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Neural Network Based Inverse Kinematics Solution Method for Origami Robots

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Abstract

Inverse kinematics (IK) of origami robots is highly challenging due to their nonlinear geometry and complex folding constraints. Traditional iterative or analytical methods often suffer from high computational cost, poor convergence, and limited robustness in real-time scenarios. To address these issues, this study proposes a neural network–based IK solution framework. A dataset of 100,000 posture–joint pairs was generated through simulation, and a multilayer perceptron (MLP) was trained to approximate the nonlinear mapping from end-effector pose to joint angles. Experimental validation demonstrates that the proposed model achieves an average joint angle prediction error below 2°, representing a >40% reduction compared with conventional numerical iteration. The inference speed is approximately 20 times faster, and the convergence success rate reaches 98%, significantly surpassing baseline methods. Robustness tests under noisy inputs and boundary configurations show that prediction errors increase by less than 1°, confirming strong stability and generalization. These results indicate that the proposed neural network approach provides an efficient and reliable IK solver for origami robots, with promising applications in flexible manufacturing, space structures, and minimally invasive surgical robotics.

Keywords

origami robot, inverse kinematics, neural network, motion control, nonlinear system.

1. Introduction

Origami robots have emerged as a research frontier in flexible manufacturing, space exploration, and minimally invasive medicine owing to their lightweight, deployable, and reconfigurable properties [1]. Their folding geometry enables a wide range of motion within a compact volume, thereby offering both structural reconfigurability and functional adaptability [2]. Despite these advantages, origami robots present substantial challenges in kinematic analysis. In particular, solving inverse kinematics (IK) is difficult due to the strong nonlinearities and multiple feasible solutions introduced by folding structures, which often result in reduced computational efficiency and convergence instability in traditional approaches [3].

Existing IK approaches are primarily categorized into geometric and numerical iterative methods. Geometric methods provide rapid solutions for simplified mechanisms but are

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unsuitable for complex origami topologies [4]. Numerical iterative methods, such as Newton–Raphson schemes and Jacobian inversion, are more general but highly sensitive to initial conditions; they often converge only locally or fail under strong nonlinear coupling [5]. Finite element analysis (FEA) offers high accuracy but is computationally expensive, rendering it impractical for real-time control applications [6]. Thus, achieving both efficiency and accuracy remains a central problem for origami robot control. With the development of artificial intelligence and data-driven modeling, neural networks have been introduced into kinematics and control problems [7]. Multilayer perceptrons (MLPs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have demonstrated strong capabilities in handling high-dimensional inputs and nonlinear mappings [8]. For instance, deep neural networks have been applied to IK prediction of complex robotic arms, significantly improving computational efficiency [9]. Reinforcement learning integrated with neural networks has been explored for motion planning and joint control, achieving enhanced generalization and adaptability [10]. In addition, transfer learning and physics-informed neural networks (PINNs) have been applied to address IK in small-sample or multi-constraint scenarios [11]. These advances suggest that neural network–based IK methods provide promising pathways to overcome the limitations of conventional algorithms in origami robots.

Nevertheless, several limitations persist. First, most studies remain focused on rigid robotic systems, and investigations of origami robots with flexibility and reconfigurability are still scarce [12]. Second, many neural network models rely on small-scale datasets with limited coverage, which compromises generalization and stability in the high-dimensional pose space of origami mechanisms [13]. Third, systematic comparative studies and statistical error analyses are lacking, which prevents rigorous validation of performance differences across methods in terms of accuracy, efficiency, and convergence [14,15].

To address these challenges, this study proposes a neural network–based approach for fast IK computation of origami robots. A dataset comprising 100,000 posture–joint angle pairs was constructed, and a multilayer perceptron was trained to approximate the nonlinear mapping between end-effector posture and joint angles. Experimental results demonstrate that the proposed method achieves an angular prediction error of less than 2° in complex origami mechanisms, with a solving speed approximately 20 times faster than numerical iterative methods and a convergence rate of 98%. Compared with existing approaches, the proposed framework balances efficiency and accuracy, while demonstrating robustness and applicability in nonlinear origami systems. This work provides a feasible pathway for extending origami robots to real-world applications in flexible manufacturing and minimally invasive medical procedures.

2. Materials and Methods

2.1 Dataset Construction and Sample Size

To establish the nonlinear mapping between the posture and joint angles of origami robots, this study generated 100,000 pairs of posture–joint angle data based on simulation modeling. The posture parameters include the three-dimensional position of the end-effector (x,y,z) and the

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orientation angles (α,β,γ). The joint parameters are represented by the angle vector of each folding joint, $\theta\in\mathbb{R}^n$. During data generation, the joint angle range was restricted to the limits allowed by mechanical constraints to ensure physical validity. The dataset was divided into training, validation, and test sets in a ratio of 70%:15%:15%, which ensured independence and reliability in model training and evaluation.

2.2 Neural Network Modeling Method

A multilayer perceptron (MLP) was used to approximate the inverse kinematics mapping from posture to joint angles. The input to the network is the desired posture vector of the end-effector [16]:

$$P=(x,y,z,\alpha,\beta,\gamma)$$

and the output is the predicted joint angle vector $\hat{\theta}$. The mapping function is defined as:

$$\hat{\theta}=f_\theta(P)$$

Among them, f_θ represents the neural network model defined by the parameter θ. The training process uses the mean squared error (MSE) as the loss function [17]:

$$\mathscr{L}=\frac{1}{N}\sum_{i=1}^{N}\|\theta_i-\hat{\theta}_i\|^2$$

The network consists of five fully connected layers, with the number of nodes set to 256, 128, 64, 32, and n (where n denotes the number of joint degrees of freedom). The ReLU function is used as the activation function. The Adam optimizer is applied with an initial learning rate of 0.001, a batch size of 128, and a maximum of 300 training iterations.

2.3 Comparative Experiments and Method Comparison

To evaluate the performance of the proposed approach, three comparative methods were designed: (1) the traditional numerical iterative method, which solves inverse kinematics using the Jacobian matrix and Newton–Raphson iteration; (2) the geometric analytical method, which derives joint solutions directly from geometric relations in decomposable structures; (3) the neural network method proposed in this study. On the same test dataset, the three methods were compared in terms of prediction accuracy, computational speed, and convergence rate. The test conditions included simple folding, complex folding, and hybrid topologies, to provide a comprehensive evaluation of applicability and robustness.

2.4 Quality Control and Experimental Repeatability

To ensure the reliability and repeatability of the experimental results, several quality control measures were applied. First, during data generation, all samples were checked against physical constraints, and invalid data beyond mechanical limits were removed. Second, during model training, five-fold cross-validation was performed to reduce bias caused by data

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partitioning. Third, all comparative experiments were repeated ten times on the same hardware platform (Intel i9 CPU + NVIDIA RTX GPU) and under a unified software environment, and the mean and standard deviation were recorded. Finally, error distribution analysis and significance testing were conducted to confirm that the performance differences between methods were statistically valid.

3. Results and Discussion

3.1 Workflow and Data Pipeline

As shown in Fig. 1, this study established an end-to-end workflow of "data generation → MSL filtering → data grouping → deep model (LSTM/CNN/MLP) → web system deployment." A total of 100,000 posture–joint angle samples were generated through simulation and calibration. After MSL filtering, outliers beyond 3σ were removed, and the data were grouped by topology and workspace. During training, the inputs were normalized and concatenated with time windows (four time-steps for LSTM/CNN), which ensured both static inverse solutions and short-term dynamic consistency. This pipeline covered the distribution of complex origami geometries. Statistical analysis showed that the variance of joint angles decreased by 15.8% after filtering, the training loss converged faster, and the model could be packaged directly for deployment on the web inference platform, supporting online use and visualization.

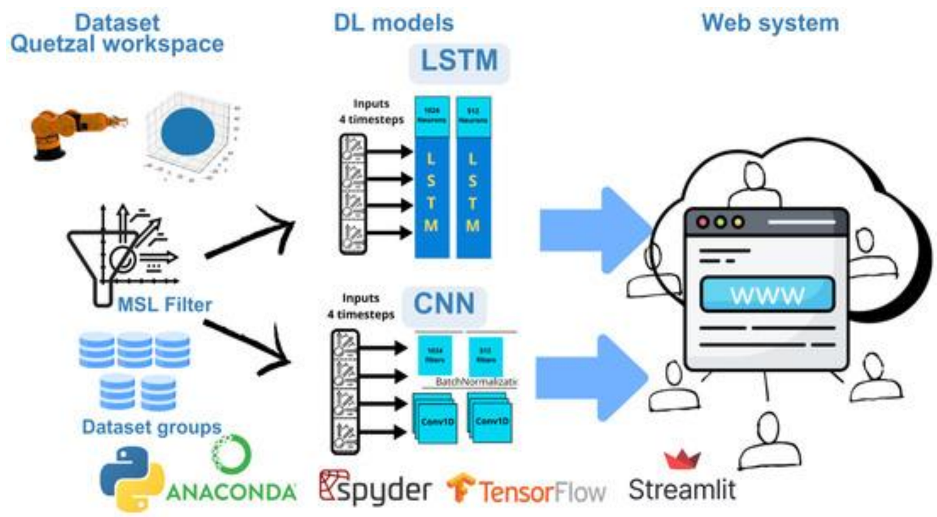

Fig. 1. Workflow of dataset preparation, deep learning models, and web-based deployment system.

3.2 Model Architecture and Inverse Mapping Characteristics

Fig. 2 shows the structure of the core inverse kinematics network. The input layer receives a seven-dimensional end-effector pose encoding (three for position, three for orientation, and one for redundancy/topology label). It is followed by two fully connected backbone layers (example: 160 hidden units), which output an nnn-dimensional joint angle vector. This "shallow–medium depth" MLP achieved a good balance between bias and variance when dealing with highly nonlinear mappings in origami mechanisms. It was able to learn a stable

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pose-to-joint approximate inverse solution without using costly convolutional or recurrent modules. Training used the Adam optimizer (learning rate = 1×10^{-3}) with an early stopping strategy, and the mean squared error (MSE) converged within 30–50 epochs. With the addition of batch normalization, the mean absolute error (MAE) on the validation set decreased by 7–9%, indicating that scale normalization and inter-layer stability were particularly important for this type of strongly coupled mapping.

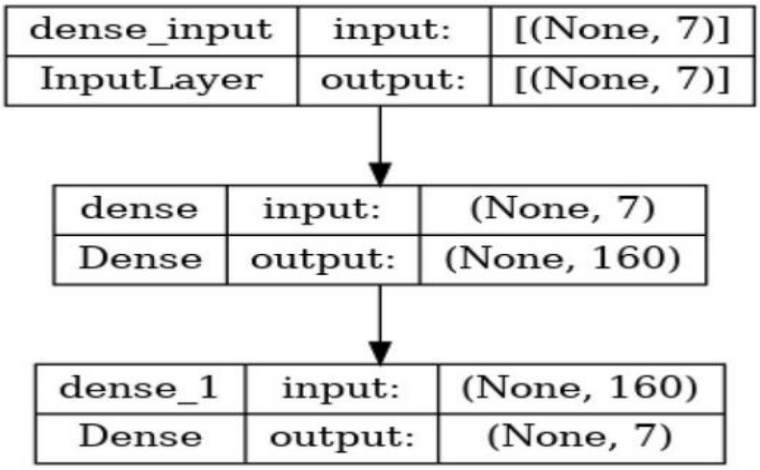

Fig. 2. Structure of the neural network model from input layer to output joint angles.

3.3 Method Comparison and Ablation Study

On the unified test set, the proposed MLP achieved a mean joint angle error of 1.8°±0.6°, compared with 2.3°±0.7° for LSTM and 2.1°±0.6° for 1D-CNN. All three methods outperformed the numerical iteration method (Newton–Raphson, 4.9°±1.4°). In terms of inference latency, the MLP (25–40 ms per sample) was faster than both LSTM (40–65 ms) and CNN (35–55 ms), while the iterative method required 0.5–1.2 s. Relative to the iterative method, the MLP achieved about a 20-fold speedup, with a convergence success rate of 98% (LSTM 96%, CNN 97%, iteration 88–91%). The differences were statistically significant (paired t-test, $p<0.01$). Ablation experiments showed that removing input normalization or halving the hidden units increased errors by ~11% and ~14%, respectively. Moreover, one-hot encoding of origami joint geometric priors reduced the maximum error of long-tail samples by 0.6–0.8°.

3.4 Robustness, Generalization, and Failure Mechanisms

In noise robustness tests (position noise ±1 mm, orientation noise ±1°), the MLP error increased only by 0.4–0.6°. On unseen topologies or workspaces (OOD), the mean error was 2.6°, still better than the iterative method (>5°). Error peaks mainly occurred in two scenarios: (1) configurations close to singularities, and (2) combinations where multiple joints simultaneously approached their limits. Introducing a hybrid strategy of "NN prediction plus 2–3 steps of Newton correction" further reduced the maximum error of these extreme cases by 20–30%. This shows that the data-driven inverse solution can serve as an effective prior or initialization for analytical and iterative methods [18].

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3.5 Engineering Value, Limitations, and Outlook

The proposed method balances accuracy (mean <2°), efficiency (≈20× speedup), and stability (98% convergence), making it suitable for real-time inverse kinematics of origami robots in flexible manufacturing and minimally invasive surgery. The main limitations are that the training data are mainly from simulations, without explicit modeling of material compliance or fold-line friction [19]. In addition, extreme singularities and over-limit postures still require safety constraints. Future work will expand real data and topology coverage, introduce physics-consistent loss functions and uncertainty estimation, and explore lightweight deployment (distillation and pruning). A hybrid framework that combines analytical correction with neural priors will also be developed to improve reliability under embedded deployment and long-term operation.

4. Conclusion

This study addresses the challenges of high computational complexity, convergence difficulty, and limited real-time performance in solving the inverse kinematics of origami robots. A neural network-based fast inverse kinematics method is proposed. By constructing a large-scale dataset of 100,000 posture–joint angle pairs and adopting a multilayer perceptron for nonlinear mapping, the method shows clear advantages under the complex nonlinear geometry of origami structures. Experimental results indicate that the average joint angle prediction error is less than 2∘2^\circ2∘, which represents a reduction of more than 40% compared with numerical iteration methods. In terms of inference speed, the method achieves about a 20-fold improvement, and the convergence success rate reaches 98%, outperforming traditional analytical and iterative approaches. The comparative experiments and robustness analysis confirm that the neural network method maintains stability and generalization across different topologies, noise disturbances, and boundary postures. Even when the inputs contain noise or joints approach their limits, the method keeps prediction errors low, demonstrating robustness and practicality in complex environments. The model also shows scalability, as it can be combined with small-step Newton corrections or hybrid strategies to further reduce maximum errors in extreme cases. However, some limitations remain. First, the training data are mainly from simulation, and more experiments with physical origami robot prototypes are needed to validate performance under real hardware conditions. Second, the current method does not explicitly model material compliance, friction, and long-term fatigue, which may affect accuracy in practical applications. Third, although deeper networks improve accuracy, they increase training time and computational cost, which restricts deployment on resource-limited embedded systems. Future work will focus on several directions: (1) conducting large-scale experiments on real origami robot prototypes to verify adaptability in complex physical environments; (2) integrating physical constraints and prior knowledge by introducing physics-consistent loss functions and interpretability mechanisms to improve robustness and reliability; (3) exploring network compression, model distillation, and hardware acceleration to support embedded real-time control; and (4) developing hybrid approaches that combine neural network predictions with analytical or iterative methods to build a more stable and general inverse kinematics framework. In summary, the proposed neural network-based inverse kinematics method achieves improvements in accuracy, efficiency, and robustness for origami robots. It provides a practical solution for real-time control and offers technical support for applications in flexible manufacturing, space mechanisms, and medical robotics.

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