

A Study of Wiring Harness Topology Perception and Cost-Aware Manipulation

Kevin Galassi, Alessio Caporali, Gianluca Palli

Abstract—The manipulation of deformable linear objects by an autonomous system, such as a robotic manipulator, represents an important task considering the plenitude of such objects both in our everyday life and in industrial applications, for instance the wiring harness assembly task in automotive industries. Nowadays, these objects are manipulated by human operators and not by robotic systems due to several challenges at perception and manipulation levels. In this paper, some preliminary results concerning a perception and manipulation framework for handling wiring harnesses are presented. A 3D perception pipeline is used to gather a topological description of the wiring harness. Thereafter, a manipulation strategy employing a 7-DoF robotic arm is implemented aiming at disentangling the wiring harness and achieving a final target configuration.

Index Terms—Robotic Manipulation, Deformable Objects, Industrial Manufacturing, Deformable Objects Perception.

I. INTRODUCTION

The manipulation of Deformable Linear Objects (DLOs), such as electrical cables and wires, is commonly performed in worldwide manufacturing and assembly industries. Automation, aerospace and automotive are just a few examples of industries in which it is possible to find DLOs.

Given the intrinsic difficulties of perceiving and manipulating an object that may change its shape during the operation, robotic applications involved in the context of DLOs are extremely limited and usually restricted to very simplified scenarios. In literature, there are studies where the problem of perception and manipulation of single, i.e. not interconnected, DLOs is tackled. Unfortunately, very few works are available considering more complex DLOs structures like wiring harnesses. In this paper, we try to draw some preliminary results concerning: 1) a perception approach for obtaining a topological description of the wiring harness under exam; 2) a manipulation strategy that takes into consideration several cost-maps aiming at disentangling the wiring harness branches for achieving a target final configuration.

Recently, from the perception side, some works have emerged focusing on the instance segmentation of DLOs. In this regard, a first solution is proposed by *Ariadne+* [1], that differently from other simpler methods based for instance on color threshold [2] or markers [3], is capable of segmenting the various

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This work was supported by the European Commission's Horizon 2020 Framework Programme with the project REMODEL - Robotic technologies for the manipulation of complex deformable linear objects - under grant agreement No 870133.

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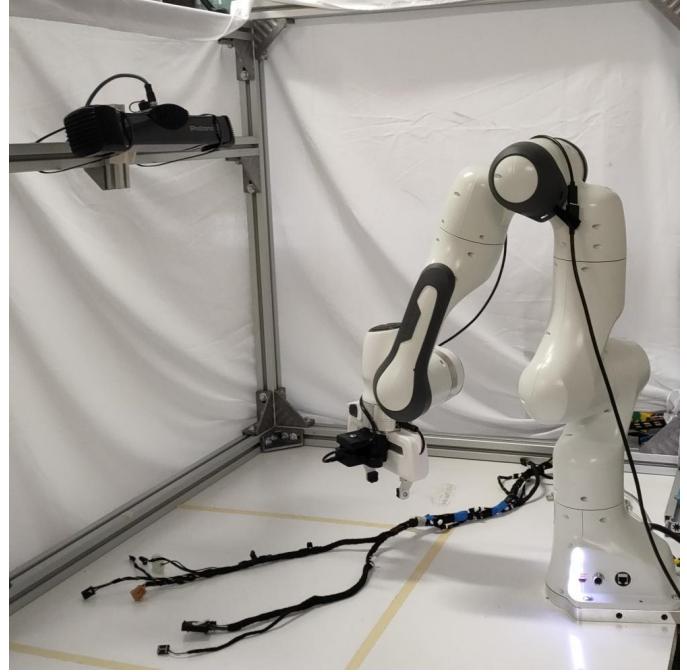


Fig. 1: Setup used for the wiring harness perception and manipulation study.

DLOs present in the scene featuring a complex background without any prior knowledge about their number. *Ariadne+* main limitation is its inference time, limited to just few Hz. Another work, named *FASTDLO* [4], shares the aim and overall pipeline structure with *Ariadne+* while improving the processing time, surpassing 20 frames per second. Concerning the 3D perception of DLOs, that is usually a quite challenging problem due to the limited thicknesses of DLOs [5], some work have proposed a triangulation approach for their 3D shape estimation [6]. More specific to wiring harnesses, in [3] the assembly process is analyzed employing, as mentioned, markers to facilitate the perception. Instead, in [7], the authors study the perception of electronic harness connector in a controlled environment.

Concerning the DLOs manipulation, in [8] the authors propose a DLO shaping approach using environmental contact surfaces such as rods and fixing clips, required especially during rotation and turning to keep the cable aligned. In [9] the authors use a reinforcement learning approach to shape a DLO like a rope in a given shape using a robotic manipulator. The manipulation of wiring harness and related components is still

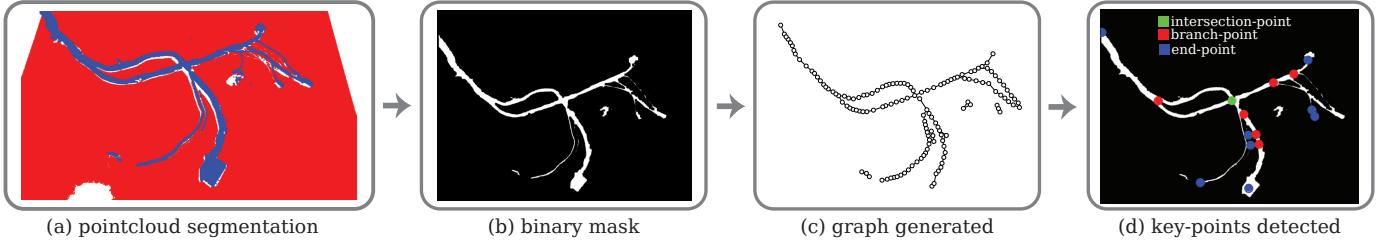


Fig. 2: Perception Pipeline.

an open research topic. Indeed, it is possible to find researches aimed at the manipulation of specific part of the harness such as the final connectors [10]. However, many of the proposed solutions are still evaluated in a simulated environment, i.e. in [11] where the authors study the planning of the robot in a simulated cluttered environment or in [12] where the authors focused on the simulation of a DLO assembly task. In this work, we present preliminary results on wiring harness perception and manipulation for automotive industries. The experimental setup, depicted in Fig. 1, is composed by a 3D industrial camera manufactured by Photoneo, a 7-DoF robotic manipulator by Franka Emika and an additional 3D eye-in-hand camera. The harness is a commercial product employed in a production vehicle, representing a realistic benchmark for this work. Indeed, the wiring harness is complex and heavy and, for simplicity, the work addressed in this paper focuses on the manipulation of a subset of branches that compose the entire harness. The paper is organized as follows: In Sec. II it is presented the concept of topological representation of a wiring harness. Then, in Sec. III the perceptions pipeline is proposed while in Sec. IV is discussed a planning approach for the manipulation of the harness. The conclusions and future works are covered in Sec. V.

II. TOPOLOGY REPRESENTATION

From a wiring harness, few key-points can be detected and their relative location can be used to characterize the structure of the object. The following key-points can be defined:

- *intersection-point*: where two or more branches cross each other;

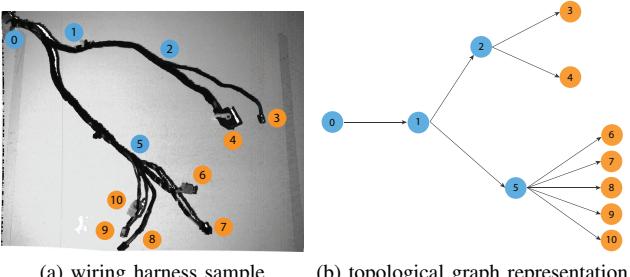


Fig. 3: Image sample of a wiring harness and its topological graph representation.

- *branch-point*: a point where a bifurcation takes place;
- *end-point*: extremity point of a branch.

Given the key-points, a topological graph representation of the wiring harness is constructed by assigning a node to each key-point. Instead, the edges are obtained by interconnecting the key-points in a meaningful and correct way, i.e. an edge exists for each DLO between two key-points.

This graph representation can be enriched with features both at node-level and edge-level. For instance, possible node features are: connector IDs (if an *end-point* denotes a connector), node size or thickness. Instead, a possible edge feature is the length of the DLO connecting the two key-points or some key-points based description of its shape.

In Fig. 3b the topological graph representation of the sample wiring harness shown in Fig. 3a is depicted.

III. PERCEPTION

The purpose of the perception pipeline is to extract the information from the scene using the statically mounted 3D camera. The pipeline processes the acquired point cloud obtaining a set of key-points which are then used for defining the manipulation strategy. The overall perception flow is depicted in Fig. 2. The graph generation step (c) is detailed in Sec. III-A whereas the key-points characterization (d) in Sec. III-B.

A. Graph Generation

A pointcloud of the scene is captured using the fixed 3D camera. From the cloud, the plane is segmented employing the RANSAC algorithm. Then, the points of the cloud that do not belong to the plane are projected in a 2D image plane obtaining a binary mask M_b of the scene, i.e. white pixels (foreground) representing the wiring harness. These steps are depicted in Fig. 2a and 2b.

An approach derived from *FASTDLO* [4] is now executed for obtaining an undirected graph-based representation of the wiring harness. From the binary mask M_b , the center lines of the DLOs composing the wiring harness are extracted via the distance transform operator [13]. This operator computes the euclidean distances between the non-zero values of M_b and the nearest boundaries (zero/black values), assigning an intensity value to each pixel based on the computed distance. The mask originated from the distance transform operator, i.e. M_{dist} , characterizes the center line of the DLOs as the pixels having a maximum value locally. From M_{dist} , nodes for the

graph representation are extracted sampling pixel locations along the DLOs center lines employing the farthest point sampling algorithm [14]. The edges are instead sampled by looking at the relative orientation between nodes in proximity. The graph structure denoted in Fig. 2c is thus obtained.

B. Topological Points Characterization

From the obtained graph, the topological points defined in Sec. II are retrieved by looking at the degree of each node. The node degree in an undirected graph is defined as the number of connected edges to the node itself. The following assignments are made based on the degree $d(n)$ of node n :

- *end-point*: $d(n) = 1$;
- *branch-point*: $d(n) = 3$;
- *intersection-point*: otherwise.

The obtained topological key-points are depicted in Fig. 2d. Given the detected topological-points, a topological graph representation of the scene is constructed following the discussion of Sec. II. As edge features of the topological graph, the sequence of node locations of the input graph in between the *branch-point* and *end-point* or any possible their combination are used. Notice that at the *intersection-point* the correct ordering of the DLOs, i.e. relation above or below, is acquired evaluating the nodes locations in the pointcloud. The edge features, in combination with the key-points, are then used to plan the manipulation strategy.

IV. MANIPULATION

The manipulation task addressed in this section aims at solving the intersections between different branches of the wiring harness. Given the output of the perception pipeline, i.e. the topological graph representation of the wiring harness in the scene, a manipulation action is executed targeting the detected intersection key-points.

A. Pick and Rotation Points

The intersection to be solved comprises two DLOs defined between the associated *branch-points* and *end-points* where each DLO is represented as a sequence of 3D coordinate. In Fig. 4a the DLOs of the sample intersection used in this paper as reference are shown. Given the DLOs, the upper one is targeted as the one to move. The rotation point of the DLO is defined as the extremity of the sequence of nodes closer to the parent branch of the wiring harness. The pick point is instead defined as the other extremity point, i.e. the opposite point to the rotation one. In Fig. 4 the pick and rotation points are shown.

B. Cost Maps

To avoid the robot moving the wiring harness outside the field of view of the camera, a cost map is defined as the weighted distance of a pixel to the image center, as:

$$F_c = 1/(p_x^2 + p_y^2) \quad (1)$$

A second cost map is introduced as function of the grasping point p_g . Aiming at moving the harness as far as possible

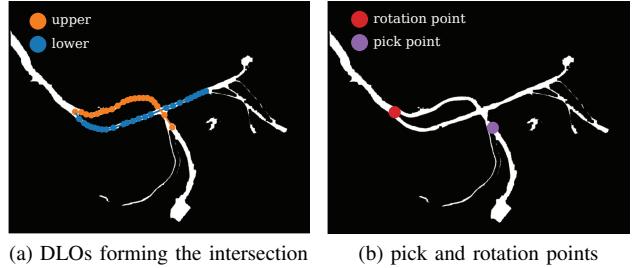


Fig. 4: Example of manipulation task for intersection solving.

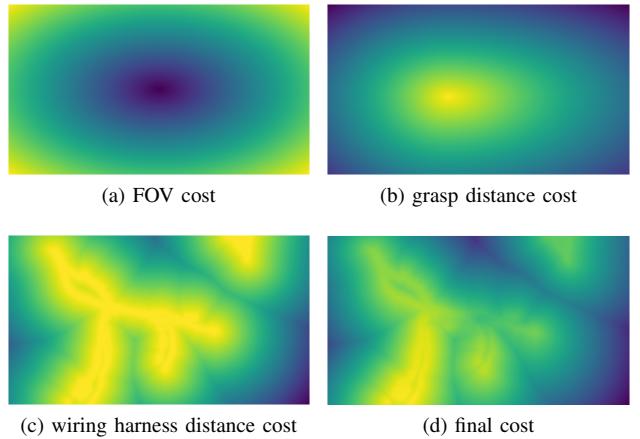


Fig. 5: Cost maps.

from the initial grasping point, hence reducing the chance of possible overlapping, the map is obtained as:

$$F_g = 1/((p_x - p_{g,x})^2 + (p_y - p_{g,y})^2) \quad (2)$$

An additional cost map is defined taking into consideration the original mask M_b . This map is used to enforce a placing point away from the region of the image already occupied by the other branches of the wiring harness. Thus, given the inverted binary mask (1 for background, 0 for wiring harness):

$$\bar{M}_b = 1 - M_b \quad (3)$$

and the normalized euclidean distance transform computed on \bar{M}_b obtained as:

$$M_{\text{dist}} = T_{\text{dist}}(\bar{M}_b). \quad (4)$$

The associated cost map is computed as:

$$F_i = 1/M_{\text{dist}} \quad (5)$$

and the final cost map is given by the normalization of the individual contributions:

$$F = aF_c + bF_w + cF_i \quad (6)$$

where $a, b, c \in [0, 1]$ and $a + b + c = 1$. In Fig. 5 the mentioned cost maps are displayed.

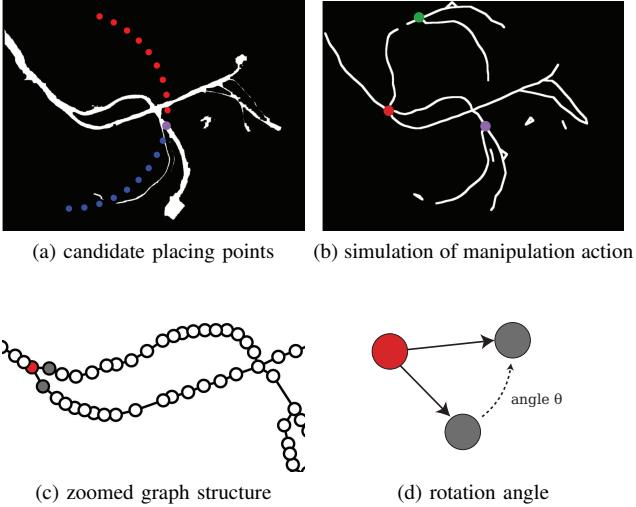


Fig. 6: Computation of placing point and estimation of final result.

C. Place Point

The place point for the manipulation action is computed starting from the cost map F . With reference to Fig. 6a, a set of candidate place points are computed for both positive and negative rotation angles. Along the circumference, the final place point is selected as the one satisfying:

- minimum cost on the map F ;
- associated motion with increasing angle at the rotation point compared to the initial condition.

Indeed, the initial angle between the DLOs at the rotation point can be easily estimated from the graph as shown in Fig. 6d. Given the pick and place points, the rotation angle can be computed and used to verify the action simulating the rotation operation on the targeted DLO and all the downstream branches, as shown in Fig. 6b.

D. Task sequence

In Fig. 7 some key-frames are extracted from a video showing the disentangling manipulation task on a sample wiring harness. In particular, in Fig. 7a the initial configuration of the wiring harness is shown. Thus, a sample pointcloud is captured by the fixed camera and processed according to Sec. III extracting the topological points from it. The detected intersection points are sorted utilizing a diameter-based measure and the biggest one targeted for the manipulation action. Thus, the grasp point, rotation point and place point are all computed according to Secs. IVA-B-C. These points are exploited for the manipulation shown in Figs. 7b and 7c. Thereafter, a new configuration of the wiring harness is reached, Fig. 7d.

V. CONCLUSION AND FUTURE WORKS

In this paper, some preliminary results concerning the perception and manipulation of an automotive wiring harness

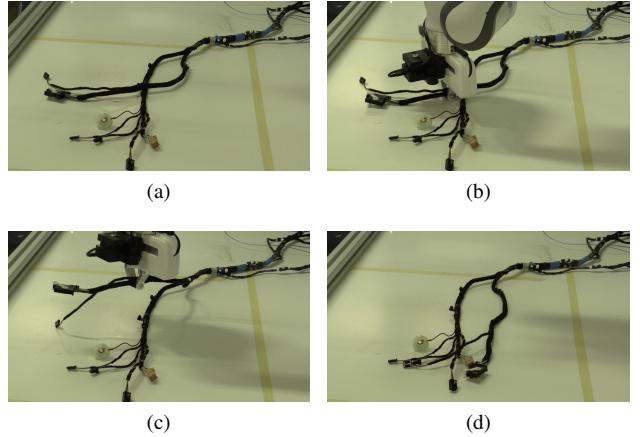


Fig. 7: Manipulation key-frames from a video showing the sequence of operations. In details: a) wiring harness initial configuration; b) grasp at pick point; c) motion towards place point; d) final configuration reached.

are presented. The perception pipeline shows how a 3D fixed camera can be employed for obtaining a topological characterization of the wiring harness, discerning the information from the scene that can be successfully used in the downstream manipulation task. The proposed manipulation approach is quite simple but able to tackle the task in the preliminary experiments performed. In the future, several improvements can be implemented. Concerning the perception, the approach should be made more robust and integrated with additional components like, for instance, an object detector for handling the connectors and thus providing an additional feedback about the key-points extracted from the graph. The manipulation approach should also be improved. The implementation of a Reinforcement Learning (RL) method for generalizing the pick and place action will be investigated. To conclude, in this work only the intersection solving task is addressed. In the future, constraining a final configuration to the wiring harness, i.e. placing a given branch or key-point in a specific location of the space, will be also investigated. In this regard, the possibility of matching a target topological graph to the one obtained from the scene is going to be an objective of research.

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