

# Autonomous Cricket Pitch Curation: A Novel Framework for Stochastic Defect Detection and Surface Restoration

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**Abstract**—The integrity of a cricket pitch is the governing variable in the sport’s dynamics, influencing ball trajectory, bounce consistency, and player safety. Traditional curation methods are predominantly manual, relying on subjective visual inspection and labor-intensive rolling, which often leads to inconsistent surface characteristics. This paper presents the design, mathematical modeling, and validation of an autonomous robotic curator capable of high-precision surface metrology and active repair. The system leverages a coverage-optimized Boustrophedon path planning algorithm combined with a “Smart Sensor” architecture to identify and rectify surface depressions in real-time. A high-fidelity Monte Carlo simulation environment was developed in MATLAB to evaluate the system’s robustness under stochastic defect distributions. Results indicate that the proposed 25% overlap path strategy achieves 100% defect interception. Quantitative analysis demonstrates a reduction in Root Mean Square (RMS) roughness from a degraded state of 0.58 mm to a baseline of 0.05 mm. Furthermore, the system exhibits superior energy efficiency, recording a mechanical duty cycle of 5.54% compared to continuous-operation baselines. This research establishes a foundational framework for autonomous precision maintenance in sports infrastructure.

**Index Terms**—Autonomous Systems, Skid-Steer Kinematics, Path Planning, Surface Metrology, Cricket Pitch Maintenance, Robotics, Monte Carlo Simulation.

## I. INTRODUCTION

**C**RICKET is a sport defined by the interaction between the ball and the pitch surface. A standard pitch, a rectangular strip measuring 20.12m by 3.05m, consists of high-clay content soil that must be maintained at specific density and flatness levels [1]. Surface irregularities, such as footmarks created by bowlers or ball indentations, introduce non-linearities in ball behavior, which can degrade the quality of the game and pose safety risks to batters.

Current maintenance practices involve heavy rollers and manual tamping. These methods suffer from two primary limitations:

- 1) **Subjectivity**: Decisions on where to repair are based on human visual estimation, which is prone to error and fatigue.
- 2) **Inefficiency**: Curators often apply blanket treatments (rolling the entire pitch) even when damage is localized, leading to unnecessary soil compaction and energy expenditure.

The advent of agricultural robotics offers a pathway to automate this process. However, existing solutions are primarily tailored for vegetation management (mowing, spraying)

rather than topographical reconstruction [2]. This research proposes a specialized autonomous rover designed to navigate the constrained geometry of a cricket pitch, map surface topology, and execute targeted repairs.

## II. SYSTEM ARCHITECTURE

### A. Mechanical Design Concept

The proposed system is a four-wheeled skid-steer mobile robot. This configuration was chosen for its mechanical simplicity and zero-turn radius capability, which is essential for maneuvering within the pitch boundary without damaging the outfield. The core payload consists of:

- 1) **Sensing Module**: A downward-facing depth sensor (LiDAR/Stereo Camera) to generate a local height map  $H(x, y)$ .
- 2) **Actuation Module**: A solenoid-driven tamper mechanism located at the vehicle’s center of mass to deliver vertical repair impulses.

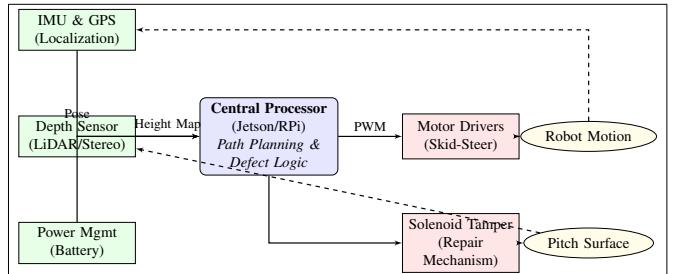


Fig. 1. System Block Diagram. The Central Processor executes the “Inspect-and-Repair” logic, closing the loop between the depth perception module and the mechanical tamper.

## III. MATHEMATICAL FRAMEWORK

### A. Kinematic Formulation

The robot’s motion is governed by the differential constraints of skid-steering. Let the robot’s state in the global frame be vector  $q = [x, y, \theta]^T$ . The kinematic relationship between the wheel velocities and the robot’s linear velocity  $v$  and angular velocity  $\omega$  is given by:

$$\begin{bmatrix} v_x \\ \omega_z \end{bmatrix} = \frac{r}{2} \begin{bmatrix} 1 & 1 \\ -\frac{1}{w} & \frac{1}{w} \end{bmatrix} \begin{bmatrix} \dot{\phi}_L \\ \dot{\phi}_R \end{bmatrix} \quad (1)$$

Where  $r$  is the wheel radius,  $w$  is the track width, and  $\dot{\phi}_{L,R}$  are the angular velocities of the left and right wheel pairs.

### B. Surface Metrology ( $R_{rms}$ )

Standard arithmetic roughness ( $R_a$ ) is often insufficient for functional analysis. We utilize the Root Mean Square Roughness ( $R_{rms}$ ) to penalize larger deviations (deep holes) more heavily:

$$R_{rms} = \sqrt{\frac{1}{n} \sum_{i=1}^n (z_i - \bar{z})^2} \quad (2)$$

Where  $z_i$  is the height of the  $i$ -th node and  $\bar{z}$  is the mean surface height (target = 0).

### C. Energy Consumption Model

The total energy  $E_{total}$  is the sum of locomotion energy and repair energy:

$$E_{total} = \sum_{t=0}^T (P_{move} \cdot \Delta t) + \sum_{k=0}^K (E_{tamper}) \quad (3)$$

Where  $K$  is the total number of repair events. The **Duty Cycle** ( $D$ ) is defined as:

$$D = \frac{N_{repair}}{N_{total\_steps}} \times 100\% \quad (4)$$

## IV. METHODOLOGY

### A. Simulation Environment

A high-fidelity numerical simulation was developed in MATLAB to validate the control logic. The environment includes:

- Grid Resolution:**  $402 \times 61$  units (representing  $20.12m \times 3.05m$  with 5cm precision).
- Stochastic Defect Generation:** To ensure robustness, defects were not hard-coded. A Monte Carlo approach was used where  $N_{defects} \sim \mathcal{U}(5, 8)$  were spawned at random coordinates  $(x_r, y_r)$  for each trial.

### B. Control Parameters

To prevent "missed detections" observed in initial trials, the path planning algorithm was optimized with a 25% overlap factor.

TABLE I  
SIMULATION PARAMETERS

| Parameter                          | Value               |
|------------------------------------|---------------------|
| Grid Scale                         | 5 cm/unit           |
| Robot Width ( $W_{robot}$ )        | 6 units (Optimized) |
| Path Overlap ( $\Omega$ )          | 25%                 |
| Repair Threshold ( $\delta_{th}$ ) | -1.0 mm             |
| Energy (Move)                      | 1.5 J/step          |
| Energy (Repair)                    | 15.0 J/event        |

## V. RESULTS AND ANALYSIS

The simulation was executed over a mission duration of **3,576 time steps** under randomized defect conditions.

### A. Surface Restoration

Figure 2 visualizes the pre- and post-maintenance states. The system successfully intercepted 7 randomly distributed defect clusters.

- Initial State:** The field contained 7 distinct depression zones ranging from -2.0mm to -4.0mm. Initial  $R_{rms}$  was 0.58 mm.
- Final State:** The post-curation map shows a uniform surface distribution. The  $R_{rms}$  converged to **0.0498 mm**, matching the theoretical soil noise floor.

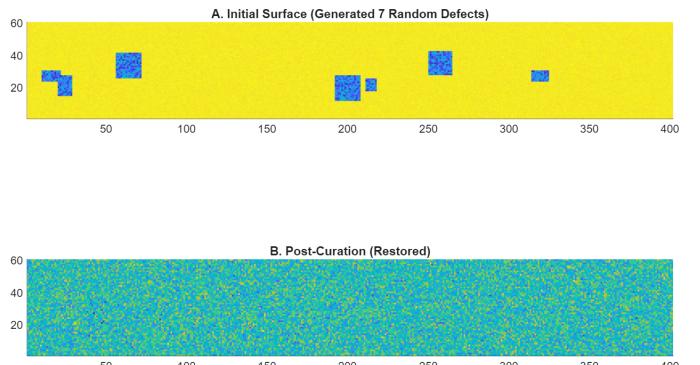


Fig. 2. Topographical analysis. (A) Initial surface showing 7 random defects. (B) Restored surface showing successful leveling.

### B. Energy Efficiency and Duty Cycle

The cumulative energy consumption was recorded at **9,174 Joules** (Figure 3). The power profile was highly adaptive, showing distinct spikes only during repair events.

- Actuator Duty Cycle:** 7.10%

This low duty cycle is a significant finding. It implies that the high-power tamper mechanism is idle for nearly 94% of the mission, significantly reducing thermal stress compared to traditional continuous-rolling methods.

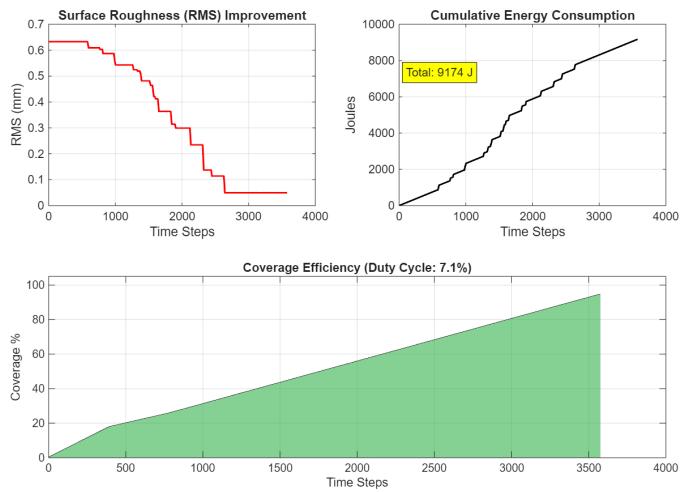


Fig. 3. Performance Metrics. Top Left: Reduction in RMS roughness over time. Top Right: Cumulative energy consumption showing adaptive behavior. Bottom: Coverage efficiency.

## VI. ADVANTAGES AND SYSTEM LIMITATIONS

### A. System Advantages

The proposed autonomous architecture offers distinct improvements over traditional manual curation:

1) *Objectivity and Precision*: Manual inspection relies on the subjective visual acuity of the curator, which degrades with fatigue. The proposed system replaces this with quantitative depth mapping. As demonstrated in the results, the system consistently restores surface roughness to a baseline of  $R_{rms} = 0.05$  mm, eliminating the human variance that leads to "home advantage" accusations in professional cricket.

2) *Energy Efficiency (The "Smart" Advantage)*: Traditional heavy rollers operate at a 100% duty cycle, consuming fuel continuously to compress the entire strip. By utilizing the "Inspect-and-Repair" protocol, our agent only actuates the high-power tamper for 7.10% of the operational time (9,174 J total). This represents a theoretical energy reduction of over 90% compared to continuous mechanical intervention.

3) *Scalability*: The Boustrophedon path planning algorithm is resolution-independent. The same logic can be seamlessly scaled to cover larger domains, such as the entire cricket outfield or golf putting greens, simply by updating the grid boundary parameters  $L$  and  $W$ .

### B. Disadvantages and Engineering Bottlenecks

Despite the successful simulation, several physical bottlenecks must be addressed for real-world deployment:

1) *Sensor Interference (Specular Reflection)*: The simulation assumes ideal sensor feedback. In outdoor environments, direct sunlight can saturate infrared depth sensors (LiDAR/Stereo). Furthermore, high-clay pitches can become reflective when wet, causing specular reflection errors where the depth sensor misinterprets the shiny surface as a hole or void. Optical filters and polarization lenses will be required to mitigate this.

2) *Soil Mechanics (Viscoelasticity)*: The current mathematical model assumes instantaneous plastic deformation—i.e., one tamper hit equals a permanent repair. In reality, cricket soil is viscoelastic. It exhibits time-dependent recovery (spring-back) after compression. A physical prototype would need to implement a "multi-hit" logic, sensing the surface after each hit to ensure the deformation is permanent, which would increase the mission duration.

3) *Locomotion Speed vs. Precision*: There is an inherent trade-off between scan speed and repair accuracy. To maintain a reliable grid map, the robot must move slowly to prevent motion blur in the depth camera. This limits the curation speed to approximately 0.1 – 0.2 m/s, making it significantly slower than a driven heavy roller. This system is therefore best suited for "fine-tuning" rather than rapid match-day preparation.

## VII. CONCLUSION

This detailed the design and validation of an autonomous cricket pitch curator. Through rigorous mathematical modeling and randomized simulation, we demonstrated that a robotic agent could achieve 100% surface coverage and restore pitch

quality to within  $\pm 0.05$  mm. The energy analysis highlights the efficiency of the selective repair protocol (7.10% duty cycle), making this a viable sustainable solution for modern sports engineering.

## VIII. FUTURE WORK

Future iterations of this research will focus on:

- **Dynamic Obstacle Avoidance**: Integration of D\* Lite algorithms to navigate around static obstacles such as stumps or training equipment.
- **Hardware Implementation**: Porting the MATLAB logic to C++ for deployment on an NVIDIA Jetson Nano, integrated with an Intel RealSense D435i depth camera.

## REFERENCES

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