Safe Grasping with a Force Controlled Soft Robotic Hand

Tran Nguyen Le, Jens Lundell and Ville Kyrki

Abstract—Safe yet stable grasping requires a robotic hand to apply sufficient force on the object to immobilize it while keeping it from getting damaged. Soft robotic hands have been proposed for safe grasping due to their passive compliance, but even such a hand can crush objects if the applied force is too high. Thus for safe grasping, regulating the grasping force is of uttermost importance even with soft hands. In this work, we present a force controlled soft hand and use it to achieve safe grasping. To this end, resistive force and bend sensors are integrated in a soft hand, and a data-driven calibration method is proposed to estimate contact interaction forces. Given the force readings, the pneumatic pressures are regulated using a proportional-integral controller to achieve desired force. The controller is experimentally evaluated and benchmarked by grasping easily deformable objects such as plastic and paper cups without neither dropping nor deforming them. Together, the results demonstrate that our force controlled soft hand can grasp deformable objects in a safe yet stable manner.

I. INTRODUCTION

A stable yet safe grasp requires a robotic hand to apply sufficient force on the target object to not harm it but still immobilize it. Recently, soft hands have been proposed for safe grasping due to their passive compliance. However, as shown in Fig. 1 even such hands can deform objects if the applied force is too high. There is, therefore, a need to control the grasping force also in soft hands.

Research on soft hands has mainly focused on hand design [1]–[8]. Only recently have works started to address the integration of sensing capabilities such as position [9], [10] and force sensing [11]. However, the authors found the existing solution for force sensing to be insufficient for contact detection, especially for small objects [11]. In this work, we aim to show that force estimation is possible to allow both contact detection as well as control of contact forces for safe grasping.

To this end, we propose to integrate off-the-shelf resistive bend and force sensors in each finger of a hand to estimate the contact force and feed it into a force controller for each finger. In order to extract reliable force measurements, we propose a data-driven sensor characterization and calibration method for such sensors. Given the calibrated sensors, the real contact force is estimated by subtracting the residual force the sensor senses when bending in free space from the actual force reading. The residual force is also learned. The estimated force is then used in a Proportional-Integral (PI) controller to control the set-point force for each finger.

The complete force controller is experimentally validated and compared to no force controller on a physical grasping experiment where the objective is to grasp deformable and fragile objects in a stable manner without neither destroying nor deforming them.

The main contributions of this work are: (i) integration of resistive bend and force sensors in a soft hand (Section III), (ii) calibration of the sensors to estimate contact force (Section IV), (iii) a force controller for the soft hand (Section V), and (iv) an empirical evaluation of the controller demonstrating that using a force controller deformable objects can be grasped in a stable yet safe manner (Section VI).

II. RELATED WORK

Most of the research in soft robotic hands has focused on the hand design itself where the main actuators have been the Soft Pneumatic Actuator (SPA) [12]. SPAs are constructed of soft and deformable matter and are pneumatically actuated. Such actuators were used in the pioneering soft hand design by Ilievski et al. in 2011 [3] where they presented a three-layer starfish inspired soft gripper using embedded pneumatic networks or PneuNets. The multilayer structures, where two active layers were separated by a passive layer, allowed the gripper to perform a wide range of motions, but due to its construction it could only withstand a small amount of pressure resulting in a weak grasping force.

Recently, alternative soft hand designs that can attain higher grasping forces have been proposed, including the well known anthropomorphic RBO Hand 2 [5] and DRL
Soft Hand [13]. The RBO Hand 2 consists of seven fiber-reinforced pneumatic continuum actuators acting as fingers and palm. Although the anthropomorphic design enabled dexterous grasping, one downside is the negative curvature of the thumb, meaning that the backside of the thumb is the primary contact surface rather than its front side, which makes it problematic to attach sensors to it. Compared to the RBO Hand 2, the kinematics of the DRL Soft Hand, where two fingers are parallel and opposes the third, allow easy sensor integration and was, therefore, the source of inspiration for the hand proposed in this work.

Despite the wide range of research in soft hand designs, few works have studied how to incorporate sensing capabilities in such hands. One possible reason for the lack of research in sensorized soft hands is the few existing cheap off-the-shelf sensors that can be integrated into a SPA. However, recently Elgeneidy et al. [9] proposed the following sensors for measuring and controlling position of SPAs: (i) conductive elastomer sensors, (ii) sensors made from liquid metal or (iii) resistive flex sensors.

Conductive elastomer sensors were used in [14] to control the displacement of the soft gripper with an adaptive neuro-fuzzy inference strategy. Unfortunately, the accuracy of such sensors quickly deteriorates as the distribution of carbon particles inside the elastomer material is disturbed by the actuator’s repeated deformation. The more durable liquid metal sensors were integrated into a soft gripper in [15] to detect the presence of grasped objects, and in [16] to acquire pressure, force, and position data which was subsequently fed to a Proportional-Integral-Derivative (PID) controller to control the position of the finger and grasping force. However, to acquire the data, they used the eGain liquid metal sensor [17] that was fabricated from scratch, which is a time-consuming and error-prone process. Additionally, the force sensor was placed at the tip of the actuator, restricting the force controller to only work with pincer grasps or on large objects. In this work, we target objects of diverse sizes, including small objects and as such the eGain sensor is not applicable.

The third sensor type mentioned in [9], the resistive bend flex sensors, are cheap, widely available, and easy to integrate in soft hands. For instance, resistive bend sensors have been used for haptic identification of grasped objects [13] and for predicting and controlling the position, i.e., bending angle of a pneumatic-driven actuator [9]. The work in [13] was later improved in [11] by adding a Force Sensitive Resistive (FSR) sensor to strengthen the grasp by detecting the contact between the hand and objects. They reported, however, that the force sensor provided unreliable data, resulting in extremely poor performance in contact detection, especially on small objects. This problem stems from placing the force sensor only at the tip of the finger, which will not make contact with small objects such as a tennis ball, resulting in no readings. In this work, we also use FSRs due to their simplicity and availability but opt for the kinds that measure forces along a wider area as they enable measuring forces even on small objects.

III. RESISTIVE BASED SENSING

To do complex manipulation tasks, robotic hands need position and force feedback [18]. To achieve this for soft hands, we propose integrating deformable resistive force and bend sensors onto the finger of the RBO Hand 2 proposed in [5]. Fig. 2 shows the sensors integrated into the fabricated actuator. The body of the fabricated actuator is divided into two parts: an extensible and an inextensible layer.

To keep the bend sensor in place, it was encapsulated in the inextensible layer shown as the orange line in the figure. In contrast to the bend sensor, the force sensor illustrated by the green line in the figure needs to be in contact with the environment to get measurements; thus it was glued directly to the outer surface of the inextensible layer using freshly mixed Dragon Skin 10 silicone. Next, we describe the design and working principle of these sensors.

A. Position sensing

To measure the internal state (position) of SPAs we used resistive flex sensors (bend sensors)\(^1\). One side of the sensor consists of a layer of polymer ink which is embedded with conductive particles, as shown in Fig. 3. The particles provide the ink with a certain amount of resistance when the sensor is straight. When the sensor bends away from the ink, the conductive particles move further apart as shown in Fig. 3 which, in turn, increases the resistance. Once the sensor return to the initial pose, the resistance also returns to the original value. Hence, the change in the resistance can be used to determine the curvature of the sensor.

\[\text{Flex Sensor 4.5"} : \text{https://www.sparkfun.com/products/8606}\]

---

\(^1\)Flex Sensor 4.5" : https://www.sparkfun.com/products/8606
B. Force sensing

To measure the grasping force applied by SPAs, we use FSRs. FSRs are designed to measure the presence and relative magnitude of localized physical pressure. The FSR used to measure the force in [11] was placed only at the tip of the finger but, given the fact that soft hands typically are developed to mimic human’s grasping behaviour, i.e., wrapping an entire finger around the surface of an object, placing the force sensor at such a location is not optimal for detecting contact between the hand and the object. Based on this, we opted for force sensors that can provide measurements along the body of the whole finger rather than only at the tip. To meet this requirement, we chose a strip FSR with rectangle shape\(^2\).

An FSR consists of a resistive polymer layer and a conductive film as illustrated in Fig. 4 and the working principle is similar to that of the bend sensor. Specifically, the spacer placed in between the two layers to avoid contact between them results in a very high resistance when no pressure is applied. When pressure is applied, the resistive polymer starts to make contact with the conductive film, resulting in more conduction paths (lowering resistance).

**Fig. 4:** The left figure shows the design of a strip FSR and its behavior when no pressure is applied. When pressure is applied on the sensor, the conductive particles move and make contact with the conductive film, resulting in more conduction paths (lowering resistance).

### IV. Data-Driven Contact Force Estimation

#### A. Internal Force Characterization

To characterize the internal force of the force sensor, a finger of our soft hand with integrated sensors was actuated in free space with a 60 kPa ramp input. Once the internal pressure in the finger reached 60 kPa, the input was zeroed, and the finger returned to its initial position. The top left plot in Fig. 5 shows the force measurement of the force sensor against the bending angle after 35 repetitions. Theoretically, the force measurements should remain zero as there is no contact between the finger and the environment. However, as seen in the figure, the force reading increases the more the finger is bent. Due to such sensor characteristics, the FSR force measurements of a bent finger are incorrect. Thus, removing the effect of the internal force from the sensor readings is crucial to enable force control of the fingers.

#### B. Contact Force Estimation

We model the actual contact force \(F_c\) for the finger by the difference between the measured force \(F_m\) and the internal force \(F_i\)

\[
F_c = F_m - F_i. \tag{1}
\]

Thus, to estimate the actual contact force \(F_c\), we 1) learn the internal force \(F_i\) caused by bending in free space and 2) subtract the estimated internal force from the measured force.

We cast the learning of the internal force model \(F_i\) for each finger as a polynomial regression problem since the relationship between internal force and bending angle of the finger is non-linear (Fig. 5). Thus the internal force is expressed as

\[
F_i(x) = \sum_{d=0}^{D} w_d x^d = w^T x, \tag{2}
\]

where \(w = [w_1, \ldots, w_D]\) are the parameters to learn, \(x\) the bending angle of the finger, and \(D\) the maximum degree of the polynomial function. We estimate the model parameters by first mapping the bending angle \(x\) to a higher dimensional feature space using the feature map \(\phi(x) = [x^d, \ldots, 1]^T\), resulting in a transformed feature vector \(x = [x^d, \ldots, 1]^T\), and then applying ordinary least squares so that the optimal parameters \(w^*\) can be found by \(w^* = (X^T X)^{-1} X^T F_i\).

To choose the model complexity, that is the maximum degree \(D\) of the polynomial function, we used the Bayesian Information Criterion (BIC) [19]

\[
\text{BIC} = \ln(n)k - 2\ln(\hat{L}), \tag{3}
\]

where \(\hat{L}\) is the maximized value of the likelihood of the model, \(n\) is the number of observations, and \(k\) is the number of parameters. The model with smallest BIC value is considered the best.

\(^2\)Force Sensitive Resistor - Long: https://www.sparkfun.com/products/9674

\(^3\)https://cdn.sparkfun.com/datasheets/Sensors/Pressure/FSR408-Layout2.pdf
V. FORCE CONTROLLER

To control the grasping force of the soft hand, we propose using a discrete PI controller

\[ u_n = K_p e_n + K_i \sum_{k=1}^{n} e_k, \]

(4)

where \( K_p \) and \( K_i \) are the proportional and integral terms respectively, \( T \) is the sampling period, and \( e_n \) is the force error between the target value and measured value at the \( n \)-th moment of sampling. The output \( u_n \) is a Pulse Width Modulation (PWM) signal.

VI. EXPERIMENTS AND RESULTS

The main questions addressed experimentally were:

1) What is the accuracy of the contact force estimation?
2) What is the accuracy of the force controller?
3) Does the force controlled soft hand enable safe grasping?

In order to provide justified answers to these questions, we conducted three experiments. The first experiment examines the contact force estimation accuracy, the second one the proposed force controller accuracy while the third evaluates safe grasping in terms of grasping deformable objects without neither damaging nor dropping them.

A. Experimental setup

All the experiments were evaluated on a soft robotic hand embedded with the bend and force sensors mentioned in Section III. For the hand design, we used the same finger structure as RBO Hand 2 [5] but opted for a kinematic structure similar to the DRL Soft Hand [13] as it allows power grasping. As a result, our soft hand consisted of three fingers, in which two fingers are on one side, and one finger is on the opposite side. The final soft hand is shown in Fig. 1.

To pneumatically control the hand, we used the soft robotics toolkit controller platform\(^4\). The input pressure was regulated with PWM, and the control rate was 60 Hz. However, at such a high control rate, the high-speed switching of PWM caused the hand to vibrate, which consequently induced noise into the force readings. To decrease the noise, we implemented the pneumatic low pass filter proposed in [20].

B. Estimating contact force

Our hypothesis is that the internal force is correlated to the curvature of the finger. To test this, we gathered force data at different bending angles for each finger. The data in Fig. 5 shows the force measurements for each finger at different bending angles. Although the data for each finger, such as bending angle range differ from each other due to the manual fabrication process, we can clearly see the correlation between the bending angle and the force. Next, we fitted a separate polynomial model (2) to the data for each finger. According to the BIC values presented in Fig. 5, a fourth-degree polynomial fitted the data for each finger best, which is also indicated by the high \( R^2 \) values.

Next, using the models to predict the internal force, we evaluated the accuracy of the estimated contact force in (1). The accuracy was measured by first actuating one finger to press against a scale until the reading on the scale reached a predefined threshold set to 200 gram (approximately 2 N). Once the threshold was reached, the actual contact force was

\(^4\)Fluidic Control Board, https://softroboticstoolkit.com/book/control-board
estimated by subtracting the predicted internal force from the force measurement obtained from the sensor.

The estimated contact force against the reference contact force is plotted in Fig. 6. Although the graph shows that the estimate contact force varies slightly around the actual contact force, the error only ranges from 0.01 to 0.15 N at most, which is within the tolerance for the objects we will later grasp. All in all, estimating the contact force by simply subtracting the internal force from the real measurement is sufficiently accurate.

C. Force Control

Before conducting the experiment, we experimentally fine-tuned the proportional $K_p$ and integral $K_i$ gains of the force controller to 10 and 1.5, respectively. To experimentally evaluate the accuracy and stability of the force controller, each finger had to reach and track a variable reference signal. First, a finger was actuated with 65 kPa pressure to make contact with a solid object. Then, the step reference signal was increased from 0 to 3 N, and after 60 seconds the reference signal was set to 2 N. The sensory feedback from the embedded sensors was continuously fed to the internal force predictive model to estimate the actual contact force. The difference between the target and current contact force was then fed to the PI controller in (4) whose output was the corresponding amount to be added to (or subtracted from) the current duty cycle signal. The experiment was repeated 5 times. The contact force response of one finger is shown in Fig. 7. The force response of the finger closely followed the step reference signals with a Root Mean Square (RMS) error of 0.1 N. Moreover, the settling time of the finger was roughly 400 ms.

To enhance the robustness of the grasping system, the force controller should only be activated when contact is detected. One option to achieve this is to utilize a switching mechanism between position and force control. We experimentally tested such a switching mechanism by having a finger reach a target contact force of 2.5 N only after contact was made. Initially, the finger was slowly actuated from a duty cycle of 0% until contact with a solid object was detected based on the estimated contact force. After contact was established, the force controller was activated to regulate the pressure to achieve the target contact force.

The duty cycle output from the controller and the contact force response are shown in Fig. 8. From the top figure, one can conclude that to achieve the target contact force the controller used a duty cycle value in the range of 45% - 55%. The main reason for the fluctuating duty cycle originates from fluctuations in the estimated contact force response caused by residual oscillations in the sensory reading. From the bottom figure, it is observed that the contact force response settled to a value of approximately 2.5 N in roughly 800 milliseconds. The RMS error between the measured and the target contact force was 0.21 N. In conclusion, regardless of the small fluctuations in the measured contact force and the output duty cycle, the proposed control strategy was successful in controlling the finger to achieve a target contact force in reasonable settling time. Furthermore, the proposed control strategy did not overshoot at the time of contact.
Table I: The grasping results for the deformable objects.

| Target contact force of the opposable finger (N) | Empty plastic cup | Empty paper cup |
|-----------------------------------------------|--------------------|-----------------|
|                                               | Dropped percentage | Deformed percentage | Dropped percentage | Deformed percentage |
| 4                                             | 0%                  | 100%             | 0%                | 100%               |
| 3                                             | 0%                  | 100%             | 0%                | 80%                |
| 2                                             | 0%                  | 90%              | 0%                | 20%                |
| 1.5                                           | 0%                  | 40%              | 30%               | 10%                |
| 1                                             | 0%                  | 10%              | 80%               | 0%                 |
| 0.5                                           | 60%                 | 0%               | 100%              | 0%                 |

Fig. 9: The target objects used in the safe grasping experiment.

Together, all these results confirm that it is possible to control the interaction force between the soft hand and objects in a safe, accurate, and fast manner. Such features are of uttermost importance in safe grasping.

D. Safe Grasping

Based on the results from the previous experiments, our proposed force controller exhibits characteristics for safe grasping. In safe grasping, the goal is to grasp deformable objects that can easily deform, such as the plastic cup seen in Fig. 1, in a stable manner. We experimentally evaluated if the proposed force controlled soft hand can do safe grasping by grasping three sensitive objects: an empty plastic cup, an empty paper cup, and an empty eggshell all shown in Fig. 9. Of these objects, the empty plastic and paper cup represents deformable objects while the empty eggshell represents a fragile object.

For this experiment, the soft hand was fixed to a handle, as shown in Fig. 1. As the soft hand had two fingers on one side and one on the opposite, to stabilize the objects the targets contact forces of the three fingers were set in such a way that the sum of the contact force of the two fingers was equal to that of the opposable finger. We tested six different force set-points for the opposable finger: 4, 3, 2, 1.5, 1, and 0.5 N. To evaluate a grasp, the hand first grasped the object until the target contact force was achieved and then we manually moved the handle upward 30 cm to lift the object and finally shook it randomly. During the process, a grasp was successful if the object neither deformed in the case of deformable objects nor broke in the case of fragile objects nor slipped away from the hand. We evaluated ten grasps for each target force amounting to 60 grasps in total.

The grasping result on the deformable objects are presented in Table I. As suspected, a higher contact force lowers the dropping rate but increases the deformation rate. The results show that even soft hands, which have been proposed for safe grasping due to their passive compliance, can completely deform objects if the force is too high. For instance, the plastic cup, which is less durable than the paper cup, can be deformed with as low a contact force as 1 N. The paper cup, on the other hand, can withstand up to 2 N of contact force. The minimum grasping force to successfully grasp deformable object can also be deduced from the results.

In addition, the experiment was also conducted on an empty eggshell to evaluate the proposed control strategy in the case of fragile objects. In this case, the eggshell never broke not even with maximum target contact forces. However, with a soft hand that can generate much larger grasping forces, crushing fragile objects is indeed feasible. All in all, the results emphasize the need for integrating sensors into soft hands to manipulate deformable and fragile objects.

VII. CONCLUSIONS

We presented a force controlled soft robotic hand and used it for safe grasping. The key component was to integrate both resistive bend and force sensors onto the hand’s fingers and apply a data-driven method to estimate the actual contact force between the fingers and the objects. The estimated contact force was then fed into a PI force controller to keep a constant grasping force. We experimentally validated our force controller by comparing it to no force controller on a grasping experiment where the objective was to grasp deformable objects in a stable manner without damaging them. The results show that the force controlled soft hand could grasp the tested objects without neither dropping them nor causing significant deformation.

All in all, the work presented here demonstrates that applying a data-driven calibration method can make otherwise unreliable force sensor readings reliable enough to be used in a force feedback controller. This, in turn, poses new interesting research questions. For instance, is it possible to learn an accurate dynamics model from the force and bend data? If so, can such a model be used to do dexterous manipulation by a soft robotic hand with, e.g., model predictive control or model-based reinforcement learning? Dexterous manipulation, together with the safety inherited from the softness properties of soft hands offer great potential for robots to interact with human in complex environments.
REFERENCES

[1] S. Schulz, C. Pylatiuk, and G. Brethauer, “A new ultralight anthropomorphic hand,” in Proceedings 2001 ICRA. IEEE International Conference on Robotics and Automation, vol. 3, May 2001, pp. 2437–2441.
[2] A. M. Dollar and R. D. Howe, “The highly adaptive sdm hand: Design and performance evaluation,” The International Journal of Robotics Research, vol. 29, no. 5, pp. 585–597, 2010.
[3] F. Ilievski, A. D. Mazzeo, R. F. Shepherd, X. Chen, and G. M. Whitesides, “Soft robotics for chemists,” Angewandte Chemie International Edition, vol. 50, no. 8, pp. 1890–1895, 2011.
[4] R. Deimel and O. Brock, “A compliant hand based on a novel pneumatic actuator,” in 2013 IEEE International Conference on Robotics and Automation, May 2013, pp. 2047–2053.
[5] R. Deimel and O. Brock, “A novel type of compliant and underactuated robotic hand for dexterous grasping,” Int. J. Rob. Res., vol. 35, no. 1-3, pp. 161–185, Jan. 2016.
[6] K. C. Galloway, K. P. Becker, B. Phillips, J. Kirby, S. Licht, D. Tchernev, R. J. Wood, and D. F. Gruber, “Soft robotic grippers for biological sampling on deep reefs,” Soft Robotics, vol. 3, no. 1, pp. 23–33, 2016.
[7] J. Zhou, S. Chen, and Z. Wang, “A soft-robotic gripper with enhanced object adaptation and grasping reliability,” IEEE Robotics and Automation Letters, vol. 2, no. 4, pp. 2287–2293, Oct 2017.
[8] P. Glick, S. A. Suresh, D. Ruffatto, M. Cutkosky, M. T. Tolley, and A. Parness, “A soft robotic gripper with gecko-inspired adhesive,” IEEE Robotics and Automation Letters, vol. 3, no. 2, pp. 903–910, April 2018.
[9] K. Elgeneidy, N. Lohse, and M. Jackson, “Bending angle prediction and control of soft pneumatic actuators with embedded flex sensors - a data-driven approach,” Mechatronics, vol. 50, pp. 234 – 247, 2018.
[10] L. Chin, M. C. Yuen, J. Lipton, L. H. Trueba, R. Kramer-Bottiglio, and D. Rus, “A simple electric soft robotic gripper with high-deformation haptic feedback,” in 2019 International Conference on Robotics and Automation (ICRA), May 2019, pp. 2765–2771.
[11] B. S. Homberg, R. K. Katzschmann, M. R. Dogar, and D. Rus, “Robust proprioceptive grasping with a soft robot hand,” Auton. Robots, vol. 43, no. 3, pp. 681–696, Mar. 2019.
[12] J. Shintake, V. Cacucciolo, D. Floreano, and H. Shea, “Soft robotic grippers,” Advanced Materials, vol. 30, no. 29, p. 1707035, 2018.
[13] B. S. Homberg, R. K. Katzschmann, M. R. Dogar, and D. Rus, “Haptic identification of objects using a modular soft robotic gripper,” in 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Sep. 2015, pp. 1698–1705.
[14] D. Petković, M. Issa, N. D. Pavlović, L. Zentner, and A. Ojbašić, “Adaptive neuro fuzzy controller for adaptive compliant robotic gripper,” Expert Syst. Appl., vol. 39, no. 18, pp. 13295–13304, Dec. 2012.
[15] R. Adam Bilodeau, E. L. White, and R. K. Kramer, “Monolithic fabrication of sensors and actuators in a soft robotic gripper,” in 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Sep. 2015, pp. 2324–2329.
[16] J. Morrow, H. Shin, C. Phillips-Grafflin, S. Jang, J. Torrey, R. Larkins, S. Dang, Y. Park, and D. Berenson, “Improving soft pneumatic actuator fingers through integration of soft sensors, position and force control, and rigid fingernails,” in 2016 IEEE International Conference on Robotics and Automation (ICRA), May 2016, pp. 5024–5031.
[17] Y. Park, B. Chen, and R. J. Wood, “Design and fabrication of soft artificial skin using embedded microchannels and liquid conductors,” IEEE Sensors Journal, vol. 12, no. 8, pp. 2711–2718, Aug 2012.
[18] K. Hertkorn, M. A. Roa, and C. Borst, “Planning in-hand object manipulation with multifingered hands considering task constraints,” in 2013 IEEE International Conference on Robotics and Automation, May 2013, pp. 617–624.
[19] G. Schwarz, “Estimating the dimension of a model,” The Annals of Statistics, vol. 6, no. 2, pp. 461–464, 1978.
[20] M. Memarian, R. Gorbet, and D. Kulic, “Control of soft pneumatic finger-like actuators for affective motion generation,” in 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Sep. 2015, pp. 1691–1697.