A Two-Stage Approach for Wire Harness Cable Description Using 3D Point Clouds for Robotic Manufacturing

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Abstract: This paper proposes a two-stage methodology for accurately describing three-dimensional cable position aiming to examine robot-based automated cable placement systems to work correctly in wire harness manufacturing. The first stage is to extract 3D points on cables from point cloud acquired using a 3D stereo camera. For extracting only the points on cables, we compare two sets of point clouds which are taken before laying cables on an assembly board which holds the cables temporarily for taping and additional works, and after laying cables. We propose a new method to eliminate unnecessary points such as points on the assembly board and noises to get points only on cables from the two point cloud sets. In the second stage, cable positions are approximated as a mathematical function, B-Spline or Bézier curve, by interpolating the extracted 3D points. We use Smoothness, Curve Length, and Chamfer Distance as the evaluation criteria to assess the fitting quality to the original cable geometry. Experiment results indicate that B-Spline provides smooth approximation, while Bézier curve can represent curve with rapid transition such as sharp bents. Measured Chamfer Distance is a few times as large as the radius of the cables or shorter, demonstrating high fitting accuracy. This approach offers a practical solution for cable recognition in automation contexts, with potential applications in automotive and manufacturing industries.

1 INTRODUCTION

With the increasing use of electronic devices in automobiles, wire harnesses, which interconnect the devices within an automobile, have become essential components. Traditionally, wire harnesses manufacturing has been a highly labor-intensive process. However, shortages of skilled workers, the demand for high efficiency, and cost-saving pressures require a new automated system for wire harness manufacturing using robotics.

The manufacturing flow of wire harnesses consists of designing the layout of wire harnesses, then routing the wire harnesses according to the layout, and finally judging whether there are any abnormalities in the wire harnesses.

Karlsson et al. presented an efficient solution to automate the complex and time-consuming wire harness design process within a customizable 3D environment (Karlsson et al., 2024). Karlsson et al. enabled the automated generation of optimized wire harness layouts, but did not deal with automatic routing of wire harnesses.

Nguyen et al. proposed a novel vision-based routing method for 3D profile extraction of wire harnesses in a robotized assembly process, addressing the complexities associated with deformable objects like wire harnesses by integrating deep learning and machine vision techniques (Nguyen and Yoon, 2021). In Nguyen et al.'s study, the robot directly grasps and manipulates the wire harnesses using a gripper and secures them into clamps during the assembly process. However, their system does not incorporate a process to leverage the inherent flexibility of cables to represent their shape smoothly.

Nguyen et al. proposed a deep learning-based automated optical inspection (AOI) system for wiring harness manufacturing, utilizing PointNet++ and synthetic point cloud data generated from CAD models to improve segmentation accuracy, address the domain gap, and reduce dependence on extensive real-world data collection (Nguyen et al., 2022). Nguyen et al.'s study improved deep learning accuracy by leveraging synthetic data for training. However, their system seg-

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ments multiple cables as a single bundle, but did not classify individual cables.

Nguyen et al. proposed a 3D vision-based method for detecting multiple wire branches in robotized wire harness assembly, utilizing Fixed Radius Nearest Neighbor (FRNN) for wire color classification and YOLO-v7 for terminal identification, enabling precise segmentation and automated handling of complex wire structures (Nguyen et al., 2024). Nguyen et al. utilized RGB-D camera color information to classify multiple cables, but did not discuss handling occlusions.

Chien et al. presented a study on classifying cable tendency using semantic segmentation by leveraging real and simulated RGB data to identify normal and abnormal (tensioned, loose, twisted) cable configurations, which is crucial for automating cable assembly processes (Chien et al., 2024). However, Chien et al. did not deal with 3D descriptions of routed cables.

These conventional studies enabled the design of wire harnesses, automated robotic arrangement, or anomaly detection. Therefore, we recognized that a critical challenge in achieving full automation lies in the ability to enable robots to identify the exact description of each cable in a 3D space.

Our approach to identify cable positions is as follows. First, using an inexpensive 3D stereo camera, we capture the shape of a wire harness consisting of multiple cables and connectors as point cloud. Then, the exact place of each cable is described as a mathematical function by interpolating the points on a cable which are extracted from the captured point cloud. Here, the challenges are to extract a set of 3D points only on a cable from a captured point cloud which includes points on other cables, connectors, assembly board, background and a lot of noises, and to calculate a set of parameters of the mathematical function out of the dispersedly placed points. Note that there may be unseen parts of a cable which are hidden behind other cables.

For the first problem, we capture two sets of point clouds; one is taken before laying cable on the assembly board and the other is taken after that. By evaluating the difference of the two, points only on cables can be extracted. For the second problem, we use B-spline and Bézier curve functions and evaluate the result. The accuracy of the approximation is evaluated using criteria of smoothness, curve length and Chamfer Distances.

Experimental result shows that our approach worked well and measured approximation accuracy was a few times as large as the radius of the cables or shorter.

2 RELATED WORK

2.1 Research on Cable Recognition

In the field of cable recognition, some studies focused on depth information.

Nguyen et al. proposed a deep learning-based data processing pipeline for automated optical inspection of wiring harnesses in automotive manufacturing, addressing challenges such as high customization and manual labor intensity by utilizing real and synthetic point cloud data (Nguyen et al., 2022). The developed pipeline employs PointNet++ for segmentation, integrating synthetic data generated through CAD and simulations to reduce reliance on real data. The results demonstrate that combining real and synthetic data enhances model accuracy, with the best-performing configuration achieving a mean IoU of 94.62% and enabling precise quality assessment of wiring harness assembly states. This approach marks a significant step toward scalable, efficient automation in wiring harness manufacturing.

Nguyen et al. presented a novel 3D vision-based method for detecting and extracting the profiles of multiple wire branches in wire harnesses to address the challenges of robotized assembly of flexible and deformable objects (Nguyen et al., 2024). By utilizing point cloud data from high-quality RGB-Depth cameras and combining techniques like YOLO-v7 for terminal identification, RANSAC for background elimination, and FRNN for color-based classification, the method efficiently detects wire terminals and reconstructs 3D wire profiles. Validated in a robotic system, this approach enabled robots to perform precise wire harness assembly tasks, including manipulation and sequential placement of wire branches in clamps, significantly reducing manual labor and enhancing assembly efficiency. This research marks a substantial advancement in automating complex assembly processes for deformable components.

Although these studies utilized 3D data to recognize cables, they did not take into account fundamental cable characteristics, such as a constant radius and smoothness, nor did they consider handling occlusions.

2.2 Point Cloud Registration

Point cloud registration is a technique used to align a reference point cloud with a target point cloud. Iterative Closest Point (ICP) is a fundamental algorithm in this field of study (Besl and McKay, 1992). ICP works by calculating the distances between the nearest neighbor points in the reference and target point clouds, then identifying the transformation matrix that minimizes these distances. However, because ICP relies solely on positional information, its accuracy can decline in cases where the geometries does not include enough unevenness or contain multiple similar regions.

To address this limitation, Colored Point Cloud Registration was introduced, incorporating both positional and color information (Park et al., 2017). By combining the two data sources, this approach finds a transformation matrix that minimizes the objective function, providing more accurate registration than that conventional ICP does.

3 3D STEREO IMAGE CAPTURING

A typical wire harness assembly process in the automobile industry is as follows. Cables are cut to the designed length and both ends are contained in connectors. Then a worker places each connector to a designated receptor on a board called "assembly board". After checking that the route of the cable is as designed and there is no kink or too much tension, the cables are taped thoroughly to complete the work. Our target for automation is the process of cable and connector placement on an assembly board. This study focuses on the cable placement examination process.

Among 3D shape measuring devices, we chose 3D stereo camera because it captures color and is relatively inexpensive and easy to handle. In this study, a RealSense D405 stereo camera, as shown in Figure 1, was used.

We captured 3D stereo images from 13 different points which are equally distributed between the left end and right end of an assembly board. From each camera position, we captured images both before and after the cable arrangement, as illustrated in Figure 2. The assembly board includes connector receptors and cable holders, through which the blue cable (1.30 mm radius) and green cable (1.15 mm radius) are routed to the receptor at right hand side. As shown in Figure 2, two patterns of cable routing were used. We used the camera's default application program to calculate point clouds from the original stereo images.

4 DATA PROCESSING

This study proposes a two-stage methodology for mathematically describing the place of each cable in

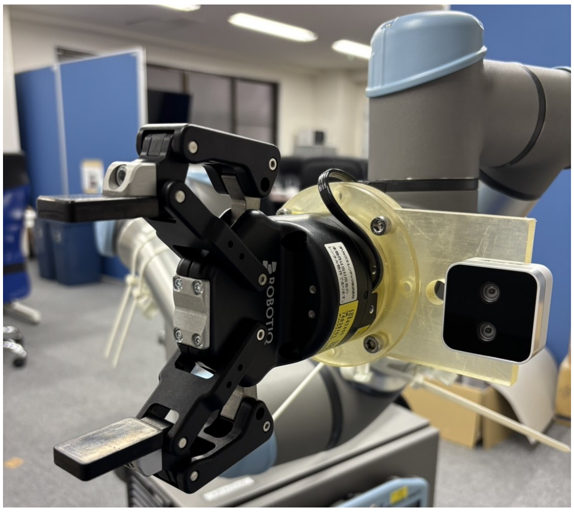

Figure 1: RealSense D405 camera mounted on UR5e robot.

wire harness as illustrated in Figure 3.

The first phase, which extracts point cloud on cables, begins with applying Colored Point Cloud Registration (CPCR) to align point clouds captured before and after cable routing, CPCR produce a transformation matrix T. This matrix is applied to point cloud $\mathbf{P}_{\text{after}}$ to be aligned with point cloud $\mathbf{P}_{\text{before}}$. Here, $\mathbf{P}_{\text{before}}$ and $\mathbf{P}_{\text{after}}$ are point cloud captured before the routing and after the routing, respectively. Applying T to $\mathbf{P}_{\text{after}}$ produces the transformed point cloud, $\mathbf{P}'_{\text{after}}$ which is defined as:

$$\mathbf{P}'_{\text{after}} = T\mathbf{q}_j \mid \mathbf{q}_j \in \mathbf{P}_{\text{after}} \tag{1}$$

where each $\mathbf{q}_j$ represents a point in $\mathbf{P}_{\text{after}}$. Next, we calculate the distance between each point $\mathbf{p}_i$ in $\mathbf{P}_{\text{before}}$ and the closest point in $\mathbf{P}'_{\text{after}}$ using a nearest neighbor search. If the distance $d(\mathbf{p}_i, \mathbf{P}'_{\text{after}})$ between $\mathbf{p}_i$ and the nearest point in $\mathbf{P}'_{\text{after}}$ exceeds a threshold θ, then the point $\mathbf{q}_i$ is considered to be a part of a cable and included in new point cloud $\mathbf{P}_{\text{cables}}$.

$$d(\mathbf{p}_i, \mathbf{P}'_{\text{after}}) = \min_{\mathbf{q}' \in \mathbf{P}'_{\text{after}}} |\mathbf{p}_i - \mathbf{q}'| > \theta \tag{2}$$

The extracted cable point cloud $\mathbf{P}_{\text{cables}}$ is then defined as:

$$\mathbf{P}_{\text{cables}} = \mathbf{q}_i \in \mathbf{P}'_{\text{after}} \mid d(\mathbf{p}_i, \mathbf{P}'_{\text{after}}) > \theta \tag{3}$$

The threshold θ will be determined by evaluating how well $\mathbf{P}_{\text{cables}}$ represents the actual cables by experiments.

The first step of the second phase is to classify points in $\mathbf{P}_{\text{cables}}$ to points on individual cable based on color similarity. We use Euclidean distance between the color of each point and the target color for classification. Let $\mathbf{c}_i = (R_i, G_i, B_i)$ be the color of point i, and $\mathbf{t} = (R_t, G_t, B_t)$ the target color. The Euclidean

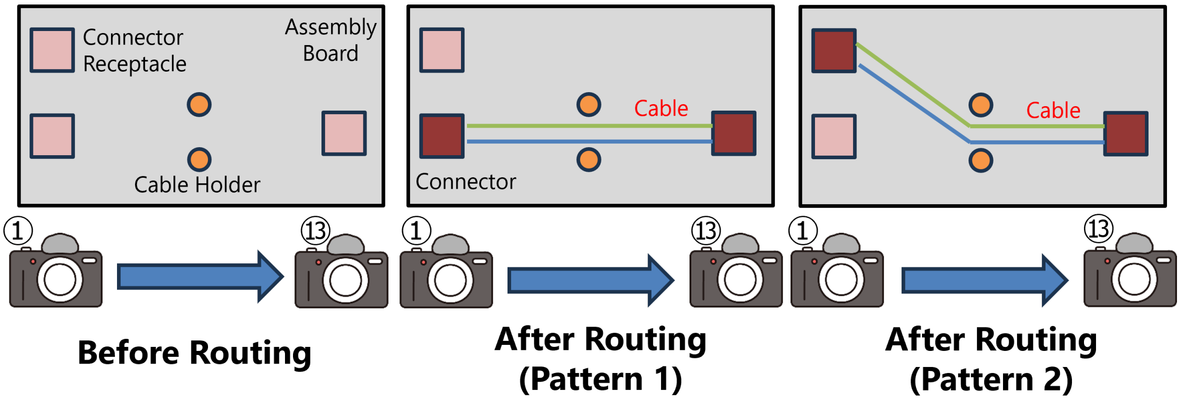

Figure 2: Overview of the assembly board.

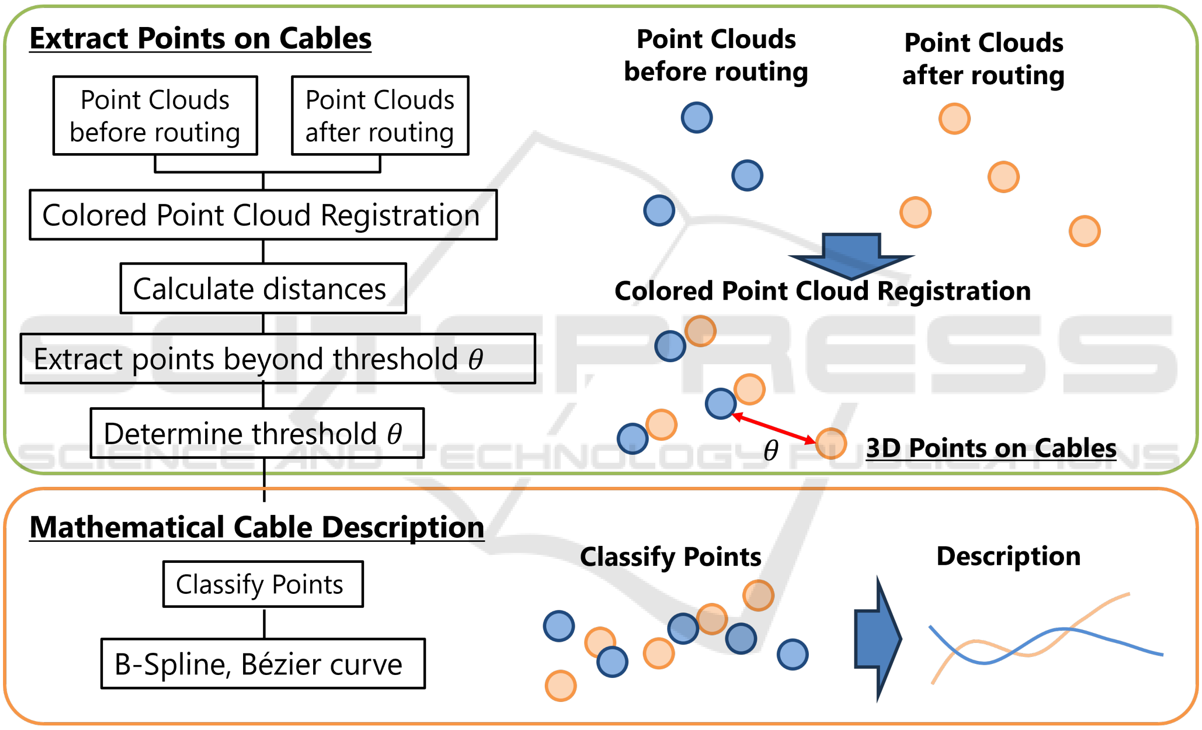

Figure 3: Illustration of our methodology.

distance d_i is given by

$$d_i = \sqrt{(R_i - R_t)^2 + (G_i - G_t)^2 + (B_i - B_t)^2} \quad (4)$$

If d_i is less than a specified tolerance, the point is selected for further processing. While selecting the color of the cable, statistical outlier removal is applied to eliminate noises. Here the points having the same color together are considered to represent the 3D shape of a cable. However, there may be portions where there is no point produced on the cable, for example portions hidden by other cables. To interpolate the obtained points and get a smooth and continuous representation of a cable, we apply a 3D spline curve using cubic B-spline interpolation. Given a sequence of points $\{(x_i, y_i, z_i)\}$, the spline curve $S(t)$ is represented as

$$S(t) = (x(t), y(t), z(t)) = \sum_{k=0}^{n} N_{k,3}(t) \cdot \mathbf{P}_k \quad (5)$$

where:

- $\mathbf{P}_k = (x_k, y_k, z_k)$ are the points on a cable,
- $N_{k,3}(t)$ is the B-spline basis function of degree 3,
- t is the curve parameter within the range $[0, 1]$.

The spline curve minimizes overall curvature, providing a smooth and continuous representation of the cable. As an alternative smooth curve-fitting method,

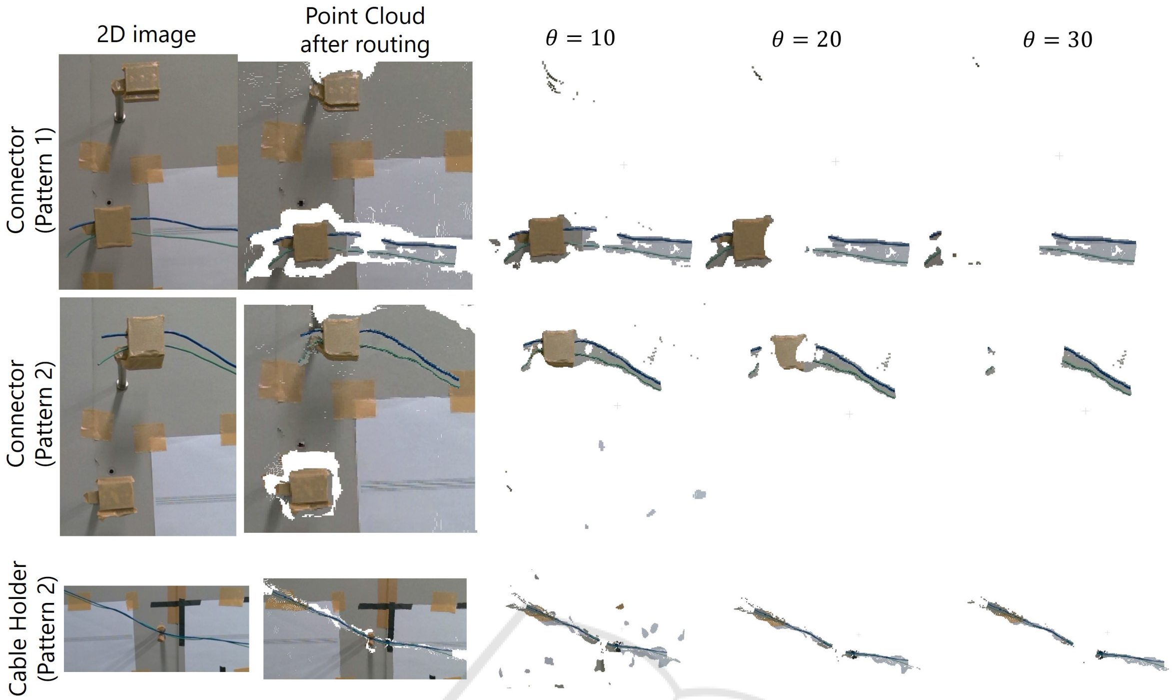

Figure 4: Results of extracting points on cables.

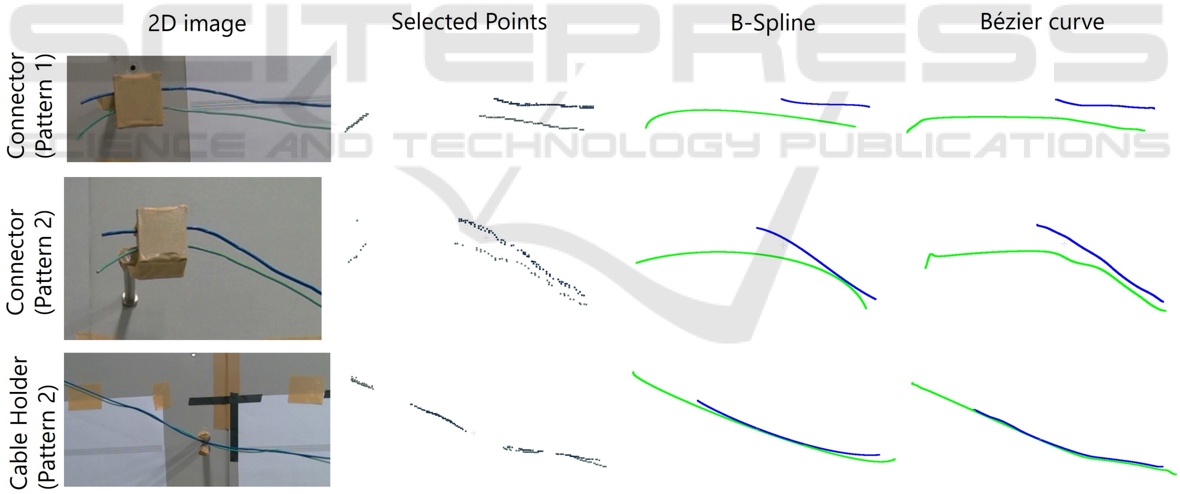

Figure 5: Results of mathematical cable description.

we use a Bézier curve, generated from a set of points. For a set of $n+1$ control points, the Bézier curve $B(t)$ is defined by the Bernstein polynomials as follows:

$$B(t) = \sum_{i=0}^{n} \binom{n}{i} (1-t)^{n-i} t^i \mathbf{P}_i \qquad (6)$$

where:

- $\mathbf{P}_i = (x_i, y_i, z_i)$ are points on a cable,
- t is the parameter of the curve, ranging from 0 to 1,
- $\binom{n}{i}$ represents the binomial coefficient.

The resulting Bézier curve provides a smooth path between points, with each point influencing the curve shape based on its position and the binomial weight.

Table 1: Evaluation metrics for B-Spline and Bézier curve fitting on blue and green cables.

Pattern	Method	Color	Smoothness [1/mm]	Curve Length [mm]	Chamfer Distance [mm]
1	B-Spline	Blue	3.29×10^{-7}	3.10×10^{2}	3.012
		Green	1.16×10^{-6}	3.74×10^{2}	3.498
	Bézier curve	Blue	1.44×10^{-6}	3.15×10^{2}	1.530
		Green	2.35×10^{-6}	3.80×10^{2}	2.146
2	B-Spline	Blue	2.21×10^{-7}	2.89×10^{2}	2.245
		Green	8.29×10^{-7}	3.50×10^{2}	3.389
	Bézier curve	Blue	9.08×10^{-7}	2.92×10^{2}	0.989
		Green	1.90×10^{-6}	3.51×10^{2}	2.156

5 EXPERIMENTS

5.1 Extracting Points on Cables from Acquired Point Cloud

Figure 4 shows experimental results of the point cloud extraction phase, highlighting the differences in point clouds completeness at varying thresholds. As shown in the Figure, the threshold θ controls the trade-off between the noise level and the coverage of points on cables. Ideally, the point clouds of connectors and cables should be extracted in this phase. Based on the observations, we chose 20 as the value of θ for optimal cable extraction.

5.2 Mathematical Cable Description

Figure 5 shows experimental results of the Mathematical Cable Description phase, illustrating how both B-Spline and Bézier curve describe the cable shapes correctly. As shown in the Figure 5, curves effectively interpolate missing sections to describe the cables. In a close observation, B-Spline provides a smoothed curve that does not strictly adhere to each selected point, while the Bézier curve aligns exactly with the selected points, creating a more precise but potentially complex curve.

To evaluate the accuracy of cable approximations, we employ three metrics: Smoothness, Curve Length, and Chamfer Distance. These metrics provide a quantitative assessments of curve quality and alignment accuracy to the original cable geometry. Each metric is calculated as an average of the values at the 13 locations for each wire routing pattern.

Smoothness quantifies the continuity and fluidity of a curve, calculated as the sum of the second derivative (curvature) along its length. Lower smoothness values indicate a smoother transition. We calculate the second derivative in each axis (x, y, and z), then sum up the curvature across all points and axes.

Curve length is calculated by summing up the Euclidean distances between consecutive points along the curve. This metric is valuable for assessing how well the B-Spline or Bézier curve fits the original cable length, providing an indication of how accurately a curve represents the real cable's path.

Chamfer Distance evaluates the fitting accuracy between the original and approximated point clouds, calculating the average squared distance from each point in the original point cloud to its nearest neighbor point on the approximated curve. A lower Chamfer Distance indicates a closer match between the original and approximated point clouds, reflecting a higher quality of approximation.

These metrics provide a comprehensive evaluation of the approximation accuracy and quality of the fitted curves. By averaging these metrics at the 13 locations for each wire routing pattern, we obtained a robust assessment of the fitting performance of the proposed method.

Table 1 summarizes the calculated values of metrics to compare the performance of B-Spline and Bézier curve fittings. B-Spline consistently demonstrates smaller values for both smoothness and curve length, indicating that a smoother and simpler curves were obtained. In contrast, the Bézier curve, which exactly traces the given control points, may be better suited for representing more complex or highly detailed curves. The obtained Chamfer Distance values, ranging from 0.989 mm to 3.498 mm across all patterns, reflect a close match between the original and the approximated point clouds. These values were about a few times as large as the cables radius (1.30 mm for blue and 1.15 mm for green ones) or shorter, indicating a high level of fitting accuracy. Also these values are much smaller than the width of the robot hand (92mm), indicating that it has no practical problem when in use. In addition, the case of four-color cables was also experimented, and the prospect of good results was obtained.

6 CONCLUSIONS

This paper has proposed a novel two-stage methodology for accurately describing cable geometry using a 3D stereo camera. Through extracting point cloud which only contains points on the target cables from the two sets of point clouds captured before and after cable arrangement and employing advanced curve fitting techniques to the obtained cable-only point cloud, the methodology produces a continuous and accurate representation of cable geometry. Using the proposed methodology, the observed approximation accuracy was about a few times as large as the radius of the cables or shorter. Future research could focus on adapting the approach to handle various cable types and exploring alternative algorithms to improve fitting accuracy further and computational efficiency. Overall, this study contributes a foundational approach to accurately modeling cable geometry in 3D, which may significantly aid in the development of automated solutions for complex wire harness routing in the automotive and manufacturing industries.

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