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Adaptive perception: learning from sensory predictions to extract object shape with a biomimetic fingertip

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***Abstract*— In this work, we present an adaptive perception method to improve the performance in accuracy and speed of a tactile exploration task. This work extends our previous studies on sensorimotor control strategies for active tactile perception in robotics. First, we present the active Bayesian perception method to actively reposition a robot to accumulate evidence from better locations to reduce uncertainty. Second, we describe the adaptive perception method that, based on a forward model and a predicted information gain approach, allows to the robot to analyse 'what would have happened' if a different decision 'would have been made' at previous decision time. This approach permits to adapt the active Bayesian perception process to improve the performance in accuracy and reaction time of an exploration task. Our methods are validated with a contour following exploratory procedure with a touch sensor. The results show that the adaptive perception method allows the robot to make sensory predictions and autonomously adapt, improving the performance of the exploration task.**

I. INTRODUCTION

Robots are expected to perform not only a variety of tasks through the interaction with the environment, but also doing them safely and accurately [1]. Safe interaction with the environment can be achieved using the sense of touch that, commonly underrated, provides an important and sophisticated nonverbal communication channel [2], [3]. Cognitive capabilities for perception and learning, together with touch, can provide intelligent systems capable to observe and adapt their decisions and actions to improve their performance [4]. This perception-action loop offers a promising framework for autonomous systems, however, computational methods for its implementation are still under development.

In this work, a computational method that allows a robot to actively perceive, make decisions and adapt based on the observation of its actions is presented. This work extends our previous work on active sensing for robot control [5]. First, the Bayesian formulation for active perception and sensing is described. This approach, together with a sequential analysis method, permits to iteratively accumulate evidence and make decisions while dealing with uncertainty from sensor measurements [6]. It has been shown that probabilistic approaches permit robots to perform better for a diversity of stimuli and in the face of sensor limitation [7], [8].

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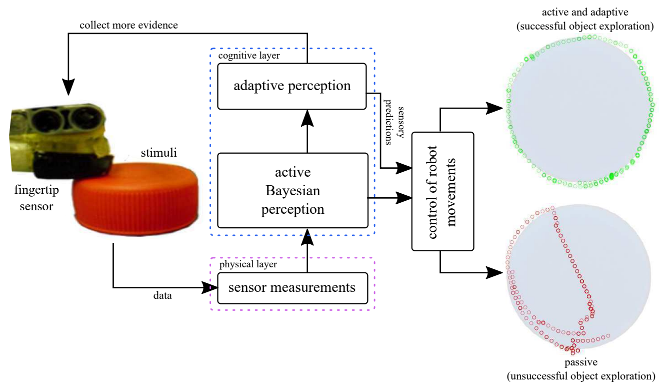

Fig. 1. Adaptive perception process that, together with an active Bayesian formulation, allows a robot to learn the sensory predictions based on the observation of its past actions to adapt during an exploration task.

For adaptive perception, we extend the Bayesian formulation with a propose method for learning of sensory predictions. The learning process is based on a forward model and a modified predicted information gain (PIG) approach [9]. First, the PIG approach gives to a robot the capability to observe and analyse 'what would have happened' if a different action 'would have been made' at previous time for an specific task. Second, the output from this observation is used by a forward model to learn the sensory predictions that allows to adapt the Bayesian formulation. Then, adaptation process is achieved by the combination of sensory predictions with the initial prior, which is inspired by the way in that humans combine sources of information to adapt to make accurate decision and actions [10], [11].

A layered architecture is used to implement our Bayesian formulation and adaptive perception method. This architecture is composed of layers for sensing, perception, decision-making, active control and adaptive perception. Layered architectures have shown to be needed for intelligent and autonomous robotics [12], [13]. Validation of our work is based on a contour following exploratory procedure to extract object shape using a biomimetic fingertip sensor. First, real-time experiments show a better performance achieved by active perception, over a passive approach, to extract object shape. Second, adaptation of the Bayesian perception process, by the use of sensory predictions, demonstrates to be able to improve the accuracy and reaction time of the exploration task over the non-adaptive active perception.

Overall, this work demonstrates that adaptation of the active perception process is needed to develop robust systems, but also to improve their cognitive capabilities to perform better perception, learning and decision-making processes during the interaction with the changing environment.

II. METHODS

A. Tactile sensor

For this work, we use a biomimetic fingertip sensor that resembles a human fingertip given its rounded shape and dimensions (Figure 2). This tactile sensory system, which is part of the iCub humanoid, allows to perform tasks such as perception, exploration and telepresence through the interaction with the environment [14], [15].

This sensor is built with a capacitive technology containing an array of twelve taxels (tactile elements) of $\sim$4 mm diameter each. These taxels cover the inner core of the fingertip with a flexible printed circuit board (PCB). Then, a dielectric layer of silicone foam of $\sim$2 mm is placed above the PCB. The flexible and conductive outer layer is composed of a carbon black-silicone material, which allows deformations of the surface of fingertip sensor, analogous to those that occur with the human fingertip. The twelve capacitive measurements read from the taxels are digitised locally using a capacitance-to-digital converter (CDC) placed in the PCB of the tactile sensor. These measurements obtained with a sample rate of 50 Hz are digitised with 8 bit resolution (0–255 values). Thus, the digital measurements are sent to a computer through a CAN-bus to be processed by our method for perception and control describe in Section II-D.

B. Robotic platform

An exploratory robotic platform was constructed to provide mobility to the fingertip sensor. The platform is composed of two different robots: 1) a Cartesian robot arm (YAMAHA XY-x series) with 2-DoF in the x- and y-axes, and 2) a Mindstorms NXT Lego robot with 1-DoF. The NXT robot is mounted on the Cartesian arm in a proper manner to generate systematic movements in the x-, y- and z-axes.

The tactile sensor, attached to the exploratory robotic platform, performs precise positioning movements in the x- and y-axes with an accuracy of $\sim 20\mu$m. The NXT robot does not allow highly precise movements, but these are good enough to perform movements along the z-axis. As result, the biomimetic fingertip sensor is capable to perform exploratory movements based on taps or palpating, and controlled by tactile feedback (Figure 2). The configuration of the robotic platform and the degrees of freedom do not allow rotations around the z-axis of sensor. Therefore, the fingertip sensor keeps the same orientation during all the experiments.

A tactile exploration based on taps or palpating was chosen for two reasons. First, to reduce damage to the sensor, otherwise, a sliding motion could deteriorate the outer layer after repeating the experiments several times. Second, to provide an exploration through repetitive palpations, useful for robotic system that are not able to slide their sensors. Third, humans typically perform palpating exploratory procedures in situations where damage may occur (e.g. on a hot or sharp surface) or for inspection (e.g. medical diagnosis).

C. Data collection

Tactile datasets, composed of angle and position classes, were systematically collected for validation. These datasets are used for training and testing our method with a contour following task. The surface of a plastic object attached to a table was used as stimulus. The data were collected with a palpating procedure over the object along its radius; starting from a flat surface, then passing through the edge, and finishing on air (see Figure 3). Each tap performed by the sensor had a duration of 2 sec, collecting a dataset of 12×100 digitised pressure measurements (sampling frequency 50 Hz and 12 taxels). The palpating movements were performed along an 18 mm distance with 0.2 mm steps, generating a total of 90 taps for each edge orientation. Then, position classes are formed by grouping 5 taps per class, thereby obtaining a total of 18 position classes of 1 mm span each. The data collection procedure was performed around the plastic object at 5 deg steps, generating 72 angle classes that cover a range of 360 deg. In total, a large dataset with 1296 classes (72 angle $\times$ 18 position classes) was formed. The complete process was repeated two times to generate two datasets, one for training and one for testing. Figure 4 shows an example of the data collected at 0 deg along 18 mm from the plastic object used as stimulus.

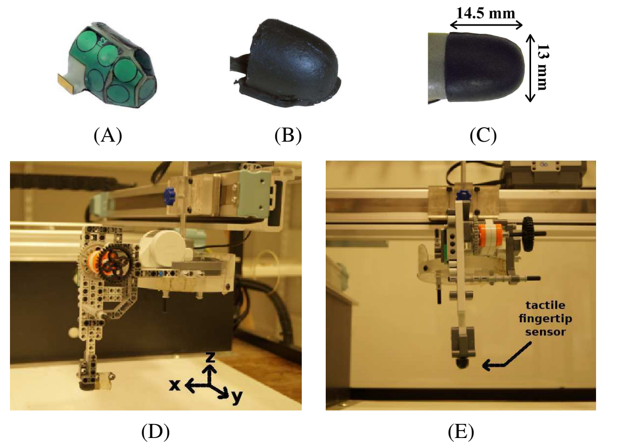

Fig. 2. Tactile sensory system and exploratory robotic platform. (A) Flexible PCB and taxels of the iCub fingertip sensor. (B) Fingertip sensor covered with dielectric silicon foam. (C) Dimensions of the biomimetic sensor. (D) Robotic platform to explore in x-,y- and z-axes. (E) Fingertip sensor mounted on the robotic platform for exploration tasks.

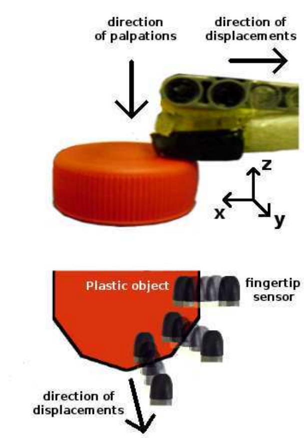

Fig. 3. Biomimetic fingertip sensor palpating over a plastic object used as stimulus for data collection. Tactile data were collected around the complete object two times, yielding a dataset for training and one for testing.

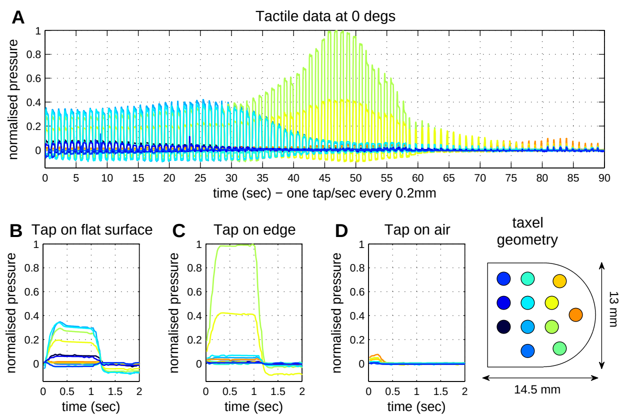

Fig. 4. Sample of tactile data at 0 degrees. (A) Normalised pressure data along 18 mm (90 taps). Sensor data from tactile contacts on (B) the flat surface, (C) edge and (D) air. (E) Arrangement of taxels in the fingertip.

D. *Adaptive Bayesian perception*

The proposed method for adaptive perception in autonomous tactile exploration is composed of two modules: 1) an active Bayesian perception approach, and 2) a forward model for learning of sensory predictions.

1) Active Bayesian perception: Our study is based on previous works on active perception applied to exploration, recognition and human-robot interaction using various stimuli [16], [17], [18]. Bayesian approaches have also shown their benefits, combined with other machine learning methods, for analysis of multimodal and big datasets [19].

The Bayesian perception, together with a sequential analysis method, recursively updates the posterior probabilities from the prior probabilities and the likelihoods obtained from a measurement model of the touch data. Here, sensor measurements are represented by z and perceptual classes are represented by $c_n \in C$. Each class c_n corresponds to a (x_l, w_i) pair where x_l and w_i are the position and angle respectively. The Bayesian update process is as follows:

$$P(c_n|z_{1:t}) = \frac{P(z_t|c_n)P(c_n|z_{1:t-1})}{P(z_t|z_{1:t-1})}, \tag{1}$$

where the posterior is defined by $P(c_n|z_{1:t})$, the likelihood and prior are $P(z_t|c_n)$ and $P(c_n|z_{1:t-1})$. We assumed the prior at time $t = 0$ uniformly distributed for all classes $P(c_n) = P(c_n|z_0) = 1/N$. The normaliser $P(z_t|z_{1:t-1})$ ensures to have all hypotheses summing to 1. Each tap performed by the tactile sensors provides a time series of digitised pressure values from the K taxels (12 taxels). The measurement model is built with a nonparametric approach based on histograms from the training datasets. These histograms are uniformly constructed over 100 bins, and they are used to evaluate a tactile contact z_t at time t to estimate the likelihood of a perceptual class $c_n \in C$. The measurement model is obtained as follows:

$$P(s|c_n, k) = \frac{h(s,k)}{\sum_s h(s,k)} \tag{2}$$

where $h(s, k)$ is the number of observed values in the histogram of taxel k. These values are normalised by $\sum_s h(s, k)$ to ensure proper probabilities that sum to 1. The, the likelihood of contact z_t given a perceptual class c_n is obtained by the evaluation of Equation (3) over all taxels as follows:

$$\log P(z_t|c_n) = \sum_{k=1}^{K_{\text{taxels}}} \sum_{s=1}^{S_{\text{samples}}} \frac{\log P(s|c_n, k)}{K_{\text{taxels}} S_{\text{samples}}}. \tag{3}$$

The updating process performed by Equation (1) is repeated until a belief threshold $\beta_{\text{decision}} = [0, 0.05, \ldots, 1]$ is exceeded to allow the robot to make a decision as follows:

$$\begin{gathered} \text{if any } P(w_i|z_{1:t}) > \beta_{\text{decision}} \\ \text{then } w_{\text{decision}} = \arg\max_{w_i} P(w_i|z_{1:t}), \end{gathered} \tag{4}$$

where w_{decision} is the angle perceived by the touch sensor. Active perception is performed by the gradual repositioning of the robot sensor, from its estimated current location x_{loc} to a preset target position x_{target}. This permits a gradual improvement in perception and is performed as follows:

$$x_{\text{loc}} = \arg\max_{x_l} P(x_l|z_{1:t}), \tag{5}$$

$$x \leftarrow x + \pi(x_{\text{loc}}), \qquad \pi(x_{\text{loc}}) = x_{\text{target}} - x_{\text{loc}}, \tag{6}$$

where $\pi(x_{\text{loc}})$ updates the value x which is the new position for the sensor. This process permits the robot to decide 'where to move next' to extract better information to improve perception. The layered architecture in Figure 5 shows the modules that compose the active Bayesian perception process (green colour lines), which has been validated in previous experiments with various stimuli [5], [13], [18].

2) Adaptive perception from sensory predictions: The adaptation of the tactile perception process is based on sensory predictions to update and adapt the prior used for the Bayesian perception method. A forward model is proposed to estimate the predicted probability during an exploration task. The forward model is defined as follows:

$$P_{\text{predicted}} = P(x_l, w_i + \Delta|z_t) \tag{7}$$

where $P(x_l, w_i+\Delta|z_t)$ is the predicted probability estimated by shifting the angle class w_i of the posterior probability using the parameter Δ. This parameter is learned during the exploration task to adapt the perception and control of the robot. For online learning of this parameter, we use a Predicted Information Gain (PIG) approach [9]. This method allows the robot to observe 'what would have happened' if a certain action 'would have been made' from the previous decision time. For the PIG method, we use $\hat{\Theta}$ to denote the estimated observations from the Bayesian perception process, while the set of actions and states is denoted by $a = \{a_1, a_2, \ldots, a_N\}$ and $s = \{s_1, s_2, \ldots, s_N\}$ with N the number of angle classes. This method is defined as follows:

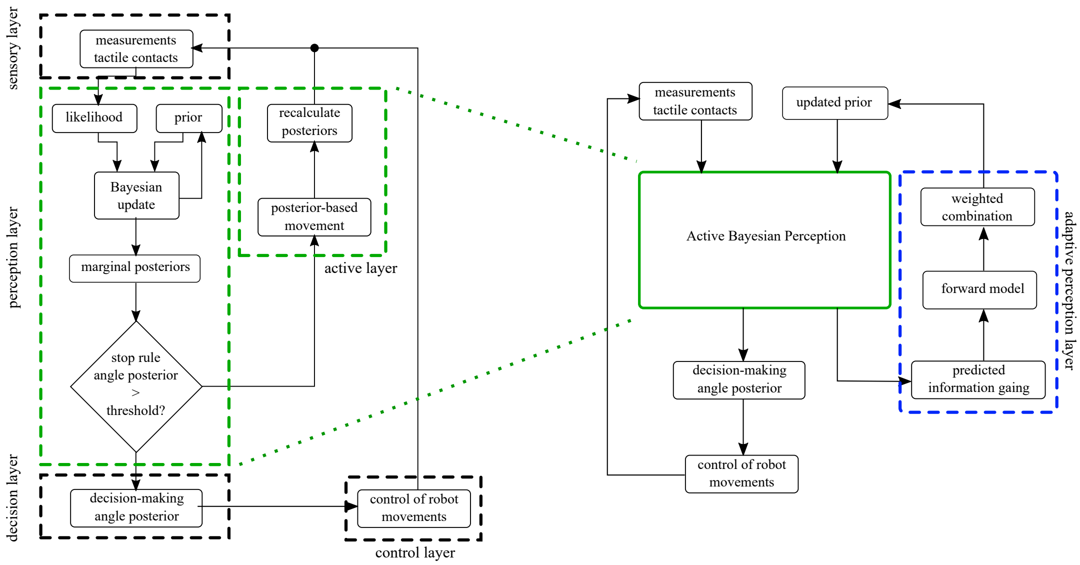

Fig. 5. Layered architecture that implements the active Bayesian perception and adaptive perception processes. (left) Active Bayesian perception flowchart (green colour lines) composed of *sensory*, *perception*, *decision*, *active* and *control layers*. (right) Adaptive perception process (blue colour lines) composed of the predicted information gain (PIG), the forward model and weighted combination of sources of information. The adaptive perception process is integrated with the modules of the Bayesian perception approach to adapt, based on sensory predictions, and improve the performance of a tactile exploration task.

$$\mathrm{PIG} = \gamma \sum_{s^*} \hat{\Theta}_{a,s,s^*} \mathrm{D_{KL}}(\hat{\Theta}_{a,s}^{a,s,s^*} || \hat{\Theta}_{a,s}) \tag{8}$$

where the estimated observations for the current state s by choosing action a are denoted by $\hat{\Theta}_{a,s}$. The hypothetical observations s^* for each action chosen in previous state s are represented by $\hat{\Theta}_{a,s}^{a,s,s^*}$. The hypothetical outcomes s^* that the perception process would have been provided by choosing action a in state s are $\hat{\Theta}_{a,s,s^*}$. This formulation is normalised by the parameter γ. The Kullback-Leibler Divergence ($\mathrm{D_{KL}}$) operation measures the difference between two distributions and provides the amount of information that would have been lost for each action performed from the previous decision time. The output from the PIG method updates a transition matrix Γ_τ to obtain the most probable value of the parameter Δ, as follows:

$$\Gamma_\tau = \eta \Gamma_{\tau-1} \mathrm{PIG} \tag{9}$$

where the transition matrix from decision time τ and $\tau - 1$ are Γ_τ and $\Gamma_{\tau-1}$, while η is the normaliser parameter. The transition matrix Γ_τ is updated as follows:

$$\Gamma_\tau = \eta \left(\left(\frac{\tau - 1}{\tau} \right) \Gamma_{\tau-1} + \left(\frac{1}{\tau} \right) \right) \mathrm{PIG} \tag{10}$$

The PIG value can be seen as a reward value in $[0, 1]$, which is recursively updated according the accuracy of actions made by the Bayesian perception approach along time. Then, the largest probability is assigned to Δ as follows:

$$\Delta = \arg\max \Gamma_\tau. \tag{11}$$

The parameter Δ is employed in Equation (7) to estimate the predicted probability. Then, adaptation of the perception process is obtained by the initialisation of the Bayesian method with a weighted combination of predicted and uniform probabilities, as follows:

$$P(c_n|z_0) = \alpha P_{\mathrm{predicted}} + (1 - \alpha) P_{\mathrm{flat}}(c_n) \tag{12}$$

where the uniformly distributed prior is $P_{\mathrm{flat}}(c_n)$, the predicted distribution is $P_{\mathrm{predicted}}$, and $P(c_n|z_0)$ is the updated prior to adapt the active Bayesian perception method. In this study, we use $\alpha = 0.5$ to assign the same weight to both source of information, and evaluate the effects of the sensory predictions in the active perception process during a tactile exploration task. Learning and adapt the parameter α is an aspect that we plan to investigate in future works. Figure 5 shows the adaptive perception process (blue colour lines) integrated with the active Bayesian perception modules.

III. RESULTS

This section presents the results from the active Bayesian perception and adaptive perception methods implemented with a contour following task, and using real tactile data from the fingertip sensor collected as shown in Section II.

A. Validation of passive and active perception

First, we validate active and passive perception with a contour following task, using data collected from a circular-shaped object (see Figure 3). The Bayesian perception method was implemented with the set of decision thresholds $\beta_{\mathrm{decision}} = [0.0, 0.05, \ldots, 1]$ to compare their performance for different levels of confidence. The traced contours from the circular object are shown in Figure 6. These results were presented in our previous work on active sensorimotor control [5], but we show them here for the purpose of comparison with the proposed adaptive perception method.

Figures 6A,B show that passive perception, with low ($\beta_{\mathrm{threshold}} = 0.2$) and high ($\beta_{\mathrm{threshold}} = 0.9$) decision

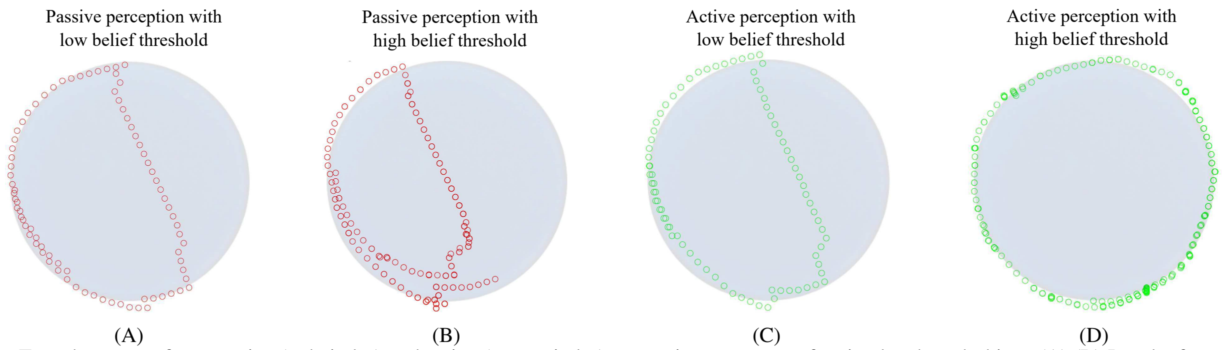

Fig. 6. Traced contours from passive (red circles) and active (green circles) perception processes of a circular-shaped object. (A),(B) Results from passive perception using low ($\beta_{\text{threshold}} = 0.2$) and high ($\beta_{\text{threshold}} = 0.9$) belied thresholds. (C) Similar behaviour observed by active perception with low ($\beta_{\text{threshold}} = 0.2$) decision threshold. (D) Successful extraction of object shape using active perception with high decision threshold ($\beta_{\text{threshold}} = 0.9$).

threshold, is not able to extract the shape of the explored object. This is related to the inability of the sensor to move towards better locations to improve perception. A similar behaviour is observed with active perception and low decision threshold in Figure 6C. This shows that the capability of the sensor to actively move to improve perception is affected by the low decision threshold, making fast but low accurate decisions. In contrast, active perception with high decision threshold allow the sensor to successfully extract the object shape as shown in Figure 6D. In this case, the sensor is able to not only intelligently move towards better locations to improve perception, but also, it has enough time to accumulate evidence, reduce uncertainty and improve decision accuracy. Angle and position accuracy results for active perception are shown by the blue colour curves in Figures 7A,B, while decision times are shown in Figures 7C,D. These results show the benefits of active over passive perception for a tactile exploration task. The performance achieved in accuracy and speed from active

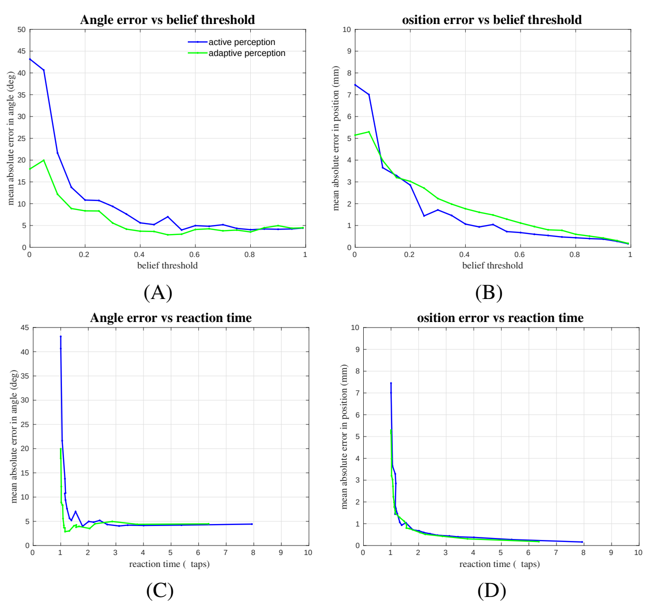

Fig. 7. Active Bayesian and adaptive perception from a contour following exploration task. (A),(B) Angle and position accuracy show an improvement in angle classes when the perception process is adaptive. (C),(D) Reaction time shows a small improvement in angle classes using adaptive perception.

perception can be improved by adaptation of the Bayesian perception process using sensory predictions. The results of the implementation of adaptive perception with the tactile exploration tasks are presented in the next section.

B. Validation of adaptive perception

In this section, we validate the adaptive perception method with a contour following task using real tactile data. We also compare the performance in accuracy and reaction time for both active and adaptive perception processes.

For training and testing we used data collected from the object shown in Figure 3 and the set of belief threshold $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 1]$ to control the decision-making process. The adaptive perception process for contour following is as follows: First, the Bayesian perception process is initiated with a uniform prior for decision time $\tau = 0$. Second, the robot makes a decision to be actively moved according to the perceived angle class. Third, the robot uses the PIG approach to observe its current state and estimate 'what would have happened' if a different action 'would have been chosen' at decision time $\tau - 1$ Equations (8)-(10). The outcome is employed for online learning of the parameter Δ, which is used by the forward model in Equation (7) to obtained the sensory predictions. The goal of the sensory predictions is to adapt the perception process based on the observations of previous decisions made and current states. This adaptation process updates the prior for new decision times by the weighted combination of the uniform distribution P_{flat} and the sensory predictions $P_{\text{predicted}}$. Here, the weighting parameter $\alpha = 0.5$ allows to assign the same

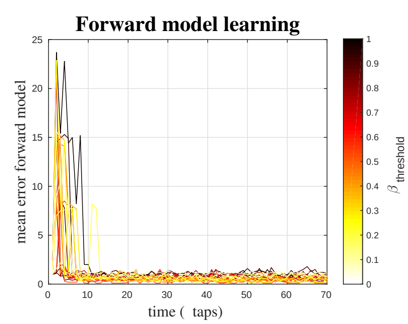

Fig. 8. Learning of the parameter Δ performed by a forward model. The initial variability is improved by observation of decisions made over time.

weight to both information sources and observe the effects of sensory predictions in the adaptive perception process.

The results in accuracy and reaction time from the contour following task, using adaptive perception are presented by the green colour curves in Figure 7. The results from the active perception method (blue colour curves) are also shown for comparison of performance. Plots (A) and (B) show the smallest angle and position errors from adaptive perception with 2.8 degrees and 1.8 mm for $\beta_{\text{threshold}} = 0.5$ and $\beta_{\text{threshold}} = 0.99$ respectively. These results show an improvement over the 4 degrees error achieved by active perception. In contrast, positions errors did not show an improvement over active perception. We argue that this is because predictions made by the forward model are for angle classes only. Plots (C) and (D) show the results in reaction time for angle and position classes. We observe that adaptive perception was able to improve the reaction time for angle classes, requiring a smaller number of samples to make a decision. These improvements in accuracy and reaction time were expected given that the perception process does not need to start from zero or uniform prior knowledge. Instead, rich information from previous decision times is used to adapt and improve the Bayesian perception approach. Figure 8 shows how the error achieved by the forward model initially presents large variability, but this is improved after some exploration and decisions made. This suggests that the forward model is able to successfully learn the parameter Δ after some exploration. The learning process also depends on the confidence $\beta_{\text{threshold}}$ used in our Bayesian perception method for accumulation of data and decision-making.

Overall, this work has shown two main results. First, active perception permits to a robotic fingertip to improve its performance during a tactile exploration task. Second, sensory predictions, learned by decisions made over time, can be used to adapt the active perception process and achieve a better performance in accuracy and reaction time.

IV. CONCLUSIONS

Humans make decisions and actions using multiple source of information, which allow them to improve and adapt their accuracy. In this work, an adaptive perception method, integrated in a active Bayesian perception approach, is proposed to improve accuracy and reaction time of an exploration task performed with a biomimetic fingertip sensor. The adaptive perception method employs sensory predictions learned by a forward model and predicted information gain approach. This approach allows to the robot to estimate 'what would have happened' if a certain decision 'would have been made' at previous time, and use this information to adapt the Bayesian perception method. Our methods are validated with a contour following exploration procedure. First, the results show that active perception is able to achieve a better performance for exploration task over passive perception. Second, we observe that using sensory predictions, learned from decisions made over time, allows to adapt the perception process of the Bayesian method, improving the tactile exploration task in both accuracy and reaction time.

All in all, this method that takes inspiration from the way that humans adapt and combine information over time, shows to be suitable to develop of autonomous robots capable to safely interact and adapt during the exploration of the unstructured and changing environment.

REFERENCES

[1] P. Haazebroek, S. Van Dantzig, and B. Hommel, "A computational model of perception and action for cognitive robotics," *Cognitive processing*, vol. 12, no. 4, p. 355, 2011.

[2] J. Dargahi and S. Najarian, "Human tactile perception as a standard for artificial tactile sensinga review," *The International Journal of Medical Robotics and Computer Assisted Surgery*, vol. 1, no. 1, pp. 23–35, 2004.

[3] U. Martinez-Hernandez, "Tactile sensors," in *Scholarpedia of Touch*. Springer, 2016, pp. 783–796.

[4] J. L. Krichmar, "Design principles for biologically inspired cognitive robotics," *Biologically Inspired Cognitive Architectures*, vol. 1, pp. 73–81, 2012.

[5] U. Martinez-Hernandez, T. J. Dodd, M. H. Evans, T. J. Prescott, and N. F. Lepora, "Active sensorimotor control for tactile exploration," *Robotics and Autonomous Systems*, vol. 87, pp. 15–27, 2017.

[6] S. Thrun, W. Burgard, and D. Fox, *Probabilistic robotics*. MIT press, 2005.

[7] U. Martinez-Hernandez, I. Mahmood, and A. A. Dehghani-Sanij, "Probabilistic locomotion mode recognition with wearable sensors," in *Converging Clinical and Engineering Research on Neurorehabilitation II*. Springer, 2017, pp. 1037–1042.

[8] U. Martinez-Hernandez, A. Damianou, D. Camilleri, L. W. Boorman, N. Lawrence, and T. J. Prescott, "An integrated probabilistic framework for robot perception, learning and memory," in *Robotics and Biomimetics (ROBIO), 2016 IEEE International Conference on*. IEEE, 2016, pp. 1796–1801.

[9] D. Y. Little and F. T. Sommer, "Learning in embodied action-perception loops through exploration," *arXiv preprint arXiv:1112.1125*, 2011.

[10] R. Shadmehr, M. A. Smith, and J. W. Krakauer, "Error correction, sensory prediction, and adaptation in motor control," *Annual review of neuroscience*, vol. 33, pp. 89–108, 2010.

[11] K. A. Hansen, S. F. Hillenbrand, and L. G. Ungerleider, "Effects of prior knowledge on decisions made under perceptual vs. categorical uncertainty," *Frontiers in neuroscience*, vol. 6, 2012.

[12] R. A. Brooks, *Cambrian intelligence: The early history of the new AI*. Mit Press Cambridge, MA, 1999, vol. 44.

[13] R. Brooks, "A robust layered control system for a mobile robot," *IEEE journal on robotics and automation*, vol. 2, no. 1, pp. 14–23, 1986.

[14] A. Schmitz, P. Maiolino, M. Maggiali, L. Natale, G. Cannata, and G. Metta, "Methods and technologies for the implementation of large-scale robot tactile sensors," *Robotics, IEEE Transactions on*, vol. 27, no. 3, pp. 389 –400, 2011.

[15] U. Martinez-Hernandez, L. W. Boorman, and T. J. Prescott, "Multisensory wearable interface for immersion and telepresence in robotics," *IEEE Sensors Journal*, vol. 17, no. 8, pp. 2534–2541, 2017.

[16] U. Martinez-Hernandez, A. Rubio-Solis, and T. J. Prescott, "Bayesian perception of touch for control of robot emotion," in *Neural Networks (IJCNN), 2016 International Joint Conference on*. IEEE, 2016, pp. 4927–4933.

[17] U. Martinez-Hernandez, N. F. Lepora, and T. J. Prescott, "Active haptic shape recognition by intrinsic motivation with a robot hand," in *World Haptics Conference (WHC), 2015 IEEE*. IEEE, 2015, pp. 299–304.

[18] U. Martinez-Hernandez, T. Dodd, T. J. Prescott, and N. F. Lepora, "Active bayesian perception for angle and position discrimination with a biomimetic fingertip," in *Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on*. IEEE, 2013, pp. 5968–5973.

[19] A. Rubio-Solis and G. Panoutsos, "Fuzzy uncertainty assessment in rbf neural networks using neutrosophic sets for multiclass classification," in *Fuzzy Systems (FUZZ-IEEE), 2014 IEEE International Conference on*. IEEE, 2014, pp. 1591–1598.