

Industry-Education Integration Case for Robot-based Retired Battery Disassembly: Learning from Demonstration

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Abstract: With the new energy vehicle industry entering a large-scale development stage, the automated and safe disassembly and recycling of retired power batteries have become key technologies and hotspots for talent demand in the industry. Compared to traditional manual methods, robot-based automated disassembly, offers significant advantages in efficiency, safety, and process consistency. To foster industry-education integration and bridge the gap between teaching and industrial practice, this study integrates a simulated laboratory environment for mechanized battery disassembly into instructional practice. However, traditional robot control methods often require high programming skills from operators. This study adopts a learning from demonstration (LfD) approach, enabling the robot to autonomously learn and reproduce optimized motion trajectories for battery module disassembly through manual guidance. The experimental results show that the robot control strategy based on demonstration is stable and effective in the simulated disassembly task, not only verifying the applicability of this method in the battery disassembly process but also providing valuable insights and practical references for future research and application in this field.

1. Introduction

The research on robot disassembly enabled by artificial intelligence mainly focuses on four major directions: disassembly sequence and strategy optimization, human-machine collaboration, computer vision integration, and collaborative security technology [1]. Among them, in the face of the challenges such as the complexity of retired battery module models and the uncertainty of incoming materials, the traditional automated method relying on precise preset trajectories is difficult to adapt. Therefore, how to enhance the environmental perception and adaptive ability of the robot has become the core of the research. Asif et al. [2] further emphasized that for the disassembly of lithium-ion batteries in electric vehicles, the intelligence level of tasks and motion planning directly determines the adaptability and safety of the system, which is the key to current technological breakthroughs.

Although the application of robot technology in the disassembly field has made significant progress, most of the existing automated solutions still rely on engineers to perform complex programming and trajectory debugging, which constitutes an important barrier to technology promotion. Especially for retired batteries with complex structures and non-standard disassembly processes, there is a significant contradiction between the rigidity of pre-programming and the diversity of on-site conditions. To lower the technical threshold of robot application and enhance system flexibility, the Learning from Demonstration (LfD) paradigm has emerged. This paradigm allows operators to directly demonstrate their operation intentions to the robot through manual guidance or remote operation, enabling the robot to autonomously learn and generalize motion trajectories, thereby avoiding complex underlying programming.

Moreno et al. [3] conducted a systematic literature review of recent related literature, indicating that LfD has shown a high level of technical maturity in the industrial assembly field. It not only can delegate programming capabilities to workshop workers to reduce implementation costs but is also a key enabling technology for adapting to the trend of transitioning from mass production to mass customization. However, this review also clearly pointed out that existing methods still have key obstacles in terms of task complexity and diversity handling capabilities, generalization performance, and industrial integration.

Currently, the research on LfD in the disassembly field is still in its infancy, especially in the specific scenario of retired power batteries. How to combine the intuitiveness of LfD with the complexity of disassembly processes to build a stable and efficient automated system while considering the stability and efficiency of the system is still an urgent frontier issue to be explored. This study takes this as the starting point, combining the robotic arm automated disassembly simulation in the laboratory environment with the LfD method, aiming to verify the applicability of this method in the battery disassembly task and provide practical references for subsequent industry-university-research integration.

2. Battery disassembly based on learning form demonstration

2.1 Learning form demonstration

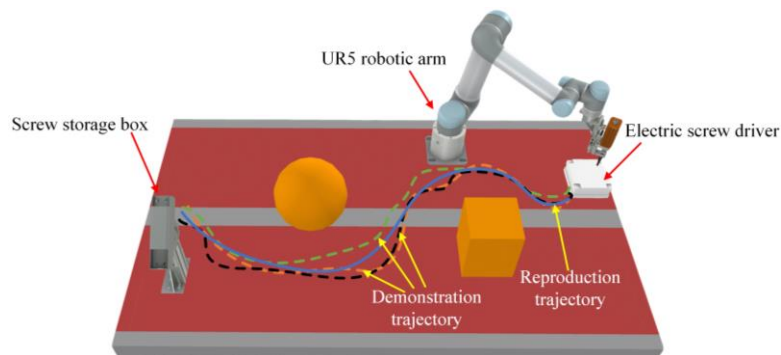


Figure 1: Task platform based on LfD

Learning form demonstration (LfD) is one of the key methods for controlling robots. It enables robots to learn new skills by imitating human actions and create new solutions in constantly changing environments. In LfD, intuitive demonstrations can facilitate human operators to control collaborative robots more efficiently and economically. To deepen students' understanding of LfD, this paper takes the typical picking-up and placing task in battery disassembly as an example to describe the LfD process in detail. As shown in Figure 1, the operator first specifies the starting position (such as the screw on the battery module) and the ending position (such as the collection

box) of the task, and then manually moves the end of the robotic arm to generate multiple demonstration trajectories (as shown by the green, black, and orange dotted curves in Figure 1), forming a series of demonstration trajectories. These trajectory data are encoded through mathematical models, and then a new reproduction trajectory is generated through a regression model (as shown by the blue solid line in Figure 1), allowing the robot to execute the disassembly operation along this trajectory. During this process, the operator does not need to possess professional programming skills, they can complete the programming of the task simply through manual demonstrate methods.

2.2 Methods and Models

LfD aims to enable robots to learn complex skills by observing human demonstrations. Among them, Gaussian Mixture Model/Gaussian Mixture Regression (GMM/GMR) and Dynamic Movement Primitives (DMP) are two of the most representative methods. They each have their own advantages in terms of theoretical foundation, implementation process, and application characteristics.

GMM/GMR is a LfD method based on probabilistic modeling. It encodes the joint probability distribution of demonstration data through the weighted combination of multiple Gaussian distributions. This method treats multiple demonstration trajectories as samples from the same random process, and uses the Expectation Maximization (EM) algorithm to learn the statistical characteristics of the data, thereby calculating the expected output given an input through conditional probability. Its theoretical foundation can be traced back to the pioneering work of Calinon et al. [4], which introduced probability theory into the field of robot LfD.

The GMM models the demonstration data $p_{j=1}^N$ as the weighted sum of K Gaussian distributions:

$$N_{gmm}(p_j) = \sum_{i=1}^K \alpha_i N_i(p_j | \mu_i, \Sigma_i) \quad (1)$$

Where K represents the number of single Gaussian models in the mixed model; α_i is the weight coefficient of each single Gaussian model, which satisfies $\alpha_i > 0$ and $\sum_{i=1}^K \alpha_i = 1$. μ_i and Σ_i are respectively the mean and covariance matrix of the i -th Gaussian component. GMR uses the joint distribution learned by GMM for regression prediction.

The implementation of GMM/GMR is divided into three steps.

- 1) Data preparation: Collect multiple demonstration trajectories and construct a data set.
- 2) GMM training: Use the EM algorithm to iteratively estimate the parameters of the GMM ($\alpha_i, \mu_i, \Sigma_i$). Usually, the number of Gaussian components K needs to be specified in advance, and multiple random initializations are conducted to avoid local optima.

- 3) GMR regression: For new time inputs, calculate the weight coefficients of each Gaussian component, and then obtain the conditional expectation as the generalized trajectory point.

The DMP was proposed by Professor Schaal's team [5], its core idea is to decompose complex movements into several basic motion units, each of which is described by a nonlinear dynamic system with self-stabilizing properties. This method is inspired by the theory of biological motion control, suggesting that biological systems can combine and adapt basic motion units to perform complex tasks. The essence of DMP is a second-order dynamic system with an attractor characteristic. It regulates the trajectory shape by adding nonlinear terms while ensuring that the

system eventually converges to the target state.

The basic form of DMP can be represented as a combination of a transformation system and a regular system. The transformation system describes the motion trajectory:

$$\tau^2 \ddot{y} = \alpha_y (\beta_y (g - y) - \tau \dot{y}) + f \quad (2)$$

Where y , \dot{y} , \ddot{y} represent position, velocity, and acceleration respectively, g represents the target state, τ is the time scaling factor, α_y and β_y are constants, and f is a nonlinear forcing term used to fit the shape of the demonstration trajectory. The forcing is defined as a weighted combination of basis functions:

$$f(x) = \frac{\sum_{i=1}^N \psi_i(x) \omega_i}{\sum_{i=1}^N \psi_i(x)} x (g - y_0) \quad (3)$$

Where $\psi_i(x)$ represents the Gaussian radial basis function, ω_i is the learnable weight, and y_0 is its actual position. The regularized system introduces the phase variable x with $\tau \dot{x} = -\alpha_x x$, which decouples the forcing term from the time variable. As a result, x monotonically converges from 1 to 0, ensuring the final stability of the system.

The implementation of DMP involves two stages.

1) The learning stage: Firstly, position, velocity, and acceleration information are extracted from a single or multiple demonstration trajectories; then, phase variables are generated through a regular system; finally, the local weighted regression (LWR) or the least squares method is used to solve the basis function weights ω_i , so that the output of DMP is as close as possible to the demonstration trajectory.

2) Recovery stage: Set a new target position or time scaling factor, start the integral transformation system and the regular system from the initial state, and generate a smooth trajectory that meets the requirements of the new task.

GMM/GMR and DMP respectively represent two different modeling approaches in LfD. DMP is based on deterministic dynamic systems, emphasizing the dynamic characteristics of trajectories and real-time control performance, and performs exceptionally well in scenarios requiring rapid online adjustment and disturbance resistance; GMM/GMR, on the other hand, is based on probability statistics, focusing on the modeling of multiple demonstration data and the expression of uncertainty, and is suitable for scenarios that require integrating multiple sources of information or assessing task risks. Taking into account the collection efficiency, this research selects DMP as the learning model. This method can quickly construct and generate replicable trajectories.

2.3 Verify the LfD method

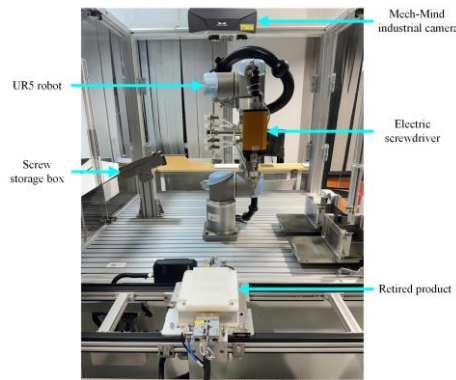


Figure 2: Experimental Setup

The approach in this study is validated in a robotic station for unscrewing battery. The setup, which is illustrated in Figure 2, consists of a UR5 collaborative robotic arm, an electric screwdriver, a Mech-Mind industrial camera, and a screw storage box.

The demonstration trajectory was created using the kinesthetic teaching method. The robotic arm was moved from the position above the screw to the placement box position in the sequence of 1-2-3-4 (as shown in Figure 3). During the dragging process, try to maintain the continuity of the trajectory and avoid excessive jittering and pauses, as this has a significant impact on the subsequent trajectory learning.

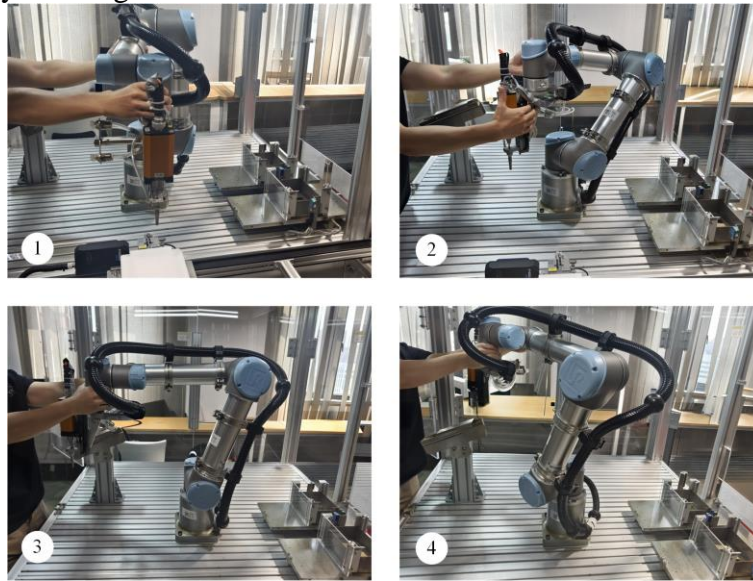


Figure 3: Demonstration process

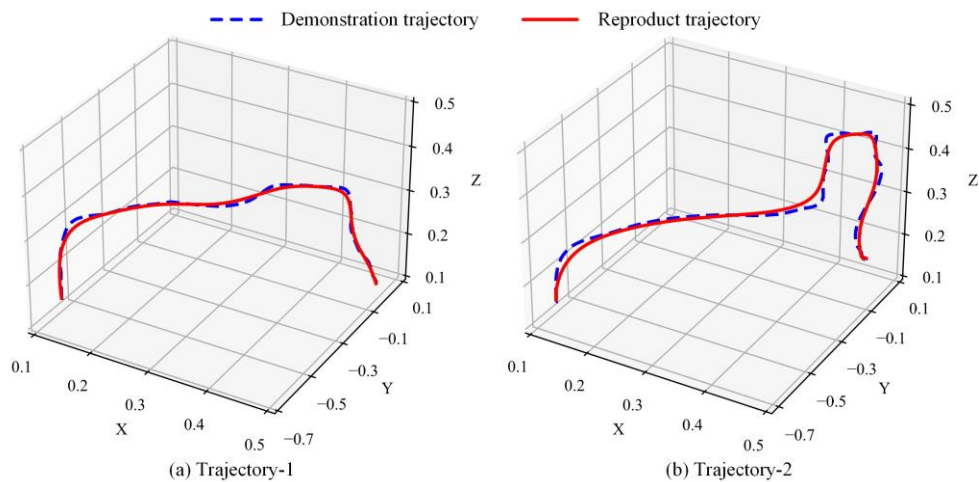


Figure 4: Comparison of trajectory quality

This study utilized the DMP method to learn and reproduce two artificial demonstration trajectories (Trajectory-1 is a simple demonstration, while Trajectory-2 is a complex demonstration including consecutive 90-degree turns). The results are shown in the figure 4. To quantitatively evaluate the quality of the generated trajectories, we used the three-dimensional curvature as the smoothness evaluation index and compared the curvatures of the demonstration trajectories and the reproduced trajectories. The analysis indicated that the DMP method effectively retained the main turning features of the original demonstration trajectory while significantly improving the

smoothness of the trajectory: The three-dimensional curvature of Trajectory-1 decreased from 11.956 to 4.634, a reduction of approximately 61.2%; the curvature of Trajectory-2 decreased from 18.360 to 9.254, a reduction of approximately 49.6%. This result demonstrates that the DMP method has a more significant smoothing optimization effect on simple trajectories, while for complex trajectories, it can still reproduce the key geometric features while achieving a reduction of approximately 50% in curvature, demonstrating a good balance between trajectory smoothness and feature fidelity. Therefore, using DMP for LfD can generate high-quality, smoother, and more easily executable trajectories for robots.

2.4 The entire process of simulating battery disassembly

In this study, we constructed an experimental platform to simulate the disassembly of retired batteries. The core of this platform is a 3D-printed battery module (due to the safety restriction of the university laboratory, the battery operated in the laboratory is a simplified mini-battery printed by 3D printers for technology demonstration and validation). This module includes the key structural components of a typical battery module: screws, upper cover, electrode sheets, and battery cells (as shown in Figure 5). To truly reflect the complexity and challenges of the actual disassembly scenario, we divided the entire disassembly process into multiple stations to simulate the assembly line operation mode of industrial production. Considering the compactness of the internal structure of the battery module and the sequence constraints of the disassembly operation, the strategy of multi-station parallel disassembly can significantly improve the overall efficiency and avoid the loss of cycle time caused by frequent replacement of the end effector by a single robotic arm.

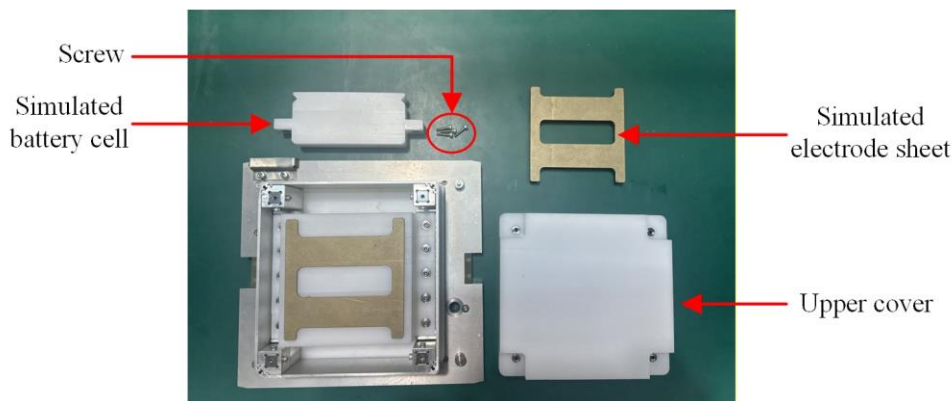


Figure 5: 3D-printed battery module

As shown in the Figure 6, the entire simulation disassembly process is set up with three consecutive workstations. The workstation-1 is responsible for performing the initial disassembly task, which involves removing the upper cover plate of the battery module and its connected fixing screws. This workstation opens the physical channel for the subsequent operations and is the basic step of the disassembly process. The workstation-2 is the key verification platform of this study, equipped with a UR5 collaborative robotic arm. Its core task is to disassemble the electrode sheets and perform the loosening operation on the cells, preparing for the final cell picking. At this workstation, we introduced a control strategy based on LfD. Through manual guidance from the operator to complete the demonstration of the optimal disassembly trajectory, the robot can autonomously learn and reproduce this complex action, effectively avoiding the high dependence on the operator's professional skills in traditional programming methods. The workstation-3 is responsible for completing the final cell picking task, extracting the loosened cells from the module and placing them in the designated recycling area.



Figure 6: Battery module disassembly workstation

It is worth noting that due to the structural inconsistencies (such as deformation, model differences, etc.) of real retired battery modules, relying solely on the preset trajectory is insufficient to ensure the universality and success rate of the disassembly process. Therefore, in the disassembly process at the workstation-2, we have integrated a machine vision module to real-time identify the key structural components, especially, the exact positions of the screws. The vision system first locates the two-dimensional coordinates of the screws through image acquisition and processing calculations, and then combines depth information to calculate their precise three-dimensional pose in the robot base coordinate system, thereby guiding the end effector of the robotic arm to accurately reach the target point to perform the disassembly operation. This visual guidance mechanism provides an environmental perception foundation for the generalization of the demonstration trajectory, enabling the robot to adaptively adjust the motion trajectory according to the actual position of the workpiece.

In conclusion, this study systematically explored the key technical paths for the automated disassembly of end-of-life batteries by constructing a simulation disassembly platform that incorporates multi-station collaboration, LfD of the robotic arm, and machine vision perception. The second station, using the UR5 robotic arm as the carrier, combines LfD with visual positioning, which not only lowers the operational threshold but also enhances the system's adaptability to uncertain incoming materials. The establishment and verification of this experimental platform not only provide an operational teaching case for the integration of industry, academia, and research, but also lay a practical foundation for the development of more flexible and intelligent disassembly equipment for end-of-life batteries in the future.

3. Conclusion

This study focuses on the application of demonstration learning in the robot battery disassembly task. Firstly, a systematic review and analysis of the mainstream demonstration learning methods were conducted, revealing their applicability in industrial operation scenarios from both theoretical mechanisms and implementation paths. Based on this, the method's good adaptability in the battery disassembly task was verified through trajectory quality assessment: on one hand, it can effectively improve the smoothness of the reproduction trajectory; on the other hand, it can well preserve the key motion features of the original demonstration trajectory.

Furthermore, this study systematically modeled and explained the battery disassembly

production line. Although the current simulation disassembly environment constructed is at the laboratory scale, its process design is highly consistent with the actual production line, which can clearly display the key process steps of battery disassembly and lay a practical foundation for the subsequent migration to real production scenarios.

In conclusion, this study systematically expounds the application potential and implementation paths of demonstration learning in the field of battery disassembly, making the integration mode of “battery disassembly + course practice” more operable and having greater teaching implementation value.

Acknowledgments

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