ADVANCED TECHNIQUES FOR REMOVING EV LIB PACK LIDS

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Primary Topic Area: Innovative Remanufacturing Technologies
Secondary Topic Area: Building a Sustainable Circular Economy for Materials & Products

Abstract

Automation in the disassembly of electric vehicle (EV) lithium-ion battery (LIB) packs is increasingly critical during both maintenance operations and end-of-life (EOL) processing. At EOL, functional battery modules can be extracted and repurposed for secondary applications, such as stationary grid storage systems, thereby extending their useful life and reducing environmental waste. Efficient removal of enclosure lids from EV LIB packs represents a critical bottleneck in the disassembly process, requiring advanced robotic manipulation and sophisticated computer vision techniques to ensure safe and effective execution. This work presents recent advancements in computer vision systems designed to support autonomous robotic disassembly of EV battery packs. A significant improvement involved replacing a dual-camera configuration—comprising a 2D RGB camera and 3D laser scanner—with a single integrated structured-light camera system. This hardware consolidation enabled fully automated registration and spatial alignment of 2D color images with corresponding 3D depth data, eliminating manual calibration procedures and reducing fastener extraction time by more than 30%. While the new camera lacks built-in machine learning processing capabilities, its direct access to raw sensor data enables highly flexible and customized algorithm development tailored to battery disassembly operations. The manuscript details comprehensive methods for processing 3D point cloud data to verify and precisely locate fasteners initially detected in 2D images through object detection algorithms. These methods include an approach for determining fastener plane orientation using first-principles geometric analysis, ensuring accurate robotic tool positioning for removal operations. Additionally, recognizing that modern EV LIB packs incorporate hermetically sealed lids with adhesive or polymer sealants to prevent water ingress and electrical short circuits, this paper introduces computer vision techniques for automated seam detection along lid perimeters. The work further describes a complete robotic approach to sealant removal, encompassing tool selection criteria, custom end-effector design, trajectory planning, and seamless integration of all components into a fully autonomous, end-to-end disassembly workflow for industrial-scale battery recycling operations.

Keywords: computer vision, machine learning, robotics, LIBs, EVs

Introduction and Motivation

Remanufacturing durable goods offers a significant opportunity to reduce landfill waste and minimize energy-intensive recycling. The process begins with a critical step: sorting and inspecting returned components, known as "cores." Today, these tasks are performed manually, making operations labor-intensive, prone to errors, and physically demanding.

Market analysis predicts that annual electric vehicle (EV) production will increase more than eightfold—from 3.1 million units in 2020 to 26.9 million by 2030 [1]. EV batteries typically reach end of life (EOL) when their capacity falls to about 70–80% of the original. Even at this stage, they retain substantial energy storage potential for secondary applications, such as grid storage, supporting functions like peak shaving and firming of the renewable energy [2].

Automating disassembly and accelerating condition assessment of used modules can enable efficient repurposing of EV batteries for less demanding applications. This approach improves throughput, yield, and safety for remanufacturers. However, automation faces significant challenges. EV lithium-ion battery (LIB) packs lack standardization, as illustrated in Figure 1, which shows the wide range of sizes and form factors examined in this study. Variations in design, module topology, spatial arrangement, and cell chemistry complicate reuse—even batteries from the same model may differ in enclosure design across production batches. These inconsistencies demand an intelligent disassembly process that makes real-time decisions based on actual conditions rather than relying solely on deterministic programming.

(a) Rivian (b) Unknown OEM (c) TESLA

Figure 1: Different size and form factors of EV LIB battery packs

Previous work by the authors [3], [4] reviewed the state of the art and introduced a technology-driven approach using computer vision and specialized end-effector designs for fastener removal. That work also demonstrated improved productivity through faster fastener and lid removal. Building on this foundation, the present paper details enhancements to the vision system for more accurate fastener detection and proposes a new approach and end-effector design for removing seals from top covers.

Review of Related Work

Kaarlela et al. [5] provide a comprehensive overview of robotic disassembly and outline future directions, emphasizing human–robot collaboration, the role of AI, and challenges stemming from non-standardized battery pack designs. Research comparing vision systems for robotic manipulation, particularly for specialized tasks like EV battery pack disassembly—remains limited. Laser cameras can achieve submicron accuracy when motion is precisely controlled to collect sufficient samples [6]. In contrast, structured-light cameras offer lower resolution (sub-millimeter) but maintain accuracy regardless of motion.

Reference [7] reviews structured-light sensing in industrial applications such as workpiece detection, geometric profiling, and 3D reconstruction. The study highlights that line-structured light provides significant advantages for high-precision measurement in automated production lines due to its non-contact nature.

In prior work [3], [4], we explored alternatives to commercial imaging systems with built-in Computer Vision/Machine Learning (CV/ML) solutions. We argued that replacing these systems with custom CV/ML implementations based on open-source software and centralized computing can accelerate development and deliver superior results.

Using the Cognex IS3D-L4300 vision system (Figure 2a), we successfully demonstrated 3D fastener detection. This camera integrates a laser scanner for three-dimensional capture and an onboard processor for object detection and localization, enabling rapid deployment in initial trials. However, as system complexity increased, several limitations became evident. First, misalignment errors between the 2D and 3D images occurred due to the use of separate cameras, necessitating frequent calibration to maintain accuracy. Second, the proprietary point cloud data was stored exclusively on the onboard processor, which prevented offline processing and limited flexibility for advanced analysis. Finally, the laser line scanning approach required synchronized motion; when mounted on a robot wrist, controller delays introduced timing errors of approximately ±20 ms, resulting in directional deviations exceeding 1 mm. These constraints highlighted the need for alternative vision solutions to ensure robust and scalable performance.

Technical Approach

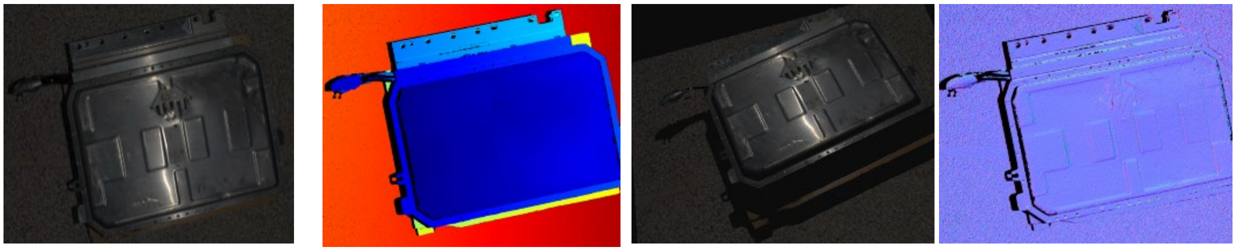
After evaluating several alternatives, we selected the Zivid structured-light camera (model Zivid2+M60), shown in Figure 2b. Structured-light technology offers distinct advantages over laser-based scanning systems, particularly in terms of acquisition speed, operational flexibility, and measurement accuracy. The Zivid camera is capable of generating dense point clouds in less than one second, which represents a substantial improvement over Cognex's eight-second acquisition and processing cycle. In addition, the system outputs point clouds in widely adopted standard formats, ensuring compatibility with common open-source libraries and facilitating integration into existing workflows.

(a) Cognex IS3D-L4300 Camera (b) Zivid Camera

Figure 2: Cameras used for fastener detection and localization

Unlike laser scanners, structured-light cameras mitigate motion-induced errors by operating from a stationary position, which is critical for applications involving dynamic environments or robotic manipulation. The selected system incorporates both 2D and 3D sensing within a single housing, guaranteeing that 2D images and 3D point clouds remain spatially aligned regardless of object height or surface geometry. This integrated design simplifies calibration and reduces potential sources of error. Furthermore, the Zivid camera includes precision dowel pin holes, enabling accurate mechanical alignment with the robot's coordinate system and ensuring repeatable positioning during installation and maintenance.

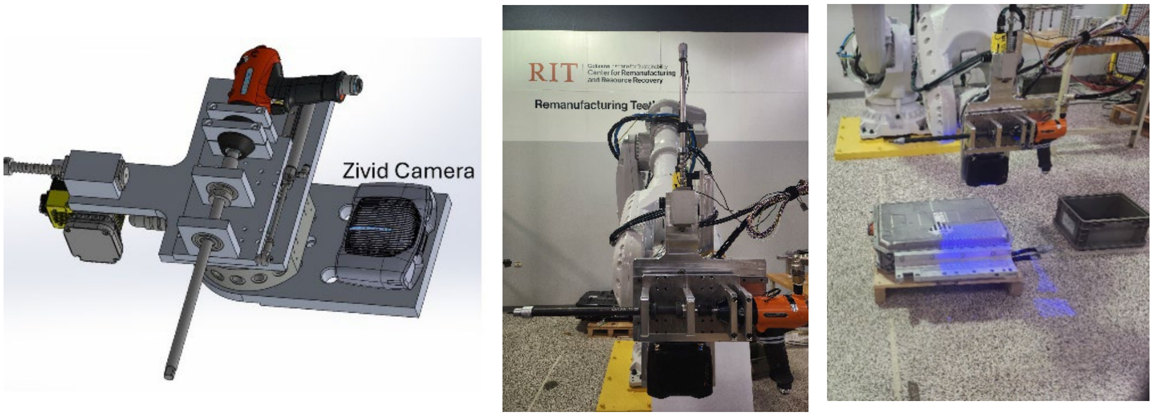
Figure 3 presents representative outputs from the Zivid camera during imaging of a battery pack. The camera natively provides RGB images, depth maps, signal-to-noise ratio (SNR) data, point clouds, and surface normals. These outputs are essential for accurate 3D reconstruction and surface characterization, enabling downstream tasks such as object localization, dimensional inspection, and robotic path planning. High-resolution RGB images support visual verification, while depth maps and point clouds provide precise spatial information for geometric analysis. Surface normals further enhance the ability to detect orientation and assess surface quality.



(a) 2DColor Image (b) Depth map (c) 3D Point Cloud (d) Surface Normal Map

Figure 3: Types of output from Zivid camera

To integrate the camera into the robotic system, the end effector was modified to include a dedicated mounting interface. The design and implementation are shown in Figure 4a and Figure 4b, respectively. This configuration ensures stable positioning and repeatable calibration during operation. Figure 4c illustrates a data capture in progress for one of the battery pack enclosures, demonstrating the system's capability to acquire comprehensive 3D data in a single capture cycle.

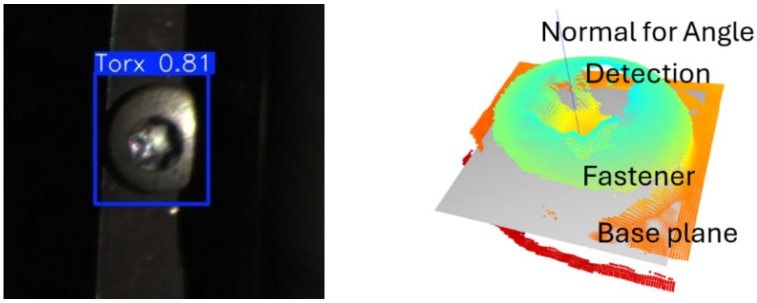


(a) Zivid end-effector design (b) Mounted on Robot (c) Data-capture in progress

Figure 4: Zivid Camera integration

To detect fasteners using the Zivid camera, the initial step remains unchanged from the previous Cognex-based solution: a You Only Look Once YOLO-based model operates on Zivid-generated 2D images to approximately localize fasteners (Figure 5a). Because the system pre-aligns 2D and 3D data, the corresponding point cloud for each fastener's bounding box can be extracted directly. To enhance robustness, the bounding boxes were expanded by approximately 1–2 mm.

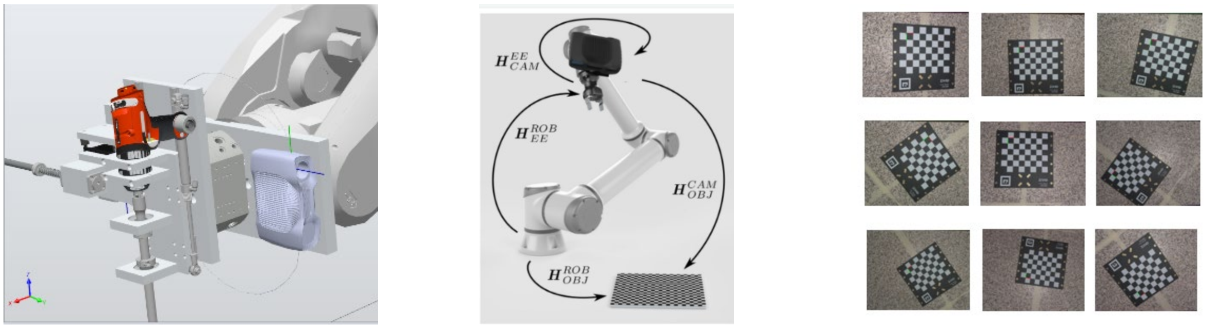
The second step, determining the fastener's precise location and orientation, required additional processing. A key advantage of the new camera is its ability to provide raw point-cloud data for analysis. In the initial implementation, we applied the RANSAC (Random Sample Consensus) algorithm to estimate the base plane (Figure 5b). The fastener's z-coordinate was derived from the plane at the center of its bounding box, while the normal vector computed from the plane equation was used to determine the fastener's angular orientation.



(a) YOLO Bounding box on detected fastener (b) Point cloud of the detected fastener

Figure 5: Fastener detection with Zivid camera

An additional step required when using the Zivid or any other 3D camera is computing the transformation matrix between the camera's coordinate system and the robot's end-effector mount. Initial tests employed a transformation matrix derived from the 3D CAD model (Figure 6a). However, this approach resulted in significant offsets between the calculated fastener coordinates and their actual positions, primarily due to manufacturing tolerances in major components. To address this issue, a hand-eye calibration procedure [8] was performed using Zivid's dedicated software (Figure 6b), which eliminated the observed discrepancies. The purpose of the hand-eye coordination step is to develop transformation matrices across the inspection volume to accurately transform point cloud data into robot coordinate system such that robotic arm (i.e. hand) can accurately reach the position detected by the vision system (i.e. eye)



(a) 3D Model of camera and end effector

(b) Hand Eye Calibration

(c) Checkerboard images for calibration

Figure 6: Zivid Camera Calibration

To perform hand–eye calibration, a calibration board was placed at a fixed location within the robot's work area. The camera captured images of the board from multiple angles (Figure 6c), enabling calculation of the board's position and orientation relative to the camera's coordinate system, while the robot recorded the corresponding wrist pose in its own coordinate system. These paired measurements were then used to compute a transformation matrix. The updated matrix significantly reduced the positional offset in the x- and y-directions—from approximately 20 mm to less than 5 mm, as shown in Figure 7. Future iterations will aim to further minimize this error. The offset in the z-direction is of minimal concern due to the compliance built into the end effector along the z-axis.

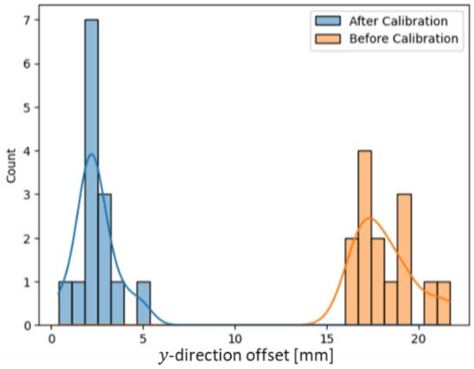
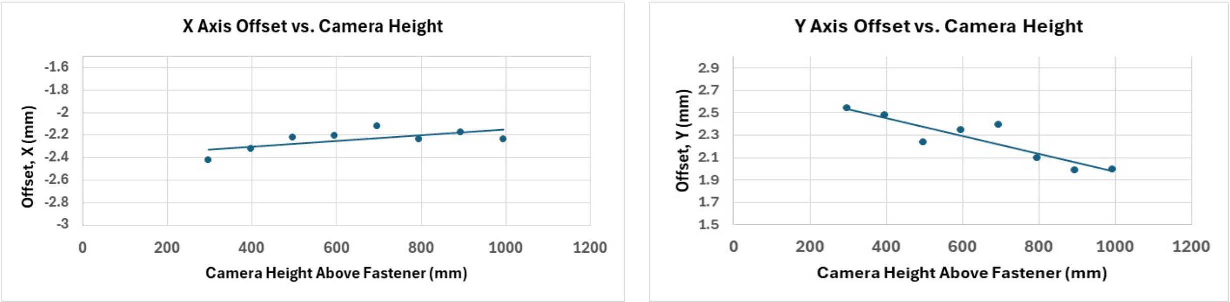


Figure 7 Improvement in the y-offset

A limitation of the Cognex camera was its height-dependent error in detecting fastener locations. To evaluate this effect, we conducted an experiment by varying the Z height of the Zivid camera while measuring the position of the same fastener. As shown in Figure 8a and Figure 8b, the random error variation with height is less than 0.4 mm, and the DC error of approximately 2 mm can be calibrated out. Figure 9 illustrates the Zivid camera field of view as a function of distance from the target. It can be seen that it can capture images at its maximum height of 1 meter while maintaining accurate fastener location measurements across its full field of view (1096 × 856 mm). For smaller packs, this capability enables capturing all fastener locations in a single snapshot.



(a) X position determination accuracy with height

(b) Y position determination accuracy with height

Figure 8: Zivid camera measurement accuracy with height

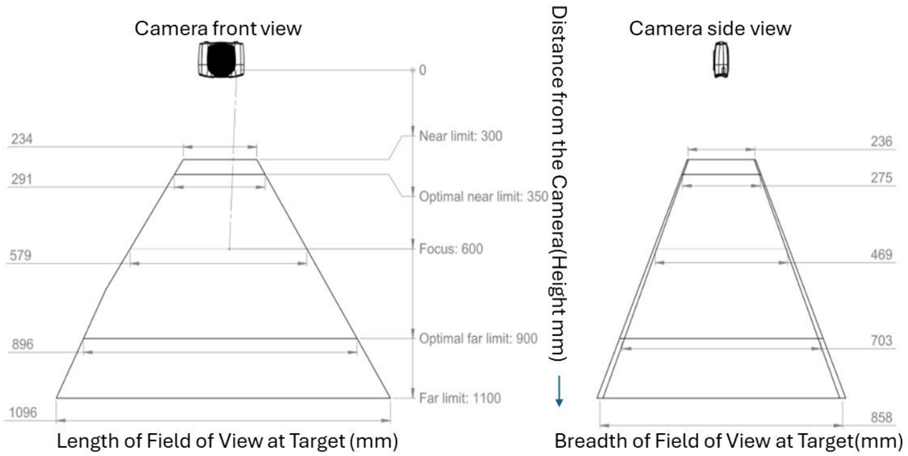


Figure 9: Zivid Camera Field of View

To evaluate how much productivity improved when we replaced the Cognex camera with the Zivid camera, we ran a timing test where we removed all the fasteners from a small battery pack. Figure 10 shows the results. With the Zivid camera, each fastener took about 9.5 seconds to remove, compared to the fastest time of 12 seconds per fastener using the Cognex camera. When we switched to a single-snapshot method for all fasteners, the time dropped even further to 8.2 seconds per fastener.

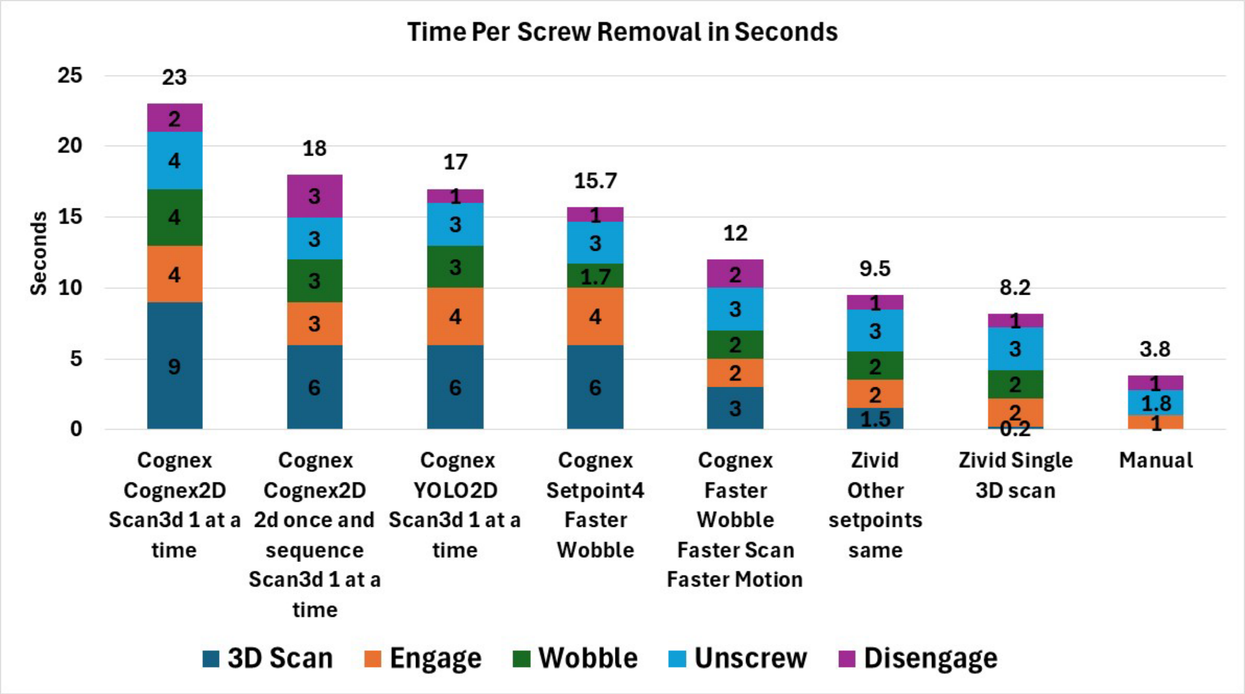
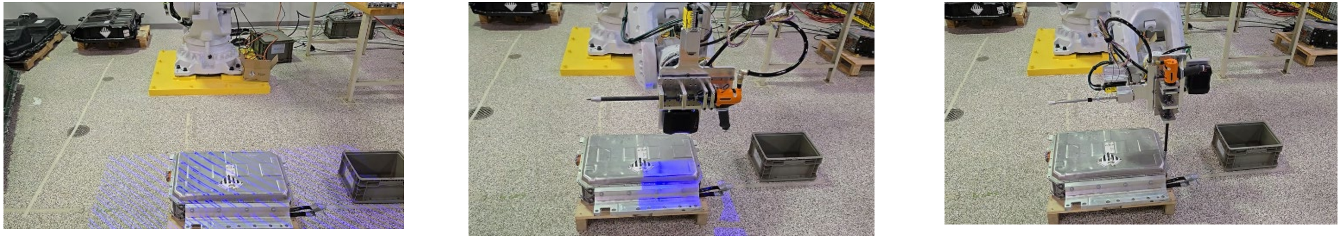


Figure 10: Productivity comparison between Zivid and Cognex camera fastener removal

In earlier work [3], we showed that manually removing the same fasteners takes only about 3.8 seconds each—much faster than any robotic method. However, that manual time reflects one person working on a single pack. Over a full day, human performance naturally declines due to fatigue and inefficiencies, while the robot's cycle time remains consistent. Because of this, automating fastener removal doesn't make sense for disassembling just one pack. It becomes viable only when operating continuously on many packs throughout the day, where consistency, operator safety, ergonomics, and reduced reliance on unskilled labor become major advantages.

It is important to note that the Cognex results exclude the time required for the 2D scan, whereas the Zivid results include it because the camera performs both 2D and 3D scans simultaneously. Beyond productivity gains, the Zivid camera offers a significant advantage: unlike Cognex, which requires multiple scans for fasteners at different Z-heights, Zivid can detect fasteners at varying heights in a single scan.

Combining all recent developments, the complete process of fastener and lid removal was successfully demonstrated using the Zivid 3D camera. This integrated workflow includes precise detection, manipulation, and removal steps, all captured in Figure 11, which presents selected frames from a video documenting the operation. The sequence begins with pack detection, where the system identifies the target pack within the workspace, followed by fastener detection to localize individual fasteners with high accuracy. Next, the robotic tool engages and loosens the fastener, after which a magnetic end-effector retrieves the detached fastener and deposits it into a designated bin. The system then scans for the next fastener to ensure continuous operation before performing a tool change to switch from the fastener tool to a lid-gripping tool. In the final stages, the lid is firmly grasped and lifted, completing the disassembly process. This demonstration highlights the robustness and adaptability of the vision-guided robotic system for automated disassembly tasks.



(a) Pack detection (b) Fastener detection (c) Fastener removal

(d) Fastener magnetic pickup (e) Fastener binning (f) Next fastener detection

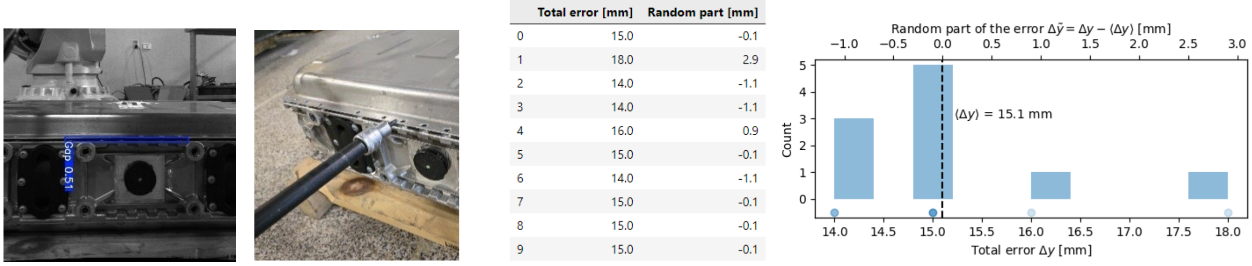
(g) Tool change (h) Gripping lid (i) Lid removal

Figure 11: Selected Frames from a video documenting fastener and lid removal using Zivid camera

Pack Seal Localization and Tracking

After successfully demonstrating lid removal on a generic lithium-ion battery (LIB) pack, the methodology was extended to an original equipment manufacturer (OEM) pack from Rivian (Figure 1a). Fastener detection and removal proceeded as expected; however, an additional challenge emerged. Unlike the generic pack, Rivian's lid is secured not only by mechanical fasteners but also by sealant materials designed to prevent electrolyte leakage and ensure environmental protection. Consequently, fastener removal alone was insufficient to detach the lid, necessitating the development of an automated sealant removal process.

Automated sealant removal requires precise seam identification and seal localization to guide the removal tool accurately along the interface. Two complementary approaches were investigated to address this requirement. The first approach employed a vision-based method using a (YOLO) model trained on seal images. Figure 12a shows an example of YOLO-based seal detection as depicted by the Gap identified between the top cover and the enclosure. However, the positional error exceeded the tolerance required for accurate tool guidance as depicted in Figure 12b where the tool misses the gap. Error analysis revealed a dominant systematic component of ~15mm, which was compensated by subtracting the bias from the predictions. This correction reduced the residual random error to less than 3mm, enabling a viable solution for robotic guidance (Figure 12c). The findings underscore the importance of systematic error modeling in vision-based localization for high-precision tasks.

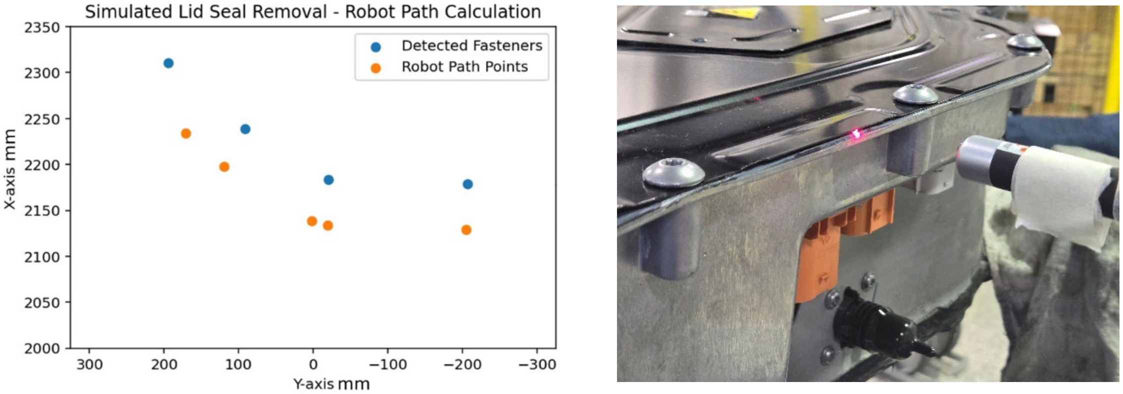


	Total error [mm]	Random part [mm]
0	15.0	-0.1
1	18.0	2.9
2	14.0	-1.1
3	14.0	-1.1
4	16.0	0.9
5	15.0	-0.1
6	14.0	-1.1
7	15.0	-0.1
8	15.0	-0.1
9	15.0	-0.1

(a) Gap detection (b) Tool misplaced (c) Residual error after subtracting the mean

Figure 12: Gap detection for seal removal

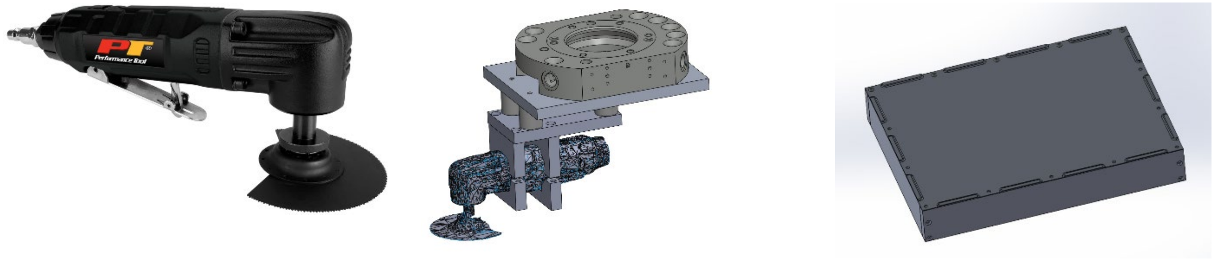
The second approach leveraged prior knowledge of pack geometry, which is typically available to OEMs. In this method, seam location was estimated using fixed offsets from detected fasteners. For the Rivian pack, seal offsets relative to fasteners were documented, and fasteners were automatically detected via computer vision. The robot then tracked these offsets to generate tool path waypoints (Figure 13a). Accuracy was validated by simulating seal removal with a laser pointer (Figure 13b). This approach offers a practical solution for OEMs with access to design data and for third parties who have previously disassembled similar models and recorded geometric relationships. Compared to vision-based detection, this method reduces reliance on image-based inference and provides deterministic positioning, which is advantageous for repeatability in industrial settings.



(a) Seal location from fastener (b) laser pointer tracking seal

Figure 13: Seal detection utilizing fastener location

Tool selection was guided by Rivian's recommendation and operational constraints within the robotic disassembly cell. A vibratory oscillating tool was identified as the most suitable option for seal removal due to its ability to cut through adhesive materials without generating excessive heat or debris. After evaluating several candidates, the Performance Tool M546 Pro Grip Pneumatic Oscillating Multi-Tool (Figure 14a) was selected for its compact design and compatibility with the existing pneumatic infrastructure. Because commercial tools typically lack CAD models, the tool was scanned using the RIT/CIMS 3D scanner, and the resulting geometry informed the design of a custom end effector (Figure 14b). To refine the seal removal technique and mitigate risk to the actual battery pack, an enclosure replicating the Rivian pack's top cover was constructed (Figure 14c). This surrogate setup enabled iterative testing under controlled conditions, facilitating optimization of tool trajectories and cutting parameters. Once validated, the methodology will be deployed on the Rivian pack.



(a) Pneumatic Oscillating tool
(b) End effector design with the oscillating tool
(c) Simulated top cover

Figure 14: Seal removal end

Integration of all components for automated seal removal is currently underway. Future work will focus on validating the system under production-representative conditions and quantifying performance metrics such as cycle time, positional accuracy, and seal removal completeness. These results will be reported in subsequent publications.

Discussion

The fields of computer vision, artificial intelligence (AI), and robotics are advancing at an unprecedented pace. Vision systems, AI algorithms, and robotic capabilities available today are far more versatile and sophisticated than those that existed when this project began only a few years ago. This rapid evolution underscores the importance of continuously monitoring emerging technologies and adapting whenever feasible to maintain efficiency and competitiveness.

At the outset, the project selected the Cognex Laser 3D camera with an onboard processor as the most practical solution for the problem at hand. This choice enabled quick deployment and early progress. However, the system soon revealed limitations that constrained long-term performance: a proprietary point cloud format that restricted interoperability, alignment errors when matching positional data with an external 2D camera, and resolution trade-offs tied to scan speed. These issues collectively signaled that the platform was approaching obsolescence.

Recent advancements in 3D imaging have addressed these challenges, particularly through the adoption of structured-light stereo cameras such as those offered by Zivid. These modern systems integrate 2D and 3D sensors within a single housing, eliminating alignment issues and enabling motion-independent static image capture with a large field of view. Furthermore, they support offline point cloud processing, which enhances flexibility and scalability. This capability allows the capture of more fasteners in a single snapshot, significantly improving throughput and overall operational efficiency. Beyond performance gains, these improvements also simplify system architecture and reduce maintenance complexity, positioning the project to leverage future AI-driven enhancements in object detection and robotic manipulation. As more battery manufacturers use sealants to fasten top covers in addition to fasteners, preliminary results show structured light camera could offer a promising solution for seal location detection.

Conclusions & Recommendations

This paper investigated improving the solution by leveraging recent advances in camera hardware and the emergence of structured-light cameras. Specifically, we evaluated the impact of replacing a dual-camera system (2D RGB + 3D laser scanner) with a single structured-light camera (Zivid2+ M60). The new system provides several notable benefits: an automated calibration procedure, a reduction in fastener extraction time by more than 30%, and support for advanced processing through an open, user-accessible point cloud format. These improvements address prior limitations related to alignment errors, proprietary data formats, and scan-speed constraints.

Beyond hardware upgrades, we explored the feasibility of vision-based seam detection and fastener-offset-based approaches, as well as the design of an oscillating tool end effector for seal removal. Together, these developments represent a significant step toward fully automated disassembly workflows for electric vehicle battery packs.

Future work will focus on achieving complete integration of seal removal automation and validating system performance under real-world variability in battery pack designs. Longer-term objectives include incorporating AI-driven vision algorithms for adaptive disassembly strategies and extending automation to additional components. These advancements will not only improve throughput and operational efficiency but also enhance safety and sustainability, supporting broader goals in electric vehicle recycling and the circular economy.

Acknowledgements

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Advanced Manufacturing Office Award Number DE-EE0007897 awarded to the REMADE Institute, a division of Sustainable Manufacturing Innovation Alliance Corp. In addition, RIT received funding, in part, from New York State Empire State Development under Grant #AC118 that supported the work on this project.
The views expressed herein do not necessarily represent the views of the U.S. Department of Energy or the United States Government or New York State.

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