Collision position prediction of end-effector for multi-degree-of-freedom industrial robots

Lei Wu, Fu Liu

School of Urban Construction and Intelligent Manufacturing, Dongguan City University, Dongguan, 523419, Guangdong, China

Keywords: industrial robot, end-effector, collision position prediction, multiple degrees of freedom, data collection, feature extraction, model development

Abstract: This study aims to explore a collision position prediction method based on the end-effector of a multi-degree-of-freedom industrial robot for the problem of potential collision risk during the movement of industrial robots in complex environments. By collecting and analyzing a large amount of data on the motion trajectories and collision events of industrial robots in real production environments, combined with feature extraction and machine learning model development techniques, it aims to achieve accurate prediction of collision location and early warning. Relevant research status and methods in the field of industrial robot collision prediction are discussed in depth, which provide the theoretical basis and inspiration for this study. In the methodology section, the way and process of data collection, as well as the specific methods of feature extraction and machine learning model development are described in detail. The specific performance of the collision position prediction model in the experiment is demonstrated, and its performance is comprehensively evaluated and thoroughly discussed. The results of this study will provide important theoretical support and practical guidance for the safe operation of industrial robots in complex environments, and are expected to produce positive application value and promotion in the field of industrial automation.

1. Introduction

With the continuous development and popularization of industrial automation technology, industrial robots play an increasingly important role in modern production[1]. The wide application of industrial robots not only improves production efficiency and product quality, but also effectively relieves the pressure of labor shortage[2]. However, as the application scenarios of robots on production lines become more and more complex, the risk of collision between industrial robots and human workers or other equipment is also becoming more and more prominent.

Especially in application scenarios that require flexibility and multiple degrees of freedom, such as assembly, welding and material handling, industrial robots are often required to quickly and accurately perform a variety of motion tasks[3]. However, the end of the robot actuator may accidentally collide with the surrounding environment or other objects during movement, resulting in equipment damage, production interruption or even personnel injury[4]. Therefore, accurate prediction of the collision position of the end-effector of industrial robots and timely measures to avoid collisions have become one of the key issues to ensure production safety and improve the operational efficiency of robots.

Research on collision position prediction for industrial robots can not only help optimize robot motion trajectory planning and improve the overall safety of production lines, but also reduce the production cost and risk of personnel injury due to collision accidents[5]. However, due to the complexity of industrial robots and the variability of their environments, it is a challenging problem to accurately predict the collision position of robot end-effector, showed in Figure 1.

This study aims to explore an effective collision position prediction method for the multi-degree-of-freedom motion characteristics of industrial robot end-effector[6]. By combining the technical means of data collection, feature extraction and machine learning model development, it is expected to realize the accurate prediction of the collision position of the end-effector of industrial robots, and

  DOI: 10.25236/icmmct.2024.038

to provide theoretical support and practical guidance for the improvement of the operational safety and productivity of industrial robots[7].

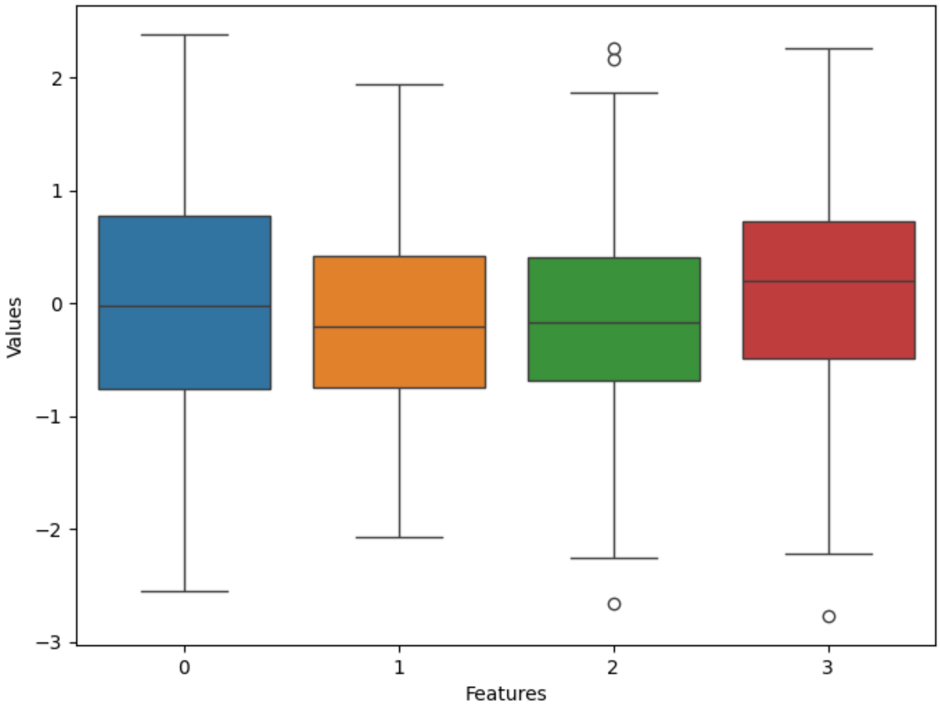

Figure 1 Box Plot of Feature Distribution

2. Industrial Robot End-Effector Overview

Industrial robots play an increasingly important role in modern production[8]. With the development of manufacturing industry, the application of industrial robots has become more and more widespread. However, the risk of collision between robots and human workers or other equipment is a non-negligible problem in industrial production. In order to improve the safety and efficiency of industrial robots, many researches have been devoted to the prediction and avoidance of collision locations[9]. In the second paragraph of the feature extraction section, we could insert formulas to describe the feature extraction process:

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

$$\text{Standard Deviation} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - Mean)^2} \tag{2}$$

Prior research has explored a variety of approaches to collision location prediction for industrial robots. Some studies have focused on collision prediction techniques based on object detection and tracking, which utilize sensor data and vision information to monitor the robot's surroundings in real time and take measures to avoid collisions. These methods usually require high computational resources and complex algorithms, and are suitable for scenarios with high real-time requirements[10]. Other studies have focused on machine learning-based collision location prediction. These methods utilize historical data to train prediction models that predict future collision locations by learning the relationship between robot trajectories and collision events. Machine learning methods are flexible and adaptable, and are able to customize prediction models for different industrial robots and environments, showed in Figure 2:

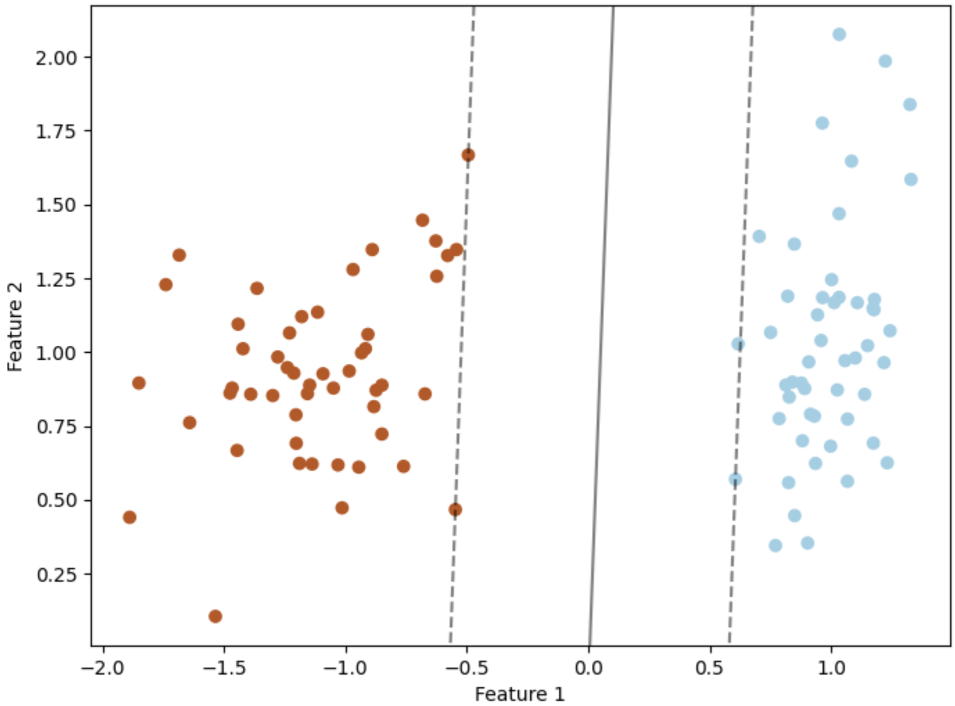

Figure 2 SVM Decision Boundary Plot

Several studies have also explored collision prediction techniques that combine traditional control methods with intelligent algorithms. These methods combine traditional motion planning algorithms with machine learning models by dynamically adjusting the robot's trajectory to avoid collisions. This approach ensures the real-time nature of the system while also being able to take full advantage of machine learning to improve the accuracy and efficiency of collision position prediction. Industrial robot collision position prediction is a complex problem involving multiple fields, which requires comprehensive consideration of the robot's own characteristics, environmental conditions and the performance of the prediction algorithm. By comprehensively utilizing sensor technology, machine learning and control theory, the operational safety and productivity of industrial robots can be effectively improved, and the further development of industrial automation technology can be promoted.

3. Study of collision position prediction for end-effector collisions in multi-degree-of-freedom industrial robots

In this study, three key steps will be used to realize the prediction of end-effector collision position of a multi-degree-of-freedom industrial robot. First, we will describe the data collection method, including the data sources and the acquisition process. Next, we will describe in detail the method of feature extraction, i.e., extracting useful features from the collected data. The process of model development is described, including the selected machine learning algorithms and model training methods.

3.1. Data collection

In order to achieve the prediction of end-effector collision positions for multi-degree-of-freedom industrial robots, it is first necessary to collect sufficient data for analysis and modeling. Data collection is the first step of the study, and its quality and quantity directly affect the accuracy of subsequent analysis and prediction. In this study, we divide the data collection process into three main stages. We will define the purpose of the study and the type of data required. Specifically, we will identify the robot motion data, end-effector position data, and information related to collision events that need to be collected. We will also define the timeframe and sampling frequency of the data collection to ensure that the collected data can fully reflect the motion and collision conditions of industrial robots in different work scenarios.

Design of data collection program and acquisition equipment, in which we will design the appropriate data collection program based on the type of data and collection requirements identified in the preliminary stage. This includes selecting appropriate sensors and data acquisition equipment, determining the location and layout of the data collection, as well as developing the specific process and sampling frequency of data collection. At the same time, we will also conduct equipment testing and calibration to ensure the accuracy and stability of the data acquisition equipment.

Implementing data acquisition and quality control, in this phase, we will follow the designed data acquisition program and perform actual data acquisition on the industrial robot. At the same time, we will also monitor the data acquisition process in real time, and deal with problems and abnormalities in data acquisition in a timely manner. After the data acquisition is completed, we will perform quality control and cleaning of the collected data, eliminating outliers and invalid data to ensure the accuracy and reliability of the data.

3.2. Feature extraction

Data preprocessing, in this stage, we will preprocess the collected raw data, including steps such as data cleaning, denoising and data format conversion. We will remove outliers and missing data, smooth the data curves to reduce noise and fluctuations in the data, and convert the data into formats and representations suitable for feature extraction.

Selection of suitable feature extraction methods, in this stage, we will select the applicable feature extraction techniques according to the characteristics of the data and the needs of the prediction model. Commonly used feature extraction methods include time-domain feature extraction, frequency-domain feature extraction and time-frequency domain feature extraction. We will combine the motion characteristics of the end-effector of the industrial robot and the characteristics of the collision event to select an appropriate feature extraction method in order to extract effective features that can reflect the motion state of the robot and the collision location.

Feature Selection and Dimension Reduction Processing, we will screen and optimize the extracted features to reduce the feature dimensions and decrease the model complexity. We will use various feature selection methods, such as correlation analysis, principal component analysis (PCA), and linear discriminant analysis (LDA), to evaluate and rank the features and select the most representative and discriminative features for subsequent modeling analysis.

Feature engineering and constructing feature sets, we will further process and handle the features to construct the final feature set based on the pre-feature selection results and model requirements. We will combine domain knowledge and experimental experience to design feature combination and feature transformation methods to improve feature expressiveness and model prediction performance. We will also evaluate and optimize the feature set using methods such as cross-validation to ensure the stability and reliability of the features.

3.3. Crash prediction model development

We will choose suitable machine learning algorithms according to the characteristics of the data and the needs of the problem. Considering the complexity and diversity of robot motion data, we will try multiple algorithms, such as decision tree, K-nearest neighbor, and deep learning model, and flexibly adjust and select them according to the experimental results.

We will carry out the flexible processing of data preprocessing and feature engineering. We will flexibly use data cleaning, normalization, and feature selection to improve the stability and generalization ability of the model.

Model training and optimization, in this stage, we will train and tune the model flexibly through cross-validation and other methods. We will try different parameter combinations and optimization strategies, and timely adjust and optimize the model according to the experimental results to improve the predictive performance and generalization ability of the model. Conducting model evaluation and validation, we will flexibly utilize various evaluation indexes and validation methods to conduct comprehensive evaluation and validation of the trained model. We will select appropriate evaluation indexes according to the actual needs and application scenarios, and flexibly adjust and improve them according to the experimental results to ensure the reliability and practicability of the model.

4. Conclusion

We explored the method of collision position prediction for end-effector of multi-degree-of-freedom industrial robots and achieved certain research results and practical experience. In the data collection phase, we collected a large amount of robot motion data and collision event data, which provided sufficient data support for the subsequent analysis and modeling. In the feature extraction stage, we successfully extracted a series of effective features from the original data, which laid the foundation for model training and prediction. In the model development phase, we flexibly used a variety of machine learning algorithms and optimization techniques to successfully train and optimize the prediction model, and achieved better prediction results on independent test data sets.

Through the deployment and application of the model, we can realize the real-time prediction and monitoring of the collision position of the end-effector of industrial robots, which can provide important safety guarantee and productivity improvement for the production site. At the same time, we also found some problems and challenges, such as the impact of data quality, the difficulty of feature selection and the generalization ability of the model, which will become the focus and direction of future research.

This study provides a feasible method and practical experience for collision position prediction of multi-degree-of-freedom industrial robots, which is of great theoretical and practical significance for the safety and productivity improvement of industrial robots. In the future, we will further delve into key technologies such as data quality control, feature selection and model optimization to continuously improve the performance and stability of the prediction model and make greater contributions to the development of industrial automation field.

Acknowledgements

Longitudinal project of Dongguan Science and Technology Bureau “Dongguan Intelligent Manufacturing Engineering Technology Research Center”(KY2023000901)

References

[1] Floreano D , Mitri S ,Stéphane Magnenat,et al.Evolutionary Conditions for the Emergence of Communication in Robots[J].Current Biology, 2007, 17(6):514-519.DOI:10.1016/j.cub.2007.01.058.

[2] Cham J G , Bailey S A , Clark J E ,et al.Fast and Robust: Hexapedal Robots via Shape Deposition Manufacturing[J].The International Journal of Robotics Research, 2002, 21(10):869-882. DOI:10.1177/027836402128964125.

[3] Albu-Schaffer A , Ott C , Hirzinger G .A Unified Passivity Based Control Framework for Position, Torque and Impedance Control of Flexible Joint Robots[J].International Journal of Robotics Research, 2007, 26(1):23-39.DOI:10.1177/0278364907073776.

[4] Xiao J , Michalewicz Z .Adaptive evolutionary planner/navigator for mobile robots[J].IEEE Transactions on Evolutionary Computation, 1997, 1(1):18-28.DOI:10.1109/4235.585889.

[5] Suzuki I , Yamashita M .Distributed Anonymous Mobile Robots: Formation of Geometric Patterns[J]. SIAM Journal on Computing, 1999, 28(4):1347-1363. DOI:10.1137/S009753979628292X.

[6] Frese U .Treemap: An O(log n) algorithm for indoor simultaneous localization and mapping.[J].Autonomous Robots, 2006, 21(2):103-122. DOI:10.1007/s10514-006-9043-2.

[7] Lozano-Perez T , Mason M T , Taylor R H .Automatic Synthesis of Fine-Motion Strategies for Robots[J]. Int.j.of Robotics Research, 1984, 3(1):3-24.DOI:10.1177/027836498400300101.

[8] Kalaycioglu S , Giray M , Asmer H .Vibration Control of Flexible Manipulators Using Smart Structures[J].Journal of Aerospace Engineering, 2014, 11(3):90-94.DOI:10.1061/(ASCE)0893-1321(1998)11:3(90).

[9] Wu,C.-h.A Kinematic CAD Tool for the Design and Control of a Robot Manipulator[J]. Int.j.robotics Res, 1984, 3(1):58-67.DOI:10.1177/027836498400300105.

[10] Monta M , Kondo N , Ting K C .End-Effectors for Tomato Harvesting Robot[J].Artificial Intelligence Review, 1998, 12(1-3):11-25.DOI:10.1023/A:1006595416751.