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Published Version:
Combining Vision and Tactile Data for Cable Grasping / Alessio Caporali, Kevin Galassi, Gianluca Laudante, Gianluca Palli, Salvatore Pirozzi. - ELETTRONICO. - (2021), pp. 436-441. (Intervento presentato al convegno IEEE/ASME International Conference on Advanced Intelligent Mechatronics tenutosi a Delft, Netherlands nel July 12-16 2021) [10.1109/AIM46487.2021.9517447].

Availability:
This version is available at: https://hdl.handle.net/11585/832137 since: 2021-10-04

Published:
DOI: http://doi.org/10.1109/AIM46487.2021.9517447

(Article begins on next page)

Combining Vision and Tactile Data for Cable Grasping

Alessio Caporali[b], Kevin Galassi[b], Gianluca Laudante[a], Gianluca Palli[b], Salvatore Pirozzi[a]

***Abstract*—In this paper, the problem of properly combining vision and tactile data to locate a deformable linear object, such as a cable, and grasp it according to a required position and orientation of the cable is considered. Tactile sensors suitably developed for this task are adopted in the experiments together with a vision algorithm based on deep learning for the detection of the cable shape from a 2D camera image. The vision system is initially adopted to locate the cable in the scene and execute the grasp, then the tactile sensor is used to estimate the cable shape and position after grasping. The capability of the systems of performing cable regrasp by correcting the grasp pose thanks to the tactile data acquired during the first grasp is considered to deal with the cases in which the vision system can't be used because of occlusions. Experimental trials show the capability of improving significantly the quality of the grasp thanks to tactile-based regrasping. Finally, the fusion between the shape estimation provided by the vision system and the one provided by the tactile sensor is also presented.**

***Index Terms*—Robotic Grasping, Deformable Objects, Sensor Fusion, Shape Estimation**

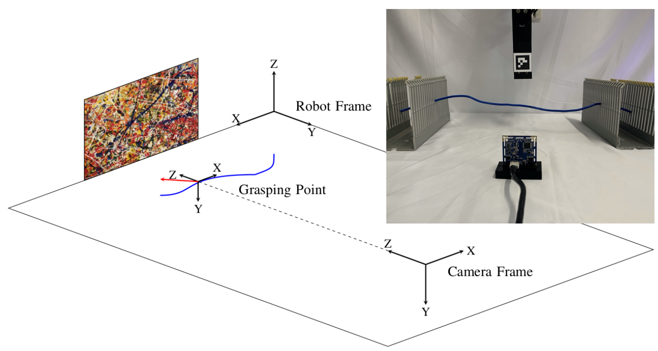

Fig. 1. Setup representation: a 2D camera is placed at a known distance from the wire positioned over two supports. Behind the cable there is a Pollock image to show the capability of ARIADNE. The different reference frames are reported.

I. Introduction

The successful manipulation of Deformable Linear Objects (DLOs) strongly depends on knowledge of their geometrical characteristics, especially because they can change shape on the basis of interaction with the environment. To tackle this kind of task the robotic systems needs to be equipped with sensing tools able to provide the correct needed information about the object to grasp. In literature, the object characteristics are very often estimated by using tactile sensors and/or vision systems. These last are almost always used due to their efficiency in data collection [1], [2]. The approaches based only on the vision may fail in presence of occlusions, light variations, obstacles and in these cases the tactile sensors can be used to overcome the encountered limitations. For these purposes, recognition strategies based on tactile sensor data have been proposed by several researchers: in [3] the authors propose to reconstruct the object models from discrete tactile point clouds; in [4] authors propose a bag-of-words approach; Meier et al. [5] present a probabilistic spatial approach; in [6] the authors propose a Bayesian approach to estimate poses of unknown objects. Recently, many researchers have been working on integrating vision and tactile data [7], [8], [9]. However, none of these past works deals with the detection of the position and the shape of DLOs. The latter, performed by exploiting both tactile sensors and/or machine vision, has been already demonstrated by the authors in [10]. In this paper the wire shape estimation, previously proposed in [11], is extended to the new tactile sensor (with 5×5 taxels) and integrated with the vision system. More in detail, this paper aims to describe possible strategies and algorithms concerning the wire grasping by exploiting the data available from a vision and tactile system. The vision system is used to recognize the cables to grasp and to implement an approaching phase through a vision-based control algorithm. After the cable grasping based on vision data, the tactile sensor is used to evaluate the grasp quality, in order to release and re-grasp the cable if the first approaching phase did not allow to obtain the desired grasp. In particular, the tactile map is used to evaluate the position and the orientation of the wire with respect to the end-effector frame and to compare it with a desired pose. The grasping pose correction is useful in all tasks where the cable have to be precisely positioned: e.g., in switchgear assembly, where the cables have to be inserted into the small connectors of the electro-mechanical components. No prior knowledge of cable mechanical characteristics (e.g., length, stiffness, diameter) are hypothesized for the proposed approach. Moreover, assuming that the location of the cable is barely known, the correction of the cable grasping pose based on the output of the tactile sensor only is also evaluated. The proposed procedures are experimentally tested with different DLOs. A fusion of the shape reconstructed by using the vision

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This research received funding from the EC H2020 research and innovation program under grant agreement n. 870133 - REMODEL (Robotic Technologies for the Manipulation of Complex Deformable Linear objects).

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system with the shape estimated by the tactile sensor is shown as starting point for future developments. A video with a sequence of sub-tasks has been prepared to clarify the various proposed phases.

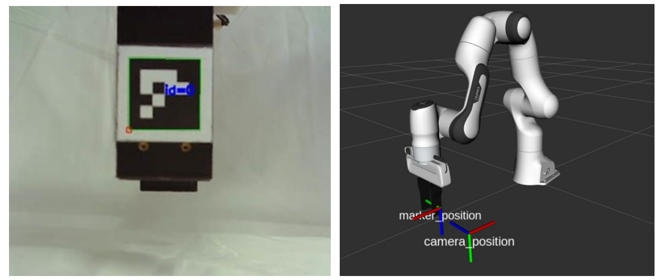
II. Use of vision data for cable detection

For the grasp test, a 2D camera is placed at a known distance from the cable. Figure 1 shows how the camera and the grasping pose reference frames are arranged in space. Moreover, a fiducial marker is placed in a known position on one finger in order to estimate the camera position with respect to the robot: the marker is detected by the camera providing its position in the camera frame, as shown in Fig. 2a, then the knowledge of the marker position in the world frame thanks to the robot kinematics is exploited to compute the camera position with respect to the robot, see Fig. 2b.

The computer vision algorithm adopted to detect the cable in the scene is based on ARIADNE [12], a framework for segmentation of DLOs in complex and cluttered backgrounds, as shown in Fig. 3. Starting from the input image provided by the camera and reported in Fig. 3a, a deep convolutional neural network [13] trained on a custom dataset [14] is used for the generation of a binary mask of the scene, see Fig. 3b. Then, a superpixel segmentation [15] is applied to the white portion of the gnerated mask to reduce the complexity and allow the generation of a region adjacency graph. Walks on the graph are executed aiming at connecting the nodes of the graph into a meaningful ordered way, i.e. nodes of the same real wire should be connected together. The result is the segmentation of the DLOs in the original image into individual instances. Each of them modelled by a B-Spline estimated starting from the graph's nodes sequence, as reported in Fig. 3c. The approximation is parametrized using a value $s \in [0,1]$ with $s = 0$ and $s = 1$ corresponding to the two ends of the cable in the image, therefore the grasping point on the cable is defined by selecting $s = 0.5$, the middle point of the curve. The orientation of the wire in the image plane is, instead, obtained by evaluating the inclination of the segment defined between the spline points at $s = 0.45$ and $s = 0.55$. The resulting reference frame is thus selected with the $x-$axis aligned to the wire direction, the $y-$axis normal to the $x-$axis and in the image plane, and the $z-$axis orthogonal to the image plane in the direction of the camera. The grasp reference frame shown in Fig. 3d is then converted in the coordinate system of the end-effector, to be used for the actual grasp. The conversion can be applied by knowing the rotation matrix $\mathbf{R}$ between the two systems and the relative position vector $\mathbf{p}$

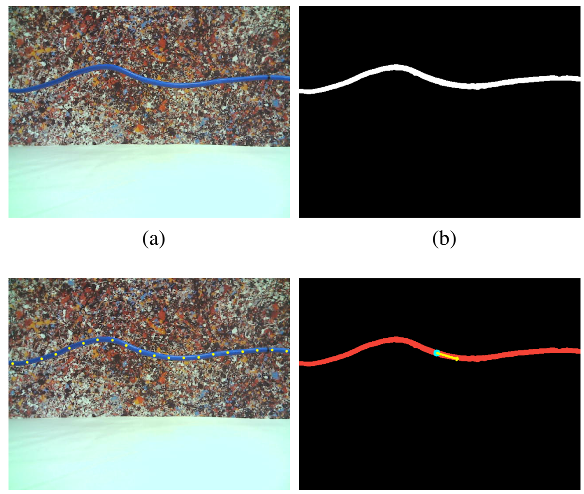
$$\begin{bmatrix} x_{\text{world}} \\ y_{\text{world}} \\ z_{\text{world}} \\ 1 \end{bmatrix} = \begin{bmatrix} R_{11} & R_{12} & R_{13} & p_x \\ R_{21} & R_{22} & R_{23} & p_y \\ R_{31} & R_{32} & R_{33} & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{\text{camera}} \\ y_{\text{camera}} \\ z_{\text{camera}} \\ 1 \end{bmatrix} \tag{1}$$

In future development, the distance z will be computed by the introduction of a second camera looking at the same scene along a different direction, by exploiting the stereophotography



(a) (b)

Fig. 2. Marker placed on the finger (a) used to detect the relative position of the camera with respect to the robot(b).



(a) (b) (c) (d)

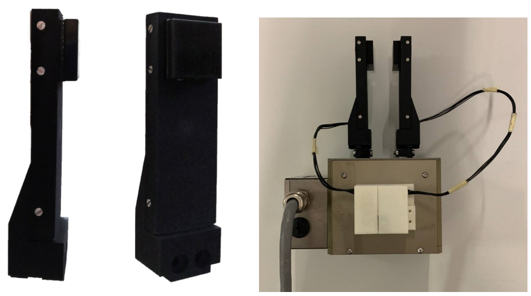
Fig. 3. Input image for ARIADNE with cluttered background (a), binary mask for object with DLO characteristic (b), the approximated spline model (c) and the final reference frame for grasp (d).

to obtain the depth of a point, which in this case coincides with the distance of the cable to grasp. Also the use of depth cameras has been evaluated but the recognition of thin cables becomes infeasible.

III. Tactile sensor for shape recognition of grasped cable

After the cable grasping, executed on the basis of cable reference frame obtained from the vision system, the only information retrieved by the vision system may not be enough to detect if the grasping has been correctly completed. Furthermore, even if the grasping phase seems completed, it is not possible to know the "quality" of the grasp by using the vision only. For these reasons, a tactile sensor can be very useful to obtain additional information about the cable handling.

The tactile sensor, used in this paper, has been suitably designed for REMODEL Project applications on the basis of original idea presented in [16], and in particular for grasping DLOs, i.e., cables, ropes and hoses. It consists in a sensorized finger (Fig. 4a) that can be mounted on typical commercial grippers (Fig. 4b). The sensing area is composed by 25



(a) (b)

Fig. 4. Tactile sensor (a) and gripper with sensorized fingers integrated into (b).

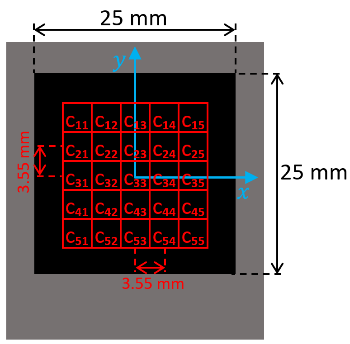


Fig. 5. Sensing area dimensions with taxel distribution.

photo-reflectors organized in a 5×5 matrix with a spatial resolution of 3.55 mm (Fig. 5) suitably assembled with a deformable silicone "cap". A photo-reflector is an optoelectronic component, consisting of a Light Emitting Diode (LED) and a PhotoTransistor (PT), which provides a voltage signal dependent on the amount of incident light. In particular, these photo-reflectors work in reflection mode: the light emitted by the LED is reflected by the bottom of the deformable layer and comes back to the PT in an amount dependent on the local deformation. Each measuring point is called "taxel". When a cable (or an object in general) is pressed against the silicon surface, by using the 25 voltage signals coming from taxels, it is possible to obtain a tactile map corresponding to the deformation of the silicone cap.

In order to read data from the tactile sensor and use the information for grasping and manipulation tasks, a suitable software system has been developed. The Robot Operating System (ROS) has been selected as framework for process scheduling and inter-process communication management, since it represents a *de facto* standard for the robotics researchers community. The whole system is pictured in Fig. 6 and it is composed of three ROS Nodes communicating with each other by means of ROS Topics.

1) read_sensor_node: The tactile sensor is equipped with a microcontroller (MCU) that accepts simple requests and communicates, through a serial interface, the sensor identifier, the number of sensing elements (in this case 25) and the raw digital signals corresponding to the photo-reflectors voltages.

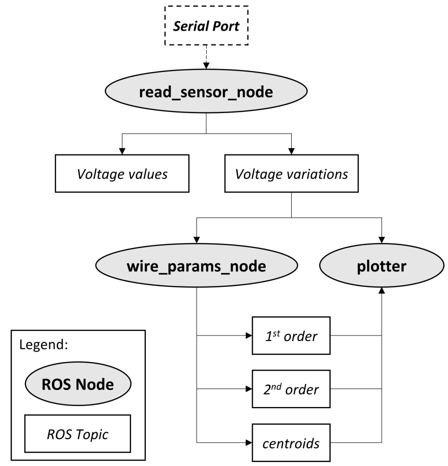


Fig. 6. Scheme of the ROS network.

The *read_sensor_node* interrogates the MCU, translates the digital signals back in voltage values and publishes information on two different ROS Topics: one with the raw voltage values as received (defined as v_{ij}, with $i = 1, \dots, 5$ and $j = 1, \dots, 5$ according to taxel numbering in Fig. 5) and another one with the same data after the bias removal (defined as Δv_{ij}). This last operation is important to make the voltage values comparable, since they could be different due to the manufacturing process of the silicon cap, and it is achieved by subtracting from the voltage value of each photo-reflector the mean value of the first 50 received samples. In this way, the final values correspond to the voltage variations with respect to the "nominal" offset voltage values of the taxels. The frequency at which this node interrogates the sensor and publishes on the ROS topics is equal to 500 Hz.

2) wire_params_node: This node estimates the shape of the cable in contact with the sensor by exploiting the data published by the read_sensor_node. In particular, it computes linear and quadratic approximations for the cable shape and publishes the corresponding parameters on two different ROS Topics. The reference system used in the following formulas is the one having the origin at the center of taxel c_{33}, i.e., the center of the silicone pad, the x-axis pointing towards taxel c_{35} and the y-axis pointing towards taxel c_{13} (see Fig. 5 for taxels numbering and reference system).

The considered linear approximation for the cable is:

$$y = mx + n \tag{2}$$

where m and n are the two parameters computed and published on the correspondent topic. Instead, the considered quadratic approximations are:

$$y = ax^2 + bx + c \tag{3}$$
$$x = ay^2 + by + c \tag{4}$$

in case of vertical and horizontal axis of symmetry, respectively. In both cases, a, b and c are the three computed and published parameters.

The algorithm for the computation of these parameters, in both cases, is constituted by three steps:

- detection of the wire direction (horizontal or vertical);
- computation of the centroid coordinates for each column (if horizontal) or for each row (if vertical);
- computation of the cable model parameters using the centroid coordinates.

The first step, i.e., the detection of the main direction, consists in computing and comparing these two quantities:

$$h = \min\left(\sum_{i=1}^{5}\Delta v_{i1}, \sum_{i=1}^{5}\Delta v_{i2}, \sum_{i=1}^{5}\Delta v_{i3}, \sum_{i=1}^{5}\Delta v_{i4}, \sum_{i=1}^{5}\Delta v_{i5}\right)$$

$$v = \min\left(\sum_{j=1}^{5}\Delta v_{1j}, \sum_{j=1}^{5}\Delta v_{2j}, \sum_{j=1}^{5}\Delta v_{3j}, \sum_{j=1}^{5}\Delta v_{4j}, \sum_{j=1}^{5}\Delta v_{5j}\right)$$

where Δv_{ij} is the voltage variation of the taxel c_{ij}. Having these two values, if $h > v$ the main direction is aligned with the x-axis (horizontal), while if $h < v$ it is aligned with the y-axis (vertical).

In the second step, the centroids computation depends on the main direction computed in the first step. If it is horizontal, the y-coordinates y_j^c of the column centroids are computed as

$$y_j^c = \frac{\sum_{i=1}^{5} y_i \Delta v_{ij}}{\sum_{i=1}^{5} \Delta v_{ij}} \qquad j = 1, ..., 5 \tag{5}$$

while, if the main direction is vertical, the x-coordinates x_i^c of the row centroids are computed as

$$x_i^c = \frac{\sum_{j=1}^{5} x_j \Delta v_{ij}}{\sum_{j=1}^{5} \Delta v_{ij}} \qquad i = 1, ..., 5. \tag{6}$$

The two terms x_j and y_i are the mechanical x-coordinate of the j-th column and the mechanical y-coordinate of the i-th row respectively. The complete coordinates of the centroids will be (x_j, y_j^c) in case of horizontal cable, or (x_i^c, y_i) in case of vertical cable.

The third and last step consists in computing the parameters m, n of the equation (2) and a, b, c of the equation (3) or (4) by using a least squares method applied to the centroids data obtained with the equation (5) or (6), respectively. At the elaboration end, the *wire_params_node* publishes the parameters for the $1-$st order (linear) and $2-$nd order (quadratic) cable approximation models and the centroids coordinates on three ROS topics (the latter are used for graphic representation by the *plotter* node).

3) plotter: As shown in Fig. 6, the *plotter* node reads from the topics published by the other two ROS Nodes and then uses this information to represent in a graphical way the tactile map and the approximation of the cable shape. This node can show different information depending on the user's choice. In fact, it can show the tactile map only or the tactile map with the linear/quadratic approximation. Examples of tactile maps together with the representations of linear and quadratic approximation are reported in Fig. 7a and Fig. 7b respectively, where the blue circles represent the tactile map (the radii of the circles are proportional to the voltage variations of the corresponding taxels), the green dots are the centroids and the red line is the shape approximation.

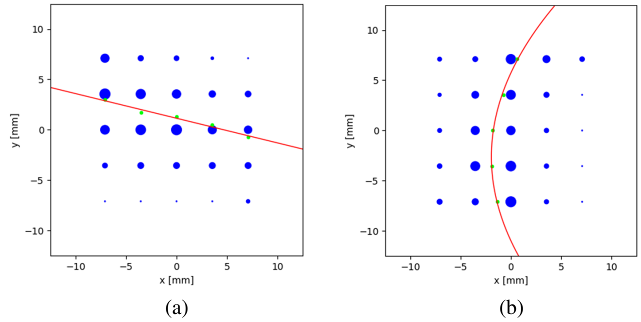


Fig. 7. Graphical representations of tactile maps together with linear (a) and quadratic (b) models for the cable.

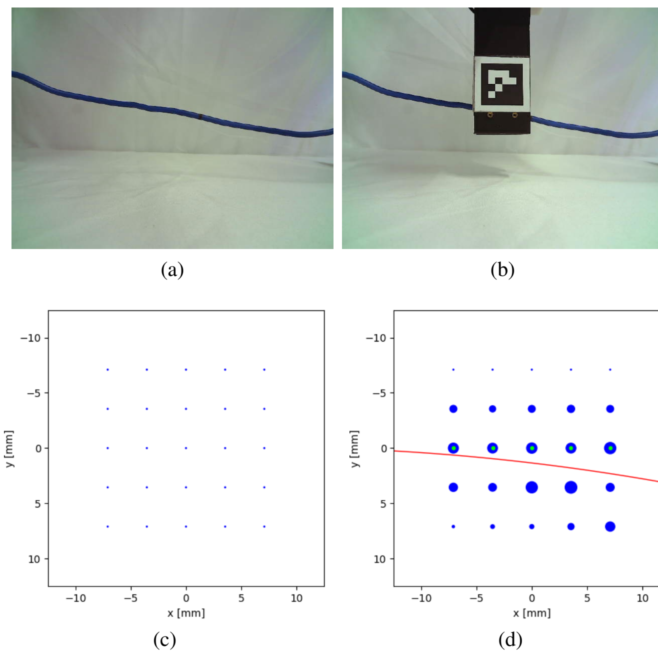
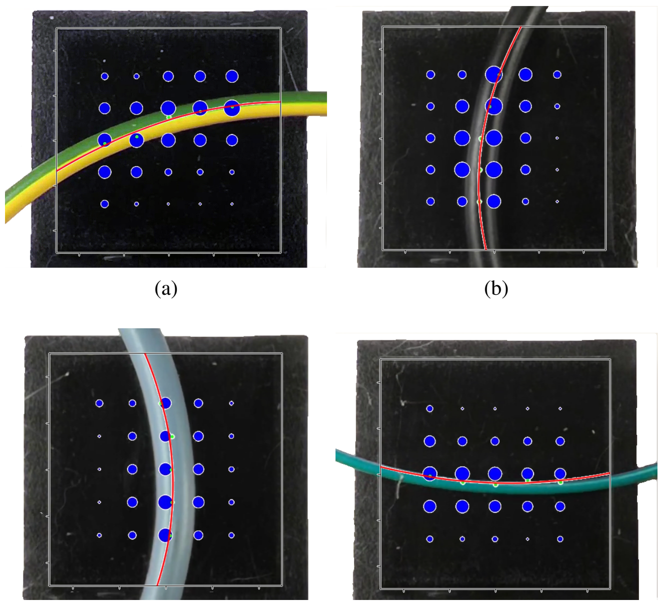


Fig. 8. Cable detection and initial grasp: pre-grasp cable configuration (a), grasp pose (b) and corresponding tactile maps (pre-grasp (c) and after the grasp (d)). A uniform background is used for clarity.

IV. Experiments

The experiments are executed by using a $7-$dof robotic arm, the Panda from Franka Emika, equipped with a Schunk PG70 parallel fingers electric gripper. The robot is controlled through MoveIt, a ROS plugin specifically designed to provide a high-level interface for trajectory and motion planning. This framework enables to control the robot by passing the desired trajectory to the low-level controller. To control the gripper instead, a ROS-service has been created to set the position of the fingers through an USB port connected with the gripper's DMI controller.

1) Cable detection and initial grasp: The result of a sample initial grasp is shown in Fig. 8. In particular, Fig. 8a shows



(a) (b) (c) (d)

Fig. 9. Shape estimations for wires of (a) 2.5 mm, (b) 3.5 mm, (c) 4.0 mm and (d) 1.5 mm diameters

the starting condition in which the cable is positioned on two supports with an initial unknown configuration. ARIADNE network elaborates this image to detect the cable and compute the reference frame to use for the cable grasping. The robot exploits the computed cable frame to implement the grasp task by reaching the grasping pose reported in Fig. 8b. The tactile maps, corresponding to two images of pre-grasp and grasp, are reported for completeness of information from the available sensing system. From Fig. 8c it is evident that no contact is highlighted by the tactile sensor, while, after the grasp, the cable information that can be extracted from the tactile map in Fig. 8d are very clear.

2) Shape reconstruction: This experiments aim to show results about the approximation of the cable shape obtained by using the procedure presented above. To test the quality of the computed shape approximations, the tactile sensor has been pressed using wires of different diameters while an external camera acquired the scene. Thus, the graphical representation of the $2-$nd order wire model and the image of the real wire have been compared by superimposing the former on the latter. These comparisons are reported in Fig. 9 for different cables, where it is possible to see how accurate are the approximations. The images also report the raw tactile maps and centroids. The less accurate is the one in Fig. 9d, also due to the small diameter of the cable (1.5 mm) with respect to the tactile sensor spatial resolution (3.55 mm).

A. Grasping correction experiment

This experiment aims to demonstrate how the cable shape estimation can be used to re-grasp the wire in order to reach a desired grasping pose. The objective is to use the parameters given by the linear approximation of the wire shape to grasp it in a desired manner, i.e., with a certain position and orientation with respect to the sensorized finger. The cable has a diameter of 2.5 mm and it is suspended between two supports to avoid eventual collisions during the grasping task (as the case reported in Fig. 8a). The experiment consists in grasping the cable two consecutive times: the first time is a "trial" grasp and the second one is the final grasp, after applying a correction to the pose of the robotic arm. For the first grasp, the cable location is obtained by using the algorithm explained in Sec. II. Then, once the fingers are closed over the cable, the linear approximation obtained by the *wire_params_node* is used to compute the new robot pose for the final grasp. In particular, the desired cable pose for this experiment is the one with the cable aligned with the $x-$axis of the reference system used for the shape approximation. In terms of the parameters m and n in the equation (2), where m is angular coefficient of the straight line and n is its distance from the center of the sensor, the desired cable pose results in having both parameters equal to zero (see Fig. 10). Once the two parameters have been computed, these are used to build the following homogeneous transformation matrix to correct the one given by the vision system and used during the first grasp:

$$T_{corr} = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 & 0 \\ \sin\alpha & \cos\alpha & 0 & n \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{7}$$

with $\alpha = \arctan(m)$.

Figure 11 shows the two grasps occurring during the experiment: the image on the left (11a) shows the "trial" grasp while the one on the right (11b) shows the final grasp, with the cable in the desired pose with respect to the fingers. In order to evaluate the effectiveness of the re-grasp, the same experiment has been repeated 20 times, starting from different initial grasps (by adding small random offset on initial reference frame), and the error with respect to desired pose has been evaluated. In particular, the mean errors, for the 20 repetitions, at the first grasp in terms of wire position (n) and orientation (α) have been computed and compared with the same mean errors computed after the re-grasp. The obtained values are 4.0 mm and 0.32 rad for the first grasp, while after the re-grasp they decrease to 1.9 mm and 0.11 rad, respectively.

Finally, the fusion between the cable shape estimation provided by the vision system and the tactile sensor is reported in Fig. 12. This figure reports on the left the shape reconstruction obtained by the fusion of ARIADNE output with linear tactile map interpolation, while in the right the shape reconstruction resulting from the fusion of ARIADNE output and the quadratic tactile map interpolation. These combinations can be exploited in future developments for the advanced wire manipulation in cases where the camera occlusions cannot be avoided.

V. Conclusion

This paper presented a possible approach for the grasp of DLOs. As shown the proposed solution exploits both

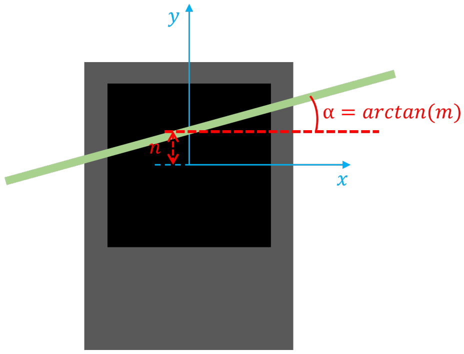
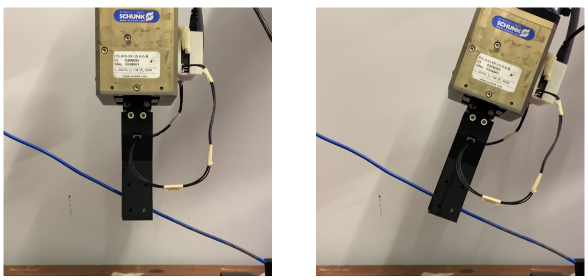


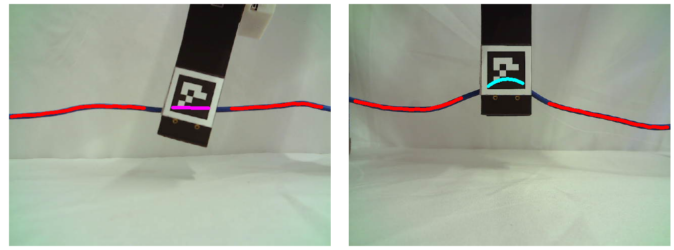
Fig. 10. Parameters of linear approximation with respect to the sensor frame.



(a) (b)

Fig. 11. Grasping correction experiment: initial grasp (a) and final grasp (b).

vision data coming from a standard 2D camera and tactile data available from tactile sensors suitably developed in REMODEL Project. The images are elaborated by using a suitably designed software package (ARIADNE). The vision data are used to recognize the wire position in order to define a frame used for the DLO initial grasp. After the initial grasp, the tactile data are used to evaluate the wire shape with respect to a known reference frame. The same data have been used to re-grasp the wire if the initial grasping pose is considered not satisfactory, by reaching a desired position and orientation for the grasped object. The attached video summarizes all proposed approaches, in order to demonstrate their effectiveness, by collecting a sequence of tasks executed with the experimental setup and the sensor system presented in the paper. In the first part, the localization of the cable by the vision sensor through the Ariadne software package is shown. The vision sensor provides the grasp pose of the cable to the robot that then executes the grasp. The second part shows side by side the tactile signals with the data related to their post processing with the estimated wire shape and the actual wire used during the experiments. Different diameters have been used. In the third, the same data are superimposed in order to allow the reader an immediate comparison between the estimated shape and ground truth. The last part reports an experiment of re-grasp on the basis of tactile data. After a first grasp where the wire shape is estimated, the wire is re-grasped in order to horizontally align the wire with respect to the tactile sensor frame.



(a) (b)

Fig. 12. Vision and tactile shape estimation fusion: with linear tactile map interpolation (a) and with quadratic tactile map interpolation (b).

REFERENCES

[1] M. Popovic, D. Kraft, L. Bodenhagen, E. Baseski, N. Pugeault, D. Kragic, T. Asfour, and N. Krüger, "A strategy for grasping unknown objects based on co-planarity and colour information," *Robotics and Autonomous Systems*, vol. 58(5), pp. 551–565, 2010.

[2] A. Saxena, J. Driemeyer, and A. Y. Ng, "Robotic grasping of novel objects using vision," *The International Journal of Robotics Research*, vol. 27(2), pp. 157–173, 2008.

[3] H. Gu, Y. Zhang, S. Fan, M. Jin, H. Zong, and H. Liu, "Model recovery of unknown objects from discrete tactile points," in *IEEE Int. Conf. on Advanced Intelligent Mechatronics (AIM)*, 2016, pp. 1121–1126.

[4] A. Schneider, J. Sturm, C. Stachniss, M. Reisert, H. Burkhardt, and W. Burgard, "Object identification with tactile sensors using bag-of-features," in *In Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2009, pp. 243—-248.

[5] M. Meier, M. Schopfer, R. Haschke, and H. Ritter, "A probabilistic approach to tactile shape reconstruction," *IEEE Transactions on Robotics*, vol. 27(3), pp. 630—-635, 2011.

[6] A. Petrovskaya, O. Khatib, S. Thrun, and A. Ng, "Bayesian estimation for autonomous object manipulation based on tactile sensors," in *In Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*, 2006, pp. 707–714.

[7] N. Lepora, K. Aquilina, and L. Cramphorn, "Exploratory tactile servoing with active touch," *IEEE Rob. and Aut. Letters*, pp. 117–124, 2017.

[8] J. Bimbo, L. Seneviratne, K. Althoefer, and H. Liu, "Combining touch and vision for the estimation of an object's pose during manipulation," in *In Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2013, pp. 4021–4026.

[9] P. Falco, S. Lu, A. Cirillo, C. Natale, S. Pirozzi, and D. Lee, "Cross-modal visuo-tactile object recognition using robotic active exploration," in *IEEE Int. Conf. on Rob. and Aut. (ICRA)*, 2017, pp. 5273–5280.

[10] D. De Gregorio, R. Zanella, G. Palli, S. Pirozzi, and C. Melchiorri, "Integration of robotic vision and tactile sensing for wire-terminal insertion tasks," *IEEE Tran. on Automation Science and Engineering*, vol. 16, no. 2, pp. 585–598, 2018.

[11] S. Pirozzi and C. Natale, "Tactile-based manipulation of wires for switchgear assembly," *IEEE/ASME Tran. on Mechatronics*, vol. 23, no. 6, pp. 2650–2661, 2018.

[12] D. De Gregorio, G. Palli, and L. Di Stefano, "Let's take a walk on superpixels graphs: Deformable linear objects segmentation and model estimation," in *Lecture Notes in Computer Science - Asian Conference on Computer Vision*. Springer, 2018, pp. 662–677.

[13] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder-decoder with atrous separable convolution for semantic image segmentation," in *Proceedings of the European conference on computer vision (ECCV)*, 2018, pp. 801–818.

[14] R. Zanella, A. Caporali, K. Tadaka, D. De Gregorio, and G. Palli, "Auto-generated wires dataset for semantic segmentation with domain-independence," in *2021 International Conference on Computer, Control and Robotics (ICCCR)*. IEEE, 2021, pp. 292–298.

[15] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Süsstrunk, "Slic superpixels compared to state-of-the-art superpixel methods," *IEEE transactions on pattern analysis and machine intelligence*, vol. 34, no. 11, pp. 2274–2282, 2012.

[16] G. De Maria, C. Natale, and S. Pirozzi, "Force/tactile sensor for robotic applications," *Sensors Actuators A: Physical*, vol. 175, pp. 60–72, 2012.