International Journal of Engineering and Advanced Technology Studies,14 (4),1-10, 2026
Print ISSN: 2053-5783(Print)
Online ISSN: 2053-5791(online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Design and Evaluation of a Dexterous Robotic Finger for Enhanced Accessibility in Narrow Operational Spaces

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doi: https://doi.org/10.37745/ijeats.13/vol14n4110 Published August 03, 2026

Citation: Kien V.N., Vinh N.P., Phuong T. (2026) Design and Evaluation of a Dexterous Robotic Finger for Enhanced Accessibility in Narrow Operational Spaces, International Journal of Engineering and Advanced Technology Studies,14 (4),1-10

Abstract: *Robotic manipulation in restricted spaces is still a great challenge as the conventional robotic hands have limited accessibility, dexterity and mobility in restricted spaces. To achieve better manipulation in confined spaces, this research presents the design and testing of a dexterous robotic finger. The proposed finger is designed based on the chopsticks used by Vietnamese people and has 3-DOFs for adaptive grasping without complex actuators. A mathematical model of contact forces between the components of fingers and grasped objects is created and investigated. A series of simulations are carried out on MATLAB to evaluate the motion behaviour, force transmission, workspace accessibility and grasp stability. Performance data are from simulation, prototype testing. An Adaptive Red Panda Optimized Dynamic Artificial Neural Network (ARPO-ANN) model is used to evaluate the quality of grasping, force distribution, and its effectiveness in manipulation. The proposed system successfully demonstrates high-level accuracy (98.2%); high success rate (98.4%); good grasp force (18.9 N); high accessibility; stability, and operational efficiency in the restricted space.*

Keywords: dexterous robotic finger, narrow operational spaces, robotic manipulation, accessibility enhancement, vietnamese chopstick-inspired design

INTRODUCTION

Robotic manipulation is one of the most important applications for modern automation systems, where accurate handling of objects is essential in industrial, medical, inspection, and service applications [1]. But, in many practical applications, robots must perform tasks in narrow and enclosed spaces with limited access to the workspace [2]. These include maintenance inside a machine, manipulation inside a pipeline, minimally invasive surgical procedures, and complex structure inspection [3]. In such cases, ordinary robotic hands can be vulnerable to the following problems: bulky structure, limited dexterity, and inability to access confined areas [4]. Recent robotic grippers are capable of stable grasping in open environments, but they are large and have complicated grasping mechanisms, which limit their use in narrow operational spaces [5]. In addition, compactness and dexterous manipulation are still a great challenge in design [6]. Hence, the demand for robotic manipulators with slender parts, adaptive grasping ability, and efficient force transmission, without adding mechanical complexity, is increasing.

Research Aim: These drawbacks were addressed by this research, presenting a compact 3-DOF robotic finger with contact force analysis and Adaptive Red Panda Optimized Artificial Neural Network (ARPO-ANN)-based evaluation to determine its efficient grasping and access to narrow space.

LITERATURE REVIEW

In recent years, dexterous robotic manipulation has been driven by research on how to coordinate, perceive, and operate robots in constrained environments. Bi-DexHands [7] presented a bimanual dexterous hand simulator to assess the performance of reinforcement learning (RL)-based manipulation, with Proximal Policy Optimization (PPO) performing well in simple cases and multi-agent RL in cooperative cases. The study pointed out that there were great difficulties in multi-task learning and few-shot learning adaptability. In order to control the precision of the Hand, HandClasNet [8] applied real-time hand gesture recognition using Red-Green-Blue-Depth (RGB-D) camera to achieve better grasping accuracy in teleoperation. Likewise, Transteleop [9] also improved the capabilities of teleoperation by combining transformer-based learning and active vision for handling markerless hands and arms, thus allowing for more complex manipulation tasks. Both systems had limitations in their robustness when tested with dynamic occlusions. The Handheld Steerable Drill (HSD) [10] was shown to be very successful in highly constrained physical environments where miniaturized articulated mechanisms could yield a dramatic increase in dexterity in confined surgical environments by using tendon-driven joints. While these studies all made contributions to robotic dexterity, teleoperation, and small robotic finger manipulation, there are still challenges to be addressed to achieve efficient, adaptive, and stable grasping of objects in narrow operational spaces using compact, standalone robotic finger architectures. A dexterous robotic finger for narrow spaces in the rectum is developed in [11] with a Hybrid Coaxial Continuum Unit (HCCU), and it achieves a ≤1.10% positioning error and 5 N payload, but it is limitedly clinically validated. This gap motivates the present research developing a dexterous robotic finger for constrained environments.

METHODOLOGY

The proposed methodology for the design and evaluation of the bio-inspired dexterous robotic finger is illustrated in Figure 1. It integrates mechanical modeling, simulation, experimental validation, and ARPO-ANN-based performance evaluation to improve manipulation efficiency in narrow operational spaces.

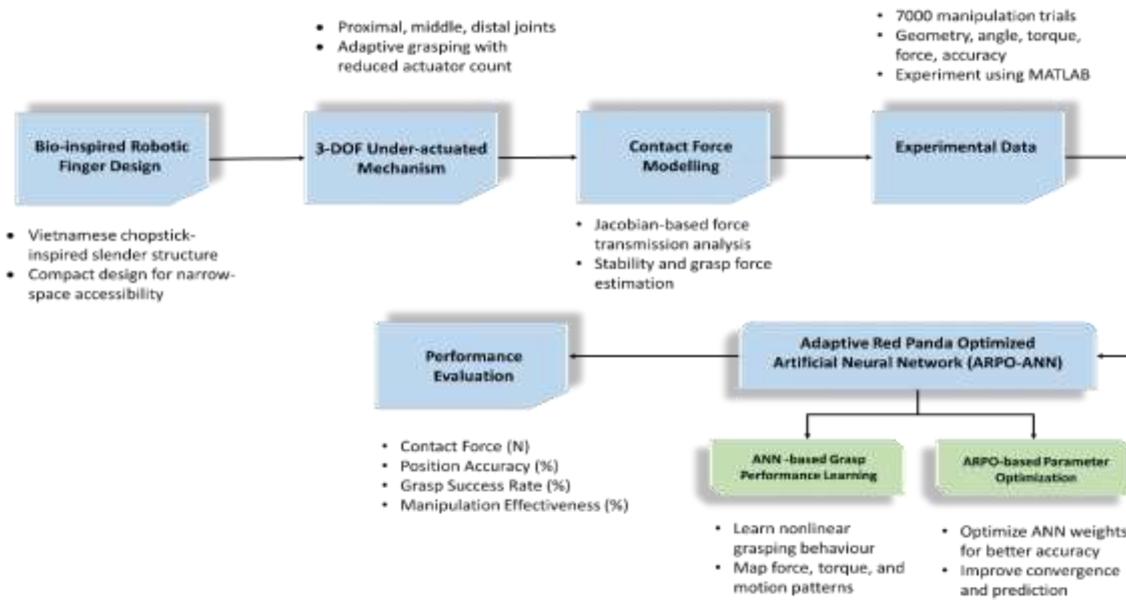

Figure 1: Proposed Workflow for Robotic Finger Design and Performance Evaluation

Robotic Arm Design

The robotic finger (Figure 2) is developed to improve the accessibility and manipulative capability in a restricted work space. The form is referred to the traditional Vietnamese chopsticks, giving it a compact and slender appearance, suitable to use in confined areas. The design is to improve the reachability, maneuverability, adaptability to grasp and efficient force transmission capabilities of the simplified under-actuated mechanism. The system is designed by a 3-DOF kinematic system and a contact force analysis model, which are used to assist accurate motion control and stable object manipulation in restricted working spaces.

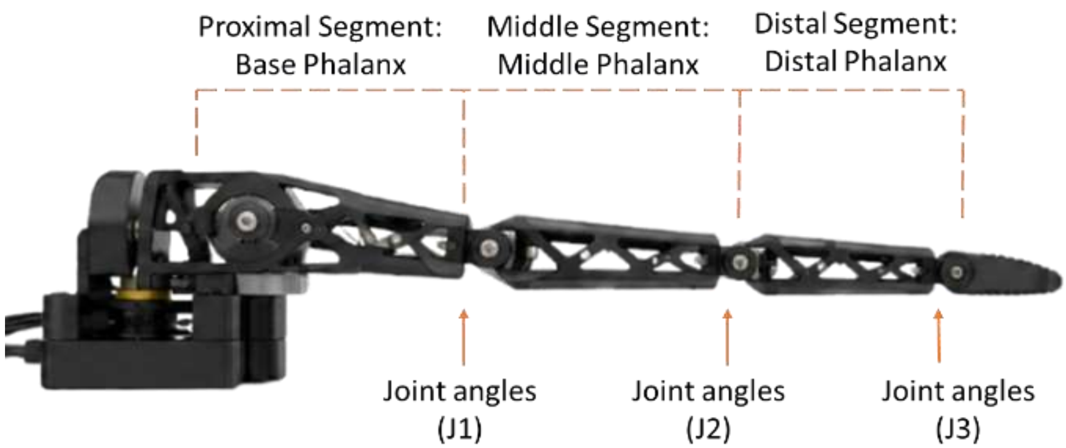

Figure 2: Kinematic Structure and Segment Classification ofThe Robotic Finger Mechanism

3-DOFfor Adaptive Dexterous Manipulation: A robotic finger with a compact 3-DOF under-actuated mechanism with revolute joints was developed for adaptive grasping, resulting in improved finger accessibility in a narrow space, and drawing inspired by Vietnamese chopsticks. The mobility of the mechanism was calculated by the Kutzbach–Gruebler criterion (1):

$$E = c(m - n - 1) + \sum_{j=1}^{n} e_j + \mu - h = 3 \qquad (1)$$

where E is the degree of freedom, c is the order of the mechanism, $m$is the number of links, n is the number of kinematic pairs, $\sum_{j=1}^{n} e_j$ represents the sum of relative degrees of freedom of all kinematic pairs, e_j is the relative degree of freedom of the j^{th}kinematic pair, μ is the number of local degrees of freedom, and h is the number of redundant constraints. According to the mobility analysis, the suggested mechanism has three effective degrees of freedom ($E = 3$), which allows for a deft grip, excellent force transmission, and stability in confined spaces.

Contact-Force Analysis for Grasp Stability Evaluation: Contact forces and joint torques were modeled as a function of the object being manipulated using the Jacobian transpose formulation (2):

$$\tau = J^T F_c \qquad (2)$$

where τ is the vector of joint torque, contact-force vector F_c is the vector at the finger-object contact interface, and J^T is the transpose of the Jacobian matrix of the proposed 3-DOF robotic finger. The model analyzes actuator-induced contact forces to evaluate force distribution, grasp stability, and manipulation effectiveness in narrow operational spaces.

Data Acquisition

Under different operational conditions, 7,000 manipulation trials were created through MATLAB simulation and prototype testing. The data was utilized for training and validation of the proposed ARPO-ANN model, with 47 features grouped into four categories: finger geometry, workspace accessibility, joint kinematics, and grasp-performance parameters (as summarized in Table 1).

Table 1: Summary of Data Features Used for Robotic Finger Performance Evaluation

Feature Group	Key Features	Type
Finger geometry	Length, width, thickness, fingertip radius, mass	Numerical
Workspace accessibility	Gap width, insertion depth, approach angle, clearance, accessibility score	Mixed
Joint kinematics & actuation	Joint angles (J1–J3), motion smoothness, input voltage, cable tension, response time	Numerical
Contact force & grasp performance	Contact force, friction coefficient, slip distance, stability index, grasp success rate, quality score	Numerical

ARPO-ANNfor Intelligent Grasp Performance Evaluation

To improve the performance of robotic fingers, ARPO-ANN combines the advantage of the adaptive learning ability of ANN and the global optimization of the RPO algorithm. ANN is initially trained on the simulated and experimental data on the relationship between contact forces, torque, motion, and accessibility. Later, ARPO improves ANN performance by exploration-exploitation, OBL, and DE strategies, which results in better convergence, prediction accuracy, grasp stability, and manipulation effectiveness under constrained environments.

ANNfor Nonlinear Grasp Behaviour Learning

The three-layer ANN uses parameters of the forces, motions, and accessibility to grasp objects to predict the quality of the grasp, the effectiveness of the manipulation, and the stability of the operation. The output of the ANN's j-th neuron is mathematically described in (3):

$$X_i = e\left(\sum_{j=1}^{m} \quad V_{ji} Y_i\right) + a_i \tag{3}$$

This is the ANN neuron equation for evaluating the grasp quality, where X_i is the output of the i^{th}neuron, e(·) is the activation function, $\sum$ is the weighted summation of inputs, Y_i are the input parameters of the robotic fingers, V_{ji} are the synaptic weights, a_i is the bias term, and m is the number of input variables. The final score of the quality of grasping is given by the ANN as (4):

$$MSE = \frac{1}{m} \sum_{j=1}^{m} \quad \left((X_j - X_i)^2\right) \tag{4}$$

Where m is the number of all robotic grasping trials, $\sum$ is the summed over all trials, X_j is the predicted grasp quality score by the ANN on the j^{th} grasping trial of the robot, and $X_i$is the experimentally measured grasp performance on the i^{th} grasping trial.

$$MAPE = \frac{1}{m} \sum_{j=1}^{m} \quad \left|\frac{X - X_j}{X_j}\right| \tag{5}$$

Equation (5) describes the total number of robotic grasping trials m, the sum of the percentage error over all trials $\sum$, the actual experimentally measured grasp performance X_j, and the ANN-predicted grasp quality score for the j^{th} manipulation task X.

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ARPOfor ANN Parameter Optimization

RPO is a metaheuristic that is able to perform a trade-off between exploration and exploitation but is prone to premature convergence and poor diversity. Thus, ARPO combines OBL and DE to optimize diversity, convergence velocity, and robotic fingers in a small operation space. **Exploration** and **Exploitation** develop and update robotic fingers to maximize accessibility, workspace coverage, grasp stability, and manipulation efficiency. **Opposition-Based Learning (OBL)** enhances diversity and convergence by leveraging opposite solutions, and **Differential Evolution (DE)** fine-tunes the parameters of the fingers, force distribution, stability, and adaptability in very limited operational ranges.

Mutation: This stage generates new robot finger designs by making weighted differences for of selected individuals. It helps to explore geometry and joint configurations, making it easier to access in small operating spaces.

$$NU_j = Xr1 + NE \times (Xr2 - Xr3) \qquad (6)$$

In Equation (6), NU_j is the mutant robotic finger design vector, $Xr1$, $Xr2$, $Xr3$ are randomly selected finger configurations, and NE controls the variation in joint, link, and actuator parameters for improved accessibility and grasp performance.

Crossover: This step generates trial designs for robotic fingers which are mutations and existing designs. It fine-tunes the inherited parameters to improve kinematics, adaptability and manipulation capabilities in constrained spaces.

$$Xji = \{NU_{j,i}\ Xji\ , if rb \leq CR || i = r \qquad (7)$$

In Equation (7), Xji denotes the robotic finger design parameters; $NU_{j,i}$ is the mutated design solution; CR is the crossover rate; rb is a random number; $i = r$ ensures the parameter inheritance, improving accessibility, grasp stability, and actuator coordination in narrow operational spaces. By optimisation, ARPO is able to improve the performance of ANN to measure grasp quality, force distribution, positioning accuracy and accessibility of the robotic finger in restricted space.

RESULT

The effectiveness of the proposed robotic finger in narrow working environments is verified by the MATLAB simulation andexperimental results. Figure 3(a) reveals that the energy per grasp is mostly concentrated between 1.5 and 2.3 J with the peak value at ~1.9 J, which indicates stable and efficient energy consumption during actuation, and low energy per grasp above ~3.0 J. Figure 3(b) illustrates that the reach accessibility remains almost constant from all approach angles (137.7–138.9 mm), and the deep reach capability is enhanced with high approach angles (143.6 mm). Figure 3(c) demonstrates motion repeatability as a function of loading, with an average error of approximately 2.0 mm, with variance increasing for high loads (up to ~3.2 mm), but overall, it is found that motion is kinematically stable under all loads.

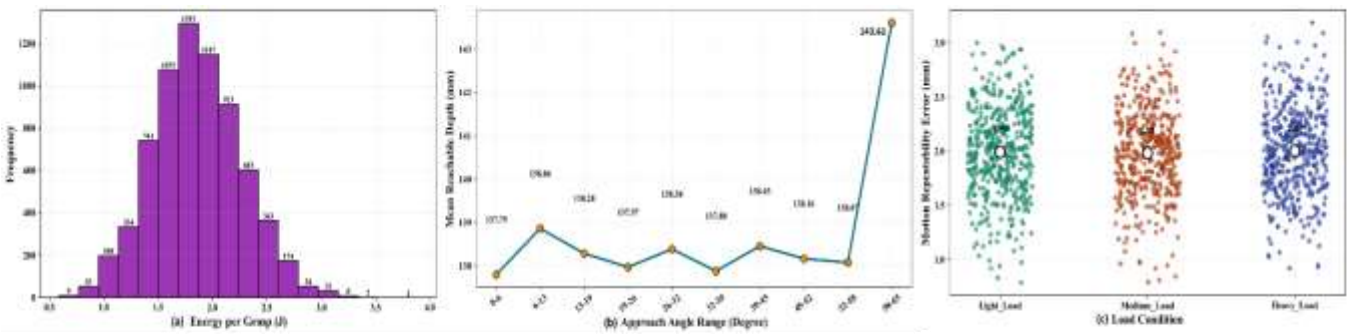

Figure 3: Evaluation of (a) Energy Consumption, (b) Accessibility, and (c) Motion Stability of the Proposed Robotic Finger

The performance data have been generated by performing multiple manipulation trials; the key mechanical and operational parameters of the proposed robotic finger were recorded under different grasping conditions. Table 2 shows representative samples from the 7000-trial data. These parameters are the input data to the train ARPO-ANN to verify the effectiveness of manipulation and predict the quality of the grasp.

Table 2: Experimental and Simulation Data Features of the Proposed Robotic Finger

Trial No.	Finger Geometry (mm)	Joint Angle (°)	Torque (N·m)	Contact Force (N)	Accessibility (mm)	Position Accuracy (%)	Repeatability (%)	Grasp Success Rate (%)	Manipulation Effectiveness (%)
1	165	28	1.4	8.5	120	91.2	92.4	88.6	89.5
2	170	35	1.8	10.2	128	92.8	93.7	90.4	91.6
3	175	42	2.1	11.8	136	94.1	94.8	92.7	93.4
4	180	48	2.5	13.6	144	95.6	95.9	94.3	95.1
5	185	54	2.9	15.4	152	96.8	96.7	95.8	96.3
6	190	61	3.3	17.1	160	97.4	97.6	97.1	97.5
7	195	67	3.7	18.9	168	98.2	98.1	98.4	98.3

Comparative Analysis

The effectiveness of the proposed robotic finger evaluation model was evaluated under different grasping conditions by comparative analysis. The performance of Standard ANN, RPO-ANN, and proposed ARPO-ANN models is compared in Table 3. The proposed resulted in the maximum contact force of 18.9 N, which is better than the other proposals, with a stable object interaction. 98.2% positioning accuracy indicates that the joints are well coordinated and kinematic deviation is minimized. The success rate of grasping (98.4%) and manipulation (98.3%) validates the stability of adaptive grasp the efficient distribution of torque, and reliable grasping of objects in a narrow operational space.

Table 3: Comparative Performance Analysis of Baseline ANN and Proposed Model for Robotic Finger Grasp Evaluation

Metrics	ANN Model	RPO-ANN	ARPO-ANN (Proposed Model)
Contact Force (N)	12.4	14.1	18.9
Position Accuracy (%)	93.8	94.9	98.2
Grasp Success Rate (%)	91.5	93.6	98.4
Manipulation Effectiveness (%)	92.2	94.1	98.3

DISCUSSION

The current developments in dexterous robotic manipulation have been mostly centered on teleoperation, reinforcement learning, and vision-based control methods, but they are prone to problems of stability, small size, and adaptability in narrow operational spaces, as reported by Transteleop [10]. Compact mechanisms such as the Handheld Steerable Drill [11] are useful for small spaces, but are task specific and lack grasp intelligence. The above restrictions motivate the design of a compact adaptive robotic finger for narrow space manipulation. The proposed approach shows well results in mechanical and intelligent evaluation steps, with a stable energy consumption (~1.9 J), high accessibility (~143.6 mm), and low motion error (~2.0 mm). Results demonstrate higher performance in nonlinear learning and control efficiency, with an 18.9 N contact force, a 98.2% position accuracy, a 98.4% grasp success rate and a 98.3% manipulation effectiveness, for the ARPO-ANN model. However, research is limited due to data dependence, which is not simulated, and simple geometry validation. Real-time deployments, multi-finger coordination, and robustness under dynamic and complex environments are future works that determination will address.

CONCLUSION

In narrow and constrained environments, robotic hands are less capable of obtaining precise, stable, and accessible object handling, and robotic manipulation has become more crucial in such situations. The design and evaluation of a dexterous compact robotic finger with an intelligent learning-based model for evaluation and enhancing the manipulation performance are presented. The proposed ARPO-ANN model possesses a strong prediction accuracy, with a contact force of 18.9 N, position accuracy of 98.2%, grasp success rate of 98.4% and manipulation effectiveness of 98.3%, and robust grasp stability. The outcomes confirm the benefit of combining under-actuated mechanical design and optimization-based neural learning for adaptive grasping and operation efficiency in the confined space. The results of this research highlight the significance and effectiveness of intelligent evaluation to enhance the performance of robots and serve as a foundation for the development of smaller and more precise robot systems applicable in real-world systems with constrained manipulations.

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