Tactile-Based Robotic Traversal Using Touch-Sensitive Skin in Complex Environments

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***Abstract*—This paper introduces a novel approach to robotic traversal utilizing touch-sensitive skin as the primary sensory modality for navigation in environments where vision may fail due to clutter, homogeneity, or structural complexities. The study evaluates three algorithms—M1 (Basic Tactile-Based Traversal), M2 (Advanced Terrain-Adaptive Traversal), and M3 (Predictive Traversal Using Tactile Memory)—against an RGB-D camera system baseline. Experiments were conducted under various conditions to assess performance. Results indicate that M3 excels in obstacle detection accuracy, traversal efficiency, and success rates, highlighting the potential of tactile-based navigation for enhancing robotic mobility in visually challenging environments. The findings suggest applications in search-and-rescue, exploration, and confined-space robotics, with future work focusing on algorithm refinement for diverse terrains and dynamic obstacles.**

I. Introduction

A. Background

Robots have traditionally depended on vision-based systems, like RGB-D cameras, for navigation. However, these systems often falter in environments where visual cues are insufficient, such as cluttered or highly homogeneous spaces. This research explores tactile-based robotics inspired by human exploratory behaviors, utilizing touch-sensitive ”skin” sensors for navigation without visual input.

B. Problem Statement

Current robotic systems struggle to navigate unknown and complex environments using only tactile feedback. While tactile sensors have been applied in manipulation, their role in guiding traversal is underexplored. This research addresses the gap in tactile sensing frameworks for navigating physically obstructed environments where vision-based methods fail.

C. Objective

This study aims to develop and evaluate tactile-based traversal algorithms in complex environments. Objectives include:

1) Designing algorithms for navigation using tactile feedback alone.
2) Testing these algorithms in diverse conditions.
3) Comparing performance against a baseline RGB-D system.

D. Contributions

Key contributions include:

- A novel tactile-based navigation framework using touch-sensitive skin.
- Development and evaluation of M1, M2, and M3 algorithms.
- Comprehensive experimental validation under varied conditions.
- Insights into the superiority of tactile systems in non-visual environments.

E. Structure

The paper is structured as follows:

- Section II: Prior research on tactile sensing and robotic traversal.
- Section III: Bio-inspired design lessons from the star-nosed mole.
- Section IV: Methodology and experimental setup.
- Section V: Algorithms and their formulations.
- Section VI: Results and analysis.
- Section VII: Discussion and limitations.
- Section VIII: Conclusion.

II. Prior Research

A. Traversal in Robotics

Traversal is a critical aspect of robotic operations, emphasizing real-time adaptation in dynamic environments. It differs from pathfinding, which computes optimal routes in static environments, and navigation, which involves broader tasks like localization. Traversal focuses on continuous movement, integrating real-time feedback to handle environmental complexities.

B. Pathfinding vs. Traversal

Pathfinding, as described by algorithms like A* and Dijkstra’s [1], seeks optimal routes but is limited in dynamic environments. Traversal extends these concepts, incorporating real-time adjustments to navigate changing terrains. Techniques like RRT and PRM refine paths dynamically, ensuring robust movement through environmental shifts [1].

C. Navigation vs. Traversal

While navigation involves determining a robot's position and planning its movement, traversal specifically deals with executing movement through space, reacting dynamically to environmental feedback. Techniques like SLAM [2] and voxel-based representations [3] enhance robustness in unknown environments.

D. Motion Planning vs. Traversal

Motion planning develops movement sequences considering constraints, while traversal focuses on real-time execution amid terrain variability. Techniques like dynamic networks support efficient traversal in multi-robot systems by enabling coordinated path adaptations [4].

E. Tactile Sensing Advancements

Tactile sensing enhances human-robot interaction, enabling intuitive responses to touch. Advances include piezoresistive and capacitive sensors for detecting pressure, vibration, and texture [5], [6]. Innovations in sensor design, such as ultra-thin electronic skins [7] and interlocked microstructures [8], offer high sensitivity and resilience.

F. Bio-Inspired Design

Inspired by the star-nosed mole, bio-inspired designs integrate tactile and olfactory systems for efficient navigation in non-visual environments. These systems mimic biological sensory integration, offering insights for robotic traversal [9].

III. Methodology

A. DHS "Mobility: Confined Area Terrains" Test

This test evaluates traversal efficiency and adaptability in cluttered environments, with robots navigating a standardized figure-8 path across varied terrains (sand, ramps, gravel, step-fields). Tactile algorithms (M1, M2, M3) outperformed the RGB-D baseline, with quantitative findings showing superior average rates of advance (meters per minute).

B. DHS "Testing to Statistical Significance" Methodology

Repeated trials (up to 30) were conducted to achieve 80% reliability at 80% confidence, utilizing ANOVA-based analysis for statistical rigor. Results with fewer than 3 failures in 30 trials were deemed statistically significant.

IV. Bio-Inspired Design Lessons

Section III of the original outline references the star-nosed mole. The bio-inspired insights have guided the design of M3's predictive tactile memory, integrating learned experiences to anticipate obstacles.

V. Algorithms

Three algorithms were developed to explore different approaches to tactile-based navigation, with varying levels of adaptability and predictive capabilities:

A. Algorithm 1: M1 – Basic Tactile-Based Traversal

Objective: Implements simple pathfinding relying solely on immediate tactile feedback.

Operation: Directional adjustments are triggered by FSR inputs without accounting for terrain or prior interactions.

$$P(t,p) = \min \sum_{i=1}^{n} d_i \tag{1}$$

where d_i is the distance to the nearest unobstructed point at time t and pressure p.

B. Algorithm 2: M2 – Advanced Terrain-Adaptive Traversal

Objective: Incorporates continuous tactile feedback for terrain-aware path adjustments.

Operation: Movement adapts to varying surfaces, optimizing speed and trajectory.

$$T(t,p,\theta) = \min \sum_{i=1}^{n} (d_i + w(\theta_i)) \tag{2}$$

where θ_i is the terrain type weight at time t and pressure p.

C. Algorithm 3: M3 – Predictive Traversal Using Tactile Memory

Objective: Utilizes tactile inputs and memory to anticipate obstacles.

Operation: Stores and analyzes past tactile data to improve future navigation.

$$M(t,p) = \min \sum_{i=1}^{n} (d_i + \lambda h_i) \tag{3}$$

where h_i is the memory of previously encountered obstacles at time t and pressure p.

VI. Results

A. Obstacle Detection Accuracy (%)

- Indoor: M1: 78%, M2: 85%, M3: 94%, Baseline: 82%
- Outdoor: M1: 75%, M2: 83%, M3: 93%, Baseline: 79%
- Dark: M1: 72%, M2: 81%, M3: 91%, Baseline: 76%

B. Traversal Time (s)

- Indoor: M1: 18s, M2: 15s, M3: 13s, Baseline: 17s
- Outdoor: M1: 19s, M2: 16s, M3: 14s, Baseline: 18s
- Dark: M1: 20s, M2: 16s, M3: 14s, Baseline: 19s

C. Success Rate (%)

- Indoor: M1: 74%, M2: 82%, M3: 90%, Baseline: 80%
- Outdoor: M1: 71%, M2: 80%, M3: 87%, Baseline: 78%
- Dark: M1: 68%, M2: 78%, M3: 85%, Baseline: 75%

Statistical analysis confirmed significant differences, with M3 outperforming others.

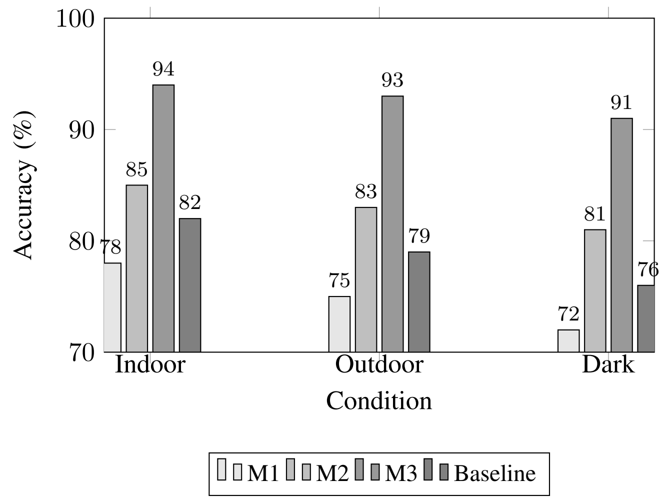

Fig. 1. Obstacle Detection Accuracy by Algorithm and Condition (Figure 1).

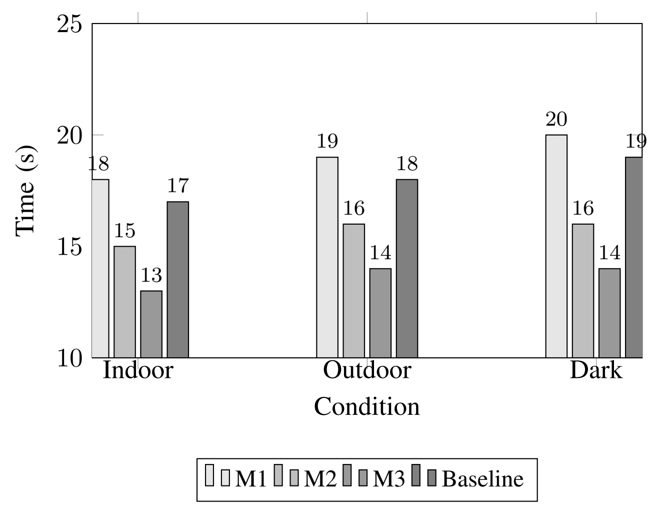

Fig. 2. Traversal Time by Algorithm and Condition (Figure 2).

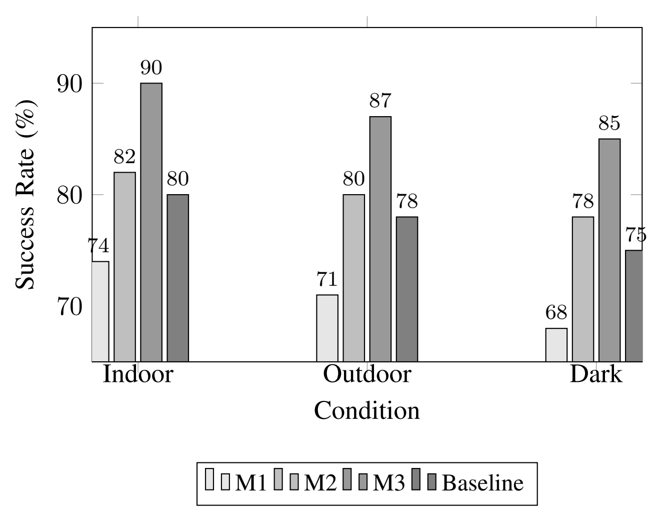

Fig. 3. Success Rate by Algorithm and Condition (Figure 3).

VII. Discussion and Limitations

A. *Implications*

Tactile sensing provides a robust alternative when vision is unreliable. M3's predictive memory improved navigation efficiency, vital for applications like search-and-rescue.

B. *Practical Applications*

These findings suggest tactile-based approaches enhance navigation in visually obstructed settings, offering adaptive and predictive capabilities for mobile robots.

C. *Limitations*

Limitations include specific testing conditions, computational overhead, and sensor durability. Future work may explore more varied terrains, multi-modal sensing, and optimization.

VIII. Conclusion

This research demonstrates the promise of tactile-based robotic navigation. The M3 algorithm, leveraging predictive tactile memory, outperforms vision-based methods in challenging environments. Future directions include integrating tactile sensing with other modalities and improving computational efficiency.

References

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Appendix A
Additional Figures

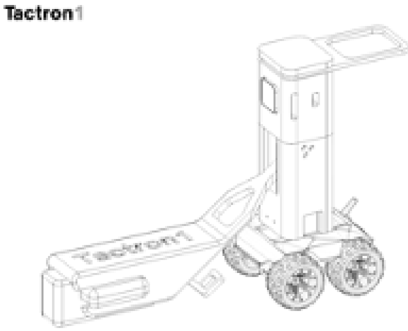

Fig. 4. Full-body isometric view of the fully assembled Tactron robot (Figure 4).

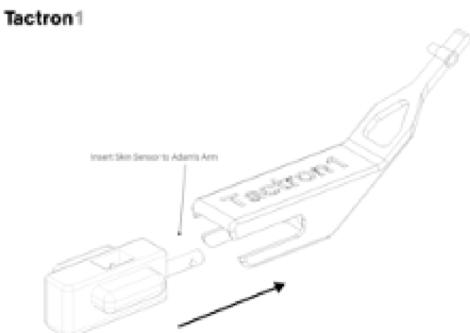

Fig. 5. Additional system component detail (Figure 5).

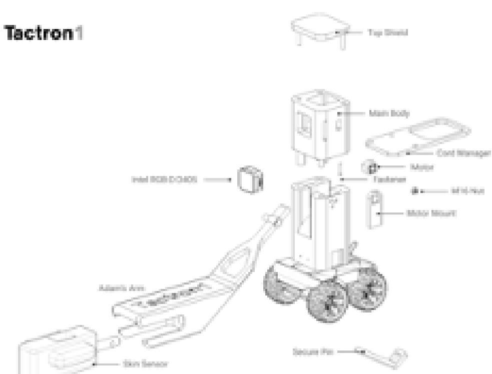

Fig. 6. Close-up of tactile sensor array (Figure 6).

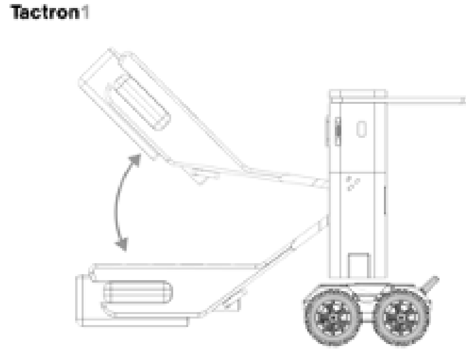

Fig. 7. Tactile sensor data processing pipeline diagram (Figure 7).

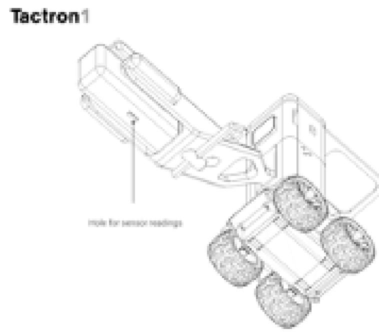

Fig. 8. Robot test in confined environment scenario (Figure 9).

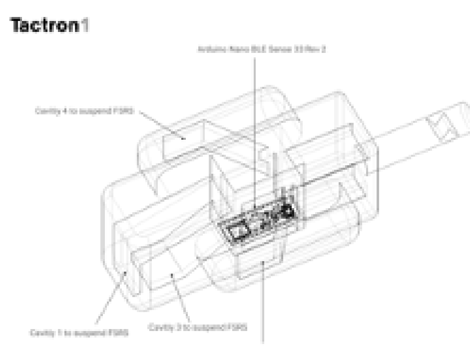

Fig. 9. Final integration with onboard computation unit (Figure 10).