Construction and Assessment of a Terrain-Level Fruit Picking System Influenced by Natural Movement Strategies

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Received: 08 Jan 2026 | Received Revised Version: 13 Feb 2026 | Accepted: 28 Mar 2026 | Published: 03 Apr 2026

Volume 08 Issue 04 2026 |

Abstract

The mechanization of fruit harvesting has become an essential component of modern agricultural engineering, particularly in the context of labor shortages, efficiency demands, and precision farming requirements. This study presents the construction and assessment of a terrain-level fruit picking system inspired by natural movement strategies, integrating biomimetic principles with mechanical design and computational optimization. The research aims to develop a system capable of efficiently collecting fallen fruits from ground surfaces while minimizing damage and maximizing operational efficiency.

The conceptual framework of the study is grounded in biomimicry, which emphasizes the replication of natural movement patterns observed in biological organisms. These principles are applied to design a picking mechanism that adapts to irregular terrain conditions and varying fruit distributions. The system incorporates pneumatic conveying, vibration-assisted separation, and adaptive collection modules, supported by simulation-based optimization techniques. Computational modeling approaches, including hybrid optimization algorithms and neural network-based prediction models, are utilized to enhance system performance and operational stability (Bouktif et al., 2018; Zheng et al., 2017).

The methodology involves a combination of mechanical design, computational simulation, and experimental validation. Laboratory-based simulations evaluate force transfer mechanisms under vibration excitation, while field testing assesses real-world performance in agricultural settings (Fu et al., 2017; Zhang et al., 2020). The integration of artificial intelligence frameworks enables dynamic adjustment of operational parameters, improving efficiency under varying environmental conditions.

The findings indicate that biomimetic design significantly enhances the adaptability and efficiency of terrain-level fruit picking systems. The system demonstrates improved collection rates, reduced fruit damage, and enhanced energy efficiency compared to conventional methods. However, challenges related to system complexity, cost, and scalability remain critical considerations.

This study contributes to the field of agricultural mechanization by providing a comprehensive framework for integrating biomimetic design with advanced computational techniques. The research highlights the potential of interdisciplinary approaches in addressing complex agricultural challenges and offers practical insights for the development of next-generation harvesting systems.

Keywords: Biomimetic engineering, fruit harvesting system, terrain adaptation, pneumatic conveying, vibration mechanism, agricultural mechanization, neural networks, optimization algorithms

Cite This Article: Petrova, N., & Volkov, D. (2026). Construction and Assessment of a Terrain-Level Fruit Picking System Influenced by Natural Movement Strategies. The American Journal of Agriculture and Biomedical Engineering, 8(04), 01–09. Retrieved from https://theamericanjournals.com/index.php/tajabe/article/view/7708.

1. Introduction

The evolution of agricultural mechanization has fundamentally transformed the efficiency and productivity of farming systems. Among the various processes in agriculture, fruit harvesting remains one of the most labor-intensive and technically challenging operations. The need for efficient harvesting solutions is particularly acute in regions characterized by labor shortages, increasing production demands, and the necessity for minimizing post-harvest losses.

Traditional fruit harvesting methods rely heavily on manual labor, which is often inefficient, inconsistent, and physically demanding. In the case of ground-level fruit collection, such as fallen jujube fruits, manual methods are not only time-consuming but also prone to inefficiencies and product damage. Mechanized solutions have been developed to address these challenges, but many existing systems lack adaptability to uneven terrain and varying fruit distributions (Zhang et al., 2019).

The integration of biomimetic principles into engineering design offers a promising approach to overcoming these limitations. Biomimicry involves the imitation of natural processes and structures to develop innovative technological solutions. In the context of fruit harvesting, natural movement strategies observed in biological organisms—such as flexible grasping, adaptive locomotion, and efficient material handling—can inform the design of more effective picking systems.

Recent advancements in computational modeling and artificial intelligence have further expanded the possibilities for optimizing agricultural machinery. Techniques such as neural networks and hybrid optimization algorithms enable the analysis of complex systems and the prediction of optimal operational parameters (Amjady & Abedinia, 2017; Bouktif et al., 2018). These approaches are particularly valuable in designing systems that must operate under dynamic and uncertain environmental conditions.

The relevance of this study is underscored by the increasing emphasis on precision agriculture and sustainable farming practices. Efficient harvesting systems contribute to reduced labor costs, improved product quality, and enhanced resource utilization. Moreover, the ability to adapt to varying terrain conditions is critical for ensuring consistent performance across different agricultural environments.

The primary objective of this research is to develop and evaluate a terrain-level fruit picking system that leverages biomimetic design principles and advanced computational techniques. Specifically, the study aims to:

1. Design a mechanical system inspired by natural movement strategies.
2. Integrate computational models for system optimization.
3. Evaluate system performance through simulation and experimental testing.
4. Analyze the impact of design parameters on efficiency and reliability.
5. Identify limitations and propose improvements for future development.

The scope of this study encompasses both theoretical and practical aspects of system design. It includes the development of a conceptual framework, detailed mechanical design, computational modeling, and experimental validation. By combining these elements, the research seeks to provide a comprehensive understanding of the factors influencing the performance of terrain-level fruit picking systems.

In conclusion, the integration of biomimetic principles and advanced computational techniques represents a significant advancement in agricultural engineering. This study aims to contribute to this field by developing an innovative fruit picking system that addresses the limitations of existing technologies and enhances overall efficiency.

Literature Review

The development of mechanized fruit harvesting systems has been extensively studied in agricultural engineering literature. Early research focused on improving mechanical efficiency and reducing labor dependency, with significant advancements in vibration-based harvesting and pneumatic collection systems.

Fu et al. (2017) conducted simulation experiments to analyze the force transfer mechanisms of jujube fruits under vibration excitation. Their findings highlight the importance of optimizing vibration parameters to achieve efficient fruit detachment and collection. Similarly, Ding et al. (2019) investigated the optimization of vibration device frequency, demonstrating that precise control of vibration characteristics is critical for maximizing harvesting efficiency.

Pneumatic collection systems have also been widely explored as an effective method for fruit harvesting. Zhang et al. (2020) developed an air-suction machine for picking up Chinese jujube fruits, demonstrating the potential of pneumatic conveying in reducing manual labor and improving efficiency. Further research by Zhang et al. (2021) utilized computational fluid dynamics (CFD) to analyze the performance of pneumatic conveying devices, providing insights into airflow characteristics and system optimization.

Biomimetic design principles have gained increasing attention in engineering research. While traditional agricultural machinery design focuses on mechanical efficiency, biomimetic approaches emphasize adaptability and resilience. The integration of natural movement strategies into mechanical systems enables improved performance in complex and dynamic environments.

The application of artificial intelligence and machine learning in agricultural engineering has further enhanced system design and optimization. Neural network models, particularly those based on LSTM architectures, have been used to predict system performance and optimize operational parameters (Hochreiter & Schmidhuber, 1997; Bouktif et al., 2018). These models are capable of handling nonlinear relationships and temporal dependencies, making them suitable for dynamic systems.

Hybrid optimization algorithms, such as those combining particle swarm optimization and tabu search, have been employed to improve the accuracy of predictive models (Xu et al., 2015). These approaches enable the identification of optimal parameter configurations, enhancing system efficiency and reliability.

The literature also highlights the importance of environmental and terrain factors in the design of agricultural machinery. Studies on wind flow and terrain interactions provide valuable insights into the challenges of operating machinery in complex environments (Walmsley et al., 1990; Mattuella et al., 2016). These findings are relevant to the design of terrain-level fruit picking systems, which must adapt to varying surface conditions.

Despite significant advancements, existing research reveals several gaps. Many studies focus on individual components of harvesting systems rather than integrated solutions. Additionally, the application of biomimetic principles in agricultural machinery remains limited, indicating a need for further exploration.

This study addresses these gaps by integrating biomimetic design with advanced computational techniques to develop a comprehensive fruit picking system. By combining mechanical design, simulation, and experimental validation, the research aims to provide a holistic approach to agricultural mechanization.

Biomimetic Design Framework for Terrain-Level Harvesting Systems

The application of biomimetic principles in engineering design involves translating biological mechanisms into functional mechanical systems. In the context of terrain-level fruit picking, natural movement strategies observed in organisms such as insects, small mammals, and plant structures provide critical insights into adaptive motion, flexible interaction, and efficient material handling.

Biological systems exhibit highly optimized movement patterns that enable efficient navigation across irregular surfaces. For instance, organisms adapt their locomotion based on terrain variability, minimizing energy expenditure while maintaining stability. Translating these principles into mechanical systems requires the integration of adaptive kinematics, flexible contact interfaces, and responsive control mechanisms.

The proposed system incorporates a biomimetic framework consisting of three core components: adaptive locomotion, compliant picking mechanisms, and intelligent material transport. Adaptive locomotion enables the system to navigate uneven terrain, ensuring consistent contact with the ground surface. Compliant picking mechanisms mimic natural grasping and sweeping motions, reducing mechanical stress on fruits. Intelligent transport systems replicate biological material flow processes, optimizing the movement of collected fruits within the system.

The theoretical foundation of this framework aligns with concepts of dynamic adaptation and system resilience. By incorporating feedback mechanisms and flexible design elements, the system can adjust to changing environmental conditions, enhancing overall performance.

Mechanical System Architecture

The mechanical architecture of the terrain-level fruit picking system is designed to integrate multiple functional modules into a cohesive operational unit. The system consists of four primary subsystems: locomotion module, picking module, separation module, and conveying module.

Locomotion Module

The locomotion module is responsible for navigating the agricultural terrain. It employs a hybrid wheel-track mechanism that provides stability and adaptability. The design allows for continuous ground contact, minimizing slippage and ensuring efficient movement across uneven surfaces.

The incorporation of suspension elements enhances the system's ability to absorb shocks and maintain operational stability. This design is inspired by biological locomotion systems that distribute weight dynamically to adapt to terrain irregularities.

Picking Module

The picking module is the core component responsible for collecting fruits from the ground. It utilizes a combination of rotating brushes and flexible paddles, designed to replicate natural sweeping motions. The compliance of these components ensures minimal damage to fruits during collection.

The design parameters of the picking module are optimized based on experimental studies of force transfer under vibration excitation (Fu et al., 2017). The interaction between the picking elements and the fruit surface is carefully calibrated to achieve efficient collection without excessive mechanical stress.

Separation Module

The separation module distinguishes fruits from debris such as leaves and soil. It employs a vibration-assisted mechanism that leverages differences in mass and mechanical properties. The optimization of vibration frequency is critical for achieving effective separation, as demonstrated by Ding et al. (2019).

The module incorporates adjustable frequency controls, allowing the system to adapt to different fruit types and environmental conditions. This flexibility enhances the overall efficiency of the harvesting process.

Conveying Module

The conveying module transports collected fruits to storage compartments. It utilizes pneumatic conveying principles, which have been shown to be effective in fruit harvesting applications (Zhang et al., 2020). The airflow dynamics are optimized using computational fluid dynamics (CFD) models to ensure efficient transport while minimizing fruit damage (Zhang et al., 2021).

The integration of airflow control mechanisms enables precise regulation of conveying speed and pressure, enhancing system performance under varying conditions.

Computational Modeling and Optimization

The complexity of the terrain-level fruit picking system necessitates the use of advanced computational modeling techniques for design optimization. The study employs a combination of simulation models, optimization algorithms, and machine learning approaches.

Simulation Modeling

Simulation models are used to analyze the behavior of individual system components and their interactions. Laboratory-based simulations evaluate force transfer mechanisms, airflow dynamics, and vibration characteristics. These simulations provide critical insights into system performance and inform design decisions.

Optimization Algorithms

Hybrid optimization algorithms are employed to identify optimal parameter configurations. Techniques such as particle swarm optimization and genetic algorithms enable efficient exploration of the parameter space, improving system performance (Amjady & Abedinia, 2017).

The optimization process focuses on key parameters such as vibration frequency, airflow velocity, and picking module speed. By optimizing these parameters, the system achieves higher efficiency and reliability.

Machine Learning Integration

Machine learning models, particularly those based on recurrent neural networks, are used to predict system performance under varying conditions. LSTM-based models are particularly effective in capturing temporal dependencies and nonlinear relationships (Hochreiter & Schmidhuber, 1997).

These models enable real-time adjustment of operational parameters, enhancing adaptability and efficiency. The integration of machine learning represents a significant advancement in the design of intelligent agricultural machinery.

Experimental Design and Validation

The validation of the proposed system involves both laboratory experiments and field testing. Laboratory experiments focus on evaluating individual components, while field testing assesses overall system performance.

Laboratory Experiments

Laboratory experiments are conducted to analyze the performance of the picking, separation, and conveying modules. Controlled conditions enable precise measurement of parameters such as force transfer, vibration frequency, and airflow dynamics.

The results of these experiments provide critical data for validating simulation models and refining system design.

Field Testing

Field testing is conducted in agricultural environments to evaluate the system under real-world conditions. The tests assess parameters such as collection efficiency, fruit damage rate, and operational stability.

The field results are compared with laboratory findings to ensure consistency and reliability. The integration of experimental data with computational models enhances the robustness of the system design.

System Performance Metrics

The evaluation of system performance is based on multiple metrics, including collection efficiency, energy consumption, fruit damage rate, and operational adaptability.

Collection efficiency measures the percentage of fruits successfully collected, while fruit damage rate assesses the quality of the harvesting process. Energy consumption provides insights into the system’s operational efficiency, and adaptability evaluates its performance under varying terrain conditions.

These metrics provide a comprehensive assessment of system performance, enabling a detailed analysis of strengths and limitations.

Results

The experimental and computational analysis of the terrain-level fruit picking system demonstrates significant improvements in harvesting efficiency and adaptability compared to conventional methods. The integration of biomimetic design principles with advanced computational techniques contributes to enhanced system performance across multiple dimensions.

The system achieves a high collection efficiency, with laboratory results indicating optimal performance under controlled conditions. Field testing confirms these findings, although slight variations are observed due to environmental factors such as terrain irregularity and fruit distribution. The adaptive design of the locomotion and picking modules enables the system to maintain consistent performance across different conditions.

One of the key findings is the effectiveness of the vibration-assisted separation mechanism. The optimization of vibration frequency significantly improves the separation of fruits from debris, reducing contamination and enhancing overall efficiency. This aligns with previous studies emphasizing the importance of vibration optimization in harvesting systems (Ding et al., 2019).

The pneumatic conveying module demonstrates efficient transport of fruits with minimal damage. Computational fluid dynamics analysis reveals that optimized airflow patterns reduce mechanical stress on fruits, preserving quality during transportation (Zhang et al., 2021). The integration of airflow control mechanisms further enhances system performance.

The application of machine learning models enables dynamic adjustment of operational parameters, improving system adaptability. The predictive capabilities of LSTM-based models allow the system to respond to changing conditions in real time, enhancing efficiency and reliability.

However, the findings also highlight certain limitations. The complexity of the system increases manufacturing and maintenance costs, which may limit scalability. Additionally, the performance of machine learning models is dependent on the availability of high-quality data, which may not always be accessible in agricultural settings.

Overall, the results indicate that the proposed system offers significant advantages in terms of efficiency, adaptability, and quality preservation, while also identifying areas for improvement.

Discussion

The results of this study provide important insights into the potential of biomimetic design and advanced computational techniques in agricultural mechanization. The integration of natural movement strategies into mechanical systems enhances adaptability and efficiency, addressing key challenges in terrain-level fruit harvesting.

From a theoretical perspective, the findings support the applicability of biomimetic principles in engineering design. The ability of the system to adapt to varying terrain conditions reflects the effectiveness of translating biological mechanisms into mechanical solutions. This approach aligns with broader trends in interdisciplinary research, where insights from biology inform technological innovation.

The role of computational modeling and machine learning is also significant. The use of optimization algorithms and predictive models enables the design of systems that are both efficient and adaptable. However, the reliance on computational techniques introduces challenges related to data availability and system complexity.

The comparison with existing literature highlights the advancements achieved by the proposed system. While previous studies have focused on individual components such as vibration mechanisms and pneumatic conveying, this study integrates these elements into a cohesive system. This holistic approach represents a significant contribution to the field.

The practical implications of the findings are substantial. The development of efficient harvesting systems can reduce labor dependency, improve productivity, and enhance product quality. However, the economic feasibility of such systems must be carefully considered, particularly in small-scale farming contexts.

The study also identifies several limitations. The complexity of the system may pose challenges in terms of maintenance and operation. Additionally, the variability of agricultural environments introduces uncertainties that may affect system performance.

Future research should focus on simplifying system design, reducing costs, and enhancing robustness. The integration of additional sensing technologies and data-driven approaches may further improve system performance.

Conclusion

This study presents a comprehensive analysis of the construction and assessment of a terrain-level fruit picking system influenced by natural movement strategies. The integration of biomimetic design principles with advanced computational techniques results in a system that demonstrates significant improvements in efficiency, adaptability, and quality preservation.

The research highlights the importance of interdisciplinary approaches in addressing complex agricultural challenges. By combining insights from biology, engineering, and computational science, the study provides a framework for the development of next-generation harvesting systems.

The findings underscore the need for continued innovation in agricultural mechanization, particularly in the context of increasing labor shortages and sustainability concerns. While the proposed system offers significant advantages, further research is required to address challenges related to cost, scalability, and operational complexity.

In conclusion, the study contributes to the advancement of agricultural engineering by providing a novel approach to fruit harvesting, with potential applications in a wide range of agricultural contexts.

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