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

Dr. Nalin Harischandra
dept. of Electrical and Electronic Engineering
Faculty of Engineering
University of Peradeniya
Peradeniya, Sri Lanka
nalin@eng.pdn.ac.lk

Dr. Isuru Nawinna
dept. of Computer Engineering
Faculty of Engineering
University of Peradeniya
Peradeniya, Sri Lanka
isurunawinne@eng.pdn.ac.lk

Asela Hemantha
dept. of Computer Engineering
Faculty of Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e19300@eng.pdn.ac.lk

Janitha Dilshan
dept. of Computer Engineering
Faculty of Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e19295@eng.pdn.ac.lk

Dulshan Chamuditha
dept. of Computer Engineering
Faculty of Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e19495@eng.pdn.ac.lk

***Abstract*—Many animals actively use moveable tactile sensors to explore near-range space, utilizing sensory feedback to navigate their environments efficiently. Inspired by biological systems such as insect antennae and mammalian whiskers, bionic tactile sensors have been developed for robotic applications, enabling real-time object detection, material classification, and 3D localization. However, a significant challenge remains the interference caused by self-sensing due to ego motion, which can lead to false positives and errors in localization accuracy. This paper reviews self-sensing cancellation techniques and 3D localization methodologies, emphasizing their application in mobile robotic systems. The study highlights key research gaps and explores solutions such as neural network-driven predictive models, proprioceptive feedback integration, and adaptive filtering approaches to enhance sensor reliability and spatial mapping capabilities.**

***Index Terms*—Self-sensing cancellation, ego motion, bionic antenna, 3D localization, robotics, machine learning, adaptive filtering, Tactile sensor, Contour-tracing, Shape recognition, Artificial neural network, Central pattern generators, dynamic modeling**

I. Introduction

In the natural world, many animals rely on active tactile sensing to explore and interact with their immediate environment. Insects, such as the 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. 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, much like a cockroach’s 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.

II. Background and Key Concepts

A. Self-Sensing Cancellation in Active Tactile Sensing

Self-sensing cancellation refers to the ability of a system to differentiate between self-generated and externally induced signals. In biological models, organisms achieve this through predictive coding mechanisms that integrate motor commands with sensory feedback. Hartmann [1] introduced adaptive filtering techniques for self-sensing cancellation in rodent whisker models, which were later adapted for robotic applications [2].

Recent advancements in self-sensing cancellation leverage deep learning models and recurrent neural networks, such as Echo State Networks (ESNs), to predict self-induced sensory disturbances and filter them from tactile inputs [3], [4]. Reinforcement learning-based approaches [5] have further improved dynamic adaptation, allowing robotic systems to refine cancellation strategies in real-time. Additionally, proprioceptive feedback systems have been implemented to enhance motion prediction and noise reduction [6].

B. 3D Localization and Mapping Using Bionic Antennae

3D localization involves estimating an object's position in three-dimensional space using tactile feedback. Various methods, such as contour tracing [7] and path integration [8], have been employed to achieve accurate spatial mapping.

Bio-inspired bionic antennae have been developed to replicate insect and mammalian tactile sensing, enabling robots to reconstruct environmental features. Active tactile scanning enhances spatial perception [9], while proprioceptive integration has been explored for object detection in unstructured environments [10]. More recent research has applied deep learning to improve localization accuracy by compensating for movement-induced disruptions [11].

The integration of multi-antenna configurations has further advanced 3D spatial mapping capabilities. By incorporating coordinated motion patterns across multiple tactile probes, systems can generate higher-resolution environmental maps, improving navigation in cluttered or low-visibility conditions. However, this introduces additional challenges, such as cross-axis interference and increased computational complexity, which require adaptive filtering solutions.

III. Review of Relevant Literature

A. Biological Inspiration for Active Tactile Sensing

In nature, many animals rely on active tactile sensing to navigate and interact with their surroundings, particularly in low-visibility environments. This biological capability has inspired the development of bionic tactile sensors, which mimic the form and function of insect antennae and mammalian whiskers to enhance robotic perception. Research into these biological models has provided essential insights into mechanoreception, active exploration strategies, and neural processing of tactile feedback, which serve as the foundation for modern bio-inspired robotic sensors.

1) Mechanoreception and Active Tactile Exploration in Insects: Insects use their antennae to detect obstacles, recognize surface textures, and coordinate movement. Dürr et al. (2003) demonstrated that insect antennae function as active tactile sensors, continuously moving to gather spatial information [12]. Antennal mechanoreceptors detect contact forces, vibrations, and airflow changes, allowing for rapid adaptation to environmental changes. Similarly, Staudacher et al. (2005) explored the neurobiology of antennal mechanoreception, revealing how sensory neurons encode tactile information to guide motor responses [14]. These findings suggest that insects use phase-dependent sensory feedback, meaning that antennal sensitivity changes depending on their movement phase.

The role of active contour tracing in insect tactile perception was further examined by Hoinville et al. (2014), who studied how insects sample object surfaces through controlled antennal vibrations [15]. This technique enables precise edge detection and shape recognition, mechanisms that have influenced the design of vibration-based robotic antennae. The principles of biomechanical modulation in insect sensing have since been applied to robotic systems, improving their ability to adapt to complex environments.

2) Whisker-Based Sensory Perception in Mammals: Mammals, particularly rodents and pinnipeds (seals, sea lions), use whiskers (vibrissae) as specialized tactile sensors for detecting object textures, mapping environments, and tracking moving prey. Prescott et al. (2011) highlighted how rats employ whisking behaviors, where their whiskers rhythmically sweep the environment to gather spatial and textural data [13]. This biological mechanism has been instrumental in the development of robotic whiskers, which use similar rhythmic scanning motions to enhance robotic perception in unstructured settings.

Solomon & Hartmann (2006) further demonstrated how robotic whiskers could be used for feature detection, showing that bio-inspired whisker-based sensors improve shape and contour recognition [16]. Their research confirmed that whisker bending patterns encode critical information about object surface geometry and orientation, which has been used to refine whisker-based robotic localization models.

The ability of whiskers to perform texture classification was studied by Pearson et al. (2007), who developed a mobile robot equipped with artificial whiskers to categorize different surface textures. Their findings indicated that whisker movement dynamics and force-based tactile sensing contribute significantly to accurate material classification, a principle now widely implemented in autonomous robotic systems [17].

3) Tactile Learning and Adaptation in Honeybees: Beyond insects and mammals, honeybees also exhibit remarkable tactile learning abilities. Erber et al. (1998) explored how honeybees use their antennae to learn and recognize tactile patterns, demonstrating their ability to develop memory-based tactile responses [2]. This research suggests that bees rely on mechanoreceptor feedback and neural learning mechanisms to adapt to changes in their environment. The concept of tactile learning and adaptation has influenced the design of AI-driven robotic sensors, enabling them to refine their tactile perception over time.

4) Implications for Bio-Inspired Robotic Sensors: The study of biological tactile sensing has directly influenced the development of robotic whiskers and antennae, improving their ability to detect objects, classify materials, and navigate cluttered environments. The research conducted by Prescott & Durr (2015) provides a comprehensive overview of how different species utilize tactile sensing, underscoring the importance of mechanoreceptors, sensory integration, and movement coordination [18].

By integrating these biological principles, modern robotic systems can now achieve enhanced spatial awareness, improved obstacle detection, and adaptive material classification. However, challenges remain in replicating the full efficiency of biological sensory systems, particularly in terms of real-time neural processing, adaptive filtering, and multi-modal sensory integration. Future advancements in bio-inspired AI and neuromorphic computing may further enhance the ability of robotic tactile sensors to function as efficiently as their biological counterparts.

B. Development of Bionic Antennae for Robotics

The development of bionic antennae for robotics has been significantly influenced by biological models, particularly insect antennae and mammalian whiskers. These sensors play a crucial role in enabling robots to interact with their environment by providing tactile feedback for object localization, material classification, and navigation. Early robotic tactile sensors were inspired by whiskers and antennae, leading to the development of mechanical and electronic transducers for contact-based sensing [19]. However, these early systems were limited in their ability to differentiate between self-generated motion and external stimuli, reducing their effectiveness in dynamic environments.

1) Early Developments in Robotic Tactile Sensing: The initial efforts in robotic tactile sensing focused on mechanical whisker-like transducers, which were designed to detect obstacles and surface features. Kaneko et al. (1998) [19] introduced active antennae for contact sensing, where whisker-like structures were embedded with sensors to measure bending forces and vibrations. These systems provided an effective means of detecting objects but struggled with motion-induced noise from self-movement. To address these limitations, MEMS-based and piezoelectric sensors were later introduced, offering enhanced sensitivity and faster response times [20].

Mongeau et al. (2013) [21] explored how locomotion affects tactile sensing in biological systems, particularly in cockroaches, which rely on antennae movements to navigate rough terrains. Their findings emphasized that self-motion artifacts can significantly impact tactile perception, making it challenging to separate contact-induced forces from movement-generated signals. These insights influenced subsequent developments in adaptive filtering and sensor fusion techniques.

2) Bio-Inspired Adaptive Sensing and State-Dependent Modulation: Recent advancements have led to the development of bio-inspired adaptive sensors that actively adjust their response based on environmental interactions. J. Okada (2004) [22] investigated active tactile sampling in insects, demonstrating how antennae movements can be precisely controlled to enhance perception. Inspired by this biological model, researchers have integrated controlled oscillations in robotic antennae to improve object recognition and texture analysis.

One of the most significant improvements in bionic antennae is state-dependent modulation, which allows sensors to adjust their sensitivity and response based on the type of contact event. Patané et al. (2012) [23] introduced an insect-inspired bionic sensor that dynamically modulates its response to improve material classification and localization accuracy. This approach mimics how insects alter their antennae movements based on external stimuli, leading to better adaptation in complex, cluttered environments.

3) Challenges in Motion Artifact Reduction and Localization Accuracy: Despite advancements in sensor design, motion-induced artifacts remain a significant challenge for bionic antennae, especially when deployed in mobile robotic platforms. Self-induced vibrations and oscillatory movements introduce false signals, making it difficult to accurately determine object positions [24]. These issues are particularly problematic in step-climbing robots and legged locomotion, where rapid antennae movements interact with terrain disturbances [26].

To address these challenges, multi-antenna configurations have been developed using coordinated motion patterns to improve spatial mapping. Research has shown that whisker-based texture classification can be enhanced by synchronizing antennae movements, reducing cross-axis interference, and improving 3D localization accuracy [25].

4) Summary and Future Directions: The evolution of bionic antennae has progressed from simple mechanical transducers to highly adaptive, state-modulated tactile sensors. The integration of biological movement patterns, multi-antenna coordination, and AI-driven motion compensation has significantly improved object detection and material classification capabilities. However, challenges related to motion artifact cancellation, real-time adaptation, and energy efficiency remain unresolved. Future research should focus on hybrid AI models, neuromorphic computing, and sensor fusion techniques to enhance the robustness and reliability of bionic tactile sensing in dynamic environments.

C. Self-Sensing Cancellation: Filtering Ego Motion Artifacts

Active tactile sensors, such as robotic whiskers and bionic antennae, face a fundamental challenge when deployed on mobile robotic platforms, self-induced motion artifacts. These artifacts arise due to oscillatory antennae movements, platform vibrations, and terrain-induced disturbances, which introduce noise into tactile signals. As a result, robots struggle to distinguish true contact-based feedback from motion-induced false positives, leading to inaccurate object localization and material classification.

To address this, researchers have explored various bio-inspired and AI-driven filtering techniques, including adaptive filtering, forward models, reinforcement learning, and deep learning-based noise suppression. The following section reviews key approaches for mitigating ego-motion artifacts in active tactile sensing.

1) Bio-Inspired Approaches to Self-Sensing Cancellation: Biological models provide crucial insights into how animals

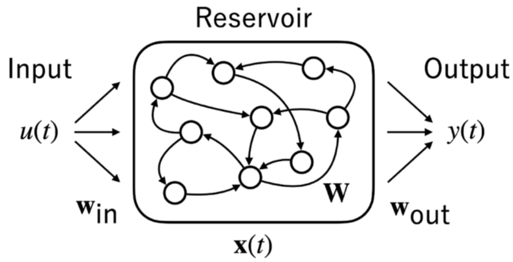

Fig. 1. Echo State Network showing the inputs u(t), outputs y(t) and Reservoir

filter out self-induced tactile noise. Hartmann (2001) [29] demonstrated that rats use proprioceptive feedback and whisking patterns to predict and subtract self-motion artifacts from their sensory input. Similarly, Solomon & Hartmann (2006) [30] applied these principles to robotic whiskers, designing a feature-detection system that actively compensates for motion artifacts using pre-learned movement models.

Miall & Wolpert (1996) [31] introduced the concept of forward models in physiological motor control, explaining how biological systems predict the consequences of self-motion and use efference copies (motor signals) to cancel unwanted noise. Inspired by these findings, roboticists have developed predictive models that estimate self-induced disturbances and compensate for them in real-time.

2) Adaptive Filtering and Kalman-Based Approaches: One of the earliest computational solutions for ego-motion artifact reduction was adaptive filtering. Kalman filters and Fourier-based filtering techniques have been widely applied to remove self-sensing interference in robotic whisker systems (Russell & Wijaya, 2003) [29]. However, these techniques are limited in dynamic environments where motion artifacts vary non-linearly and require real-time adjustments.

Reinforcement learning-based filtering has been introduced, allowing robots to adaptively adjust their filtering parameters based on sensory feedback and motor movements. This approach significantly improves artifact rejection in varying terrain conditions but remains computationally expensive.

3) Echo State Networks for Motion Artifact Cancellation: Reservoir computing models, such as Echo State Networks (ESN), have emerged as a promising approach for self-sensing cancellation. Harischandra & Dürr (2012) [27] developed an ESN-based predictive model that uses motor efference copies and proprioceptive signals to dynamically filter out self-generated noise. This technique enables real-time noise suppression, even in highly dynamic environments where traditional filters struggle.

Jaeger & Haas (2004) [30] further refined ESN-based filtering by demonstrating that nonlinear reservoir computing models could predict and remove chaotic motion artifacts from sensory data. Their approach has been successfully applied in bio-inspired tactile sensing, significantly improving the accuracy of object localization and texture recognition.

4) Deep Learning for Motion Artifact Suppression: Recent advancements in deep learning have provided new ways to separate self-induced noise from external tactile signals. Deep learning models, such as convolutional neural networks (CNNs), have been applied to classify tactile material properties while simultaneously filtering motion artifacts. Research indicates that deep learning-based filtering outperforms traditional methods, particularly in complex, multi-sensor environments.

However, deep learning approaches require large datasets and are computationally expensive, making real-time deployment in robotic systems challenging. A hybrid approach, integrating reinforcement learning with ESN-based predictive filtering, could offer a more efficient and scalable solution for self-sensing cancellation. Additionally, shape-dependent reinforcement learning has been explored for active tactile exploration, demonstrating the potential for adaptive filtering techniques in dynamic environments [26].

5) Comparative Analysis of Self-Sensing Cancellation Techniques: To determine the most effective self-sensing cancellation technique, we compare Kalman filtering, Echo State Networks (ESN), and deep learning-based approaches. Table 1 summarizes the key advantages, limitations, and real-world applications of these techniques.

TABLE I
COMPARISON OF SELF-SENSING CANCELLATION TECHNIQUES

Technique	**Mechanism**	**Performance**	**Limitations**
Kalman Filtering	Real-time processing, low computational cost	70–80% artifact reduction in structured environments [29]	Fails with non-linear vibrations (e.g., legged robots)
Echo State Networks (ESN)	Reservoir computing for dynamic noise modeling	90% reduction in unstructured settings [27]	Requires GPU acceleration for real-time use
Deep Learning (CNN/RNN)	Combines spatial feature extraction (CNN) with temporal prediction (ESN)	95% accuracy in texture classification [33]	High computational cost (>1 TFLOPs)

6) Discussion of Results:

- Kalman Filtering is computationally efficient and works well in structured, predictable environments but fails in non-linear, rapidly changing conditions.
- Echo State Networks (ESN) improve adaptability and learn from real-time interactions, making them useful in complex robotic systems. However, they require large datasets for training, making deployment difficult in real-time applications.
- Deep Learning approaches offer the highest accuracy in self-motion filtering but are computationally intensive and require extensive labeled training data.

Given these trade-offs, hybrid models combining adaptive filtering with neural network-based prediction could enhance real-time self-motion cancellation while maintaining computational efficiency.

D. 3D Localization and Mapping Using Tactile Sensors

3D localization and mapping using tactile sensors present unique challenges and opportunities, particularly in environments where visual or LiDAR-based methods are impractical [32]. Unlike optical sensors, tactile sensors rely on physical contact, making them suitable for low-visibility or confined spaces. However, this reliance on contact leads to sparse data collection, requiring active exploration by the robot to build accurate maps and localize within them [32], [33]. Additionally, self-induced motion artifacts, such as vibrations from robot movement, can interfere with accurate perception, necessitating advanced filtering techniques.

1) Tactile Mapping and Localization Techniques: One approach to address these challenges involves creating a dense tactile map of an object offline, which serves as a reference for data association during manipulation tasks [33]. The mapping process includes several key steps like below.

1) **Local Shape Estimation:** Tactile imprints are analyzed, often using Convolutional Neural Networks (CNNs), to estimate local shapes.
2) **Global Shape Mapping:** Tactile data is combined with robot kinematics to reconstruct the object's overall shape.
3) **Identification and Localization:** New tactile readings are compared to the map, and pose estimates are refined using algorithms like Iterative Closest Point (ICP) [33].

Shape reconstruction relies on accurate robot kinematics, gripper calibration, and precise height maps derived from tactile imprints [33]. The process begins by constructing a point cloud in the sensor's frame using calibrated intrinsic parameters of the sensor's camera. This point cloud is then transformed into the world frame, assuming a rigid transformation between the sensor, gripper, and robot arm. Multiple point clouds from different views are integrated into a single, comprehensive representation of the object [33]. Tactile data can be treated as point clouds, enabling techniques like RANSAC for database matching and localization [32], [33].

2) Bayesian Filtering and Active Tactile Perception: Bayesian filtering offers another method for integrating tactile and visual data to improve localization accuracy [32], [34]. By modeling motion with Gaussian noise and using feature descriptors like SIFT extracted from both tactile and visual images, belief distributions can be updated through feature matching. This approach allows for recursive refinement of the estimated location of the tactile sensor on the object [32].

Active tactile perception, achieved through robotic palpation with squeeze-and-release motions, provides dynamic information about the object. Sequences of pressure images can be represented as 3D tensors, capturing the changing pressure distribution over applied force, which can be analyzed using 3D CNNs for object classification [35], [36].

3) Bio-Inspired Approaches and Sensor Fusion: Bio-inspired approaches, such as those observed in insects, have significantly influenced tactile localization strategies. For example, stick insects and ants use antennae to detect obstacles and navigate complex terrains. Techniques like active tactile scanning, contact-based path integration, and phase-synchronized antennae movements have been adapted for robotic systems to improve mapping and navigation [24], [39]. Contour-tracing techniques, combined with vibration-based tactile sensing, allow robots to reconstruct detailed 3D spatial models, enhancing path-planning capabilities [38], [39].

Sensor fusion, particularly using tactile skin with multiple sensors and the BRICPPF approach, enables robust object recognition, localization, and robot self-localization [32]. The BRICPPF method combines particle filters, ICP, and feature-based RANSAC, enabling efficient management of high-dimensional spaces and effective database matching [32]. Exploration strategies, such as edge following and the widest unexplored cone approach, guide the tactile sensor to gather informative data and improve mapping accuracy [37].

4) Challenges and Future Directions: Despite significant advancements, tactile-based 3D localization faces challenges such as scalability to multi-antenna systems, computational efficiency for real-time navigation, and improved long-distance navigation. Cross-axis interference in multi-antenna arrays can degrade localization accuracy, requiring advanced signal-processing techniques and decentralized control algorithms for synchronization. AI-driven filtering techniques, such as Echo State Networks (ESNs), provide effective noise reduction but are computationally demanding. Future research should focus on optimizing neural network architectures and exploring hardware-efficient implementations like neuromorphic computing [27], [40].

Hybrid sensor fusion, combining tactile sensing with inertial measurement units (IMUs) and low-resolution depth sensors, could enhance navigation efficiency in large-scale environments. Predictive motion planning techniques, anticipating object locations based on limited tactile feedback, could further improve long-range navigation capabilities.

In conclusion, tactile-based 3D localization and mapping offer promising solutions for environments where traditional sensors fall short. By leveraging bio-inspired strategies, advanced filtering techniques, and sensor fusion, robotic systems can achieve greater autonomy and reliability in tactile perception and navigation [32], [33], [35]–[37].

IV. Case Studies and Real-World Applications

To demonstrate the effectiveness of bionic antennae and whisker-based tactile sensing, several real-world robotic applications have been explored. These include search-and-rescue missions, underwater exploration, and industrial automation, where optical sensors often fail due to environmental constraints.

A. Whisker-Based Robots for Search-and-Rescue Missions

Researchers have developed autonomous search-and-rescue robots equipped with artificial whiskers to navigate collapsed buildings and disaster zones where visibility is limited. For example, a mobile robot utilizing whisker-based texture classification was designed to identify surfaces and obstacles in dark, cluttered environments [17]. These robots enhance navigation and hazard detection, particularly in situations where traditional sensors such as cameras and LiDAR struggle due to dust, smoke, or debris.

B. Underwater Tactile Sensing Inspired by Harbor Seal Whiskers

Seals rely on their whiskers to detect water currents and moving objects in low-visibility environments. Inspired by this natural ability, biomimetic whiskers have been developed for underwater robots, enhancing their capacity to track objects and measure fluid flow patterns [30]. This technology has significant applications in autonomous underwater vehicles (AUVs), aiding in oceanic exploration, military reconnaissance, and environmental monitoring.

C. Industrial Applications of Bionic Antennae in Automation

In manufacturing, robots equipped with bionic tactile sensors can perform quality control and material classification more efficiently than traditional cameras. For instance, deep learning-based tactile sensing has been applied to improve object recognition in robotic assembly lines, reducing the reliance on visual inspection systems [28].

V. Gaps and Future Research Directions

Despite significant advances in bionic tactile sensing, two major challenges remain unresolved. They are:

1) The cancellation of self-sensing interference due to ego motion, which disrupts accurate perception.
2) Accurate 3D localization using bionic tactile sensors, which remains difficult due to motion-induced noise and computational constraints.

These challenges limit the effectiveness of robotic systems using bionic antennas for navigation and object detection, making them unreliable in dynamic environments. Addressing these gaps is the primary focus of our research.

A. Self-Sensing Cancellation Due to Ego Motion

An issue arises when bionic antennae move, generating self-induced vibrations and oscillatory signals that interfere with external contact-based sensing. The challenge lies in the difficulty of existing self-sensing cancellation techniques, such as Kalman filtering and adaptive thresholding, to effectively distinguish between true tactile feedback and motion-induced noise, particularly in unstructured environments. Future research aims to address this challenge by developing real-time predictive models using Echo State Networks (ESN) and reinforcement learning to dynamically filter out ego-motion artifacts. Additionally, bio-inspired proprioceptive feedback systems will be implemented, allowing robots to actively predict and subtract self-induced motion noise based on motor commands. Further exploration will focus on hybrid AI models that combine deep learning-based classification with adaptive filtering techniques for enhanced self-sensing cancellation.

B. Challenges in 3D Localization with Bionic Antennae

An issue arises with bionic tactile sensors, as they rely on contact-based feedback, which limits their ability to perform real-time 3D mapping, unlike optical or LiDAR-based localization methods. The challenge lies in the current 3D localization techniques, such as contour tracing and tactile scanning, which lack the necessary speed and accuracy for real-time navigation. Additionally, self-motion artifacts introduce errors in object position estimation, causing localization to drift over time. Future research will focus on developing multi-antenna tactile localization models that utilize coordinated motion patterns to create high-resolution 3D spatial maps. Another direction will involve designing self-learning localization frameworks that combine tactile feedback with proprioceptive sensing to enable continuous recalibration. Additionally, implementing sensor fusion techniques that integrate bionic tactile data with inertial measurement units (IMUs) will provide more robust spatial awareness.

C. The Need for Real-Time Adaptive Processing

An issue with both self-sensing cancellation and 3D localization is the need for high-speed processing to be effective in real-world applications. The challenge arises from AI-driven filtering techniques, such as deep learning models, which require substantial computational power, making it difficult to deploy on low-power embedded systems. Future research will focus on exploring lightweight AI algorithms optimized for edge computing, enabling real-time artifact suppression and localization. Additionally, investigating neuromorphic computing techniques will be essential to facilitate energy-efficient self-sensing cancellation.

VI. Summary of Key Research Focus

In summary, the core contribution of our research is to:

1) Develop novel techniques for self-sensing cancellation, allowing bionic tactile sensors to function without interference from ego motion.
2) Improve 3D localization accuracy by integrating multi-antenna motion strategies and adaptive learning-based spatial mapping.

By addressing these gaps, our research aims to enhance the reliability of bionic tactile systems in dynamic, real-world environments, particularly in autonomous robotics, search-and-rescue, and industrial automation.

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