Real-time cable tracking by wire segmentation and Coherent Point Drift

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Abstract

In this paper, a real-time cable tracking system by fast segmentation method and Coherent Point Drift (CPD) is proposed. Fast cable segmentation based on color space is inaccurate because of background contrast. Therefore, this technique uses edge information from the image to address this problem. The method consists of three processes: threshold processing in the Luv color space, edge processing using a Laplacian filter, and processing for extracting the common region of the binary images generated by each process. In the experiments, the accuracy of the segmentation region and the processing time required for each process of the tracking system are shown.

Keywords: Deformable Linear Objects, Segmentation, Three-dimensional Tracking, Real-time systems

1. Introduction

Our research focuses on automating cable routing tasks that are common in the manufacturing process. Cable routing tasks mainly require the operation of hanging the cable on the routing target. However, cables easily change state during manipulation, so it is difficult to hang them on the target with pre-planned movements. Therefore, it is necessary to track the cable to modify the movement depending on the deformation. In our experimental environment, a 6-DOF DENSO COBOTTA robot, cables, and pins to be placed are set on a base plate as shown in Fig. 1. The cables are recognized using RGB and depth images captured by the environmental camera. In the process, the robot and the pins prevent recognition. Our main research strategy is feedback control that includes a predictive model of cable behavior. If we can acquire cable status in real time, the accuracy of cable behavior prediction will be improved. Based on the above considerations, a high-speed cable tracking system that is robust to occlusion is required. There is a tracking method using markers [1], but it is not suitable because it is poor at handling occlusions. Therefore, we implement a tracking system with a function to acquire a cable point cloud and a function to place cable nodes in the point cloud.

The cable point cloud is obtained by overlaying a depth image and a cable mask image. The basic method for rapid processing of cable mask images is the color space-based method. Using this method, a segmentation method that uses a chain model to deal with occlusion [2] has been proposed. However, this method works only if there are no objects in the environment that are the same color as the cables. There is also an instance segmentation method [3] that uses superpixelization and graphs to deal

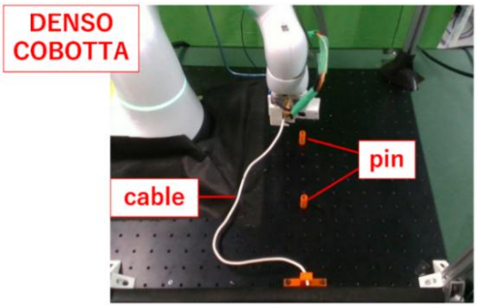

Fig. 1. Our experimental environment. There is DENSO COBOTTA robot and a white cable, and a pin to hang the cable.

with complex environments, but its processing is expensive. Learning-based methods have a trade-off between accuracy and inference time. As a fast model, Caporali et al. (2022) proposed a method for instance segmentation of cables [4]. The method uses deep learning to obtain cable regions, and subsequently superpixelizes them and solves the graph connection. Cable tracking is performed by placing cable nodes on the point cloud. Kicki (2023) et al. proposed a fast tracking [5] that applies β-spline functions to a thin cable point cloud. However, it was not tested in the case of global occlusion. On the other hand, Xiang (2023) et al. proposed a fast and robust tracking method [6] using CPD to place nodes stochastically in a point cloud even in the presence of global occlusions.

In this study, we propose a system that acquires a cable point cloud from a masked image by fast segmentation without learning, and tracks it by CPD. The segmentation method is using Laplacian filter and Luv color space so that the accuracy is not affected by the background contrast. In experiments, we checked the accuracy of

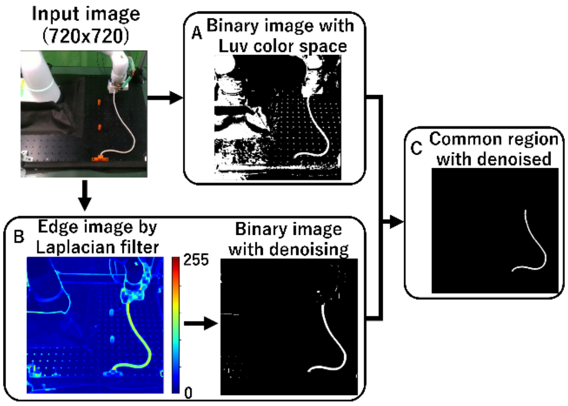

Fig.2 Flow of the cable mask image generation.

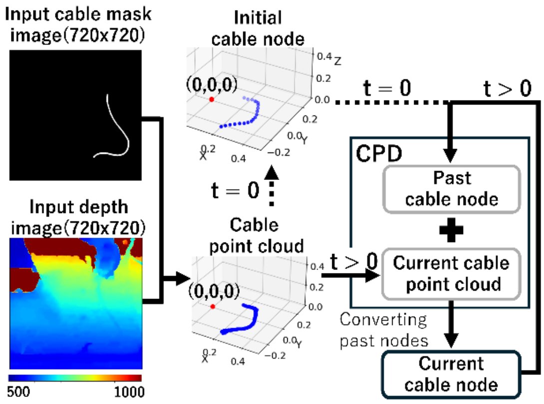

Fig.3 Node placement process for cable point clouds by CPD (D).

segmentation and the processing time of each tracking process.

2. Methodology

The system consists of cable mask image generation and cable node placement by CPD including point cloud processing. The flow of the cable mask image generation is shown in Fig. 2. The input image is an image cropped to 720x720. The method includes three steps: (A) threshold processing in the Luv color space, (B) edge processing using Laplacian filters, and (C) extracting common regions in the mask images generated by (A) and (B). After that, a node placement process (D) is applied to the cable point cloud, as shown in Fig. 3. The following is a description of each of these parts.

2.1. Binarization using Luv color space

For brightness-aware color detection, the RGB images are converted into the Luv color space with a brightness component (L) and a chromatic component (u, v). The value range of the target cable was determined by overlaying the evaluation cable mask image and the Luv color space image. The output binary image is shown in Fig. 2-A. If the value is within the threshold range, it is 255; otherwise, it is 0.

2.2. Binarization using Laplacian filter

The process generates a cable mask image of a region of edges, paying attention to the long and narrow shape of cables. The Laplacian filter used in the process is a filter that performs second-order differentiation in the image. There are Canny and Sobel filters for acquiring image edges, but Laplacian filter is used because it is fast and isotropic. In this method, a Laplacian filter with a ddepth of CV_16U and a kernel size of 7 is applied to the input image. The edge image is then grayscaled and filtered with a Blur filter. The resulting heat map is the image on the left of Fig. 2-B. After that, the greyscale image is denoised by a closing process and a thresholding process produces the binary image on the right of Fig. 2-B.

2.3. Common region extraction

In this section, a cable mask image is generated by taking the common region of two binary images and removing the noise. First, a bitwise AND operation is performed on the binary image in the LUV color space (A) and the binary image using Laplacian filter (B) to extract their common region. Then, a cable mask image shown in Fig. 2-C is generated by morphological transformation and denoising based on area.

2.4. Cable node placement

The tracking is performed by repeatedly placing the previous step's cable nodes on the current cable point cloud, as shown in Fig. 3. The cable point cloud is acquired by overlaying the depth image and the cable mask image. Before processing, the point cloud is transformed into the world coordinate system and downsampled using the Voxel Grid. As an initial process, 10 nodes are placed at constant intervals in the cable point cloud by convergence calculations. After that, the robot grasps at the 9th node coordinate of the cable and performs a tracking movement. The employed CPD method is the Bayesian coherent point drift [7] proposed by Hirose (2021). Cable fixed point is added as a constraint condition to improve tracking stability.

Table 1. Evaluation of segmentation accuracy

	Luv (A)	Laplacian (B)	Common (C)
Recall	0.981	0.918	0.891
Dice	0.076	0.550	0.813

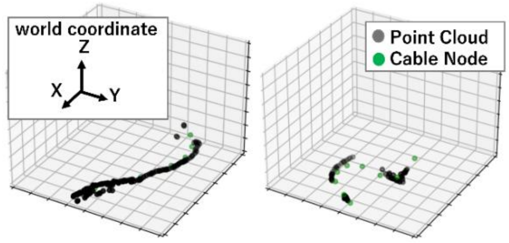

Fig. 4. Results of tracking by CPD. Left: node placement with no missing parts in the point cloud; right: node placement with missing parts in the point cloud.

Table 2. Processing time (msec)

Luv (A)	Laplacian (B)	Common (C)	CPD (D)
3.68	5.62	1.28	41.51

3. Evaluation experiments and results

3.1. Segmentation evaluation data preparation

In the evaluation experiments, 20 annotated images of cables following specific rules are used. The reason is that the method uses edge images, so evaluation with clear boundary data is suitable. The creation of evaluation data involves four steps and exception processing. First, images are taken with and without the robot holding the cable. Next, it takes the difference between the two images. Then, the Canny edge of the image with the cable is taken, and the edge is overlaid on the difference image to create an outline of the cable. Finally, the outlines are filled in. The exception is an image whose cables make a loop. In this image, the inside of the loop is also filled. Therefore, this issue is dealt with by taking a common region with the white region.

3.2. Evaluation of segmentation accuracy

The accuracy of the segmentation was evaluated by Recall: how well the correct region was covered, and Dice coefficient: how appropriate the generated region was. When evaluating accuracy, it is necessary to determine the threshold for converting the edge image to the binary image. In this study, the Dice coefficient was taken by changing the threshold value by one, and the threshold value of 113 was adopted as the maximum Dice coefficient. Table 1 shows the evaluation results of the binary images generated by each process. Compared to processes (A) and (B), the binary image from common region extraction (C) has a lower Recall score, indicating a larger unsegmented region, but a higher Dice coefficient, which means less noise and better segmentation.

3.3. Evaluation of the acceptability of tracking

Tracking is evaluated based on whether the cable node can be updated to the end for one robot movement. It was performed 20 times on a specific tracking route and in various cable conditions. The results were 95% tracking success rate. The one failed tracking attempt was the case of a large cable deformation and a large part of the cable point cloud missing. Fig. 4 shows the node placements at a certain time when the tracking was continued, respectively without and with missing parts in the point cloud. This explains that tracking is robust to deficiencies caused by occlusions and other factors.

3.4. Evaluation of processing times

Processing was implemented in Python and run on an Intel Core i7-8700K, 3.70 GHz. The results of the processing times for binary image generation (A), (B), (C) and tracking (D) without point cloud processing are shown in Table 2. All binary image generation is an average of 1000 processing times. The average processing time of the tracking process (D) by the CPD is the time taken to update the nodes in 20 tracking operations. All segmentation processes are mainly composed of thresholding and filtering, so the processing times did not widely fluctuate. On the other hand, tracking fluctuated significantly, with an average of 10.03 iterations inside the CPD and a maximum of 63 iterations.

4. Conclusion

A fast and robust for occlusion cable tracking system was proposed. In our experimental environment, there were objects with the same color as the cables, but our segmentation technique was able to extract the cable regions. In accuracy evaluation experiments, we confirmed that the accuracy was improved by overlaying the binary image by Luv and the binary image by edges. In processing time evaluation, we confirmed that all processes, including tracking by CPD, were fast. Future work is robot motion using real-time cable behavior prediction.

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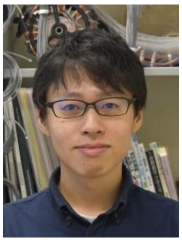

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