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Battery Disassembly Exemplification Employing a Vision Sensor for Educational Purposes in Robotics Courses

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Abstract: With the emergence of Industry 5.0, industrial systems are increasingly adopting intelligent manufacturing and human-machine collaboration models. In this context, the recycling of old batteries has become a significant research field. Old batteries contain numerous harmful substances that, if not properly handled, can cause severe environmental pollution. Therefore, the development of efficient and environmentally friendly technology for recycling old batteries has become one of the current focal points of research. The utilization of vision sensors plays a crucial role in automated production lines designed for dismantling old batteries. By employing RGB and depth vision sensors, we can acquire more comprehensive information about target states and utilize advanced image processing algorithms to achieve precise positioning of battery components and guide robots in performing disassembly tasks.

1. Introduction

With the emergence of Industry 5.0, industrial systems are increasingly adopting intelligent manufacturing and human-machine collaboration models. In this context, the recycling of old batteries has become a pivotal research field due to their potential environmental hazards if not properly managed. Anna et al. emphasize that the widespread use of electric vehicles has significantly contributed to an upsurge in end-of-life lithium-ion batteries, necessitating urgent development of efficient dismantling and recycling technologies [1]. Therefore, the development of efficient and environmentally friendly old battery recycling technology has become one of the current research hotspots.

The application of vision sensors is essential in the automated dismantling production line for recycling old batteries. Vision sensors not only provide real-time monitoring and feedback on various parameters along the production line but also enable precise positioning and disassembly of old battery components through advanced image recognition technology. Zhang et al. demonstrated that by utilizing depth cameras and UR10 cooperative robots in battery disassembly experiments, the system's attitude estimation error is minimized to ensure a 100% success rate [2]. The image captured by the vision sensor is processed and recognized to extract valid information, using methods such as object recognition, pose estimation, and other techniques for high-precision automatic operation.

Object recognition technology improves dismantling efficiency by accurately distinguishing individual components in the battery. Wang achieved a new height in speed and accuracy with an AP value of 56.8% using the YOLOv7 deep learning algorithm for target detection [3]. Pose estimation technology enables accurate determination of the spatial position and orientation of the battery, facilitating precise disassembly operations for robots. Moreover, to achieve collaborative tasks with humans, collaborative robots (Cobots) have emerged that not only work alongside humans but also autonomously make decisions and collaborate on tasks based on image information acquired through vision sensors.

In summary, vision sensors play a crucial role in the automated production line for recycling old batteries. Various types of vision sensors can capture diverse information, including but not limited to the battery's appearance characteristics, position, and shape. For instance, an RGB vision sensor (see Figure 1) can provide a color image that enables differentiation between different battery types; while a depth vision sensor (see Figure 2) can acquire three-dimensional shape data of the battery to facilitate precise robot operations. After acquiring these images and information, they undergo processing and analysis, including image recognition algorithms and pose estimation algorithms. Image recognition algorithms are primarily used to extract target object features from images for classification and recognition purposes. The application of deep learning technology has significantly enhanced the accuracy and efficiency of such algorithms. Zhang et al. developed a Transformer-CNN hybrid model for robot grasping detection, achieving target detection accuracies of 96.9% and 92.4% respectively on the same dataset, while the grasping experiment with Elite 6Dof robot achieved an accuracy of 93.3% [4]. The pose estimation algorithm is primarily utilized for determining the spatial position and orientation of an object, which is crucial for ensuring precise robot operations. Common methods include feature point-based pose estimation and model-based pose estimation. The feature point-based method detects feature points on the object's surface and calculates their three-dimensional coordinates to determine its spatial position and orientation. Zhang et al. proposed a multi-task parameter sharing approach to enhance the accuracy of pose estimation, enabling end-to-end target capture through target positioning and pose estimation [5].

The focus of this paper is to investigate the application of vision sensors and recognition algorithms in the disassembly production line for old batteries, while also designing a comprehensive system for old battery disassembly that integrates vision sensors, recognition algorithms, and cooperative robots.

2. Old Battery Disassembly Production Line Design

2.1. The Disassembly Platform

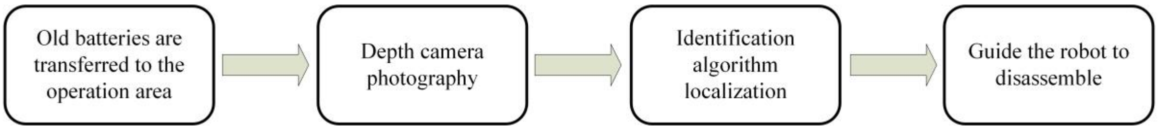

Figure 1: The composition diagram of the disassembly system.

The battery disassembly platform, as depicted in Figure 1, comprises conveyor belts, depth cameras, robots, end-effectors, and other electronic control devices. Once the dismantling task commences, the old battery is transported to the dismantling operation area by the conveyor belt. The depth camera captures images of the battery for positioning and pose estimation purposes while employing a recognition algorithm to precisely locate it. Subsequently, the system guides the robot to utilize an appropriate end-effector (such as an electric batch, clamp or suction cup) for executing the disassembly task and categorizing the disassembled parts. This process significantly enhances efficiency and accuracy in dismantling operations by minimizing manual intervention and improving safety.

2.2. Collaborative Robots and Vision Sensors

In industrial settings, the dismantling of old batteries is often carried out using either industrial robots or collaborative robots, as depicted in Figure 2. Industrial robots are capable of disassembling larger batteries efficiently; however, their programming complexity and high-risk factor should be taken into consideration. On the other hand, collaborative robots offer greater flexibility and can swiftly adapt to various task scenarios due to their intuitive programming capabilities.

In the disassembly platform, the visual sensor depth camera plays a crucial role in guiding the robot through dismantling tasks by capturing images. Two common camera loading methods, namely eye-in-hand and eye-out-of-hand, are illustrated in Figure 2. Out-of-the-hand loading is often preferred on highly integrated operating platforms due to its simplicity and efficiency, while on flexible operating platforms, the eye-on-the-hand loading method is typically employed to expand the camera's field of view based on robot movement and cover a wider operational area.

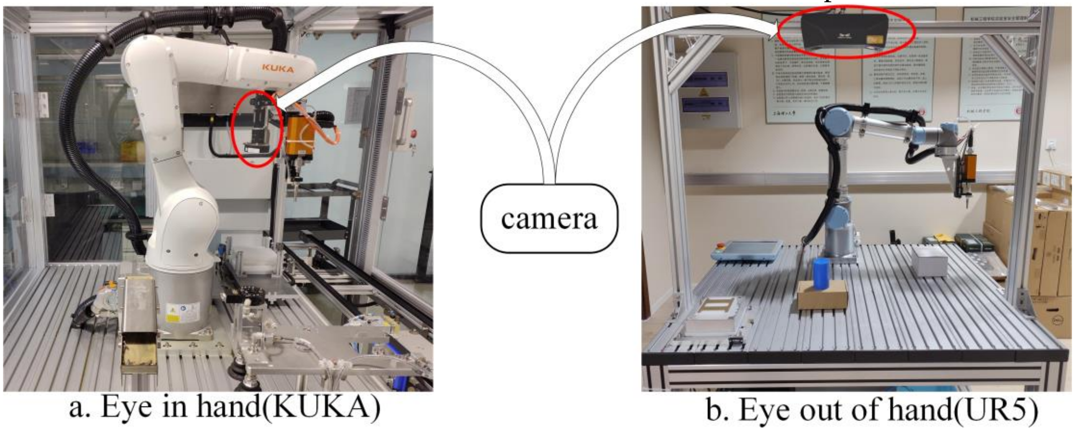

Figure 2: Comparison of loading methods of different robot cameras.

2.3. The Application of Vision Sensor for Disassembly Process of Old Batteries

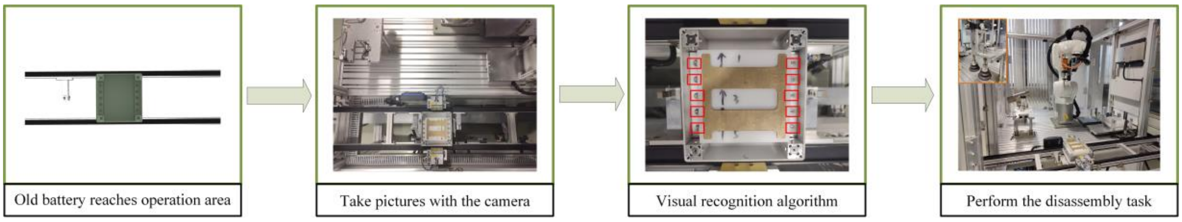

Figure 3: Old battery disassembly schematic.

As depicted in Figure 3, the disassembly process of the old battery comprises four sequential steps. In this process, a vision sensor captures images and employs a visual recognition algorithm to acquire location information regarding the target object for disassembly. This information guides the robot to utilize an appropriate end-effector for executing the disassembly task. The underlying principle of obtaining target position information through vision sensors is as follows:

The first step involves conducting hand-eye calibration, as illustrated in Figure 4 (in this study, the eye located outside the hand is taken as an exemplar).

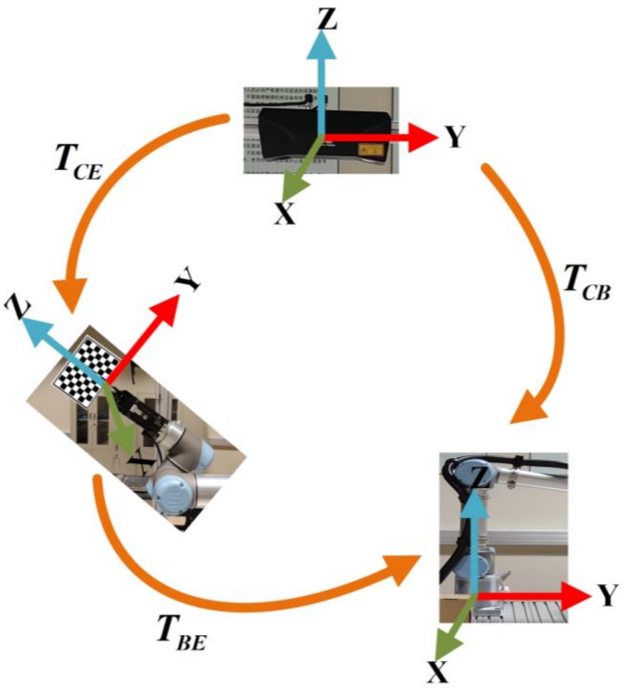

Figure 4: The hand-eye calibration flow chart.

1) The transformation matrices $\boldsymbol{T}_{CB}$ and $\boldsymbol{T}_{BE}$, which represent the conversion from the camera coordinate system to the robot base coordinate system and from the robot end coordinate system to the robot base coordinate system respectively, are obtained at various positions. For each position i, record the corresponding transformation matrix as follows:

$$\boldsymbol{T}_{CB}^{(i)} = \begin{bmatrix} \boldsymbol{R}_{CB}^{(i)} & \boldsymbol{t}_{CB}^{(i)} \\ 0 & 1 \end{bmatrix} \tag{1}$$

$$\boldsymbol{T}_{BE}^{(i)} = \begin{bmatrix} \boldsymbol{R}_{BE}^{(i)} & \boldsymbol{t}_{BE}^{(i)} \\ 0 & 1 \end{bmatrix} \tag{2}$$

- $\boldsymbol{R}_{CB}^{(i)}$: Rotation matrix from camera coordinate system to robot base coordinate system.
- $\boldsymbol{t}_{CB}^{(i)}$: Translation vector from camera coordinate system to robot base coordinate system.
- $\boldsymbol{R}_{BE}^{(i)}$: Rotation matrix from robot end coordinate system to robot base coordinate system.
- $\boldsymbol{t}_{BE}^{(i)}$: Translation vector from robot end coordinate system to robot base coordinate system.

2) Rotation matrix solution: Solve the rotation matrix $\boldsymbol{R}_{CE}$ according to the least square method:

$$\boldsymbol{R}_{CB}^{(i)} \boldsymbol{R}_{BE}^{(i)} = \boldsymbol{R}_{CE} \tag{3}$$

- $\boldsymbol{R}_{CE}$: Rotation matrix from camera coordinate system to robot end coordinate system, describing how camera coordinate system rotates to robot end coordinate system.

3) Translation vector solution: Using linear equations to solve the translation vector $\boldsymbol{t}_{CE}$

$$\boldsymbol{R}_{CB}^{(i)} \boldsymbol{t}_{BE}^{(i)} + \boldsymbol{t}_{CB}^{(i)} = \boldsymbol{R}_{CE} \boldsymbol{t}_{CE} \tag{4}$$

- $\boldsymbol{t}_{CE}$: Translation vector from the camera coordinate system to the robot end coordinate system, describing how the camera coordinate system is translated to the robot end coordinate system.

4) Find the transformation matrix $\boldsymbol{T}_{CE}$:

$$T_{CE} = \begin{bmatrix} R_{CE} & t_{CE} \\ 0 & 1 \end{bmatrix} \quad (5)$$

The image is then fed into the recognition algorithm to determine the precise pixel position of the target within the image. Subsequently, the transformation matrix $\boldsymbol{T}_{CE}$ is converted to align with the world coordinate system, enabling accurate guidance for robot disassembly operations. Commonly employed image recognition algorithms encompass Faster R-CNN, RetinaNet, and YOLO.

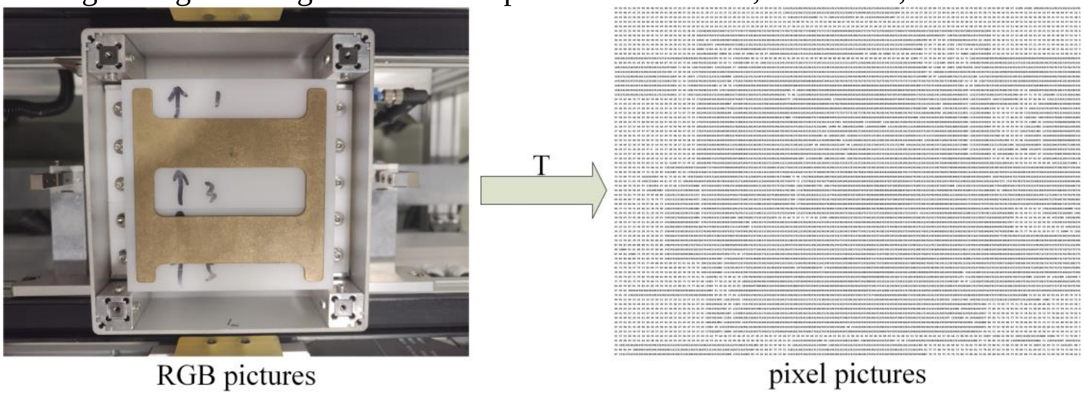

Figure 5: The convert RGB pictures to pixel pictures.

As depicted in Figure 5, an RGB image is inputted (the size of the image in this article is 2048×1536). YOLOv7 consists of two components: Backbone and Head. The role of the Backbone is to extract image features, serving as the foundation for the entire YOLOv7 network. It primarily comprises CBS and ELAN modules. The ELAN module achieves feature enhancement and extraction by combining multiple CBS modules, while the MP1 module performs feature downsampling through maximum pooling operations. The Head component processes the features extracted by the Backbone and generates the final detection results, encompassing ELAN-H module, SPPCSPC module, and up-sampling module. The ELAN-H module improves upon ELAN by introducing additional convolution layers to enhance feature extraction capability. Through multi-scale pooling operations, the SPPCSPC module captures features at different scales. Multi-scale feature fusion combines different scale features via up-sampling and feature splicing operations. Ultimately, YOLOv7 produces a detection box for each screw by integrating convolution layers with sigmoid function.

3. Conclusion

In this study, we extensively explored the application of vision sensors and recognition algorithms in used battery dismantling production lines, affirming their significant value in enhancing dismantling efficiency and system reliability. By employing RGB and depth vision sensors, we are able to acquire more comprehensive target state information, and through advanced image processing technology-related algorithms, achieve precise positioning of battery components and guide the robot in executing disassembly tasks. This study underscores the pivotal role that vision sensors play in the recycling process of old batteries, providing a scientific foundation and technical support for intelligent manufacturing within the context of industry 5.0. Future research can delve deeper into the following areas to enhance the effectiveness of vision sensor-assisted robots in dismantling old batteries:

1) Algorithm optimization: Image recognition and pose estimation algorithms are further optimized to cope with more complex disassembly tasks and diverse working environments.

2) Vision Sensor integration: Explore more types of vision sensor combinations to provide more

comprehensive and accurate battery disassembly information.

3) Application expansion: The vision sensor and robot collaboration technology in this study will be applied to other fields, such as automotive, medical, etc., in order to achieve extensive integration and innovation of technologies.

Acknowledgements

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