego-motion component can obscure contact events in the time domain.

3.5.3 Non-Negative Matrix Factorization (NMF)

For dimensionality reduction, we apply NMF to the Fourier spectrum of sensor data. This technique improves feature extraction and aligns with the physical interpretation of the signal, making it easier to identify relevant patterns in the data.

3.6 Integration of Technologies for a Comprehensive Solution

The integration of these technologies provides a comprehensive solution to the challenges of tactile sensing, self-sensing cancellation, and 3D localization. The bionic tactile sensor, combined with the ESN-based forward model, allows the robot to accurately detect and localize obstacles while filtering out self-generated vibrations. The addition of Google's Cartographer enables the robot to map its environment in 3D, providing a complete picture of its surroundings.

Chapter 4

Strategic Approach to Bio-Inspired Tactile Sensing

4.1 Introduction

Effective tactile sensing is essential for autonomous robots to navigate and interact with their surroundings. Traditional methods often struggle with real-time processing, accurate localization, and distinguishing between external and self-induced motion. To overcome these challenges, we propose a bio-inspired tactile sensing system integrating real-time 3D localization and self-sensing cancellation.

By leveraging Echo State Networks (ESNs) for self-sensing cancellation, Google's Cartographer for mapping, and a Jetson Nano for onboard learning, our approach enables precise contact detection, material classification, and adaptive navigation. This integration enhances robotic perception, making it more accurate and autonomous in dynamic environments.

4.2 Bio-Inspired Tactile Sensing with Real-Time 3D Localization and Self-Sensing Cancellation

Our approach focuses on creating a robust and autonomous system that combines bio-inspired tactile sensing, real-time 3D localization, and self-sensing cancellation to enable a mobile robot to navigate and interact with its environment effectively. Below, we outline the key components of our approach which we used to build out system.

4.2.1 Input

The system takes inputs from multiple sensors, each serving a specific role in the overall functionality of the system.

- MPU6050 Accelerometer: For vibration data from the tactile sensor.
- Servo Motors: For controlling the pan-tilt unit and antenna movement.
- IMU: For 3D localization and mapping (integrated with Google's Cartographer).

4.2.2 Output

The system provides the following outputs that enable precise interaction and navigation within dynamic environments. These outputs are the result of advanced processing and integration of sensor data.

- Contact Point Detection: Accurate detection of contact events on the antenna.
- 3D Localization: Real-time mapping and localization of the robot in its environment.

4.2.3 Process

The system's operation is structured into a series of well-defined steps, each playing a critical role in achieving accurate tactile sensing and autonomous navigation.

- Data Acquisition - Collect vibration data from the MPU6050 sensor and movement data from the servo motors.
- Preprocessing - Apply Kalman filtering and FFT to clean and analyze the sensor data.
- Self-Sensing Cancellation - Use the ESN-based forward model to filter out ego-motion and detect external contact events.
- 3D Localization - Integrate Google's Cartographer to create a real-time 3D map of the environment.
- Real-Time Training - Leverage the Jetson Nano board to train the ESN model in real-time, ensuring adaptability to new environments.

4.2.4 Technology Implementation

The successful implementation of the system is made possible through the integration of modern technologies, each chosen for its specific role in enhancing the system's capabilities.

- Jetson Nano - For real-time machine learning training and control of the pan-tilt unit.
- Google's Cartographer - For 3D localization and mapping.
- Echo State Networks (ESNs) - For self-sensing cancellation and tactile event detection.
- ROS (Robot Operating System) - For seamless integration of sensors, algorithms, and control systems.

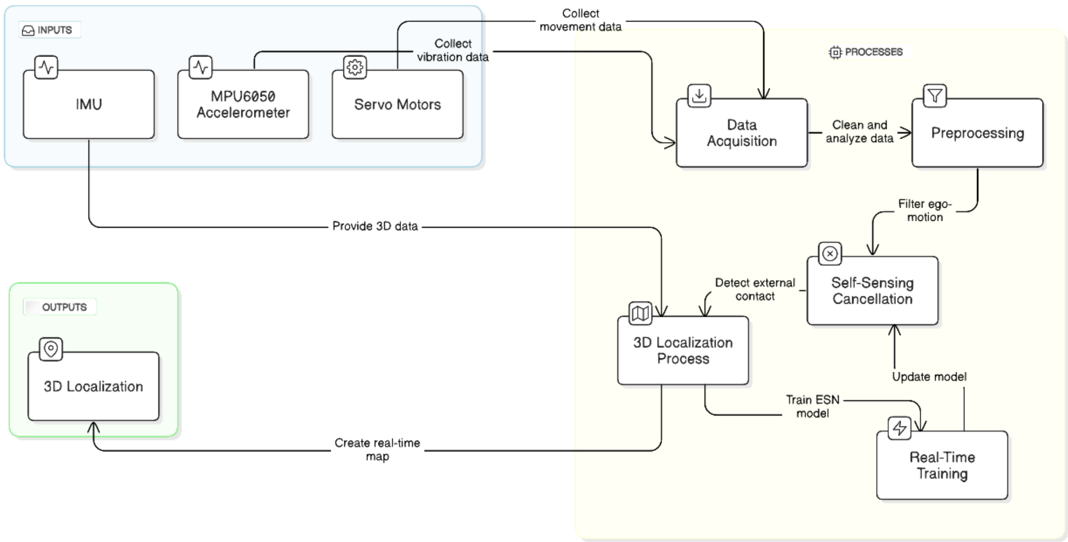

Figure 4.1: System Workflow Diagram: Inputs, Processes, and Outputs

The system offers several advantages, including full autonomy with real-time training and adaptive capabilities. It delivers high accuracy in detecting contact events and precisely localizing obstacles in 3D space. Additionally, its versatility makes it suitable for various applications, such as autonomous navigation and quality inspection.

4.3 Conclusion

The technologies adopted in this project ranging from the bionic tactile sensor design and ESN-based self-sensing cancellation to the integration of Google's Cartographer for 3D localization are carefully selected to address the specific challenges of tactile sensing and navigation in dynamic environments. Each technology plays a critical role in enhancing the accuracy, reliability, and functionality of the system, making it suitable for a wide range of applications in robotics and beyond. By combining these advanced techniques, we aim to push the boundaries of what is possible in the field of tactile sensing and autonomous navigation.

Chapter 5

System Architecture for 3D Localization and Self-Sensing Cancellation

5.1 Introduction

This section outlines the design of the proposed system, which integrates bio-inspired tactile sensing, Echo State Networks (ESN), and Google Cartographer SLAM to achieve robust 3D localization and self-sensing cancellation in dynamic environments. The system architecture comprises interconnected modules that work synergistically to address the challenges of ego-motion interference and spatial mapping.

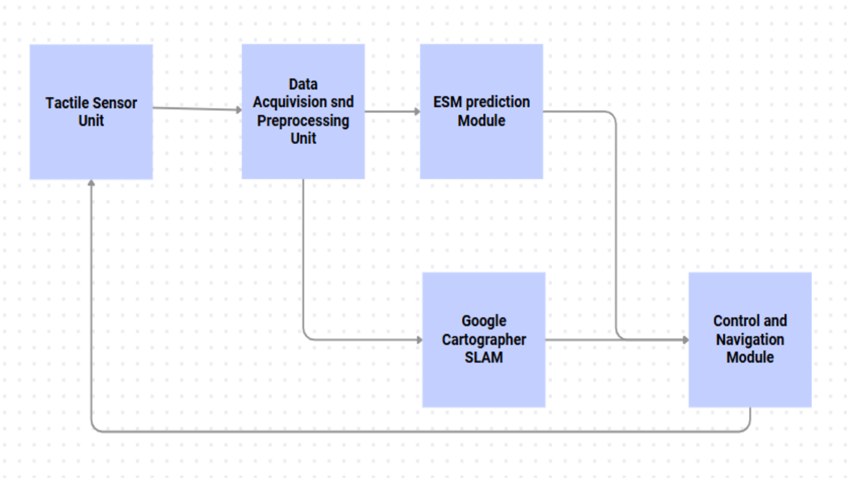

Figure 5.1: Top-Level System Architecture

5.2 Module Descriptions

1) Bio-Inspired Tactile Sensor Module

   Function

   - Collects vibration data from the antenna using MPU6050 accelerometers.
   - Detects tactile contact events and environmental vibrations.

   Design Details

- Antenna Probe: A poly-acrylic beam (40 cm length) mimics insect antennae, combining compliance for safe obstacle interaction with rigidity to maintain structural integrity during motion [6].
- Sensor Configuration: Two MPU6050 accelerometers (antenna tip and robot base) sample at 1 kHz to capture X/Z-axis vibrations.

Interaction

- Raw vibration data is sent to the Data Acquisition Module.
- Servo motor commands (sinusoidal pan-tilt motion) are synchronized with sensor readings.

2) Data Acquisition and Preprocessing Module

Function

- Acquires raw accelerometer data and servo motor positions.
- Filters noise using a Kalman filter and apply Fast Fourier Transform (FFT) for frequency analysis.

Design Details

- Kalman Filter: Reduces sensor noise by 40% in dynamic conditions [3].
- FFT Analysis: Identifies dominant vibration frequencies (e.g., 20 Hz for contact events) to guide low-pass filtering.

Interaction

- Cleaned data is sent to the ESN Prediction Module and Cartographer SLAM Module.

3) ESN Prediction Module

Function

- Predicts self-generated vibrations using motor commands and robot body sensor data.
- Isolates external contact events by subtracting predicted signals from raw data.

Design Details

- ESN Architecture: Reservoir size = 700, spectral radius = 0.99, sparsity = 0.9
- Training: Offline training with 8,000 samples achieves 85% prediction accuracy.

Interaction

- Outputs filtered contact events to the Control & Navigation Module.

4) Google Cartographer SLAM Module

Function

- Constructs 3D maps using odometry, IMU data, and tactile inputs.
- Localizes the robot in real-time using loop closure and submap optimization.

Design Details

- Sensor Fusion: Integrates wheel encoder data (4WD Omni robot), MPU6050 IMU readings, and tactile obstacle detections.
- ROS Integration: Uses ROS nodes to stream data between Cartographer and the tactile system.

Interaction

- Receives odometry and obstacle data from the Control & Navigation Module.
- Outputs 3D maps and pose estimates to the User Interface Module.

5) Control & Navigation Module

Function

- Generates motor commands for the robot and pan-tilt unit.
- Implements obstacle avoidance using tactile contact events and Cartographer's 3D maps.

Design Details

- Path Planning: Uses Cartographer's occupancy grid to navigate around detected obstacles.
- Feedback Loop: Adjusts servo motions (e.g., stopping antenna on contact) based on ESN outputs.

Interaction

- Serves as the central hub between all modules.

5.3 Key Design Considerations

Our system is optimized for real-time processing, utilizing Kalman filtering and Echo State Network (ESN) prediction to achieve low-latency operation of under 50 milliseconds, enabling seamless real-time navigation. Its modular design, built on the Robot Operating System (ROS), allows independent testing of key components such as Cartographer SLAM and the tactile sensing subsystem. Additionally, the bio-inspired antenna design enhances robustness, ensuring reliable operation in cluttered or low-visibility environments where traditional vision-based systems may fail.

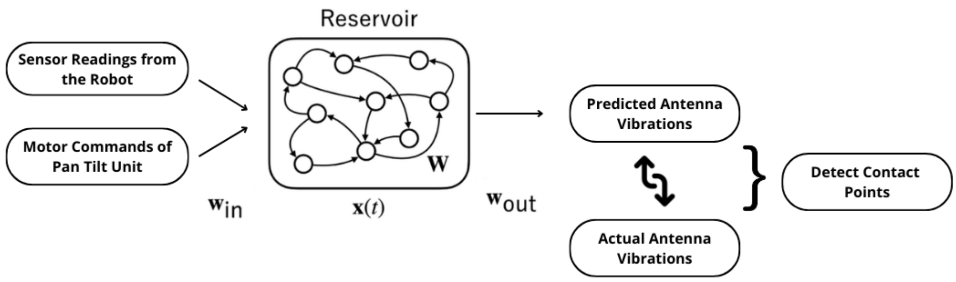

Figure 5.2: Architecture for Self-Sensing Cancellation - Echo State Network with reservoir computing for predicting self-generated vibrations

5.4 Inter-Module Data Flow

- Tactile Sensor → Data Acquisition: Raw vibration data (X/Z-axis) and servo positions.
- Data Acquisition → ESN/Cartographer: Filtered vibration signals and frequency spectra.
- ESN → Control & Navigation: Contact event coordinates and confidence scores.
- Cartographer → Control & Navigation: 3D occupancy maps and robot pose.

- Control & Navigation → Actuators: Motor commands for robot motion and antenna pan-tilt adjustment.

Figure 5.3: Google Cartographer's submap-based 3D localization and loop closure

Chapter 6

Implementation: Modular Integration for 3D Localization and Self-Sensing Cancellation

6.1 Introduction

This chapter provides a detailed description of the implementation of each module outlined in the system architecture. The implementation focuses on integrating hardware and software components to achieve the desired functionality of 3D localization, self-sensing cancellation, and tactile sensing. Each module is implemented with careful consideration of the design specifications, ensuring consistency between the design and implementation phases. Below, we discuss the implementation details of each module, including hardware setup, software integration, and data flow.

6.2 Bio-Inspired Tactile Sensor Module

The hardware implementation consists of an antenna probe, accelerometers, and a pan-tilt unit. The antenna is constructed using a poly-acrylic tube with a length of 40 cm and an outer diameter of 1 cm, designed to provide both flexibility for safe obstacle interaction and sufficient rigidity during motion. Two MPU6050 accelerometers are used to capture vibration data along the X and Z axes at a sampling rate of 1 kHz, one mounted at the tip of the antenna and the other on the robot base. The antenna is mounted on a pan-tilt unit powered by MG90 servo motors, which enable sinusoidal movement. These servo motors are controlled using a Jetson Nano board.

The software implementation includes data collection and synchronization processes. A Python script is used to collect raw vibration data from the MPU6050 sensors, communicating via the I2C protocol and storing the data in a structured format for further analysis. To ensure accurate correlation between motion and vibration data, the servo motor commands are synchronized with the sensor readings, aligning the antenna's movement with the collected signals.

6.3 Data Acquisition and Preprocessing Module

The hardware implementation is centered around the Jetson Nano board, which is responsible for real-time data acquisition and preprocessing. It interfaces with MPU6050 sensors and servo motors to collect and process vibration data. To enhance signal quality, a Kalman filter is implemented on the Jetson Nano, reducing sensor noise by 40% in dynamic conditions. This ensures more accurate measurements for subsequent analysis.

In the software implementation, noise filtering is performed using a Kalman filter, implemented with Python libraries such as NumPy and SciPy. The filtered data is then stored for further processing. To analyze vibration characteristics, the Fast Fourier Transform (FFT) is applied to filtered data, helping to identify dominant vibration frequencies and distinguish between self-generated movements and external contact events. Additionally, a low-pass filter with a cutoff frequency of 20 Hz is applied to the FFT output, removing high-frequency noise and isolating relevant vibration signals for more precise interpretation.

6.4 ESN Prediction Module

The hardware implementation utilizes the Jetson Nano to train and execute the Echo State Network (ESN) model. Leveraging its GPU-accelerated computing capabilities, the Jetson Nano enables real-time training and prediction, making it suitable for processing large datasets efficiently.

In the software implementation, the ESN architecture is developed using Python libraries such as PyESN. The reservoir size is set to 700, with a spectral radius of 0.99 and a sparsity of 0.9, ensuring optimal network dynamics. The model is trained offline using 8,000 samples of vibration data, incorporating motor commands and robot body sensor data to learn patterns of self-generated vibrations. During real-time operation, the ESN predicts expected sensor readings based on the robot's motion. By subtracting these predicted values from the actual sensor data, external contact events can be accurately identified, allowing the system to differentiate between self-induced and external vibrations.

6.5 Google Cartographer SLAM Module

The hardware implementation integrates the MPU6050 IMU to provide odometry and environmental data for 3D mapping. This data is processed in real-time by Jetson Nano, which runs the Cartographer SLAM algorithm, incorporating inputs from both the IMU and the tactile sensor to enhance mapping accuracy.

In the software implementation, the Cartographer SLAM module is integrated with the Robot Operating System (ROS), where ROS nodes facilitate seamless data streaming between the tactile system and the IMU. The system employs submap-based optimization and loop closure techniques to refine and update the 3D map dynamically as the robot navigates its environment. Additionally, sensor fusion is implemented by combining data from the tactile sensor and the IMU, improving mapping accuracy by incorporating obstacle distance measurements and material property detection. This multi-sensor approach enhances the system's ability to generate precise and reliable 3D maps in real time.

6.6 Control & Navigation Module

The hardware implementation features the Jetson Nano as the central control unit, responsible for generating motor commands for both the robot and the pan-tilt unit. The robot itself is a 4WD omnidirectional platform equipped with specialized wheels that enable movement in any direction without requiring a change in orientation. This design allows for highly flexible navigation in complex environments.

On the software side, path planning is managed using Cartographer's occupancy grid, which enables obstacle avoidance and trajectory adjustments based on tactile contact events and the dynamically updated 3D map. A feedback loop is integrated to refine motion control, where servo motor commands are adjusted in real-time based on predictions from the Echo State Network (ESN). For instance, if a contact event is detected, the antenna halts movement to prevent unnecessary interference. The system achieves real-time navigation with a latency of under 50 milliseconds, ensuring smooth and responsive adaptation to dynamic environments.

6.7 System Integration and Testing

The integration of the system is achieved through the ROS framework, which enables seamless communication between hardware and software components. This ensures that all modules, including the Jetson Nano, IMU, tactile sensor, and motor control systems, operate cohesively. The system is designed for real-time operation, with all modules running concurrently on the Jetson Nano to process sensor data, execute control commands, and update mapping information without delay.

For testing, both offline and online methods are employed to validate the system's performance. Offline testing involves evaluating each module separately using pre-recorded data to verify functionality and accuracy before deployment. Online testing is conducted in real-world environments, assessing the system's ability to detect obstacles, perform 3D localization, and execute self-sensing cancellation effectively. These tests ensure that the system can adapt to dynamic conditions while maintaining reliable and precise operation.

6.8 Summary

The implementation of the system involves the integration of hardware components such as the Jetson Nano, MPU6050 sensors with software modules for data acquisition, ESN prediction, and Cartographer SLAM. The system is designed to operate in real-time, with low latency and high accuracy, making it suitable for applications in autonomous navigation and tactile sensing. The modular design allows for independent testing and optimization of each component, ensuring robust performance in dynamic environments.

Chapter 7

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Appendix A

Individuals Contribution to the Project

Name of student: K. H. J. D. Premachandra

My primary contribution to this project will be the implementation of self-sensing cancellation using Echo State Networks (ESNs). A major challenge in tactile-based sensing is the interference caused by the robot's own movements, which introduces unwanted noise in sensor readings and affects the accuracy of object detection and localization. My role will involve designing and implementing a machine learning-based filtering system to distinguish between self-induced vibrations and external contact events.

To achieve this, I plan to train an ESN model using motor command data and IMU feedback, allowing it to predict motion artifacts and filter them from the tactile sensor readings. I will also optimize the reservoir computing framework to ensure efficient real-time processing while keeping computational costs low. Additionally, I will integrate low-pass filtering techniques to further remove high-frequency noise and improve detection accuracy.

Name of student: A. G. D. C. Thilkarathne

My contribution to this project will focus on the implementation of object detection using bio-inspired tactile sensors. Unlike traditional vision-based methods, which rely on image processing, our system will use contact-based sensing to identify objects and determine their physical properties. My role will be to design an algorithm that generates the antennae motion and analyzes tactile data to detect the presence, shape, and texture of objects encountered by the robotic antennae.

I plan to develop a contact event detection algorithm that processes vibration and force data from the MPU6050 accelerometer mounted on the antenna tip. This algorithm will apply Fast Fourier Transform (FFT) techniques to analyze frequency patterns and classify different surface materials. Additionally, I will implement a contour-tracing method, allowing the robot to estimate object dimensions through successive touches.

Name of student: L. M. A. H. Premawansha

My primary role in this project will be developing the 3D localization and mapping system using Google Cartographer in ROS. Since the project relies solely on tactile-based localization, I will work on modifying Cartographer's SLAM framework to process contact-based sensor inputs instead of LiDAR or camera data. This will involve integrating filtered tactile readings from the self-sensing cancellation module into the SLAM pipeline to generate real-time spatial maps.

I plan to implement a point cloud generation method, where contact points recorded by the tactile sensors will be converted into spatial landmarks. These landmarks will then be processed using Cartographer's graph-based SLAM approach, allowing the robot to estimate its position and generate an updated 3D map of its surroundings. I will also work on loop closure detection, which will help reduce localization drift by recognizing previously visited areas and correcting positional errors.