Proceedings Paper:

Salazar, P.J. and Prescott, T.J. orcid.org/0000-0003-4927-5390 (2022) Tactile and proprioceptive online learning in robotic contour following. In: Pacheco-Gutierrez, S., Cryer, A., Caliskanelli, I., Tugal, H. and Skilton, R., (eds.) Towards Autonomous Robotic Systems: 23rd Annual Conference, TAROS 2022, Culham, UK, September 7–9, 2022, Proceedings. 23rd Annual Conference, TAROS 2022, 07-09 Sep 2022, Culham, UK. Springer International Publishing , pp. 166-178. ISBN 9783031159077

https://doi.org/10.1007/978-3-031-15908-4_14

Tactile and Proprioceptive Online Learning in Robotic Contour Following

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Abstract. Perception of physical features through touch requires the execution of exploratory movements. Modifying the state parameters of the sensory apparatus to obtain relevant information to achieve a task contributes to an efficient manner for exploration of object properties. These principles have served as inspiration in the development of robotics and autonomous systems. Following the contour of an object poses multiple challenges in the perception of the geometry of an object such as identifying the angle of the sensor relative to the edge to perform tangential exploratory motions, and localising the sensor to place it where the angle tends to be perceived with more accuracy. The variability in the acquisition of tactile data may induce inaccuracies in the predictions from the sensor model. This work examines the influence of integrating proprioceptive information for the assessment and update of the parameters of a Bayesian probabilistic model. This inclusion leads to an increment in the number of task completion relative to performing the task with a model trained solely with data collected offline. Studies in biological touch suggest that tactile and proprioceptive information converge synergistically to drawing conclusions about the feature that is in contact with the sensory apparatus, this work provides a method for improving the modelling of the sensor responses to actively perform object exploration under variability of tactile data in the acquisition process.

Keywords: Active Touch · Online Learning · Contour Following · Exploratory procedure.

1 Introduction

Tactile sensing provides the capability of interacting with the world by establishing direct contact with objects and surfaces to extract relevant properties for achieving a task. The required interaction implies that specific movements need to be performed to elicit the tactile properties associated to the executed motion [11]. The relevance of the tactile information needed to achieve a desired outcome is translated into the active nature of touch. Active touch involves the execution of an action-perception loop in which dedicated actions are intended to guide the spatially constrained sensory apparatus [6]. The execution of these actions is conducted by taking into account the tactile and proprioceptive sensory information, its prior understanding , as well as knowledge about the task that is being executed [21].

The human hand has evolved to serve as a skillful tool for perception of tactile properties. The hand consists of glabrous and non glabrous skin; being the former, present in the palmar skin, the most receptive part to mechanosensation due to its high density innervation that is correlated with psychophysical spatial acuity [2]. This highly innervated area contains four types of receptors that respond to low thresholds of skin deformation, contact events, and sensitivity to high frequency stimuli. When these receptors receive a stimulus related to the sensitive-related physical property, the information is conveyed to the somatosensory cortex to be processed and encoded [22]. Studies in non-human primates have identified four areas in the primary somatosensory cortex, i.e. Broadmann areas 3a, 3b, 1 and 2, these areas have been described as being hierarchical and interconnected [8, 7, 5]. In that sense, higher-in-hierarchy areas, with the function of processing more complex information, receive information from their lower-in-hierarchy counterparts, as well as information from areas dedicated to sensing and execution of motor behaviour. According to these studies, at the base of the hierarchy, 3a area receives proprioceptive spatial information form muscle spindles; 3b area retrieves information from receptors located closer to the skin surface; area 1 obtains information from rapidly adapting fibers; and area 2 receiving proprioceptive signals, as well as information from the previously mentioned areas to process complex touch. The processed information in the primary somatosensory cortex is conveyed to the the secondary somatosensory cortex which processes information that is conveyed to cortical areas in charge of the execution of motor commands and recognition of physical properties [4].

Apart from apprehending semantic representations from mechanoreception, tactile and proprioceptive information contribute to the processing of complex touch as well as active touch by means of the intentional exploration of surfaces and objects. The exploratory essence of touch has been characterised under the term of 'Exploratory Procedures'. EPs are described as stereotypical movements that subjects execute when prompted to learn about a certain tactile property [12]. Material properties of an object can be retrieved by performing characteristic actions such as lateral motion for texture, pressure for compliance and static contact for temperature. Geometric properties such as global shape and volume can be obtained with the enclosure exploratory procedure; the exact shape and volume can be retrieved through following the contour of the object [13]. These characteristics of human touch are inspiring the development of technologies and tactile systems to result in remarkable sensing capabilities [15].

Providing robotic systems with the capacity to sense and draw conclusions about tactile data can be essential for the achievement of tasks that require feedback from physical interaction with the environment; such tasks include grasping, in-hand manipulation, and object exploration [10]. The execution of these tasks can be benefited by possessing knowledge about the shape of the object. Retrieval of geometric object information through touch is generally attained by mapping from data related to sensor deformation to the pose of the sensing device relative to the object [17]. This process contributes with information for the control and guidance of movement of the sensory apparatus to extract the global or exact shape according to the objectives of the perceiver.

Tactile perceptual systems are restricted to the size of the sensor, thus acquiring geometric information through touch has been a compelling object of study in examining methods to effectively place the sensor where information relevant to the task can be obtained [23]. Retrieval of tridimensional surfaces have been achieved through the registering of coordinates where the event of touching the object has occurred. These coordinates are used as an input in a function approximator that provides an estimate of the object shape in three dimensions [24]. The implicit hurdle in using these models is determining the next sampling position to attain a fast and accurate shape estimation [9, 20, 3]. Inspired from psychophysical studies in touch, the obtention of the exact shape of an object has been investigated by means of the replication of contour following exploratory procedures in robotic platforms [19]. Tactile information related to sensor deformation has been related to allocentric sensor localisation to follow the contour of objects. These methods rely on Bayesian inference in which the hypotheses for perceptual classes given the tactile data are updated with the acquisition and accumulation evidence to make a decision regarding a perceptual outcome [18, 16].

Although the implementation of contour following exploratory procedure using Bayesian methods using only tactile data in robotic platforms has demonstrated the feasibility of successfully obtaining the exact shape of the contour of an object, the effect of taking into account the proprioceptive information from the robotic platform for assessing and updating a probabilistic model remains to be studied. Obtaining the exact shape of an object through tactile information requires perception models that can accurately infer a position of the sensor with respect to an object using tactile data. However, tactile data acquisition can be effected by sensor noise, hysteresis-induced errors, and the wear and tear off of the sensor [10]. These possible issues can lead to deficiencies in the repeatability of tactile measurements, and consequently a reduction in accuracy of perceptual outcomes. In that sense, the mapping of tactile data into sensor position can be supported by the millimetric, precise and accurate information that robot proprioception can provide.

The present work evaluates the effects of implementing a Bayesian probabilistic model for sensor localisation with respect to an object to execute a contour following exploratory procedure with tactile data. Additionally, examining the integration of proprioceptive information in the assessment and updating of the model. Improvements in task completion are verified through the use of the ground truth information provided by the sensor position against the initial model that uses solely tactile information.

2 Methods

2.1 Robotic Setting

The robotic system used for the aqcuisition of the tactile information and movement of the sensor to perform a contour following exploratory procedure consists of a TacTip biomimetic tactile sensor [1] mounted on a robotic platform able to perform movements in the Cartesian space. This setting is used in an action-perception closed loop to execute the exploratory procedure with information obtained from the tactile sensor.

Robotic Platform The robotic platform is composed of a Yamaha XYX robot and an Actuonix P-16 linear actuator, providing horizontal and vertical movements respectively, as can be seen in Fig. 1a. The Yamaha robot has been used in previous studies on active touch with fingertips and artificial whiskers [14] offering an accuracy of about 20μm in the positioning of the sensor in the $x-y$ plane. The linear actuator spans a stroke of 50mm allowing a vertical motion of the sensor. The robotic platform allows the execution of precise movements in the x and y axes for the positioning of the sensor to establish a relationship between the acquired tactile data and the location of the sensor relative to the object.

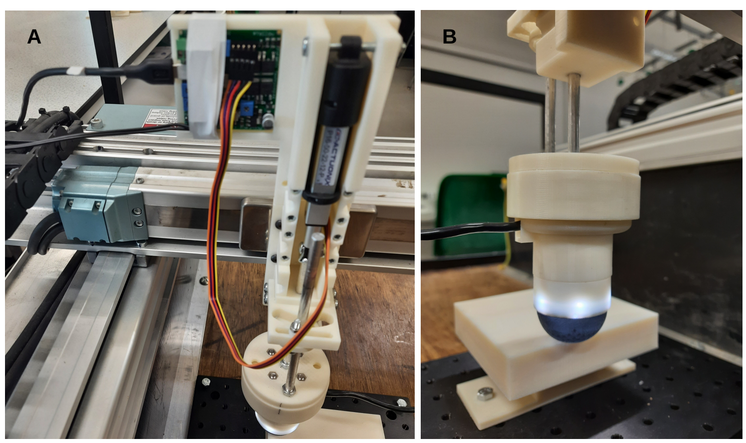

Fig. 1. Robotic setting. A) The Robotic platform consists of a Yamaha XYX robot and an Actuonix P-16 linear actuator. B) TacTip sensor [1] and object for contour following

Tactile fingertip sensor The TacTip Sensor (Fig. 1b) is a biomimetic soft optical tactile sensor. Inspired in the shallow layers of glabrous skin, the sensor contains a 20mm-radius hemispheric compliant pad with 127 pins acting as markers whose shear displacement is related to the deformation of the compliant component. The behaviour of the markers is captured by a webcam with a resolution of 640 x 480 pixels, sampled at approximately 20 fps. The software for marker detection and tracking, implemented in [16], provides data of the displacement of each marker in the x and y axes. The information obtained from the sensor is used to train a Bayesian probabilistic classifier for the localisation of the sensor with respect to an allocentric origin of coordinates and identification of angular classes for exploration.

Sensorimotor Integration The control of the robotic platform is achieved through serial communication between the computer and the robotic devices. The Yamaha robot and the linear actuator provide position feedback and position control. Both are integrated in a python script. Similarly, the data obtained from the TacTip data processor are included as an input to a probabilistic classifier that relate tactile information to sensor position. The action-perception loop obtains information from the sensor, and executes the movements for the completion of the task, i.e. contour following of an object, taking into account the predictions of the probabilistic classifier.

Acquisition of Tactile Data Tactile data acquisition follows a tapping procedure against the surface close to the edges to elicit a displacement of the internal markers of the TacTip Sensor. Vertical taps along a range between -9mm and 9mm in an interval of 1mm with respect to each of the edges comprise the data for each angular class. In that sense, an angular class contains 19 taps, and position classes as can be observed in Fig. 2. Each position class consists of two time series streams of data corresponding to the tracking of 127 marker positions (Fig. 2c) for x axis (Fig. 2a), and y axis (Fig. 2b). The data collection process is replicated for perceptual angles of $[0, 90, 180, 270]$degrees giving a total of 76 perceptual classes to train a probabilistic Bayesian classifier.

2.2 Bayesian Probabilistic Classifier

A Multinomial Naive Bayes Classifier is implemented as a sensor model for the mapping from tactile data to angle and position of the sensor. In which, the probability of a class given a measurement is proportional to the likelihood of the measurement given the class multiplied by the prior probability of the class:

$$P(c|z)\, \alpha\, P(c) \prod_{1 \leq k \leq n_b} P(z_k|c), \tag{1}$$

where $P(z_k|c)$ is interpreted as a quantification of the contribution of the evidence z_k to the correctness of class c. Tactile data is spatiotemporally encoded in histograms. Each stream of data corresponding to a single tap is distributed into a histogram composed of 100 bins. Specifically, each bin of the histogram contains the number of times that a marker displacement in the x and y axes

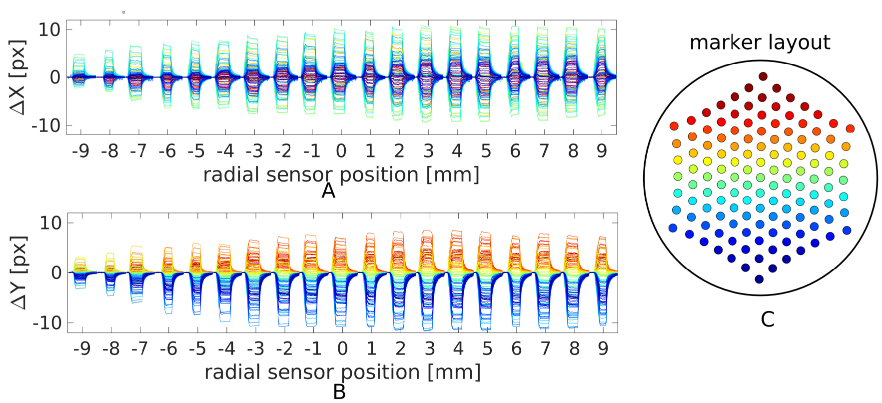

Fig. 2. Tactile data for 19 position classes corresponding to angle perceptual class: 0 degrees. A) Tracking of marker displacement in x axis (ΔX). B) Tracking of marker displacement in y axis (ΔY). C) Layout of 127 markers, colours on each plot correspond to the shown marker position

occur within a certain pixel variation range. $[z_1, z_2, ..., z_n]$ corresponds to each marker displacement belonging to a bin in the histogram, being n_z the number of samples from the stream of sensory data.

The best class for each tap from the Bayesian model corresponds to the most likely or $maximumaposteriori$ (MAP) class c_{map}:

$$c_{map} = \arg\max_{c \in C} \hat{P}(c|z) = \arg\max_{c \in C} \hat{P}(c) \prod_{1 \leq k \leq n_z} \hat{P}(z_k|c). \tag{2}$$

The values of the parameters $\hat{P}(c)$ and $\hat{P}(z_k|c)$ are estimated from the training data. The prior probability is estimated with the assumption that all classes are equally likely to occur, thus flat priors are set for each class, being N_c the number of classes:

$$\hat{P}(c) = \frac{1}{N_c} \tag{3}$$

The conditional probability $\hat{P}(z|c)$ is calculated as the relative frequency of marker displacements corresponding to a certain pixel range that belongs to class c:

$$\hat{P}(z|c) = \frac{Z_{cz}}{\sum_{z' \in V} Z_{cz'}}, \tag{4}$$

where Z_{cz} is the number of occurrences of a marker displacement in a pixel variation range for a tap stream data from class c. An independence assumption has been made between samples for each tracked marker in the x and y axes for model simplification. Even though this assumption might not be fulfilled in the real world, the outcomes from the model tend to be still reasonable [25].

Due to the sparseness that may occur within the encoding of the sensory data, a Laplace smoother is implemented by adding a one to each count:

$$\hat{P}(z|c) = \frac{Z_{cz} + 1}{\sum_{z' \in B}(Z_{cz'} + 1)}. \quad (5)$$

This smoothing method can be interpreted as a uniform prior for the occurrence of a certain displacement in a pixel variation range stated by the encoding histogram.

2.3 Active Bayesian Tactile Sensing

Tactile sensing for contour following requires an active approach for perception and selection of action. Active sensing implies modifying the state parameters of the sensor in order to acquire information relevant to the completion of the task. In this work, the perception of the angle of the sensor relative to the edge of an object is pertinent for the execution of exploratory tactile data acquisition to follow the contour of an object. An accurate perception of the angular perceptual class relies on modifying the radial position of the sensor. The repositioning of the sensor requires the localisation of the sensor with respect to the edge of the object. Sensor localisation is performed by the implementation of a probabilistic Bayesian classifier. The Bayesian model outputs the most likely perceptual class regarding to angle and position of the sensor. Given that some position classes will provide a more accurate angular perception, the sensor needs to be radially moved to the place where accuracy tends to be higher. This procedure leads to a correct perception of angular class for the execution of further tangential exploratory movements.

Active Contour Following The process for contour following takes place when a taping procedure against the object elicits the deformation of the compliant component of the sensor. The data from the tracking of maker displacement is then spatiotemporally encoded, and incorporated as evidence for the perceptual classes. The most likely class is selected by obtaining the $maximum a posteriori$ of all classes. A fixation range in which the data acquisition can provide an accurate angular class is selected offline. The selection of the range takes into account the accuracy of the classifier on test data. Being the case that the perceptual outcome from the classifier states that the sensor is localised outside of the fixation range, the sensor will be radially moved to be located within that range. When the sensor is placed in the fixation range, and the outcome of the classifier determines that the sensor is within that range, a exploratory tangential motion is executed. A scheme of the process can be observed in Fig. 3a

Online Learning Robot proprioception provides accurate information about the location of the robot in the workspace. This information can be used for supporting the mapping from tactile data to angle and position of the sensor

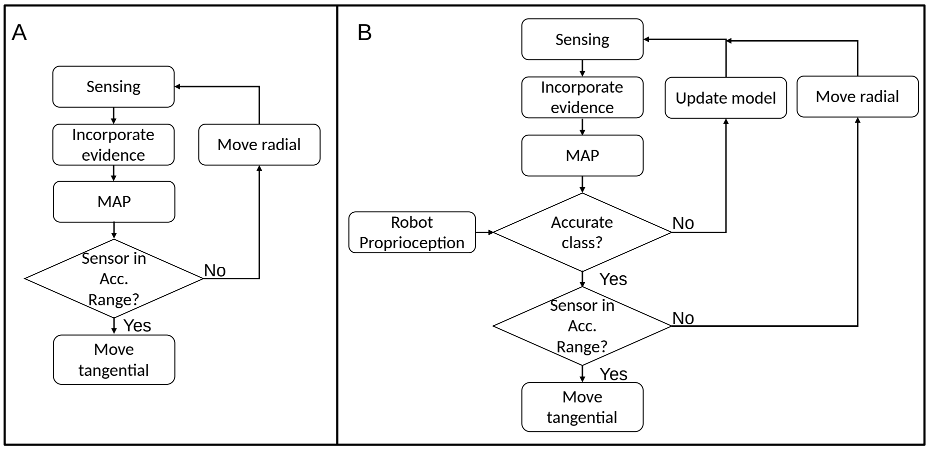

Fig. 3. Active Bayesian tactile sensing. A)Active sensing process B) Active sensing with online learning

with respect to an edge of the object. This information can be transformed to act as an automatic label provider given that the position of the object is previously known. Therefore, proprioceptive data is included in the process to assess the accuracy of the probabilistic classifier. In that sense, the angle and position outcomes from the classifier are compared with the labels from proprioception. Given the case in which the model does not provide an accurate perceptual class, the encoded tactile information becomes a training data point with the label given by the actual perceptual class followed by the updating of the model parameters. Conceding that the angle and position classes provided by the model are accurate, the process follows similar steps as in the active contour following process as seen in Fig. 3b

3 Results

3.1 Angle and position perception

The Bayesian probabilistic classifier is tested offline with a set of data obtained with the same procedure as for the acquisition of training data. The classification absolute error for the angular classes (Fig. 4a) provides us with understanding of the position classes in which the angle is correctly classified, thus the fixation range can be determined. Furthermore, the absolute classification error for the position classes contributes to the identification of a fixation point. The fixation point is the location where the perception of angle and position tends to be correct. Results in Fig. 4b suggest that the fixation point should be designed as the $-1mm$ position perceptual class given the accurate response for angle and position classification. The fixation point is extended into a fixation range, this position span will eventually be the location where angular perceptual classes are likely to be perceived with more accuracy. Correct perception of angular classes leads to the execution of proper exploratory movements to achieve the completion of the task.

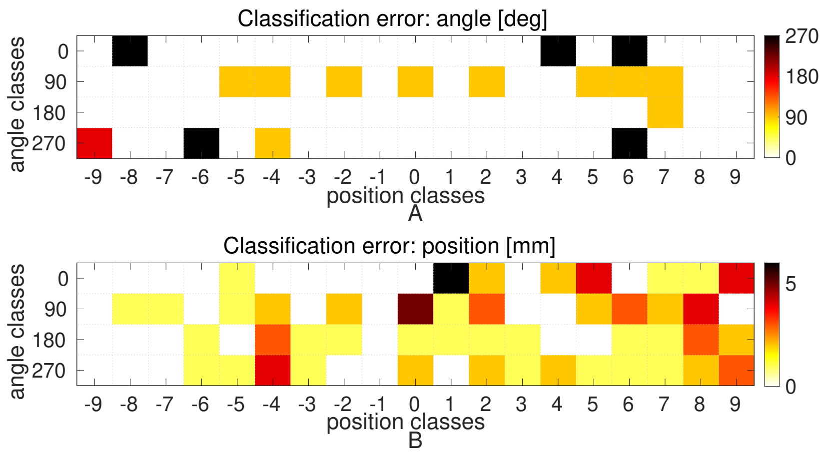

Fig. 4. Angle and position discrimination from the probabilistic Bayesian classifier. A) Absolute error for angle classification. B) Absolute error for position classification

3.2 Online Learning

Proprioceptive information from the robot is used to generate the ground truth of each perceptual class. Knowledge of the actual angle and position classes is employed to assess the accuracy of the sensor model. Fig. 5 presents the ground truth as a solid line; each point illustrates the place where the robot executed a tap for data acquisition. The assessment and learning procedure is executed for each tap. When the model provides an inaccurate prediction, the ground truth serves as a label to update the conditional probability of the data belonging to the actual class. The learning process is carried on until the model produces an accurate prediction. As the figure displays, the distribution of the data points that require one or two times of model updating are concentrated outside of the corners. This effect can be attributed to the variation in consistency of the behaviour of the linear actuator when executing vertical movements. Additionally, as presented in the figure, the data points that require more than three times to update the model parameters are located on the corners of the object. This increase in the number of model updating might be given that the training data was not acquired by directly tapping on the corners of the object. The initial model might provide correct predictions of perceptual classes. However, the prediction of data streams subject to variability in the execution of vertical movements demands the update of the parameters to improve the output of the

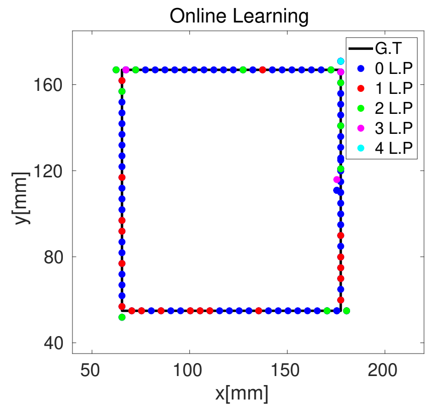

Fig. 5. Online learning in a contour following setting. Black solid line represents the ground truth of figure contour. Each point represents a tap on the edge of the object. Blue, red, green, magenta, cyan points correspond to the number of taps used for learning and updating the model

model. Therefore leading to a reduction of inaccuracies in prediction of angular and position classes.

3.3 Active Contour Following

The initial and updated models are tested under the same conditions as previously presented in Fig. 3a where the movement policy relies on executing radial motions to place the sensor within a fixation range, and perform tangential exploratory movements to follow the contour of the object. In that sense, three trials were executed for both models. Contour following with the initial model represented in Fig. 6a states that the contour following procedure was completed only in one out of three trials. It has to be highlighted that the initial model was not trained with data where the sensor is placed on the corners; thus, the inaccuracy of the probabilistic classifier had incidence in predicting the required angular class to perform tangential exploratory movements for the completion of the task. Testing the updated model for contour following results in the completion of the task on three out of three trials, as presented in Fig. 6b. This result shows that an accurate perception of angular classes leads to the execution of the necessary exploratory taps to completely follow the contour of the object. The updated model outperforms the outcome of the initial model not only in the completion of the task, but in the number of taps required to follow the contour of the object. While 208 taps were needed to complete the task with the initial model, contour following of the object using the updated model was achieved with 131, 144, and 152 number of taps for each trial. This reduction of the number of taps to complete the task reveals an improvement in the time required for its achievement.

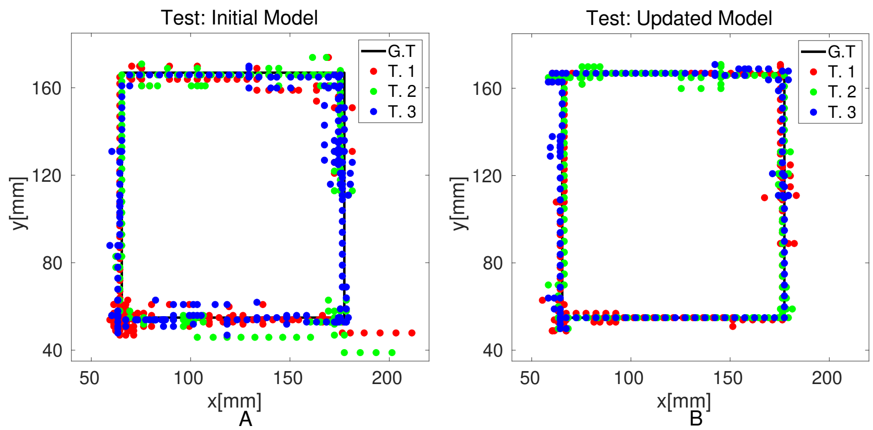

Fig. 6. Active contour following test. Where black solid line represents the ground truth of the figure contour. Each point depicts the position of an executed tap. Red points: first trial; green points: second trial; blue points: third trial. A) Trials on contour following: Initial model. B) Tests on contour following: Model after parameter updating.

4 Discussion

In this work, a sensorimotor action-perception loop was implemented for following the contour of an object. A Bayesian probabilistic classifier was trained as a sensor model to map from tactile data to angle and position classes relative to the edges of the object. The predictions of the classifier were used for the localisation of the sensor and the identification of angular perceptual classes to perform exploratory movements. Inspired from the processing of complex touch in the hierarchical structure of somatosensory processing. Specifically, in the integration of tactile and proprioceptive information for guidance and control of the sensory apparatus. The data from robot proprioception was taken into account for the assessment of the model and performing online learning when required. The initial and updated models were tested under the same circumstances on three trials for each classifier. The effect of incorporating proprioceptive information for evaluating and updating a Bayesian probabilistic classifier in the context of contour following with tactile data was studied. As showed in the results section, taking into account the ground truth for assessing the predictions of the classifier, and updating the parameters of the model had an incidence in the completion of the task by resulting in three out of completed trials; as opposite to one out of three completions of the task for the initial model. Therefore, the assessment and updating of the model with proprioceptive information can result convenient in situations where there is variability in the execution of vertical movements for the tapping procedure in the tactile data acquisition. This variation in the consistency of tactile data might be present in real world applications, thus the improvement of the parameters of the sensor model displays the potential to attain robust perception, and scalability to implement the method in further robotic platforms.

Acknowledgments

This work is supported by European Union's Horizon 2020 MSCA Programme under Grant Agreement No 813713 NeuTouch

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