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# Learning from sensory predictions for autonomous and adaptive exploration of object shape with a tactile robot

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**Abstract**

Humans use information from sensory predictions, together with current observations, for the optimal exploration and recognition of their surrounding environment. In this work, two novel adaptive perception strategies are proposed for accurate and fast exploration of object shape with a robotic tactile sensor. These strategies called 1) adaptive weighted prior and 2) adaptive weighted posterior, combine tactile sensory predictions and current sensor observations to autonomously adapt the accuracy and speed of active Bayesian perception in object exploration tasks. Sensory predictions, obtained from a forward model, use a novel Predicted Information Gain method. These predictions are used by the tactile robot to analyse 'what would have happened' if certain decisions 'would have been made' at previous decision times. The accuracy of predictions is evaluated and controlled by a confidence parameter, to ensure that the adaptive perception strategies rely more on predictions when they are accurate, and more on current sensory observations otherwise. This work is systematically validated with the recognition of angle and position data extracted from the exploration of object shape, using a biomimetic tactile sensor and a robotic platform. The exploration task implements the contour following procedure used by humans to extract object shape with the sense of touch. The validation process is performed with the adaptive weighted strategies and active perception alone. The adaptive approach achieved higher angle accuracy (2.8 deg) over active perception (5 deg). The position accuracy was similar for all perception methods (0.18 mm). The reaction time or number of tactile contacts, needed by the tactile robot to make a decision, was improved by the adaptive perception (1 tap) over active perception (5 taps). The results show that the adaptive perception strategies can enable future robots to adapt their performance, while improving the trade-off between accuracy and reaction time, for tactile exploration, interaction and recognition tasks.

*Keywords:* active and adaptive perception, sensorimotor control, autonomous tactile exploration, Bayesian inference

## 1. Introduction

Active perception in robotics is related to control strategies for intelligent acquisition of data to reduce uncertainty, which involves processes such as reasoning, decision-making, prediction and control [1]. Active perception in tactile sensing is employed by humans to explore and enhance the perceptual information from an object, through intelligent movements of their hands and fingers [2, 3]. Recent advances in technology have permitted to develop a large variety of biomimetic, small and reliable tactile sensors for robotic platforms with different morphologies. This evolution in sensor technology has enlarged the repertoire of research on active touch with robots that mimic human touch sensing [4].

Artificial tactile sensors, as in the human sense of touch, provide noisy measurements, which create uncertainty for making decisions and actions [5]. Humans overcome uncertainty by actively sensing their environment, but also by integrating various streams of information simultaneously. In robotics, Bayesian frameworks offer a systematic approach to deal with uncertainty, while defining how to combine multiple information sources to make optimal decisions [6].

In this work, first an active perception method is presented, using a Bayesian formulation, to make a tactile robot able to decide where to move next during the exploration of an object. The active perception approach allows the robot to explore better object locations that improve perception accuracy. Previous works have shown that active Bayesian perception, controlling the robot movements by tactile feedback, offers a suitable method for autonomous exploration with various stimuli and sensors [7, 8]. Active perception is validated using a touch sensor to perform the contour following exploratory procedure, commonly employed by humans to extract object shape. In this exploration task the touch sensor makes decisions about where to move next, collecting better information while following the object shape. Second, two strategies called 'adaptive weighted prior' and 'adaptive weighted posterior', are proposed. These strategies enhance the active perception method by an adaptive integration of tactile sensory predictions and current observations from the exploration task. Preliminary results and initial analysis of the adaptive weighted prior strategy were presented in [9]. Both strategies use a novel adaptive Bayesian perception method, which extend our previous work on sensorimotor control, where learning and control parameters were manually

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predefined, together with a set of assumptions used for combination of information sources [10]. The adaptive weighted prior and posterior strategies implement a forward model for estimation of sensory predictions, using a Predicted Information Gain (PIG) approach. This predictive approach analyses 'what would have happened' if a certain decision 'would have been made' at previous decision times. Additionally, these adaptive strategies evaluate the accuracy of their own sensory predictions to adapt the combination of information sources, assigning a larger weight to the more reliable source. This approach ensures the optimal performance and trade-off between perception accuracy and reaction time for robot exploration tasks. The adaptive approach is systematically validated with the recognition of angle and position classes from a contour following exploration task, commonly employed by humans for extraction of object shape. This experiment, implemented with a biomimetic fingertip sensor and an exploratory robotic platform, allows the analysis and comparison of performance, in recognition accuracy and reaction time, of the adaptive strategies and the active perception approach.

Overall, the results from all experiments show that the novel adaptive approach provides a high accuracy recognition for angle (2.8 deg) and position (0.18 mm) classes, but also improves the reaction time (1 tap) of the decision-making process. These values contrast with the results from active perception alone (5 deg, 0.18 mm and 5 taps). Furthermore, the adaptive strategies show their capability to improve the trade-off between accuracy and reaction time during the tactile object exploration procedure. These are important features for the development of robots capable of interacting with humans and the surrounding environment, autonomously and safely.

The remainder of this article is organised as follows: Section 2 presents the related work on touch sensing and perception. The robot platform, tactile sensor and methods employed are presented in Section 3. Experiments and results are described in Section 4. Finally, discussion and conclusions are shown in Section 5 and Section 6, respectively.

## 2. Related work

Traditionally, image processing have been used for analysis and recognition with tactile data [11]. Predefined sequences of tactile contacts and geometric moments were implemented with robotic grippers for object recognition [12, 13]. Tactile images and joint angles were employed, together with a five-fingered robotic hand, for shape and object recognition using a fixed number of palpation and grasping movements [14]. Shape extraction and classification, performed with a dexterous robot hand, used an approach based on tactile images and kurtosis [15]. Image processing methods have also been implemented together with algorithms for classification such as Self-Organising Maps (SOM), Artificial Neural Networks (ANN), Principal Component Analysis (PCA), Bag-of-Features models and Fuzzy Logic methods [16, 17, 18, 19]. An advanced control framework for tactile exploration, allowed a robot arm to touch and follow the shape of different objects, using a large planar sensor array, filters and geometrical moments [20]. All these methods showed to be accurate, however, they are constrained by the sensor size, sensor geometry and the requirement to get data from the whole sensor surface. Furthermore, the fixed and predefined sequence of tactile contacts used in these works follows a passive perception approach, which limits the robot capability to explore better object locations to improve perception.

Active perception overcomes the limitations of passive perception by making robots able to autonomously explore better object locations to improve perception, as humans do [2, 21]. Tactile robotic platforms, with different morphologies, have taken advantage from active perception to decide where to move next in exploration tasks [22, 23, 24]. Biomimetic fingertip sensors and robotic hands have been able to perform a variety of tactile tasks, such as contour following, texture recognition, shape extraction and object recognition [25, 26, 27]. These works, based on probabilistic frameworks and intrinsic motivation models, permitted the robot hands and fingers to autonomously explore, accumulate evidence from the interaction with the environment, perceive and make decisions about the objects being explored. Active exploration of surfaces has also been studied using touch attention mechanisms implemented with Bayesian methods [28]. This touch attention approach was validated with the autonomous exploration of different objects and materials. Other works have used Bayesian methods for exploration of object shape, extraction of local properties, activity recognition and object localisation combining force and touch sensors [29, 30, 31]. Gaussian Processes (GP), which are a probabilistic formulation, have been used for autonomous active exploration and recognition of objects using biomimetic tactile sensors, force sensors and geometrical information [22, 32]. In general, probabilistic approaches have demonstrated to be suitable for autonomous robotics, providing flexibility and robustness to deal with sensor limitations, noise and uncertainty observed in the changing environment [7, 33, 34].

Normally, humans make decisions based on the combination of multiple streams of information –for instance, predicted and current observations [35]. This combination of information and decision-making processes are crucial to control human movements, performed by the central nervous system (CNS), and ensure accurate motor actions [36, 37]. Predicted and current sensor observations, employed for perception and sensorimotor control in [10], allowed a touch sensor to improve its perception accuracy and reaction time during an exploration task. The parameters for prediction of sensory observations were manually set, but also, the combination of information sources was manually controlled using a predefined weighting parameter. Hierarchical multimodal perception showed that fusion of observations, from multiple sensory inputs, was able to achieve better results over the use of individual perceptions [38]. Exploration and learning in robotics have used predictive knowledge-based models of intrinsic motivation, based on the knowledge gained over time and predictions from a learned forward model [27, 39, 40]. Forward models are essential to allow robotic systems to perform autonomous decisions, based on the prediction of the effects from their motor actions [35, 41]. Prediction of sensory observations for combination with current measurements was studied in [9], where an initial weight prior strategy was implemented, showing preliminary results in perception accuracy with a robotic sensor. This approach was implemented with a forward model, based on the Predicted Information Gain (PIG) method [42], during a tactile exploration task. Other works employed curiosity-driven models and Predicted Information Gain (PIG) approaches to engage the robot to learn actions and estimate the expected information during an exploration task [43, 44].

Previous works have shown that active perception, learning of actions and combination of streams of information improve the robot performance. However, the individual use of these approaches do not maximise the trade-off between accuracy and speed during a robotic task. In this work, a method to predict sensory observations for the adaptation and control of an active tactile exploration is presented in Section 3. This method, based on a probabilistic formulation and Predicted Information Gain method, learns a forward model to estimate sensory predictions and combine current and predicted observations, which are used to adapt the performance of an active perception process. Thus, the proposed adaptive perception approach allows the robot fingertip sensor to actively explore, adapting its decisions and actions, but also to improve the trade-off between perception accuracy and speed, which are important aspects for the development of autonomous and intelligent robots.

## 3. Methods

### *3.1. Biomimetic tactile sensor*

A biomimetic fingertip sensor, which is part of the tactile sensory system of the iCub humanoid robot, is used for this research work [45, 46]. This tactile sensory system provides the iCub humanoid robot with capabilities to explore and interact with its environment [47, 48]. The biomimetic tactile sensor resembles the human fingertip with rounded shape and dimensions of 14.5 mm long × 13 mm wide, as shown in Figures 1A,B,C,D. The iCub fingertip sensor uses an array of twelve tactile elements (taxels of 4 mm diameter each), build with a capacitive technology. The taxels cover the inner core of the fingertip with a flexible printed circuit board (PCB). A 2 mm dielectric layer of silicone foam is placed above the PCB. The flexible and conductive outer layer allows deformations of the surface of sensor, analogous to those that occur with the human fingertip. Sensor measurements from the twelve taxels are read with a sampling rate of 50 Hz and locally digitised with 8 bit resolution (0–255 values). These values are sent to a computer through a CAN-bus for their subsequent processing.

The technology used in the iCub fingertip sensor resembles the mechanical and sensory structure of the human fingertip, allowing the study of perception of pressure, curvature and edge orientation [23, 49, 50]. Interestingly, the taxels in the fingertip sensor respond analogously to human mechanoreceptors to brief and sustained response from tactile stimuli.

### *3.2. Robotic platform*

An exploratory robotic platform was built to provide mobility to the fingertip sensor in $x$-, $y$- and $z$-axes. The robot

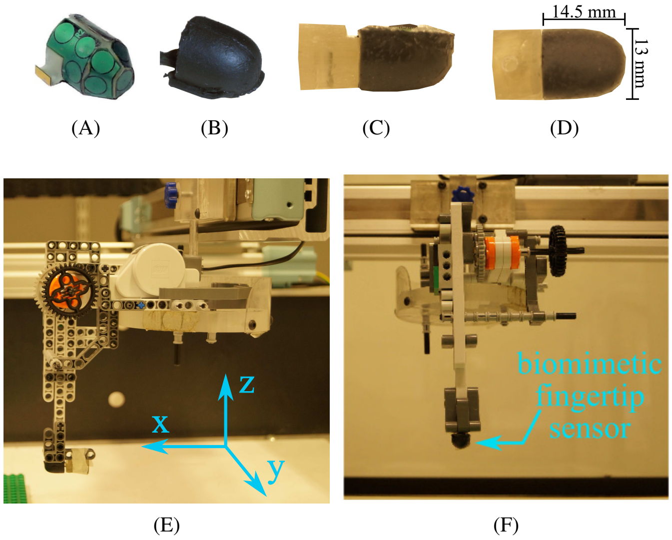



Figure 1: Tactile sensory system and exploratory robotic platform. (A) Flexible PCB and taxels of the iCub fingertip. (B) Fingertip sensor covered with dielectric silicon. (C) Lateral view of the sensor. (D) Dimensions of the biomimetic sensor. (E),(F) Robotic platform for tactile exploration in $x$-,$y$- and $z$-axes.

platform is composed of two robots: (1) a Cartesian robot arm (YAMAHA XY-x series) with 2-DoF that provides mobility in the $x$- and $y$-axes, and (2) a Mindstorms NXT Lego robot with 1-DoF for sensor mobility along the $z$ axis. Both, the Cartesian and NXT robots are coupled in a proper manner to generate sensor movements in the $x$-, $y$- and $z$-axes.

The tactile sensor was mounted on the robotic platform for precise positioning movements in the $x$- and $y$-axes with an accuracy of $\approx 20\mu$m. Even though the reduced capabilities of the NXT robot, it allows to achieve movements along the $z$-axis. On the one hand, these robots allow the sensor to perform exploratory procedures. On the other hand, robot movements are controlled by tactile feedback provided by the biomimetic fingertip sensor. The sensor mounted on the exploratory platform is shown in Figures 1E,F. The available degrees of freedom of the robotic platform do not allow rotations along the $z$-axis of the tactile sensor. Therefore, the fingertip sensor keeps the same orientation during all the object exploration experiments.

In this work, we chose a tactile exploration procedure (EP) based on taps or palpation. This EP reduces the damage to the sensor that, in contrast, a sliding motion could deteriorate the outer conductive layer after several repetitions of the experiments. The selected EP also generates an alternative tactile exploration movement, useful for robotic systems that are not able to slide their sensors. Even though humans typically slide their fingertips during an exploration procedure, there are situations where they palpate for exploration of a sharp surface and diagnosis through medical inspection.

### *3.3. Data collection*

For validation of the accuracy and speed of the active and adaptive tactile perception methods, multiple tactile datasets composed of angle and position classes were systematically

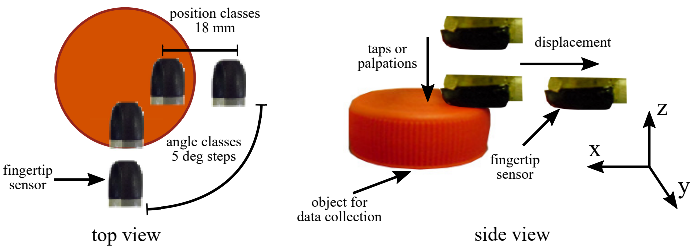



Figure 2: Stimulus used for data collection while tapping on the object along the $z$ axis. Angle and position data are recorded with 5 deg and 0.2 mm steps respectively. Two tactile datasets, composed of 72 angle and 18 position classes each, are collected for training and testing the proposed exploration methods.

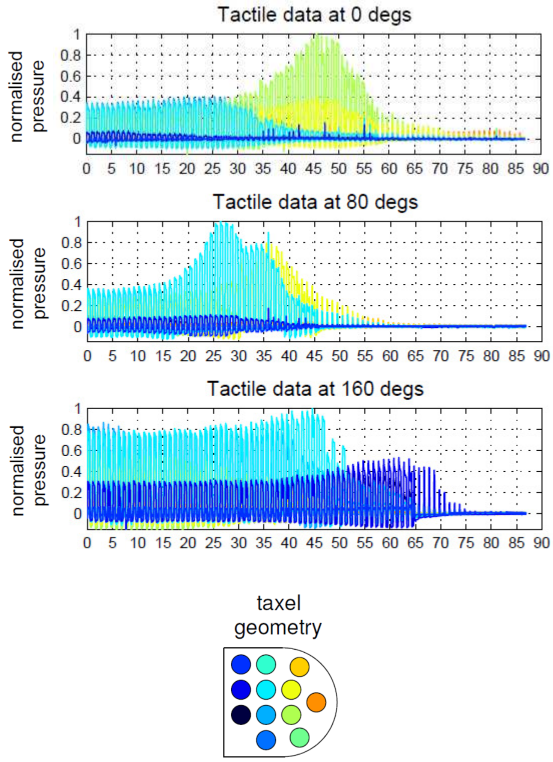



Figure 3: Sample of data collected with the biomimetic fingertip sensor. Datasets for orientation of the fingertip sensor at 0 deg, 80 deg and 160 deg along 18 mm (90 taps) over the plastic object used as stimuli. Normalised pressure measurements from activated taxels are shown by a coloured code.

collected and used for contour following exploration tasks. For tactile stimuli, the surface of a plastic object attached to a table was used. The data were collected with a palpating procedure over the object along its radius; starting from the flat surface of the object, then passing through the edge, and finishing on air as shown in Figure 2. Each tap or palpation, with a duration of 2 sec, yielded a dataset of 12×100 pressure measurements (sampling frequency 50 Hz and 12 taxels). The exploration 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 were formed by grouping 5 taps per class, obtaining a total of 18 position classes of 1 mm span each. Forming groups of 5 taps per class allow the sensor to be actively repositioned to collect more data and improve the accuracy for recognition of position classes. This approach for grouping the data from the taps performed by the fingertip sensor has been validated in a previous work on object exploration [10]. The data collection procedure was repeated at 5 deg orientation steps around the complete plastic object, which provided 72 angle classes. Finally, a large dataset composed of 72 angle × 18 position classes = 1296 classes was constructed. The complete process was repeated two times to collect one dataset for training and one dataset for testing. Examples of the data collected from the circular object, with the sensor orientated of 0 deg, 80 deg and 160 deg along 18 mm are shown in Figure 3.

The data collected from the fingertip sensor are used for object exploration with a contour following procedure. For this task, the active perception method, described in Section 3.4, uses the sensor position and angle information relative to the object contour for the exploration task. First, position information is used for active repositioning of the sensor, perpendicularly to the object edge, to improve perception accuracy. Second, recognition of the sensor angle, relative to the object edge, is used to move the sensor to the next exploration position along the object contour. This active repositioning and recognition process ensures a successful accomplishment of the exploration task as shown in the experimental results in Section 4.

### *3.4. Active Bayesian perception*

The intelligent control of sensor movements improves the performance in decision speed and perceptual accuracy of a robot exploration task. This process, known as active perception, implemented with a Bayesian formulation, has been validated with different stimuli and various robotic sensors. In this work, the Bayesian formulation uses the following notation:

- $C$, a finite set of perceptual classes with $N_{\text{pairs}} = |C|$. Each perceptual class $c_n$ is composed by a $(u_k, v_l)$ pair, where $u_k$ with $k = 1, 2, \ldots, K$ and $v_l$ with $l = 1, 2, \ldots, L$ are position and angle classes, respectively.
- $z$, sensor measurements from the biomimetic fingertip sensor.
- $n$, denotes a specific class from the set of $N_{\text{pairs}}$ angles and position pairs.

The Bayesian formulation implements a recursive estimation of the posterior probabilities from the product of the prior probabilities and likelihoods, as follows:

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

where $P(c_n|z_{1:t})$ and $P(z_t|c_n)$ are the posterior probability and likelihood at exploration time $t$. $P(c_n|z_{1:t-1})$ is the prior probability at time $t-1$. The variable $u_k$ with $K = 18$ represents the position class for each angle class $v_l$ with $L = 72$. The sensor measurements from each tap or palpation are represented by $z$.

For the initial exploration time, $t = 0$, uniform prior probabilities are assumed, which considers that all classes $N_{\text{pairs}}$ have the same probability, as follows:

$$P(c_n) = P(c_n|z_0) = \frac{1}{N_{\text{pairs}}} \tag{2}$$

For time $t > 0$ the prior is updated using the posterior estimated at time $t-1$. From each tap performed by the sensor, a time series with $N_{\text{samples}} = N_{\text{taxel}} \times 100$ samples of digitised pressure values are collected, with $N_{\text{taxels}} = 12$. This information is used to built the nonparametric measurement model based on histograms, which are uniformly constructed by binning tactile data into bins $b$ with $N_{\text{bins}} = 100$, as follows:

$$P_k(b|c_n) = \frac{h_{kn}(b)}{\sum_{b=1}^{N_{\text{bins}}} h_{kn}(b)} \tag{3}$$

where $h_{kn}(b)$ is the sample count in bin $b$ for taxel $k$ over all training data in class $c_n$. The mean log likelihood of a test tactile contact $z_t$ over all samples and taxels is obtained as follows:

$$\log P(z_t|c_n) = \sum_{k=1}^{N_{\text{taxels}}} \sum_{j=1}^{N_{\text{samples}}} \frac{\log P_k(s_k(j)|c_n)}{N_{\text{samples}} N_{\text{taxels}}} \tag{4}$$

where $s_k(j)$ is the sample $j$ in taxel $k$. Normalised values are ensured with the marginal probabilities conditioned from previous sensor observations, as follows:

$$P(z_t|z_{1:t-1}) = \sum_{n=1}^{N_{\text{pairs}}} P(z_t|c_n) P(c_n|z_{1:t-1}) \tag{5}$$

Each estimated class $c_n$ corresponds to a $(u_k, v_l)$ pair, which denotes the joint probability for position and angle perceptual classes. Then, individual position and angle beliefs are obtained with the following marginal posteriors:

$$P(u_k|z_{1:t}) = \sum_{l=1}^{L} P(u_k, v_l|z_{1:t}) \tag{6}$$

$$P(v_l|z_{1:t}) = \sum_{k=1}^{K} P(u_k, v_l|z_{1:t}) \tag{7}$$

where position beliefs are summed over all angle classes, and angles beliefs are summed over all position classes. The recursive accumulation of evidence stops once a predefined belief threshold is exceeded, to make a decision using the *maximum a posteriori* (MAP) estimate, as follows:

$$\begin{gathered} \text{if any } P(v_l|z_{1:t}) > \beta_{\text{threshold}} \text{ then} \\ \hat{v} = \arg\max_{v_l} P(v_l|z_{1:t}) \end{gathered} \tag{8}$$

where $\hat{v}$ is the angle perceived by the fingertip sensor. The belief threshold $\beta_{\text{threshold}} \in [0, 1]$ is used to control the amount of evidence needed to make a decision. The estimated angle is employed in the contour following task presented in Section 4.

Previous works have shown that the iCub fingertip sensor is able to perceive with higher accuracy towards its centre [10, 23]. This means that the active perception approach needs to intelligently move the sensor towards its centre, in order to gradually improve the perception accuracy of the object being explored. Active perception is defined as the position $u_{\text{fix}}$, the centre of the sensor, which the active control seeks to gradually attain by repositioning the sensor from an initial random and unknown fingertip location. The sensor movement policy is determined from the current position estimation, as follows:

$$\hat{u} = \arg\max_{u_k} P(u_k|z_{1:t}) \tag{9}$$

$$u = u + \pi(\hat{u}), \quad \pi(\hat{u}) = u_{\text{fix}} - \hat{u} \tag{10}$$

where $\pi$ and $\hat{u}$ are the movement policy and current estimated position, respectively. The movement policy $\pi(\hat{u})$ updates $u$, which defines the new position for exploration by the fingertip sensor. The complete perception process is described by the flowchart in Figure 4A, which groups all processes into layers. The active repositioning of the sensor is repeated and controlled by $\beta_{\text{threshold}}$. Previous works on passive and active tactile sensing have shown that small belief thresholds, $\beta_{\text{threshold}} \approx 0$, allow robots to respond fast but with low perception accuracy. Conversely, large belief thresholds, $\beta_{\text{threshold}} \approx 1$, are highly accurate but require large amounts of evidence, increasing the response time. In Section 3.5 a method for adaptation of the active Bayesien perception process is presented. This method, based on sensory predictions and combination of information sources, improves the trade-off between accuracy and reaction time taking the best from both worlds.

### *3.5. Adaptive perception*

Weighted prior and weight posterior sensorimotor strategies were presented in [10], where the forward model and combination of information sources were manually controlled to improve the performance of a tactile exploration task. A preliminary analysis of the weighted prior strategy, with a contour following task, was presented in [9]. In this work, both the weighted prior and posterior strategies are analysed in detailed and extended by autonomously learning the forward model and adapting the combination of information sources, and thus, to allow the fingertip sensor to adapt its performance during the exploration task. This process is achieved with an adaptive Bayesian perception method, that observes 'what would have happened' if a different action 'would have been made' at previous decision times. This approach allows the touch sensor to make predictions about the expected sensory observations for the next exploration step, which combined with current sensor observations, enables the sensor for adaptation of its perception accuracy and speed during the object exploration procedure.

#### *3.5.1. Adaptive weighted prior strategy*

This strategy performs a weighted combination of a uniform prior with sensory predictions estimated over time. The resulting combination is used as the new prior for the begin-

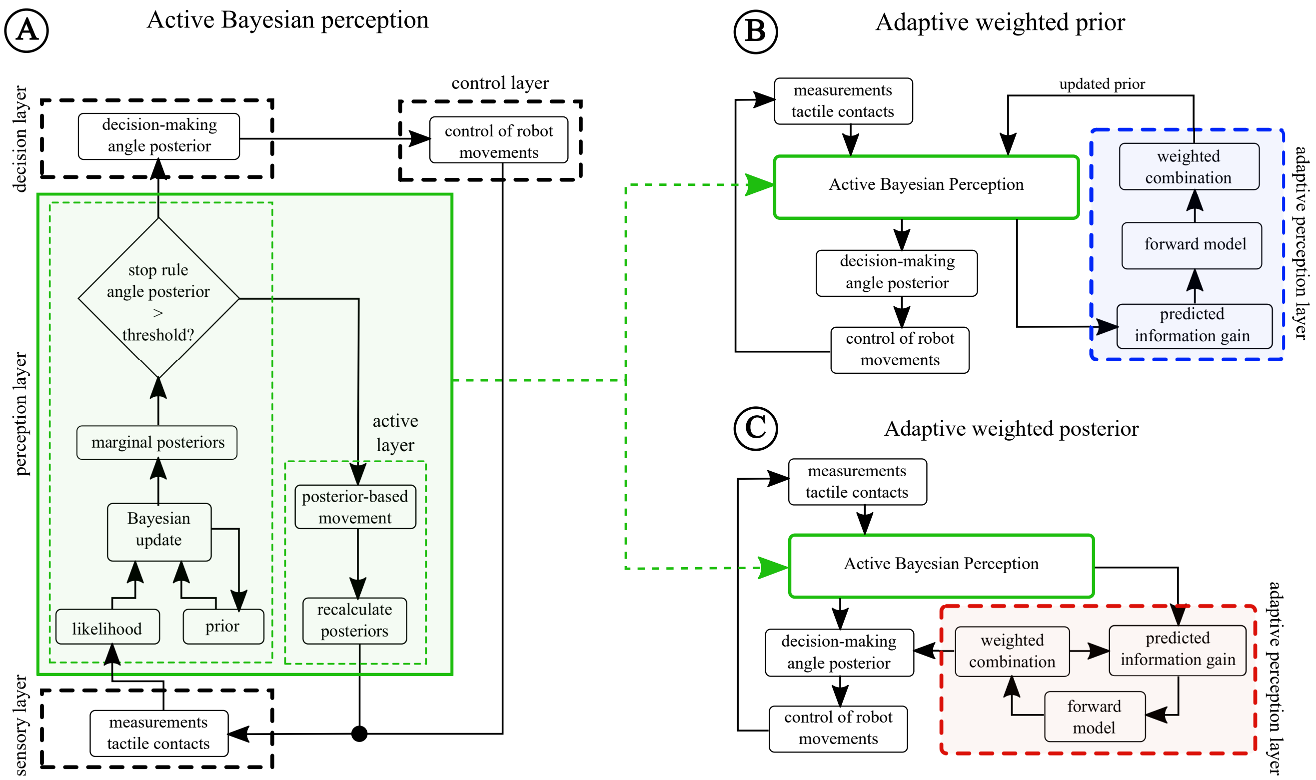



Figure 4: Flowcharts for active perception and adaptive strategies. (A) Active Bayesian perception composed of five layers: *sensory*, *decision*, *control* (black colour boxes), *perception* and *active* (green colour boxes). Perception layer accumulates evidence while actively reposition of the sensor by the active layer. Decision-making, by the decision layer, controls the movements of the robot platform in the control layer. (B) Adaptive weighted prior strategy (blue colour box) extends the active Bayesian perception (green colour box) using sensory predictions and combining them with current observations. This strategy, applied at the beginning of the perception process, impacts on the prior probability. (C) Adaptive weighted posterior (red colour box) allows the active perception to make sensory predictions and combine information streams, but in this case, this strategy takes place at the end of the perception process, impacting the posterior probability.

ning of a new decision-making processes performed by the active Bayesian perception approach, as follows:

$$P_{\text{prior}}(c_n|z_0) = \alpha P_{\text{predict}} + (1-\alpha)P_{\text{flat}}(c_n) \tag{11}$$

where the initial uniformly distributed prior is $P_{\text{flat}}(c_n)$, the predicted probability distribution is $P_{\text{predict}}$, and $P_{\text{prior}}(c_n|z_0)$ is the new prior for the active Bayesian perception. The confidence parameter $\alpha \in [0,1]$ controls and adapts the contribution of each information source in Equation (11). The confidence parameter is autonomously adapted, based on the accuracy observed by the sensory predictions, $P_{\text{predict}}$, as described in Section 3.5.4. The use of this adaptive strategy, together with active Bayesian perception, is shown by the flowchart in Figure 4B.

### *3.5.2. Adaptive weighted posterior strategy*

This strategy combines the posterior probability with the sensory predictions estimated over time. The resulting combination is applied at the end of the Bayesian perception process, once the belief threshold $\beta_{\text{threshold}}$ has been exceeded. This process is performed as follows:

$$P_{\text{posterior}}(c_n|z_{1:t}) = \alpha P_{\text{predict}} + (1-\alpha)P(c_n|z_{1:t}) \tag{12}$$

where the posterior and predicted probability distributions are $P(c_n|z_{1:t})$ and $P_{\text{predict}}$, respectively. The updated posterior used to make a decision is represented by $P_{\text{posterior}}(c_n|z_{1:t})$. Similar to the weighted prior, the contribution of each information source is controlled by the adaptive confidence parameter $\alpha$. This adaptive strategy together with the active Bayesian process is shown in Figure 4C. The predicted probability distribution, $P_{\text{predict}}$, employed by both the adaptive weighted prior and posterior strategies, is defined by the following forward model:

$$P_{\text{predict}} = P(u_k, v_l + \Delta|z_t) \tag{13}$$

where $P_{\text{predict}}$ uses the posterior probability distribution to shift the angle classes $v_l$ by a parameter $\Delta = \{1,2,\ldots,L\}$, with $L$ angles classes. Shifting the angle classes provides an estimation of the sensory observations for the next angle classes during the exploration process. The approach for learning and adapting the parameter $\Delta$ is described in Section 3.5.3. The approach to adapt the parameter $\alpha$, used to autonomously control the combination of information sources, is described in Section 3.5.4. The used of both parameters allows the fingertip sensor to achieve a better performance and trade-off between accuracy and reaction time during the exploration of an object.

### *3.5.3. Forward model learning*

Forward models allow robots to predict sensory observations from actions performed at previous time steps. These models are crucial for the development of autonomous robots capable of learning, adapting and making optimal decisions and actions [35, 41]. The forward model in Equation (13) depends on the learning and adaptation of the parameter $\Delta$, which is used for prediction of sensory observations for the next angle classes during the exploration task. This approach allows the fingertip sensor to adaptively combine the predicted or expected sensory observations with current sensor observations. The learning process is based on a Predicted Information Gain (PIG) approach, which has been studied for prediction of observations using complete knowledge of the environment [42]. In this work, the PIG approach has been modified to allow the fingertip sensor to observe 'what would have happened' if a certain action 'would have been made' from the previous decision time. This learning and adaptive process extends our previous work in [10], where the parameter $\Delta$ was predefined for all the object exploration process. In the PIG approach, the parameter $\hat{\Theta}$ denotes the estimated observations from the active Bayesian perception process, while the set of actions (fingertip movements) and states (angle perceived) is denoted by $a = \{a_1, a_2, \ldots, a_L\}$ and $s = \{s_1, s_2, \ldots, s_L\}$ with $L$ number of angle classes. The PIG approach is defined as follows:

$$\mathrm{PIG} = \gamma \sum_{s^*} \hat{\Theta}_{a,s,s^*} \mathrm{D_{KL}}(\hat{\Theta}_{a,s}^{a,s,s^*} \| \hat{\Theta}_{a,s}) \tag{14}$$

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 denoted by $\hat{\Theta}_{a,s,s^*}$. This formulation is normalised by the parameter $\gamma$. The Kullback-Leibler Divergence ($\mathrm{D_{KL}}$) provides the amount of information that would have been lost for each action performed at the previous decision time as follows:

$$\mathrm{D_{KL}}(\hat{\Theta}_{a,s}^{a,s,s^*} \| \hat{\Theta}_{a,s}) = \sum_{s^*}^{L} \hat{\Theta}_{a,s}^{a,s,s^*} \log\left(\frac{\hat{\Theta}_{a,s}^{a,s,s^*}}{\hat{\Theta}_{a,s}}\right) \tag{15}$$

The result from Equation (14) is used to update the transition matrix, $\Gamma_\tau$, which is employed to obtained the most probable shifting value for $\Delta$, as follows:

$$\Gamma_\tau = \eta \Gamma_{\tau-1} \mathrm{PIG} \tag{16}$$

$$\Gamma_\tau = \eta\left(\left(\frac{\tau-1}{\tau}\right)\Gamma_{\tau-1} + \frac{1}{\tau}\right)\mathrm{PIG} \tag{17}$$

where the transition matrix at decision time $\tau$ and $\tau-1$ are $\Gamma_\tau$ and $\Gamma_{\tau-1}$, respectively. The normalising parameter $\eta$ ensures probabilities in $[0,1]$. In previous works, this approach has been studied for online estimation of parameters using fixed or constant reward values [51]. Conversely, here we use the PIG measurement as a reward, which takes adaptive values in $[0,1]$ according to the decisions and actions made by the perception system. Then, the position of the largest probability from the transition matrix $\Gamma_\tau$ is assigned to the parameter $\Delta$, as follows:

$$\Delta = \arg\max(\Gamma_\tau) \tag{18}$$

The online adaptation of the parameter $\Delta$, used by the forward model in Equation (13), provides the predicted probability distribution used by both the adaptive weighted prior and posterior strategies. This is an important improvement over our previous work in [10], where the parameter $\Delta$ was manually set to a predefined value for all the exploration task. The predictions, made by the forward model, need to be assessed to ensure an optimal performance for the weighted combination of information sources. The proposed method for assessment of predictions is described in Section 3.5.4.

### *3.5.4. Forward model assessment*

The predictions made by the forward model need to be assessed to obtain an optimal performance during the object exploration task. The assessment process is used to control the confidence parameter $\alpha$, used in Equations (11) and (12), for the adaptive weighted combination of information sources. For this process a Dynamic Bayesian Network (DBN) is employed, permitting to dynamically control the contribution from the predictions made by the forward model, according to their accuracy observed over time, as follows:

$$H_\tau = \eta \xi_\tau \tag{19}$$

where $H_\tau$ contains the angle observations updated from decision time $\tau-1$ to $\tau$. The normalising factor is represented by $\eta$. The evaluation of predictions from the forward model is performed by $\xi_\tau$, as follows:

$$\xi_\tau = \left(\frac{\tau-1}{\tau}\right)P_{\mathrm{predict}} + \left(\frac{1}{\tau}\right)P(c_n|z_{1:t}) \tag{20}$$

where $P_{\mathrm{predict}}$ is the prediction from the forward model and $P(c_n|z_t)$ is the posterior from the Bayesian perception process, obtained once the belief threshold has been exceeded. The confidence parameter $\alpha$ is updated as follows:

$$\alpha_\tau = \left(\frac{\tau-1}{\tau}\right)\alpha_{\tau-1} + \left(\frac{1}{\tau}\right)H_\tau(v^*) \tag{21}$$

$$v^* = \arg\max P_{\mathrm{predict}} \tag{22}$$

where $\alpha_\tau$ is the updated confidence parameter, $\alpha_{\tau-1}$ is the confidence parameter from the previous assessment at decision time $\tau-1$, and $H(v*)$ is the probability of the MAP estimate angle class $v^*$ from the forward model. The updated parameter $\alpha_\tau$ is used in Equations (11) and (12) for controlling the contribution from each information source. This process ensures the optimal weighting and use of both, the predicted and current sensor observations. Overall, the proposed adaptive perception method allows the fingertip sensor to autonomously adapt its performance, in order to achieve the optimal trade-off in perception accuracy and speed during the tactile exploration procedure.

Flowcharts in Figure 4 show the processes for active Bayesian perception, and its integration with the adaptive weighted prior and posterior strategies. In Section 4, these methods are tested using the tactile exploratory platform presented in Sections 3.1 and 3.2 to perform a contour following exploration procedure.

## 4. Results

This section presents the results from the adaptive weighted prior and posterior strategies implemented with a contour following exploration procedure. Commonly, humans employ this exploration procedure for extraction and recognition of object shape using their hands and fingers. The experiments were performed using real tactile data collected from the fingertip sensor and plastic object presented in Section 3.

### *4.1. Active tactile exploration of object shape*

For the first experiment, active Bayesian perception was implemented to observe the performance in accuracy and reaction time of the sensor to explore, follow and extract the contour of an object. For this task, a circular-shaped object was built using real tactile data previously collected (see Section 3.3), for exploration of object shape in offline mode. The fingertip sensor performed 10,000 repetitions of the exploration process, randomly selecting the initial position for each repetition of the contour following task. Then, after selecting the initial position, the fingertip sensor performed the contour following task using the approach presented in Section 3.4. The set of belief thresholds $\beta_{\text{threshold}} = \{0, 0.05, \ldots, 0.99\}$ was used to observe how the amount of evidence accumulated affects the performance of the object exploration task. Figure 5 shows the recognition accuracy of angle and position classes against belief threshold and reaction time. Accurate recognition of angle and position classes is required to allow the fingertip sensor to perceive its location and decide where to move next during the contour following task. Results in Figures 5A,B show that small belief thresholds ($\beta_{\text{threshold}} \approx 0$) do not allow the robot to accumulate enough evidence, which is reflected in the low recognition accuracy for both, angle (43 deg error) and position (7.5 mm error) classes. In this case, the perception system is able to make rapid decisions (1 tap) and performing a fast object exploration. The use of large belief thresholds ($\beta_{\text{threshold}} \approx 0.99$) shows an improvement in accuracy, reducing the recognition error for angle and position classes to 5 deg and 0.18 mm, respectively. However, the reaction time is affected, increasing to 5 and 8 the number of sensor contacts needed for recognition of angle and position classes, respectively (Figures 5C,D). The accuracy and reaction time present a gradual and smooth improvement for increasing belief thresholds. With these results it is possible to select the parameter $\beta_{\text{threshold}}$ for the appropriate trade-off between accuracy and speed. The result from the contour following task with a small belief threshold ($\beta_{\text{threshold}} = 0.0$) is show in Figure 6A, where the sensor was not able to extract the object contour accurately. The increment of the belief threshold to $\beta_{\text{threshold}} = 0.5$ improves the exploration accuracy, but there are still regions of the object contour that were not accurately recognised by the sensor (Figure 6B). In contrasts, the exploration procedure was successfully performed using a large belief threshold of $\beta_{\text{threshold}} = 0.99$ (Figure 6C).

### *4.2. Adaptive weighted prior strategy*

The adaptive weighted prior strategy was tested with the contour exploration of a circular-shaped object built with real

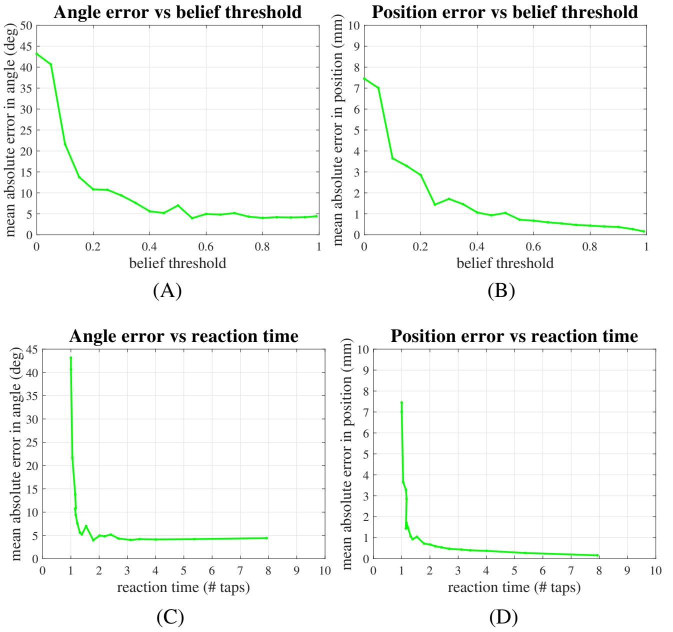



Figure 5: Perception accuracy and reaction time for recognition of angle and position perceptual classes from a contour following task with active Bayesian perception. (A),(B) Perception accuracy against belief threshold is improved for larger belief thresholds. (C),(D) Reaction time required for decision-making increases for larger belief thresholds. These results shows that active perception can be adjusted to perform either fast decisions with low accuracy or highly accurate decisions with large number of tactile contacts.

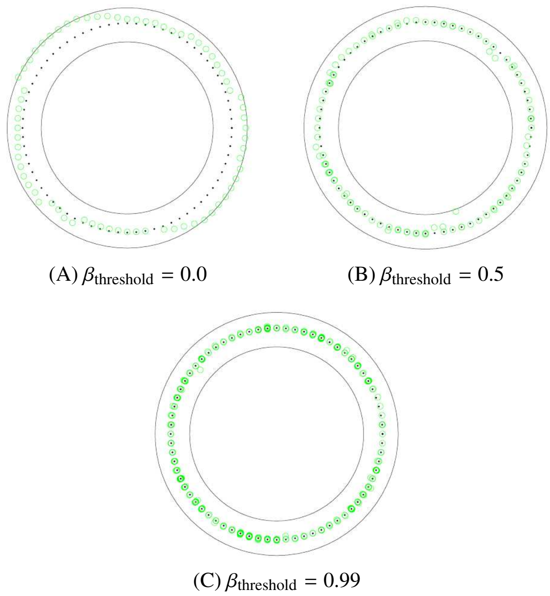



Figure 6: Tactile contour following results from a circular-shaped object using active perception and a biomimetic fingertip sensor. The object contour is defined by the black dotted line, sensor movements are represented by the green colour circles and the black solid line defines the exploration limits according to the collected datasets. (A) Active perception with belief threshold, $\beta_{\text{threshold}} = 0.0$, does not allow the touch sensor to extract the object shape. (B) Active perception with belief threshold, $\beta_{\text{threshold}} = 0.5$, improves the exploration process but still the object shape is not extracted successfully. (C) Large belief thresholds, $\beta_{\text{threshold}} = 0.99$, allow the active perception approach to successfully follow and extract the object shape.

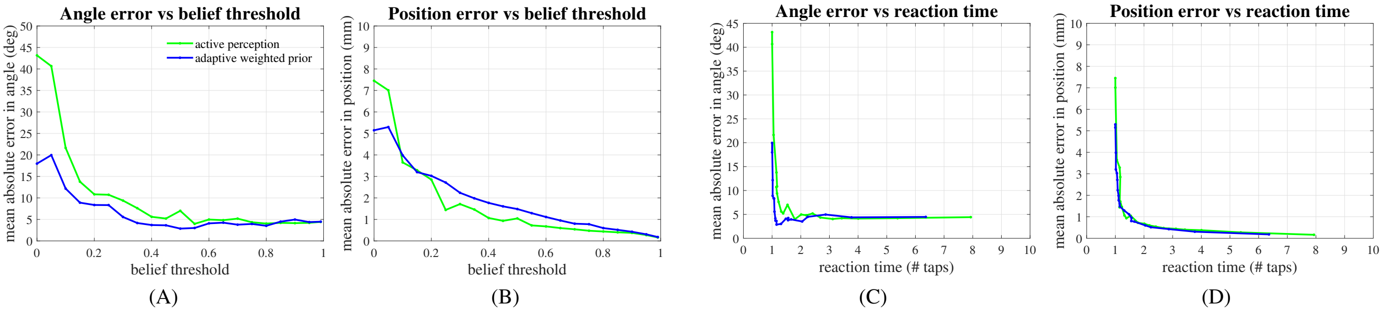



Figure 7: Adaptive weighted prior strategy employed with active perception for recognition of angle and position perceptual classes during a contour following exploration procedure (blue colour curves). (A) Angle perception accuracy is improved requiring small belief threshold values to achieve high accuracy. (C) This result also improves the reaction time for angle perception. (B,D) Recognition of position classes and reaction time do not show improvement by the adaptive weighted prior strategy. Results from the use of active Bayesian perception alone are included (green color curves) for comparison of performance.

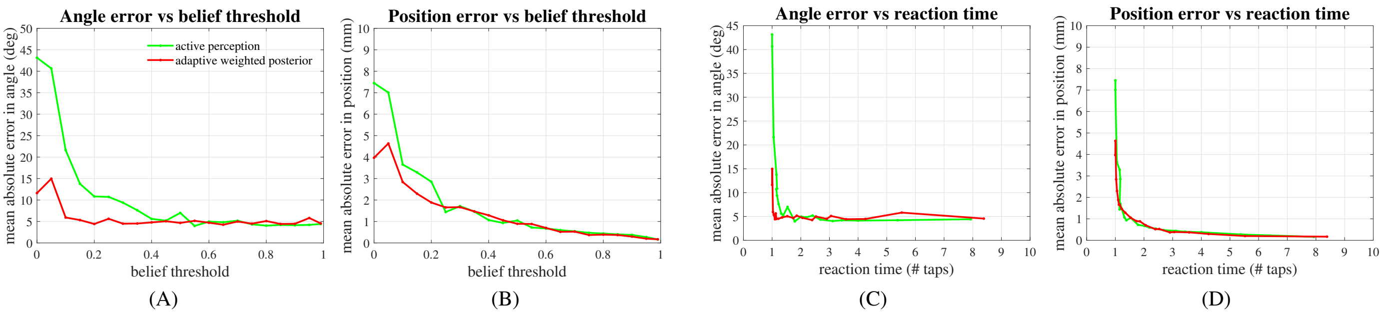
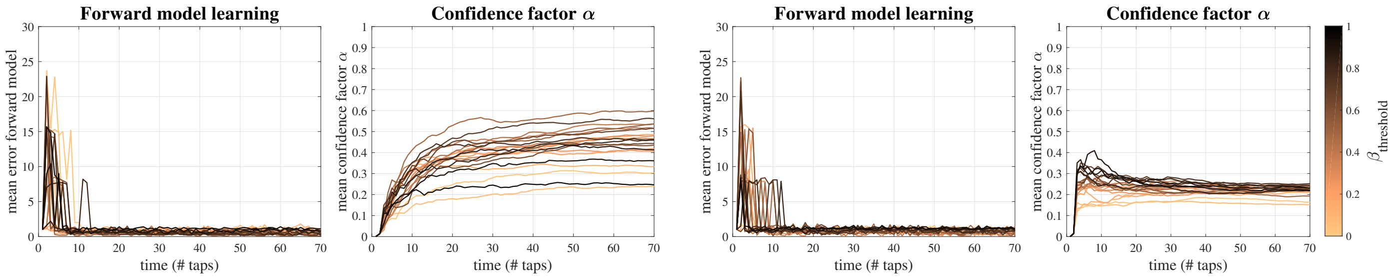



Figure 8: Adaptive weighted posterior strategy employed with active perception for recognition of angle and position perceptual classes during a contour following exploration procedure (red colour curves). (A) High angle recognition accuracy is achieved with small belief threshold values. (C) Reaction time is also improved requiring less number of tactile contacts to make a decision. These results improve the performance of active perception alone. (B) Recognition of position classes shows slight improvement for small belief thresholds. (D) However, reaction time for recognition of position classes does not show improvement. Results from the use of active Bayesian perception alone are also included (green color curves) for comparison of performance.

tactile data. The exploration process was repeated 10,000 times, randomly selecting the initial position for exploration. The results from this adaptive Bayesian perception process are compared with the results from active Bayesian perception alone. The implementation of the adaptive strategy is based on the flowchart in Figure 4B. In this experiment, real tactile data were used for both training and testing phases, and a set of belief thresholds was used to control the performance in accuracy and reaction time of the object exploration as in Section 4.1.

The adaptive weighted prior allows the active Bayesian perception to use a non-uniform prior probability, which is learned and adapted based on the observation of decisions and actions made. This approach makes the tactile robot capable of autonomously adapt its perception accuracy and reaction time. The results from this adaptive strategy are shown in Figure 7, where the recognition of angle and position classes, against belief threshold and reaction time, are represented by blue colour curves. For comparison of performance, results from active Bayesian perception are included (green colour curves). The adaptive weighted prior achieved the smallest angle and position errors of 2.8 deg and 0.18 mm with $\beta_{\text{threshold}} = 0.5$ and $\beta_{\text{threshold}} = 0.99$, respectively (Figure 7A,B). Angle perception accuracy is improved even for small belief thresholds. In contrast, no improvement was observed for perception of position classes. Similar to active perception, the adaptive weighted prior shows a gradual reduction of errors for the transition region from small to large belief thresholds. Angle and position accuracy against reaction time in Figures 7C,D, show an improvement in the number of tactile contacts ($\approx$ 1 tap) required for the highest accuracy in angle perception. However, no effects were observed in reaction time for perception of position classes with the adaptive weighted prior strategy.

The accuracy of predictions made by the forward model, based on the observation of decisions and actions, are shown in Figure 9A. The forward model shows large variability and low accurate prediction at the beginning of the experiment. However, the performance of the forward model is improved over time, when more decisions and observations have been made. Adaptation of the confidence parameter, $\alpha$, used for controlling the combination of information sources, is shown in Figure 9B. The confidence parameter is adapted according to the accuracy of predictions with respect to what was perceived in the current decision time. The results shown in Figure 9 were obtained with the belief threshold $\beta_{\text{thresholds}} = \{0, 0.05, \ldots, 0.99\}$. This adaptive method is capable of improving the active Bayesian perception process, permitting the development of intelligent




(A) Adaptive weighted prior (B) Adaptive weighted prior (C) Adaptive weighted posterior (D) Adaptive weighted posterior

Figure 9: Forward model and confidence parameter implemented by the proposed adaptive strategies. These results are obtained from a contour following exploration procedure using a biomimetic fingertip sensor and evaluated with a set of belief threshold $\beta_{\text{threshold}} = \{0, 0.05, \ldots, 0.99\}$, which are represented by coloured curves. (A) Adaptive weighted prior strategy; accuracy of the forward model for prediction of sensory observations improves over time. (B) Confidence parameter adapts over time, based on the accuracy of predictions, to control the combination of information sources by the adaptive weighted prior strategy. (C) Adaptive weighted posterior strategy; forward model accuracy improves over time. (D) Adaptive confidence parameter, based on the accuracy of prediction, which permit to control the combination of information sources by the weighted posterior strategy.

tactile systems that autonomously combine information sources to adapt its exploration performance.

### *4.3. Adaptive weighted posterior strategy*

The contour following task was repeated using the adaptive weighted posterior strategy. The flowchart in Figure 4C shows the processes for this adaptive strategy. Similar to the experiments in Section 4.2, real tactile data were used for training and testing the adaptive strategy, using a set of belief thresholds for the analysis of performance in accuracy and reaction time.

The adaptive weighted posterior strategy does not affect the prior probability of the active Bayesian perception process, as with the weighted prior strategy. This strategy combines sensory predictions with the posterior probability from the active Bayesian perception, once the belief threshold has been exceeded. The decisions are made based on the combination of current and predicted probability distributions. This process allows the tactile exploration system to adapt its performance, making decisions based on observations from previous decision times. Figure 8 shows the performance in accuracy and reaction time for recognition of angle and position classes during the contour following of a circular-shaped object. Results from the adaptive weighted posterior strategy (red colour curves) are compared with results achieved by active Bayesian perception alone (green colour curves). The smallest recognition errors for angle and position classes against belief threshold are 5 deg and 0.18 mm for $\beta = 0.2$ and $\beta = 0.99$, respectively (Figure 8A,B). Recognition of angle classes was improved with small belief thresholds, reaching smaller errors than active Bayesian perception. In this case, the accuracy presented a steady behaviour for belief thresholds from 0.2 to 1. Recognition of position classes presented an improvement for small belief thresholds, but it showed a similar performance to active Bayesian perception for the transition between small and large belief thresholds. The adaptive weighted posterior also showed an improvement in reaction time, requiring 1 tap for the smallest angle recognition error. However, this method did not affect the reaction time for recognition of position classes, presenting similar results to the use of active Bayesian perception alone.

The adaptive behaviour of the forward model and confidence parameter is shown in Figures 9C,D. These results were obtained from the exploration task using the set of belief threshold $\beta_{\text{threshold}} = \{0, 0.05, \ldots, 0.99\}$. Predictions made by the forward model presented a large variability at the beginning of the exploration task, but they improved when more decisions and observations were made. Similarly, the confidence parameter was adapted over time, according to the accuracy of predictions from the forward model. This process permits to control the combination of information sources, but also to control the contribution made by predictions in the decision-making process. Thus, decisions rely more on predictions when they are accurate, otherwise, decision rely more on the output from active perception alone. Results show that this adaptive strategy allows the development of intelligent tactile exploration systems that, capable of autonomously adapt over time, achieve a better performance and trade-off between accuracy and reaction time.

A statistical analysis, using the one-way analysis of variance (ANOVA), was used to observe whether the angle and position classes, recognised by the adaptive weighted strategies, are statistically different from the recognition performed by active perception alone. Thus, we analyse the null-hypothesis $H_0$: there is no difference between the recognition of angle and position classes performed by the active perception, adaptive weighted prior and adaptive weighted posterior methods. The hypothesis testing employs information from angle and position classes, recognised by the active and adaptive methods from all the contour following exploration tasks performed by the fingertip sensor. Statistical information from these variables is presented in Table 1.

First, ANOVA is applied to all angle and position classes obtained from the active perception method and adaptive weighted prior strategy. The results from analysis, composed by the mean square columns (MSC), mean square errors (MSE), $F$-statistics and $p$-value, are shown in Table 2. For angle recognition, the $F$-statistics value of 12.52 (MSC/MSE = 45.38/3.62), together with the $p$-value of 0.0004 for a significance level $\alpha = 0.001$, indicate that the null-hypothesis is rejected. This means that there is a statistically significant difference between angle recogni-

Table 1: Statistical information (mean, standard deviation, median, minimum and maximum values) from the angle and position classes recognised by active perception, adaptive weighted prior and posterior methods. This information was obtained from the object shape exploration implemented with the contour following procedure using the tactile sensor.

| | active perception | | adaptive weighted prior | | adaptive weighted posterior | |
|---|---|---|---|---|---|---|
| | angle | position | angle | position | angle | position |
| mean | 2.09 | 1.74 | 1.31 | 1.86 | 1.15 | 1.33 |
| standard deviation | 2.41 | 2.05 | 1.19 | 1.55 | 0.74 | 1.25 |
| median | 1.02 | 0.91 | 0.86 | 1.35 | 0.91 | 0.85 |
| minimum / maximum | 0.49 / 12.97 | 0.11 / 8.11 | 0.21 / 6.87 | 0.02 / 6.62 | 0.34 / 5.87 | 0.04 / 5.19 |

Table 2: Statistical analysis of active perception and the adaptive weighted prior strategy. The parameters MSC/MSE, $F$-statistic and $p$-value show the difference between results from active perception (no adaptive approach) and the adaptive weighted prior strategy for recognition of angle and position classes.

| active perception (no adaptive) vs adaptive weighted prior | | | | | | |
|---|---|---|---|---|---|---|
| angle | | | position | | | significance level |
| MSC/MSE | $F$-statistics | $p$-value | MSC/MSE | $F$-statistics | $p$-value | $\alpha$ |
| 45.38/3.62 | 12.52 | 0.0004 | 1.19/3.32 | 0.35 | 0.54 | 0.001 |
| | reject $H_0$ | | | fail to reject $H_0$ | | |

Table 3: Statistical analysis of active perception and the adaptive weighted posterior strategy. The parameters MSC/MSE, $F$-statistic and $p$-value show the results from active perception (no adaptive approach) and the adaptive weighted posterior strategy for recognition of angle and position classes.

| active perception (no adaptive) vs adaptive weighted posterior | | | | | | |
|---|---|---|---|---|---|---|
| angle | | | position | | | significance level |
| MSC/MSE | $F$-statistics | $p$-value | MSC/MSE | $F$-statistics | $p$-value | $\alpha$ |
| 65.65/3.18 | 20.61 | $8.23\times10^{-6}$ | 12.13/2.89 | 4.18 | 0.041 | 0.001 |
| | reject $H_0$ | | | fail to reject $H_0$ | | |

Table 4: Statistical analysis of the adaptive weighted prior and adaptive weighted posterior strategies. The parameters MSC/MSE, $F$-statistic and $p$-value show the statistical analysis from the recognition of angle and position classes performed with the contour following experiments.

| adaptive weighted prior vs adaptive weighted posterior | | | | | | |
|---|---|---|---|---|---|---|
| angle | | | position | | | significance level |
| MSC/MSE | $F$-statistics | $p$-value | MSC/MSE | $F$-statistics | $p$-value | $\alpha$ |
| 1.86/0.99 | 1.88 | 0.17 | 20.94/1.98 | 10.53 | 0.0013 | 0.001 |
| | fail to reject $H_0$ | | | fail to reject $H_0$ | | |

tion from the active and adaptive weighted prior. In contrast, for position recognition, the adaptive weighted prior failed to reject the null-hypothesis, given the $p$-value of 0.54 and significance level $\alpha = 0.001$. In other words, there is no statistically significant difference between the active and adaptive weighted prior methods for the recognition of position classes.

Second, the results from ANOVA applied to the active and adaptive weighted posterior methods are shown in Table 3. For the case of angle recognition, the null-hypothesis is rejected based on the $p$-value of $8.23\times10^{-6}$. Conversely, the adaptive weighted posterior method failed to reject the null-hypothesis for recognition of position classes, given the $p$-value of 0.041 for $\alpha = 0.001$. The results from Table 3 show that there is statistically significant difference, between the active and adaptive weighted posterior methods, for the recognition of angle classes. However, this difference was not observed for the recognition of position classes.

Third, the statistical analysis is applied to both adaptive weighted strategies as shown in Table 4. This analysis shows that there is no statistically significant difference between the angle and position recognised by both adaptive weighted strategies (fail to reject the null-hypothesis). This result is indicated by the $p$-values of 0.17 and 0.0013 for angle and position classes, respectively, with significance level $\alpha = 0.001$. These results also correspond to the performance observed from angle and position perception by both adaptive weighted strategies in Sections 4.2 and 4.3.

## 5. Discussion

This work presented an investigation on adaptive strategies that, combining sensory predictions and current observations, enhance the active perception process for autonomous tactile exploration. First, this research showed that tactile exploration is improved by active control of robot movements using tactile feedback. Second, it was shown that sensory predictions from a forward model, combined with current sensory observations, permitted the autonomous adaptation of active Bayesian perception to improve perception accuracy, reaction time and their trade-off during robot tactile exploration and recognition tasks.

For validation of the adaptive strategies for object exploration, real tactile datasets were collected using a biomimetic fingertip sensor and a plastic object as stimuli. Sensor movements were systematically controlled by a 3-DoF robot with an exploratory procedure based on taps or palpations. This exploratory procedure (1) is inspired by humans in situations when they touch a sharp surface or perform a medical inspection, (2) it reduces damage to the surface of fingertip sensors and (3) offers an alternative exploration approach for robots that are not capable to slide their tactile sensors. In this work, a circular-shaped object was selected for all the experiments for the following reasons. First, the circular object gives the fingertip sensor the possibility to test all the angles classes, while covering the 360 degs around the plastic object. This type of object allows us to observe the accuracy and speed for recognition of all angle classes. Second, building the circular object using real tactile data, for exploration in offline mode, is not as computationally expensive as building other objects, e.g., sellotape. Exploration of other object shapes, may not allow the fingertip sensor to test all the angle classes for validation of the active and adaptive perception methods.

First, active perception method was tested with the contour following exploration to extract object shape (see Figures 5 and 6). This perception approach, which has been tested in a previous work [10], is included here to motivate the research on the novel adaptive strategies for perception, exploration and combination of information sources. Active tactile movements, and large evidence accumulated from the interaction with the environment, permitted the sensor to achieve a gradual improvement in perception accuracy during object exploration (see Figure 6B). The accumulation of evidence is controlled by a belief threshold, which needs to be exceeded to allow the fingertip sensor to make a decision. These results fit with studies from psychology and neuroscience, which have shown that humans make reliable decisions once they have sufficient evidence [52]. Large belief thresholds provide better perception accuracy, however, the larger the belief threshold the larger the reaction time (number of taps) required to make a decision. This effect is expected given that humans explore actively moving their hands and fingers, but also they employ the needed time to reach the sufficient level of confidence about the object being explored [53]. This work has focused on active sensing, but for a description of the benefits of active over passive sensing refer to the following works [10, 23].

Humans rely on multiple information sources to make accurate and fast decisions. For example, the use of current information from the environment, and knowledge gained over time, allow humans to make predictions, learn and adapt their performance while interacting with the environment [6, 36, 37]. In this work, the adaptive weighted prior and posterior strategies, that present a novel approach for adaptive combination of information sources and prediction of sensory observations, were implemented to improve the performance of the active Bayesian perception method. First the adaptive weighted prior, applied at the beginning of the Bayesian perception process, combines a uniform and a predicted probability distribution. A preliminary study of the adaptive weighted prior was presented in [9], and here a detailed and systematic analysis was undertaken. Second, the adaptive weighted posterior, applied at the end of the active Bayesian perception process, combines a posterior and a predicted probability distribution. These adaptive strategies permit the observation of the effects in performance when sensory predictions, combined with current sensory observations, are applied at different stages of the active Bayesian perception process. Sensory predictions employed by these methods were obtained with a forward model using a predicted information gain approach [42, 54], which in this work was modified to analyse ‘what would have happened’ if a certain action ‘would have been made’ at previous decision time. This process allowed the autonomous adaptation of the forward model based on the observation of decisions and actions made. The benefit of these adaptive methods is that if predictions are accurate, then tactile perception will improve using a combination of information sources than relying on current sensory observations alone. Essentially, this means that decisions made by active Bayesian perception will be more accurate by the combination of what it was predicted and current sensory observations, which overcomes the assumptions and manual control of parameters employed in previous works [10]. The adaptive weighted strategies were systematically validated with the recognition of angle and position classes from the contour following exploration procedure. In this experiment both strategies improved the performance of angle recognition, with small recognition errors and small belief thresholds, over the results obtained by active perception alone. This demonstrates that adaptation of active perception allows the fingertip sensor to perform more accurate and fast decisions, while improving the trade-off between accuracy and reaction time in autonomous robot exploration tasks (Figures 7 and 8). For recognition of position classes, an improvement was observed with the adaptive weighted posterior strategy. However, no improvement was observed with the adaptive weighted prior strategy. This performance in position classes is related to the design of the forward model, which only takes into consideration the angle classes for estimation of sensory predictions. Then, both adaptive strategies are optimised for perception of angle classes but not for position classes. For that reason, for the future work we consider to extend the forward model to make predictions about expected angles and positions. With this approach, we plan to improve the performance in accuracy and speed for both angle and position classes during exploration tasks. Figures 7 and 8 show the improvements from the adaptive strategies and their comparison with active Bayesian perception.

To ensure reliable combination of information sources, predictions from forward model need to be evaluated and weighted [35]. A confidence parameter was employed to weight the combination of information sources for both adaptive strategies. This parameter autonomously adapts over time, according to the accuracy of what it was predicted and what it was perceived. Therefore, this parameter controls the contribution from predictions used in the combination of information sources, ensuring reliable, accurate and fast decisions from the Bayesian perception process. The adaptation of the forward model and confidence parameter for both adaptive strategies is shown in Figure 9. We observed that the forward model started with large variability, providing inaccurate predictions, however, the forward model improved its performance once more observations and prediction were made. Thus, the confidence parameter was adapted according to the reliability of predictions, to ensure a better performance in accuracy and reaction time. Results showed that accurate predictions benefit the active perception process, but even if predictions are not accurate they do not degrade or negatively affect the perception process. The proposed adaptive perception and weighted combination processes offer a robust approach for various robotic applications. For instance, human-robot interaction and collaboration need of robots capable to predict human actions, performing safe and adaptive robot control and reducing the risk of injuring the human operator. Assistive robots need to understand and predict the intention of human movement, in order to safely apply the required assistance at the appropriate time. Wearable robots for rehabilitation is another application where adaptation, according to the recovery progress estimated by the robot, is crucial to deliver a reliable and beneficial rehabilitation to the patient. Recognition, prediction and adaptation, using data from multiple information sources, are essential to develop autonomous robots capable to learn and adapt to their surrounding changing environment. Another important aspect in robotics, and which we plan to investigate in future works, is the adaptive combination of multiple sensing modalities, e.g., touch, vision, audio, which represents a challenging and crucial topic to gradually deliver intelligent and highly safe autonomous systems for interaction with their surrounding environment as humans do.

The experiments shown in this work employed rigid objects only, however, nowadays non-rigid or soft objects are becoming attractive for robotics research. Non-rigid objects are gaining attention because of their compliance and deformable physical characteristics, which are essential for safe human-robot interaction, assistive robots and autonomous exploration robots. Currently, the tapping procedure for data collection, implemented by our proposed method, uses a predefined threshold for contact detection with the fingertip sensor. Thus, for contact detection of non-rigid object, our method needs to be extended with a module that adapts the contact threshold according to the softness of the object being explored. This adaptive contact detection module would also allow the fingertip sensor to explore objects made of a mixture of different materials. However, the modules for active and adaptive perception, and control of the fingertip sensor, would not need to be modified. The development and integration of modules for dealing with non-rigid object is part of our plans for future works. All in all, this work proposes a method to allow the development of intelligent systems capable of autonomously control the combination of information sources, relying more on predictions when they are accurate and relying more on current observations otherwise.

Autonomous robots, capable to understand their surrounding environment, require methods for tactile perception and decision-making, but also for adaptation over time. Overall, this work presented two novel computational methods, that integrating both active and adaptive perception processes, enable robots to perceive and autonomously adapt their performance and the trade-off between perception accuracy and reaction time during tactile exploration, recognition and interaction tasks.

## 6. Conclusions

In this work, the adaptive weighted prior and posterior strategies were developed to improve the performance of active perception in tactile exploration tasks. These strategies presented a novel method for adaptive combination of current and predicted sensory observations. Both adaptive strategies employed the novel Predicted Information Gain (PIG) method, to learn the forward model responsible for providing sensory predictions. A confidence parameter was learned for the evaluation of the accuracy of predictions, and adapt the combination of information sources. The adaptive strategies were systematically validated with the recognition of angle and position data extracted from the exploration of object shape, using a tactile robotic platform. Angle class accuracy of 2.8 deg, and reaction time of 1 tap, were improved by the adaptive approach over the performance achieved by active perception of 5 deg and 5 taps. Position class accuracy of 0.18 mm was similar for all perception methods. The results demonstrate the benefits, in accuracy and reaction time, when multiple information sources are adaptively combined. Overall, the novel adaptive weighted strategies can enable tactile robots to autonomously improve their performance in exploration and recognition tasks, and in the interaction with humans and the surrounding environment.

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