Soft robotics approach to autonomous plastering

Bruno Maric, Marsela Polic and Matko Orsag

***Abstract*— This paper presents an industrial soft robotics application for the autonomous plastering of complex shaped surfaces, using a collaborative industrial manipulator. In the core of the proposed system is the deep learning based soft body modeling, i.e. deformation estimation of the flexible plastering knife tool. The estimation relies on visual feedback and a deep convolution neural network (CNN). The transfer learning approach and specially designed dataset generation procedures were developed within the learning phase. The estimated deformation of the plastering knife is then used to control the knife inclination with respect to the treated surface, as one of the essential control variables in the plastering procedure. The developed system is experimentally validated, including both the CNN based deformation estimation, as well as its performance in the knife inclination control.**

I. INTRODUCTION

The latest surge in the demand for robotics shifts towards small and medium manufacturing enterprises, which work with small customer-oriented manufacturing. This approach requires fast and frequent changes to the production line, and drives the robotics research towards new applications and requirements. For instance, the product finishing manufacturing niche, which involves sanding, plastering, and painting requires precise compliant control of end effectors. While most traditional robotic tasks involve manipulation of rigid objects with rigid end effectors, product finishing involves manipulating deformable objects, which has become possible with the development of sensing and computational capabilities.

This paper focuses on robotic plastering application, which involves a flexible robotic tool, as an example of one product finishing application. Other examples of compliant deformable object manipulation exist in fabrics and clothing industry, flexible cable manufacturing [1], food and agriculture robotics [2], medical applications [3], and even robotic art [4]. Plastering application extends the capabilities of previously developed collaborative robotic framework, in which we have developed a robotic sanding system [1] [5].

In this work, we propose a deep learning based control feedback for manipulation of a deformable object in an industrial task. Similar to other work in the field, we choose a set of deformation features that enable the control to account for tool deformation. One classical approach models position and shape information independently in the deformation features [3].

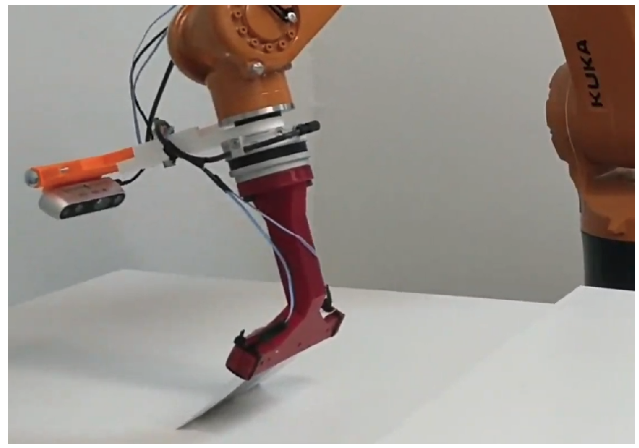

Fig. 1: While most traditional robotic tasks involve manipulation of rigid objects with rigid end effectors, the domain of deformable object manipulation is becoming ever more interesting with the development of sensing and computational capabilities. Robotic plastering, involving a flexible robotic tool, is an example of one such application. It requires the control of contact force, position and attitude towards the surface, which is the focus of this paper.

II. Shape modelling and control

When plastering manually, workers apply the plastering material to the treated object using a plastering knife. In this work we equipped a KUKA KR 10 robot with one such off-the-shelf knife tool, using a custom designed mount as shown in Fig. 2. The mounted plastering knife is flexible and mounted together with an Intel RealSense RGB-D camera. The camera is mounted so that it captures the complete plastering knife within the camera frame. Inspired by the results from vision-based tactile sensing development [6], the plastering tool was enriched with visual cues for easier deformation modeling through image analysis. These fiducial markers can be used to estimate the deformation with different techniques of computer vision.

In order to properly execute plastering tasks, the robot needs to control both the knife inclination angle to the treated object and the contact force. Since the shape of the tool is a result of the contact between the plastering knife tool and the treated object, we have designed the control system that decouples the system into two parallel control

Authors are with the LARICS Laboratory for Robotics and Intelligent Control Systems, University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb 10000, Croatia `(bruno.maric, marsela.polic, matko.orsag) at fer.hr`

Authors would like to thank Frano Petric for fruitful discussion

[1] Effective Robotic GriNDing of Surface Areas through HORSE framework, `https://larics.fer.hr/larics/research/endorse?`

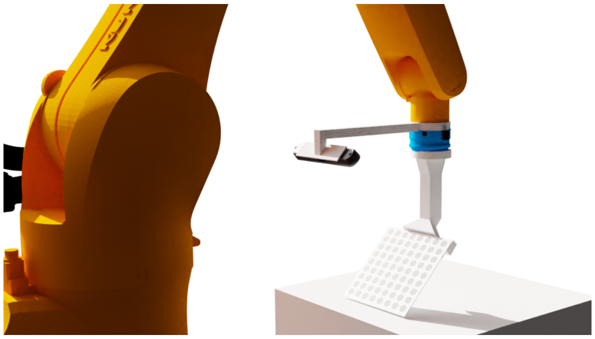

Fig. 2: Flexible knife tool is mounted on the robot end effector along with the sensory aparatus consisting of an Intel RealSense RGB-D camera and a torque sensor. Camera is placed so that the entire tool is visible during manipulation, and the torque sensor is deployed to measure contact forces with the treated surface.

system by measuring the shape of the knife. First the knife inclination is controlled, where the robot flange is rotated to provide the desired inclination of the knife in the current shape regardless of the contact force. At the same time the contact force is controlled through the impedance based Forward Dynamics Compliance Controller (FDCC) [7].

We focus on the knife inclination angle control, and leave the contact force and trajectory planning discussion for future work. The trajectory planning is assumed as a higher level planning algorithm that generates a series of desired knife tip waypoints, $\mathbf{T}_{d_B^\kappa}$, that take into account the desired poses and inclination angles of the knife, w.r.t. to the robot's base. The surface normal $\mathbf{n}_B$ and the desired force of contact define a nonlinear mapping of the knife shape under deformation, namely Δz, Δx and $\Delta\phi$, i.e. in the desired inclination and the position of the tip with respect to the treated surface.

Planned trajectories rely on the known shape of the treated surface, and an ideal shape of the knife. To make sure that the knife tip position and tangent orientation maintains the desired knife tip pose, we propose the following control strategy. Let us assume the knife is bent around the shape shown in Fig. 3 at an angle $\Delta\phi$ w.r.t. the fixed part of the knife tool. Also, let us assume the current knife tangent is $\mathbf{x}_B^\kappa$, while the desired one is $\mathbf{x}_{d_B^\kappa}$. The control strategy is to rotate the robot flange $\mathbf{L}_B^F$ so that the current knife tip tangent vector $\mathbf{x}_B^\kappa$ is aligned to the desired $\mathbf{x}_{d_B^\kappa}$, while keeping the knife tip $\mathbf{p}_B^\kappa$ at the same position. In other words, the robot flange is to be rotated around the estimated knife tip position, for an angle $\Delta\alpha$:

$$\Delta\alpha \sim \frac{\|\mathbf{x}_{d_B^\kappa} \times \mathbf{x}_B^\kappa\|}{\|\mathbf{x}_{d_B^\kappa}\| \, \|\mathbf{x}_B^\kappa\|} \tag{1}$$

calculated as a small angle approximation of the vector product between the desired and the actual orientation.

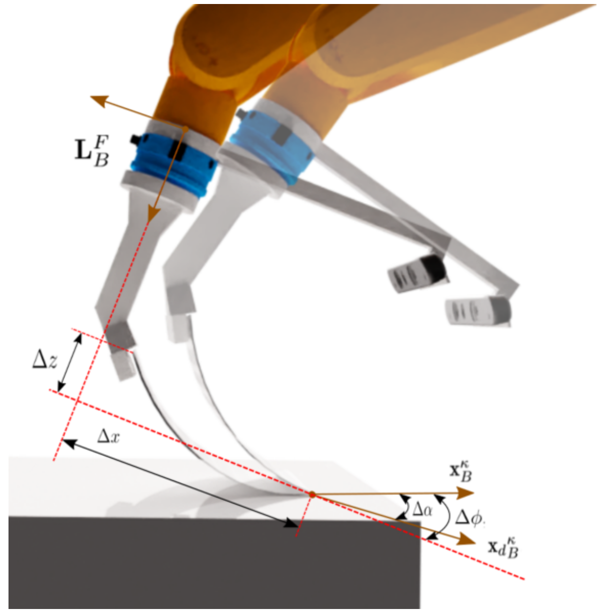

Fig. 3: Showing the values of the knife deflection estimation and knife inclination control concept. The knife is in a bent position (robot left pose), with estimated values of deflection ΔX, ΔZ, $\Delta\phi$. The estimated approach vector of the knife tip is shown as $\mathbf{x}_B^\kappa$, while the desired one is $\mathbf{x}_{d_B^\kappa}$. The control goal to compensate the angle error $\Delta\alpha$ by rotating the robot flange (robot right pose).

III. Knife shape estimate

Estimating plastering tool deformation is essential for a successful task execution. The net effect of the relative knife pose and the exerted force can be described with three deformation features, which are then estimated. Our estimation method is based on a deep CNN based black-box model with a MobileNet V2 architecture [8]. The history of CNN development is closely related to visual scene analysis, resulting in models trained for object detection and semantic segmentation. In this work, we build upon the network pretrained on the ImageNet dataset [9] and train it for deformation estimation via transfer learning.

For the learning phase, a dataset collection experiment is conducted, during which the ground truth labels for the three deformation features are extracted from the point cloud recordings of Intel RealSense D435 RGB-D camera. First, the 3D point-cloud data of a single reading is transformed into the 2D reading, as a vertical slice of the data in a predefined patch. This transformation maps the tool shape deformation in 2D space, and produces a mean descriptor of tool slices. The procedure used in the dataset collection is an example of an alternative method for measuring the same deformation, using point cloud input data. Such method can be deployed using an RGB-D camera as in this work, or with linear laser scanners.

Such procedures however require de-novo analytical

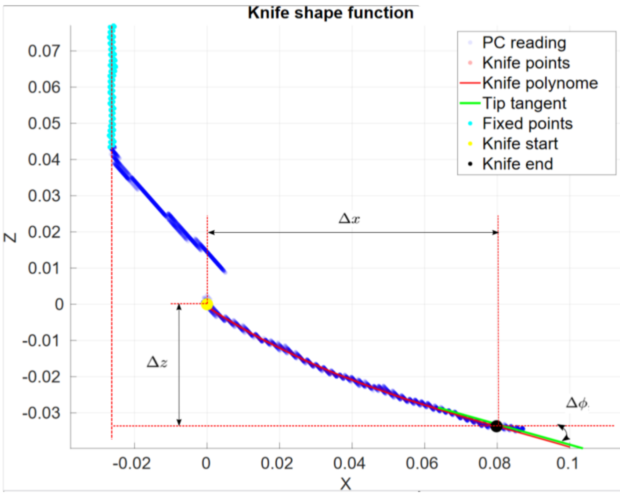

Fig. 4: Showing knife shape function, where three features of knife deflection are calculated. The transparent blue points present point-cloud reading, of a central part of the knife tool. In the next step, the flexible part of the knife tool is located, shown in transparent red, $X \in [0, 0.08]$. The beginning and end point of the flexible part are shown as yellow and black points. The red line presents polynomial fitted to points presenting flexible part of the tool. Using the given polynomial, knife tip angle is derived thought tip tangent, shown in green. The final knife deflection angle is derived as angle between tip tangent and fixed knife tool part shown in cyan.

modelling for each new estimated variable and additional point cloud manipulation, which is computationally expensive. CNNs are more easily expanded for estimation of multiple variables, and are better fit for highly non-linear estimation problems.

When generating the ground truth, the tool shape information can be extracted either with visual cues in the RGB spectrum, or using depth information. The latter approach is deployed here, where a discontinuity in the derivative along z axis in the local camera frame is identified as one end point of the tool. With an a priori known length of the knife, the points belonging to the tool are filtered from the identified end point next to the mount all the way to the tip. Finally, a third order polynomial curve is fitted to the extracted knife profile. Two positional deformation features, ΔX and ΔZ, are obtained from the position of the knife tip, and the third feature $\Delta\phi$ describing orientation is obtained as a derivative of the fitted polynomial at the tool tip with respect to the tool mount. This process is also depicted in Fig. 4.

IV. Experimental results

The evaluation of the proposed estimation method and control system is conducted though experiments using industrial manipulator KUKA KR10, equipped with force-torque sensor, Intel RealSense RGB-D camera, and specially designed plastering tool. The robot is controlled

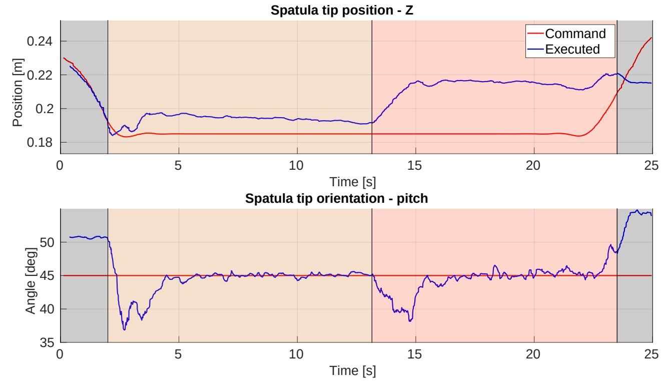

Fig. 5: Showing global position of knife tip in robot base frame during the close-loop motion. The results show that the robot adjusts the spatula tip position (Z-axis) in order to compensate for the disturbance in the orientation (pitch angle).

through the ROS environment and previously developed impedance based FDCC [7] controller. The experiment is conducted as plastering task on a piecewise-flat surface, with a single discontinuity between two flat surfaces. This is used to evaluate the dynamic response of the knife inclination control. The measurements of the experiment are shown in Fig. 5. The results clearly show the surface discontinuity at $t \approx 12s$, causing the knife deformation witch is adjusted with global position change upon coming into contact with a protruding surface profile.

V. Conclusion

In this work, deep learning is deployed in an industrial task involving deformable object manipulation. A pretrained CNN architecture is trained via transfer learning paradigm. From the raw camera images, a neural network estimates the values of the deformation features of the flexible robot tool. Even though deep learning has long ago found its roles in various robotic applications, including industrial, these were mostly at a higher control level, e.g. as decision modules in the state machine.

In this work, we show promising results for deployment of deep learning based inference within the lower level robot control as well, such as in the position control loop. To validate this, a reduced scope experimental setup was tested, where a single deformation feature of a flexible robot tool was controlled with the feedback signal provided by a neural network model. The experimental results show that the provided control architecture ensures the tip of the knife tracks the desired attack angle, even when submitted to abrupt (i.e. step) disturbances of the surface level. The remaining deformation features, as well as estimated contact force, will be used in the future work, where the approach will be extended with a coupled force-position controller. In this scenario, all the measured features will be used as feedback variables, ensuring proper knife inclination, position and applied force through the impedance based FDCC closed control loop.

ACKNOWLEDGMENT

This work has been supported by Croatian Science Foundation under the project Specularia UIP-2017-05-4042 [10]

References

[1] J. Sanchez, J.-A. Corrales, B.-C. Bouzgarrou, and Y. Mezouar, "Robotic manipulation and sensing of deformable objects in domestic and industrial applications: a survey," *The International Journal of Robotics Research*, vol. 37, no. 7, pp. 688–716, 2018.

[2] M. Polic, M. Car, F. Petric, and M. Orsag, "Compliant plant exploration for agricultural procedures with a collaborative robot," *IEEE Robotics and Automation Letters*, pp. 1–1, 2021.

[3] D. Navarro-Alarcon, H. M. Yip, Z. Wang, Y.-H. Liu, F. Zhong, T. Zhang, and P. Li, "Automatic 3-d manipulation of soft objects by robotic arms with an adaptive deformation model," *IEEE Transactions on Robotics*, vol. 32, no. 2, pp. 429–441, 2016.

[4] L. Scalera, S. Seriani, A. Gasparetto, and P. Gallina, "Watercolour robotic painting: a novel automatic system for artistic rendering," *Journal of Intelligent & Robotic Systems*, vol. 95, no. 3, pp. 871–886, 2019.

[5] B. Maric, A. Mutka, and M. Orsag, "Collaborative human-robot framework for delicate sanding of complex shape surfaces," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2848–2855, 2020.

[6] M. Polic, I. Krajacic, N. Lepora, and M. Orsag, "Convolutional autoencoder for feature extraction in tactile sensing," *IEEE Robotics and Automation Letters*, vol. 4, no. 4, pp. 3671–3678, 2019.

[7] S. Scherzinger, A. Roennau, and R. Dillmann, "Forward dynamics compliance control (fdcc): A new approach to cartesian compliance for robotic manipulators," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 4568–4575, Sep. 2017.

[8] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "Mobilenetv2: Inverted residuals and linear bottlenecks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4510–4520, 2018.

[9] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, "ImageNet Large Scale Visual Recognition Challenge," *International Journal of Computer Vision (IJCV)*, vol. 115, no. 3, pp. 211–252, 2015.

[10] M. Orsag *et al.*, "Specularia." http://specularia.fer.hr, 2019. Accessed: 2019-09-08.