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Active haptic shape recognition by intrinsic motivation with a robot hand

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***Abstract*— In this paper, we present an intrinsic motivation approach applied to haptics in robotics for tactile object exploration and recognition. Here, touch is used as the sensation process for contact detection, whilst proprioceptive information is used for the perception process. First, a probabilistic method is employed to reduce uncertainty present in tactile measurements. Second, the object exploration process is actively controlled by intelligently moving the robot hand towards interesting locations. The active behaviour performed with the robotic hand is achieved by an intrinsic motivation approach, which permitted to improve the accuracy for object recognition over the results obtained by a fixed sequence of exploration movements. The proposed method was validated in a simulated environment with a Monte Carlo method, whilst for the real environment a three-fingered robotic hand and various object shapes were employed. The results demonstrate that our method is robust and suitable for haptic perception in autonomous robotics.**

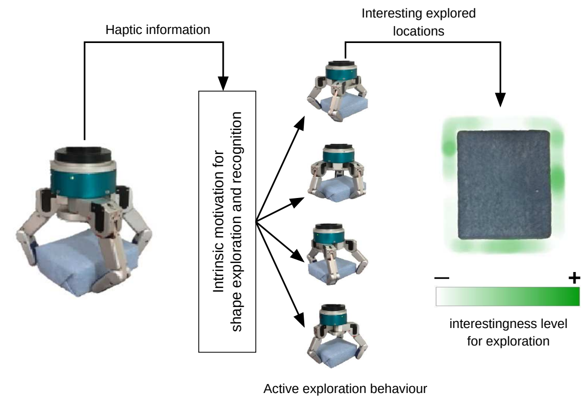

Fig. 1. Haptic object exploration and recognition by the three-fingered robotic hand. Active behaviour is used for object exploration, which is controlled by an intrinsic motivation approach.

I. INTRODUCTION

To feel and understand the state the surrounding environment is crucial for the development of intelligent autonomous robots. Haptics in robotics, composed by information from touch and limbs positions, offers a way for interaction and understanding of the changing environment by directly feeling, exploring and extracting interesting object properties. The use of haptics also enables robots with capabilities for object manipulation and safe interaction.

Haptic object shape recognition is investigated in this work using touch and proprioceptive information from a three-fingered robotic hand. Various objects are explored using an active behaviour performed by the robotic hand controlled by an intrinsic motivation method. This approach permits to reduce uncertainty for the recognition process by exploring interesting locations from an object, similar to the intelligent exploratory procedures employed by humans [1], [2].

A probabilistic approach based on a Bayesian method is used for accumulation of evidence and inference during an exploration process. The high perception accuracy achieved by this approach has been observed with an object shape extraction process using a biomimetic fingertip sensor [3], [4] and simultaneous object localisation and identification process [5], [6]. The improvement in perception accuracy with the proposed probabilistic approach is based on the accumulation of evidence from better locations for perception.

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The active exploration behaviour is obtained with a proposed intrinsic motivation method that intelligently moves the robotic hand towards interesting object locations. Studies from psychologists show that Intrinsic motivation is essential for cognitive development [7], [8], offering a robust approach for exploration and manipulation in robotics [9], [10]. Active exploration, based on intrinsic motivation, also corresponds to investigations on tactile sensing which have shown that sensing is an active rather than a passive process [11], [12].

Previous works have investigated on haptic object recognition using touch and proprioception with a traditional Self-Organising Map (SOM) approach [13] and a mixture of multiple SOMs for combination of information [14]. A comparison of different methods for haptic object recognition using proprioceptive information from a robotic hand e.g. Principal Component Analysis (PCA), SOM and Image moments, was undertaken to observed their performances in perception accuracy [15]. Even though these methods were able to perform object recognition, they are based on passive exploration using only one or a fixed sequence of tactile contacts, without exploiting the possibility to direct the robotic exploration to better locations for perception.

A sensorimotor architecture was developed to implement our methods and control the robot exploration movements for an object recognition process. Our proposed methods were validated in simulated and real environments with an object shape exploration and recognition process. For the simulated environment we used datasets collected from the exploration of 6 different test objects. For the real environment, we used a robotic platform composed by a three-fingered robotic hand and a positioning robotic table for haptic exploration. For both environments, the exploration was performed using passive and active behaviours in order to compare their performances in speed and accuracy. The results demonstrate that our method for haptic shape exploration and recognition is highly accurate, which also provides a suitable and robust method for haptic exploration in autonomous robotics.

II. Methods

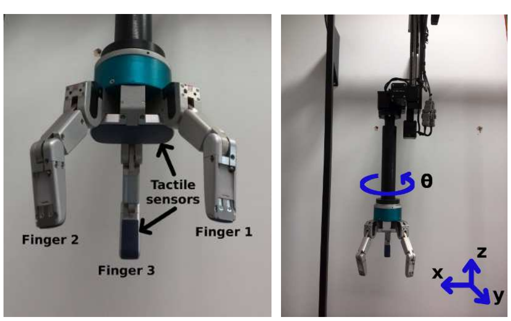
A. Robotic platform

The robotic platform used in this work is composed of a three-fingered robotic hand and a positioning robotic table shown in Figure 2.

The three-fingered robotic hand from Barrett Technology has 4-DoF; 1-DoF in each finger that permits its opening and closing, and 1-DoF for spreading the fingers around the palm of the hand (see Figure 2a). This robotic hand is integrated with tactile and force sensors. Each finger is composed by 22 taxels (tactile elements), whilst the palm contains 24 taxels of 12 bit resolution each. The strain sensors, for detection of force, are located in each finger, which permit to safely stop the finger movement once a force threshold is exceeded. Also, it is possible to obtain proprioceptive information (joint angles) from the fingers of robotic hand in real-time. Touch and proprioceptive provide important information, employed for robot exploration and perception with the proposed methods presented in next sections.

The positioning robotic table with 4-DoF permits to achieve precise movements in x-,y-and-z axes, and rotations on *theta* (see Figure 2b). The three-fingered robotic hand is mounted on the positioning robotic table to allow a larger set of exploration movements: 1) opening and closing of fingers; 2) spreading the fingers around the palm; 3) rotation of the wrist (*theta*); and 4) displacements of the robotic hand. The configuration of this robotic platform permits the exploration of a large variety of objects by the synchronisation and control of the fingers and table movements.

A controller for the robotic platform was developed and embedded in a microcontroller Arduino. Data collection and exploration movements performed by the robotic platform are controlled in real-time by tactile feedback. Synchronisation of the software and hardware modules that compose the robotic platform was precisely achieved by the use of the YARP (Yet Another Robot Platform) middleware developed for robot control [16].



(a) (b)

Fig. 2. Robotic platform used for data collection and validation of the proposed haptic object recognition method. (a) Three-fingered robot hand with 4-DoF from Barrett Technology. (b) Positioning robotic table that provides mobility to the robotic hand.

B. Data collection

Our work is focused on object shape exploration and recognition with robotic hands using haptics. For this purpose, we collected information from tactile sensors, position and orientation of the robotic fingers in real-time mode for each exploration performed on the set of test objects.

Figure 3 shows the sequence of movements performed by the robotic hand around two test objects. Each test object was mounted on an fixed exploration base located at a predefined position. First, each finger moves independently towards the unknown object. They stop as soon as a contact is detected by exceeding a tactile pressure and force thresholds. The fingers keep in contact with the object for 1 sec, giving enough time for collecting 50 samples of proprioceptive information from the complete hand. Second, the fingers are opened to a predefined home position, and then the wrist is rotated to collect data from the test object with a new orientation of the robotic hand. The wrist performs 30 rotations of 12 degrees step each, covering a total of 360 degrees, thereby exploring the complete object. Figure 3 shows only four orientations of the robotic hand during the object exploration due to space limits. This process was repeated 5 times per object, obtaining 1 dataset for training and 4 datasets for testing.

The data collected is stored in a $50{\times}5$ matrix per contact. The first three columns contain the positions of contacts detected by each finger, the fourth column contains the value of the spread motor, and the fifth column contains the angle orientation of the hand for each contact detected.

C. Probabilistic estimator

Robotics has made used of Bayesian methods to develop a variety of applications and estimate an state given the observations. Here, we use a Bayesian approach to estimate the most likely object been explored by using haptic information from a robotic hand.

This probabilistic approach uses the Bayes' rule with a sequential analysis method, estimating the posterior probabilities recursively updated from the prior probabilities and

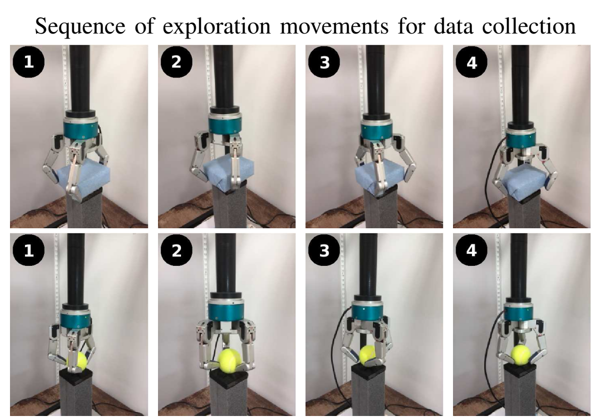


Fig. 3. Sequence of movements performed by the robotic hand around the test objects for data collection. For each contact, proprioceptive information from the position and orientation of robotic hand was recorded. A total of 30 contacts were performed for each object and repeated five times, thus having one dataset for training and four datasets for testing. For visualisation purposes, here we only show a sequence of four contacts.

likelihoods obtained from a measurement model. Then, the robotic hand makes a decision once the belief threshold about the object being explored is exceeded. This method has been tested for object shape extraction [3], [4] and simultaneous object localisation and identification [5], [6] using the fingertip sensors from the iCub humanoid robot [17], [18].

Prior: an initial uniform prior probability is assumed for all the test objects to be explored. The initial prior probability for an object exploration process is define as follows:

$$P(c_n) = P(c_n|z_0) = \frac{1}{N} \tag{1}$$

where $c_n \in C$ is the perceptual class to be estimated, z_0 is the observation at time $t = 0$ and N is the number of objects used for the exploration and recognition task.

Measurement model and Likelihood estimation: each contact performed by the robotic hand during the object exploration task provides proprioceptive information from M motors: position and spread of the three fingers, and orientation of the hand. This information is used to construct the measurement model with a nonparametric estimation based on histograms. The histograms are used to evaluate a contact z_t performed by the robotic hand at time t, and estimating the likelihood of a perceptual class $c_n \in C$. The measurement model is obtained as follows:

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

where $h(s, m)$ is the number of observed values s in the histogram for motor m. The observed values are normalised by $\sum_s h(s, m)$ to have properly probabilities that sum to 1. Evaluating Equation (2) over all the motors, we obtained the likelihood of the contact z_t as follows:

$$\log P(z_t|c_n) = \sum_{m=1}^{M_{\text{motors}}} \sum_{s=1}^{S_{\text{samples}}} \frac{\log P(s|c_n, m)}{M_{\text{motors}} S_{\text{samples}}} \tag{3}$$

where $P(z_t|c_n)$ is the likelihood of a perceptual class c_n given the measurement z_t from M motors at time t.

Bayesian update: the posterior probabilities $P(c_n|z_t)$ are updated by the recursive implementation of the Bayes' rule over the N perceptual classes c_n. The likelihood $P(z_t|c_n)$ at time t and the prior $P(c_n|z_{t-1})$ obtained from the posterior at time $t-1$ are combined as follows:

$$P(c_n|z_t) = \frac{P(z_t|c_n)P(c_n|z_{t-1})}{P(z_t|z_{t-1})} \tag{4}$$

Properly normalised values are obtained with the marginal probabilities conditioned from previous contact as follows:

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

Stop decision for object recognition: the accumulation of evidence with the Bayesian update process stops once a belief threshold is exceeded, making a decision about the object being explored. The green dashed-line box in Figure 4 shows the application of the Bayesian estimator and the stop decision process. The object perceptual class is obtained using the *maximum a posteriori* (MAP) estimate as follows:

$$\begin{aligned} &\text{if any } P(c_n|z_t) > \theta_{\text{threshold}} \text{ then} \\ &c_{\text{decision}} = \arg\max_{c_n} P(c_n|z_t) \end{aligned} \tag{6}$$

where the object estimated at time t is represented by c_{decision}. The red dashed-line box in Figure 4 shows the decision-making step for object recognition. The belief threshold $\theta_{\text{threshold}}$ permits to adjust the confidence level for the decision making process. We defined the belief threshold to the set of values {0.0, 0.05, . . . , 0.999} to observe their effects on the accuracy of the object recognition process.

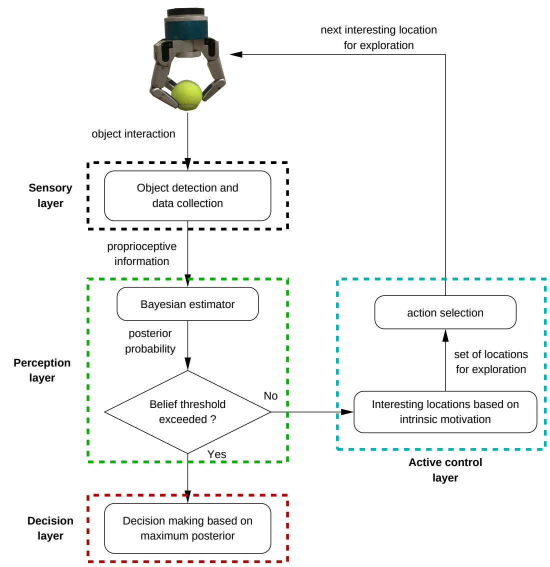


Fig. 4. Flow diagram for intrinsically motivated active object exploration. Proprioceptive and tactile data are collected from each contact. The robot is actively moved to interesting locations to improve perception based on the intrinsic motivations approach. Finally, a decision about the object being explored is made once the belief threshold is exceeded.

D. Intrinsic motivation for active exploration

A computational method based on intrinsic motivation to develop an active exploration behaviour is proposed. Intrinsic motivation, which is primordial to humans for engaging them to explore and manipulate their environment, has been studied by psychologists for cognitive development [7], [8].

In this work we use a predictive novelty motivation model, where interesting locations for exploration are those for which prediction errors are higher [9]. This approach is defined as follows:

$$I(\text{SM}(t)) = E_I(t-1) \cdot E_I(t) \tag{7}$$

where the interesting location I for the sensorimotor state SM is obtained by the prediction error $E_I(t)$ at time t multiplied by the prediction error $E_I(t-1)$ at time $t-1$.

We define the prediction error $E_I(t)$ as the distance between the MAP from the Bayesian approach and the belief threshold value for making a decision:

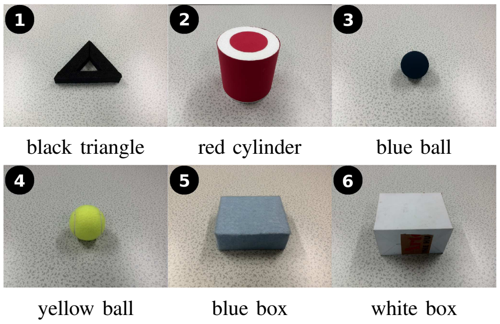


Fig. 5. Test objects used for the experiments in both simulated and real environments. The validation in simulated environment was performed using real data collected from these objects. For the validation in the real environment, the objects were placed and explored one at a time on a table.

$$E_I(t) = \arg\max_{c_n} P(c_n|z_t) - \theta_{\text{threshold}} \tag{8}$$

The active exploration performed by the robotic hand then is intelligently controlled by Equation 7, selecting the action for the highest SM state:

$$a = \arg\max_{\text{SM}} I(\text{SM(t)}) \tag{9}$$

where a is the action selected by the robotic hand. The cyan dashed-line box in Figure 4 shows the intrinsic motivation method and the action selection for the next exploration step. The exploration process presented in this section, composed by a Bayesian and intrinsic motivation method, is repeated until the belief threshold for making a decision about the object being explored is exceeded.

III. Results

In this section we present the results from object exploration and recognition with passive and active modalities in simulated and real environments. Figure 5 shows the objects used for validation of the proposed methods.

A. Object exploration in simulated environment

We developed an object exploration and recognition task in a simulated environment using the data collected from Section II-B. One dataset was used for training and four datasets for testing. The objects were randomly drawn from the testing datasets with 10,000 iterations for each belief threshold in the set of values $\{0.0, 0.05, \ldots 0.999\}$.

Passive object exploration: First, the simulated robot moved the hand and fingers around the object to obtain an initial belief of the object being explored. Next, the hand and fingers were randomly moved, accumulating evidence from each contact and making a decision once the current belief threshold was exceeded. The perception accuracy and reaction time were evaluated for each belief threshold.

Figure 6a shows the results in perception accuracy for the object exploration process with passive perception (red curve). It is observed that the robotic hand achieved the minimum perception error of 60% for a belief threshold of 0.75. Similarly, the reaction time which refers to the number

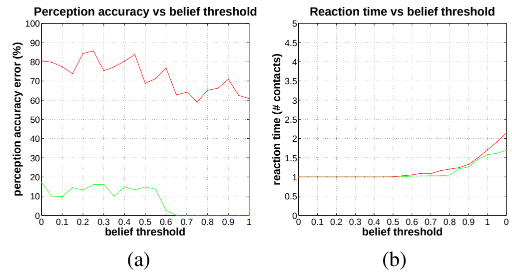


Fig. 6. Results from passive (red line) and active (green line) object recognition in simulated environment. The experiment was performed for the set of belief threshold of $\{0.0, 0.05, \ldots, 0.999\}$ with 10,000 iterations each. Results show an improvement in perception accuracy with active perception, whilst reaction time is not highly affected.

of contacts required for making a decision with passive perception (red curve) is shown in Figure 6b. The number of contacts increased for large belief thresholds, where a maximum of $\sim$2 contacts were required to make a decision for a belief threshold of $\sim$0.999. The results for perception accuracy and reaction time shown in Figure 6a and Figure 6b were obtained by averaging all perceptual classes over all trials for each belief threshold.

The confusion matrices (top) shown in Figure 7 permit to observe the performance of the classification accuracy with passive perception for each object and for different belief thresholds. These results show an slightly improvement of the classification accuracy with 68.28%, 71.77% and 76.18% for the belief thresholds of 0.0, 0.5 and 0.999. These errors still can be reduced if the robotic hand intelligently moves to interesting locations to reduce uncertainty.

Active object exploration: For the object recognition process with active perception, the robotic hand performed an exploration around the object to have an initial belief of the object being explored, similar to passive perception. Next, the robotic hand was actively moved, based on the proposed intrinsic motivation approach, towards interesting places around the object to improve perception. The active exploration process was repeated until the belief threshold was exceeded to make a decision. Similar to passive perception, the objects to be recognised were randomly drawn from the testing datasets with 10,000 iterations for each belief threshold in the set of values $\{0.0, 0.05, \ldots, 0.999\}$.

The perception accuracy results from active exploration are represented by the green curve in Figure 6a. It is clearly observed the improvement in accuracy by actively moving the robotic hand towards interesting locations for exploration, achieving an error of 0% for the belief thresholds of 0.65 to 0.999. This result validates our method for active exploration. The reaction time required for making a decision is shown in Figure 6b. We observe that the reaction time for active and passive perception increases for large belief thresholds, where $\sim$2 contacts are required to make a decision with a belief threshold of $\sim$0.999. The results were averaged over all trials for each belief threshold.

The classification accuracy for each object is presented by the confusion matrices (bottom) in Figure 7 for different belief thresholds. It is observed the gradual improvement

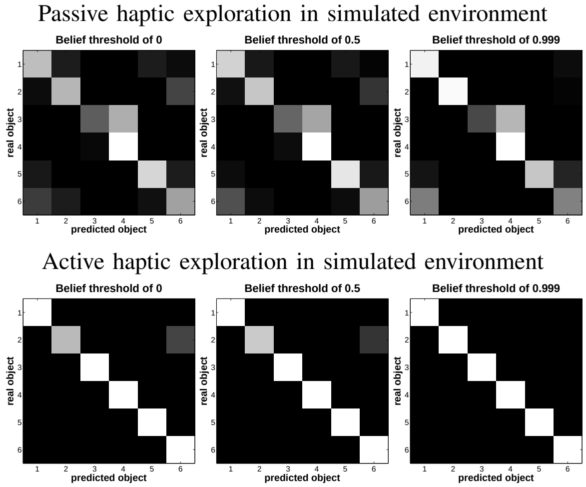


Fig. 7. Confusion matrices from object recognition with passive (top) and active (bottom) exploration. The test objects used for the experiment are: 1) black triangle, 2) red cylinder, 3) blue ball, 4) yellow ball, 5) blue box and 6) white box. Validation results with passive perception (top matrices) show a small improvement in object recognition for large belief thresholds. Validation results with active perception (bottom matrices) show higher perception accuracy over passive perception.

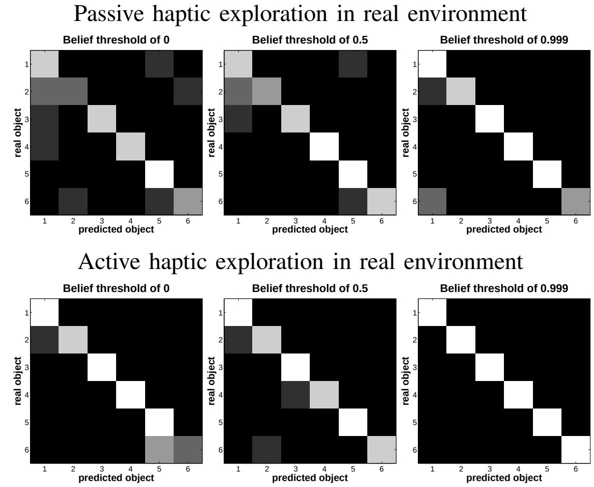


Fig. 8. Confusion matrices from object recognition with passive (top) and active (bottom) exploration in real environment. The test objects used for the experiment are: 1) black triangle, 2) red cylinder, 3) blue ball, 4) yellow ball, 5) blue box and 6) white box. Validation results with passive perception (top matrices) show a small improvement in the object recognition for large belief thresholds, achieving an accuracy of 90% for the belief threshold of 0.999. Active perception (bottom matrices) shows a higher perception accuracy of 100% for the belief threshold of 0.999.

of accuracy, achieving a 95.49%, 96.41% and 100.0% for the belief thresholds of 0.0, 0.5 and 0.999 respectively. The accuracy obtained by actively exploring an object is clearly superior to the passive exploration process.

B. Object exploration in real environment

To validate our methods in a real environment, we implemented the object exploration and recognition task with the robotic platform described in Section II-A. For this validation we used the test objects shown in Figure 5.

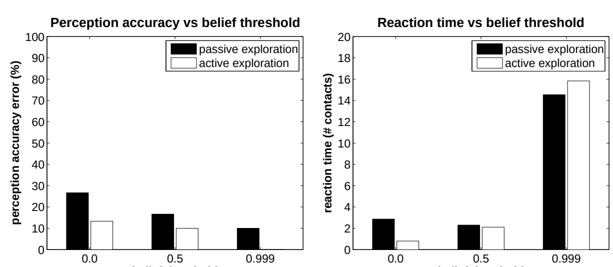
Passive object exploration: For the passive object exploration and recognition, the test objects were placed on a table one at a time. The robotic hand performed an exploration around the object through a fixed set of movements, building an initial belief of the object being explored. Next, the robotic hand started the random action selection of exploration movements, accumulating evidence to reduce uncertainty from the object being explored. The exploration process was repeated until the belief threshold was exceeded, making a decision about the current object.

Perception accuracy results are shown in Figure 9a for different belief thresholds. We observe that the error achieved for the object recognition process is improved with 26.66%, 16.66% and 10.0% for the belief threshold of 0.0, 0.5 and 0.999 respectively. The reaction time results required for making a decision are presented in Figure 9b. This result shows that for achieving the smallest error of 10% with passive perception, it was required $\sim$15 contacts, whilst for the largest error of 26.66% it was required $\sim$3 contacts by the robotic hand. These results still can be improved by the use of our proposed method for exploration.

The classification accuracy for each object based on passive perception is presented by the confusion matrices (top) in Figure 8. The exploration task achieved the perception accuracies of 73.33%, 83.33% and 90.0% for the belief threshold of 0.0, 0.5 and 0.999 respectively.

Active object exploration: For the validation of the active exploration in a real environment, the test objects were placed on a table and explored by the robotic hand through a fixed set of movements. This step permitted to construct an initial belief of the object being explored. On the contrary to passive perception, here the robotic hand selected the next action movements towards interesting locations of the object to improve perception. A decision about the object being explored was made once the evidence accumulated exceeded the belief threshold.

Figure 9a shows the perception accuracy results for the active exploration. We observe that the errors achieved for the object recognition process is improved with 13.33%, 10.0% and 0.0% for the belief thresholds of 0.0, 0.5 and 0.999 respectively. The reaction times required for making a decision are presented in Figure 9b. It is clearly observed that to achieve the best error of 0.0% it was required 16 contacts, whilst the error of 13.33% was obtained with 1 contact.



(a) (b)

Fig. 9. (a) Perception accuracy and (b) reaction time results from passive and active object recognition in a real environment. The experiment was performed with the belief thresholds of 0.0, 0.5 0.999. Passive perception was able to achieve the smallest error of 10% with 15 contacts for the belief threshold of 0.999. In contrast, active perception was able to achieve an error of 0% with 16 contacts for the belief threshold of 0.999.

The classification accuracy for each object based on active perception is presented by the confusion matrices (bottom) in Figure 8. The exploration task achieved the perception accuracies of 86.66%, 90.0% and 100.0% for the belief thresholds of 0.0, 0.5 and 0.999 respectively. These results are improved over the accuracies obtained by passive perception. On the one hand, these results in simulated and real environments demonstrate the benefits of active over passive perception. On the other hand, they also validate the accuracy of our proposed method for active object exploration based on intrinsic motivation for autonomous robotic systems.

IV. Conclusion

In this work we presented a method for object recognition using active exploration with a robotic hand under the presence of uncertainty. Our active exploration method, composed by a probabilistic and an intrinsic motivation approach, was able to achieve accurate results.

We used a set of test objects for training and testing our methods for intrinsically motivated active object exploration with a robotic hand. Tactile sensors were used for contact detection, whilst proprioceptive information composed by the position of the fingers and orientation of a robotic hand was used for object recognition. The robotic hand performed 30 contacts around each test object, which was repeated five times, to have one training dataset and four testing datasets.

A Bayesian method for uncertainty reduction through the interaction with an object was presented. This approach, together with a sequential analysis method, permitted the robotic hand to autonomously decides, based on exceeding a belief threshold, when to finish the exploration and make a decision about the object being explored.

The active exploration behaviour was obtained with an intrinsic motivation approach by moving the robotic hand towards the more interesting locations for exploration. Interesting locations were represented as the locations with large variances, obtained from the distance between the posterior probability obtained from the Bayesian approach and the belief threshold. The use of the Bayesian and the intrinsic motivation approach permitted to obtain an active exploration behaviour, accumulating evidence and reducing uncertainty by exploring the most interesting locations of the object.

Our method was validated in simulated and real environments comparing its performance using passive and active exploration. In the simulated environment, the robotic hand achieved the perception error of 0% for the belief thresholds of 0.65 to 0.99. This result contrasts with the error of 60% achieved for the belief threshold of 0.75 with passive exploration modality (Figure 6a). We did not observed large difference for the reaction time with both exploration modalities, where $\sim$2 contacts were required to make a decision for the smallest perception errors (Figure 6b).

The validation in a real environment also shows the high accuracy achieved by the robotic hand using our proposed method. For active perception, the smallest error of 0% was achieved by the robotic hand with a belief threshold of 0.999 (Figure 9a). For passive perception, the smallest error of 10% was achieved for the belief threshold of 0.999. Similar to the validation in the simulated environment, the reaction time required to make a decision for the best accuracies did not present large difference, with 15 and 16 contacts for passive and active perception respectively. The validations from simulated and real environments show the benefits of our proposed method for object exploration.

Overall, we have observed how active movements performed by the robotic hand to explore interesting locations based on intrinsic motivation, improve the perception accuracy and decision making for an autonomous exploration task. For future work, we plan to extend our methods combining them with vision and implementing them with more complex robots to autonomously explore their environment.

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