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# Tactile manipulation with biomimetic active touch

Luke Cramphorn, *Student Member, IEEE*, Benjamin Ward-Cherrier, *Student Member, IEEE*,  
Nathan F. Lepora *Member, IEEE*

**Abstract**—Tactile manipulation is the ability to control objects in real-time using the sense of touch. Here we examine tactile manipulation from the perspective of active touch with a biomimetic tactile sensor, which combines tactile perception with control of sensor location. Experiments are performed with the tactile fingertip mounted as end effector to a robot arm, to manipulate (roll) a cylinder in contact with the fingertip. Performance is validated with offline (cross-validation) and online (real-time operation) assessments. Location perception is finer than the sensor resolution, leading to superresolved tactile manipulation along a complex trajectory. However, the original methods were non-robust to large unknown disturbances of object location, necessitating modification of the perceptual process to diminish prior beliefs relative to past posterior beliefs. In consequence robust and accurate tactile manipulation was attained. In general, it appears there is a trade-off between the responsiveness to unknown change and manipulation accuracy, which must be set appropriately for each task.

## I. INTRODUCTION

Tactile manipulation — the ability to control objects in real-time using the sense of touch — is both a key contributor to the success of humans as a species and a capability whose instantiation in artificial devices could revolutionize industrial and service robotics. Applications range from sorting, positioning and assembling parts in manufacturing to assisting, lifting and interacting with humans in healthcare.

Here we study tactile manipulation with a biomimetic fingertip using active touch. A principal aspect of tactile perception, and arguably all natural perception, is that touch is active: we do not just touch, we feel [1], [2]. That understanding of touch has motivated recent work on methods integrating tactile sensor control and perception [3], [4] with a variety of approaches such as dynamical systems, neural networks and statistical inference [5]–[7]. Our aim here is to apply recent progress on biomimetic active perception, where action aids perception, to active manipulation, where perception aids action.

Our approach for tactile manipulation is based on methods for active touch that implement optimal decision making while controlling sensor location [7], [8], which were shown recently to attain superresolved spatial acuity [9], [10]. Past work on active perception has controlled the tactile sensor to move to a good location for perception, by using tactile

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LC, BWC and NL are with the Dept of Engineering Mathematics, University of Bristol and Bristol Robotics Laboratory, University of the West of England, Bristol, UK. Email: {ll14468, bw14452, n.lepora}@bristol.ac.uk

The data used in this letter can be accessed in the repository at [http://lepora.com/publications/cramphorn\\_et\\_al2016icra\\_data.zip](http://lepora.com/publications/cramphorn_et_al2016icra_data.zip)

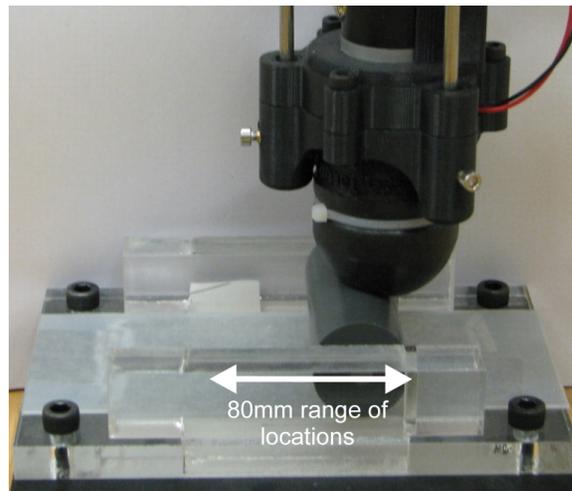


Fig. 1. Experimental setup. A tactile fingertip (the TacTip) is mounted as end-effector on an ABB robot arm. This is used to manipulate (roll) a cylinder mounted on a fixed housing along the range indicated.

data to infer intermediate estimates of location. Here we use the same approach for perception, but redefine the control policy to move the tactile sensor along a target trajectory. In consequence, the tactile sensor can control an object that it is in contact with using only the sense of touch.

The effectiveness of tactile manipulation is here assessed using a robot comprised of a biomimetic fingertip mounted as end effector to a robot arm. This robot has previously been applied to active perception of fixed objects, such as localization of a hemicylinder [10]. Here we use a novel experiment comprised of a cylinder that rolls within a fixed housing under lateral movements of the tactile sensor (Fig. 1). We validate performance with offline (cross-validation) and online (real-time operation) assessments of controlling the cylinder location. Subtleties were indicated under large unexpected disturbances of the cylinder, which required modification of how prior beliefs are defined for perceptual decision making. Superresolved manipulation at sub-millimeter accuracy was then robustly attained both offline and online. Although the manipulation was validated with a simple task, we expect the approach generalizes to more complex scenarios.

## II. BACKGROUND AND RELATED WORK

Many different kinds of tactile sensors have been developed for manipulation purposes [11]. Tactile sensors have been used for object recognition [12], improving grasp stability with force control [13] and object exploration/manipulation through edge or surface following [14]. Tactile servoing [15] has been applied to object manipulation

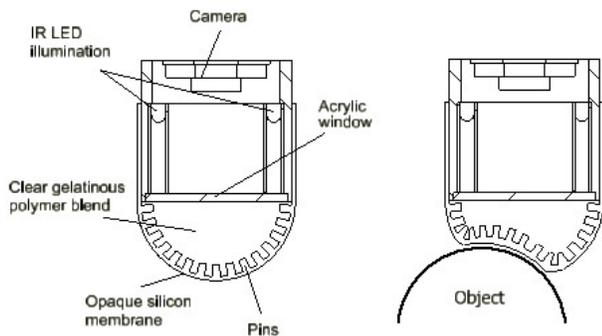


Fig. 2. Diagram of the TacTip (left) with pins shown on the inside surface of a silicon membrane, which are LED illuminated and imaged by an internal camera. The right diagram is a representation of the deformation of the membrane as it impinges on a test object (a 40 mm dia. cylinder).

on an industrial robot arm [16] and particle filter methods for controlling how to push objects using tactile feedback [17]. Bayesian methods have been proposed for in-hand manipulation [18], [19]; here we examine tactile manipulation from the perspective of biomimetic active perception.

Active perception combines a method for controlling a sensor with interpretation of that data [1] (see also [3], [4]). Recent work on active touch with biomimetic fingertips has focussed on algorithms for sensor control and perception [5]. Contemporary statistical approaches to active touch treat percepts as hypotheses. One example, termed Bayesian exploration, selects tactile data that disambiguates a leading percept from its alternatives [6]. Another approach, termed active Bayesian perception, sets a control policy to guide sensor location (‘where’) during optimal decision making of object identity (‘what’) [7], [8], typically fixating the sensor over the object. This latter method can result in superresolved spatial perception [9], [10] and closely relates to the approach used here, by having the control policy guide active manipulation rather than active perception.

Active touch has been demonstrated on several biomimetic fingertips having discrete tactile elements (taxels), including capacitive sensors (*e.g.* iCub fingertip) [7]–[9], MEMS sensors [5] and barometric sensors (*e.g.* biotac) [6]. Here we use an optical tactile sensor called the TacTip (Tactile fingerTip) developed at Bristol Robotics Laboratory [10], [20]–[22]. The TacTip’s principal novelty as an optical tactile sensor is that it has an array of pins molded inside the skin that indicate deformations of the surface, with displacements analogous to sensor readings from taxel-based devices.

### III. METHODS

#### A. Details of the tactile sensor and data collection

1) *The Tactile fingertip*: The TacTip is an optical tactile sensor developed at Bristol Robotics Laboratory [10], [20]–[22] that has several highly useful properties (Fig. 2): (i) the casing is 3D-printed and hence readily customizable and inexpensive; (ii) it uses a standard CCD web-camera (LifeCam Cinema HD, Microsoft) to collect data, which is also inexpensive and connects to a PC via a USB interface;

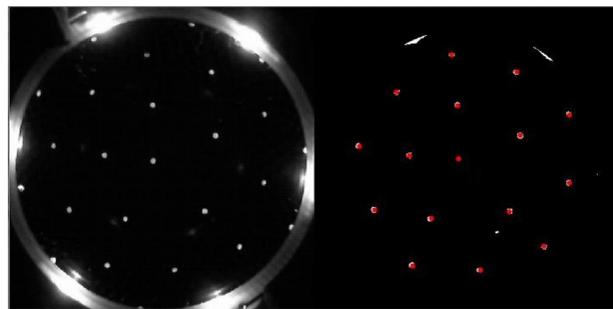


Fig. 3. Left: typical image captured by the internal camera. Right: filtered image with tracking over 18 pins (shown in red).

(iii) it has a molded silicon outer membrane that is robust to wear and easily replaced if damaged; and (iv) between the outer membrane and the electronics is a clear compliant gel (RTV27906, Techsil UK) that both enables tactile sensing through compression and protects the delicate parts of the sensor.

The particular design of TacTip used here has a 40 mm diameter hemispherical sensor pad with 18 pins arranged in a regular array on its underside. Six LEDs are mounted on a ring around the base of the pad to illuminate the pins, whose tips have been coated with white paint to give good contrast with the black silicon outer membrane (Fig. 2).

2) *Data collection*: The TacTip is mounted as an end-effector on a six degree-of-freedom robot arm (IRB 120, ABB Robotics). The arm can precisely and repeatedly position the sensor (absolute repeatability 0.01 mm).

The present study focusses on the localization of a cylinder rolled by lateral movements of the tactile sensor used as a manipulator (Fig. 1). As the cylinder rolls its position on the sensor surface changes, permitting localization through touch. A custom roller was built to constrain movements of the roller to one dimension: this consisted of a flat perspex bottom plate that the cylinder rolls over, with two perspex walls separated by 100 mm, the same length as the cylinder (100 mm long, 40 mm dia., cut from plastic). The bottom plate was covered with rubber to ensure the cylinder rolls rather than slips as the fingertip moves laterally. Magnets were mounted at the ends of the cylinder and one end of the roller to give a home position for the cylinder.

Data were collected while the tactile sensor moved 80 mm laterally over the test cylinder, comprising 800 increments  $\Delta x = 0.1$  mm. Over about 50 mm and 150 mm at the start and end of the range the TacTip does not contact the cylinder; in the central  $\sim 600$  mm portion the TacTip is in continuous contact and each lateral movement rolls the cylinder, changing its contact position on the sensor surface. Each incremental move  $\Delta x$  lasted 1 sec and resulted in a time series of sensor readings ( $N_{\text{samples}} = 15$  per increment). The data used later in this paper were collected twice to give distinct training and test sets. This approach for validation ensured that the results are based on sampling from an independent data set to that used to train the classifier.

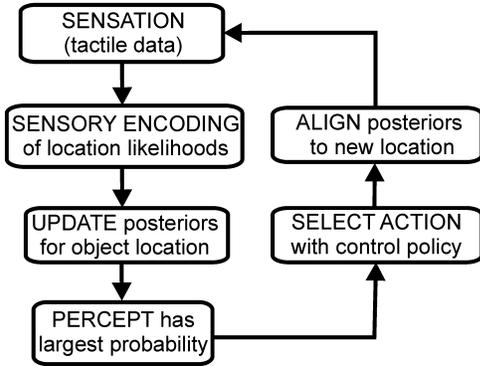


Fig. 4. Algorithm for tactile manipulation. Tactile data is used to determine likelihoods for object location, which update location posteriors; the estimated location from the maximal posterior feeds into the control policy, and the probabilities are then realigned with the resulting move.

3) *Data preprocessing*: The TacTip collects tactile data as images (resolution  $640 \times 480$  pixels, sampled at 15 fps), which are filtered to detect and track displacements of pins molded to the underside of the outer membrane. Images were captured and filtered using opencv (<http://opencv.org/>). The data preprocessing differed from previous studies with this tactile sensor to ensure good pin tracking performance when the sensor is in continuous contact with a surface. Past work has used punctual contacts and a Lucas-Kanade algorithm to track pins from frame to frame [10]; however, that algorithm suffers from drift over extended periods of tracking, compromising its effectiveness for the present experiments.

Thus, to track the  $x$ - and  $y$ - coordinates of the pin centers, the images were first captured, filtered and thresholded in opencv (<http://opencv.org/>). The center of the pins were then detected for each frame using contour detection and their  $x$ - and  $y$ -coordinates recorded. Each pin is identified based on its proximity to a default set of pin positions recorded when the TacTip is not in contact with the surface; if no pin is detected within a radius of 4 mm from its default, then the position from the previous frame is used instead. The two dimensional  $s_x$  and  $s_y$  pin displacements  $s_k(j)$  are treated as distinct data dimensions, with  $1 \leq k \leq N_{\text{dims}} = 18$  and  $1 \leq j \leq N_{\text{samples}} = 15$ .

The TacTip was also modified to aid the effectiveness of the pin tracking (Fig. 3), by having only 18 pins spaced  $\sim 8$  mm apart (compared with  $\sim 500$  pins in the original design). Using less pins with greater separation prevented the wrong pin from being identified when the sensor surface deforms greatly; it also gave lower information transfer rates.

### B. Algorithms for location perception and manipulation

We use a recursive Bayesian approach for tactile perception that been previously applied to passive [23] and active touch [7]–[10]. Past work has focussed on making a perceptual decision, when the belief passes a threshold. The present approach differs by applying the active perception methods to continual tactile manipulation of an object (Fig. 4).

Formally, the algorithms apply to sequences of contact

data  $z_{1:t} = \{z_1, \dots, z_t\}$  that are multi-dimensional time series of sensor values,

$$z_t = \{s_k(j) : 1 \leq j \leq N_{\text{samples}}, 1 \leq k \leq N_{\text{dims}}\}, \quad (1)$$

with indices  $j, k$  labeling the time sample and data dimension respectively. This contact data gives evidence for the present location  $x_l$ ,  $1 \leq l \leq N_{\text{loc}}$  with a range of distinct locations. (Here  $N_{\text{loc}} = 800$  locations spanning 80 mm are used.)

1) *Measurement model and likelihood estimation*: The location likelihoods  $P(z_t|x_l)$  use a measurement model of the training data for each location  $x_l$

$$\log P(z_t|x_l) = \sum_{k=1}^{N_{\text{dims}}} \sum_{j=1}^{N_{\text{samples}}} \frac{\log P_k(s_k(j)|x_l)}{N_{\text{samples}} N_{\text{dims}}} \quad (2)$$

constructed by assuming all data dimensions  $k$  and samples  $s_k(j)$  within each contact are independent (so individual log likelihoods sum). Here this sum is normalized by the total number of data points  $N_{\text{samples}} N_{\text{dims}}$  to ensure that the likelihoods do not scale with the sample number of a contact.

Following other work on robot tactile perception [23], the probabilities  $P_k(s_k(j)|x_l)$  are found with a histogram method applied to training data for each location  $x_l$ . The sensor values  $s_k$  for data dimension  $k$  are binned into equal intervals  $I_b$ ,  $1 \leq b \leq N_{\text{bins}}$  over their range (here with  $N_{\text{bins}} = 100$ ). The sampling distribution is given by the normalized histogram counts  $n_{kl}(b)$  for training class  $x_l$ :

$$P_k(s_k|x_l) = P_k(b|x_l) = \frac{n_{kl}(b) + \epsilon}{\sum_{b=1}^{N_{\text{bins}}} n_{kl}(b)}, \quad (3)$$

where  $n_{kl}(b)$  is the sample count in bin  $b$  for dimension  $k$  over all training data in class  $x_l$ . Technically, the likelihood is ill-defined if any histogram bin is empty, which is fixed by regularizing the bin counts with a small constant ( $\epsilon \ll 1$ ).

2) *Bayesian belief update*: Bayes' rule is used after each successive test contact  $z_t$  to recursively update the posterior location beliefs  $P(x_l|z_{1:t})$  for the perceptual classes with the location likelihoods  $P(z_t|x_l)$  of that contact data

$$P(x_l|z_{1:t}) = \frac{P(z_t|x_l)P(x_l;t)}{P(z_t)}, \quad (4)$$

from background information given by the prior location beliefs  $P(x_l;t)$  at time  $t$ . The marginal probabilities are

$$P(z_t) = \sum_{l=1}^{N_{\text{loc}}} P(z_t|x_l)P(x_l;t). \quad (5)$$

A sequence of contacts  $z_1, \dots, z_t$  results in a sequence of posterior beliefs  $P(x_l|z_1), \dots, P(x_l|z_{1:t})$  initialized from uniform priors  $P(x_l|z_0) = 1/N_{\text{loc}}$ .

Here we differ in an important way from past work in specifying a relation between the prior location beliefs  $P(x_l;t)$  and previous posterior beliefs, rather than assuming the two are identical. We assume a *prior belief model* that the two are related by a (normalized) power law

$$P(x_l;t) = \frac{[P(x_l|z_{1:t-1})]^\alpha}{\sum_{l=1}^{N_{\text{loc}}} [P(x_l|z_{1:t-1})]^\alpha}. \quad (6)$$

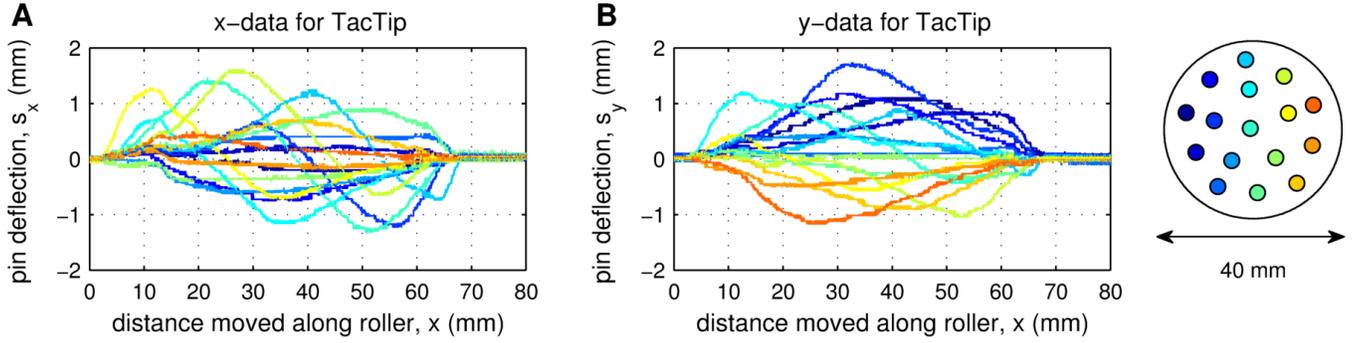


Fig. 5. Tactile data for TacTip rolling the test cylinder (40 mm dia.). Discrete lateral movements of 0.1 mm spanned an 80 mm location range over 800 increments. Data is shown for the pin  $s_x$ -displacements (panel A) and  $s_y$ -displacements (panel B). Pins are colored according to location on the fingertip.

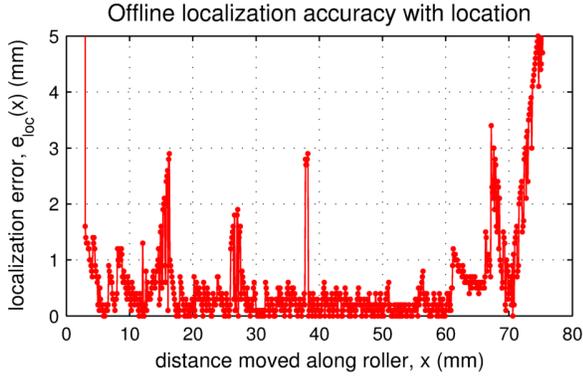


Fig. 6. Dependence of location error  $e_{\text{loc}}(x)$  on location  $x$ . Location classification uses maximum likelihood estimation. The dependence has an underlying (noisy) U-shaped function with good perception across the central range. (Results over 10000 Monte Carlo iterations.)

The parameter  $\alpha$  represents the influence of past posteriors on the prior: for  $\alpha = 1$  the priors equal the previous posteriors  $P(x_l; t) = P(x_l | z_{1:t-1})$  and the method becomes standard recursive Bayesian inference; for  $\alpha = 0$  the priors are flat  $P(x_l; t) = 1/N_{\text{loc}}$  so the posteriors equal the location likelihoods  $P(x_l; t) = P(z_t | x_l)$ ; and for  $0 < \alpha < 1$ , the prior belief model interpolates between these two cases.

3) *Location perception*: Here we infer the location of the object relative to the fingertip from the maximal posterior belief  $P(x_l | z_{1:t})$ , with estimated location  $x_{\text{est}}$  at time  $t$  of

$$x_{\text{est}}(t) = \arg \max_{x_l} P(x_l | z_{1:t}). \quad (7)$$

In the special case  $\alpha = 0$  of flat prior beliefs, the location perception reduces to maximum likelihood estimation

$$x_{\text{est}}(t) = \arg \max_{x_l} P(z_t | x_l), \quad \alpha = 0, \quad (8)$$

with the perception made only from the present contact data  $z_t$ , disregarding the contact history.

4) *Active manipulation*: Here we use a control policy  $x \leftarrow x + \pi$  to move the sensor and hence object based on the present beliefs of relative object-fingertip location. We consider a control policy that seeks to move the object along a target trajectory  $x_{\text{traj}}(t)$  relative to the fingertip

$$x \leftarrow x + \pi(t), \quad \pi(t) = x_{\text{traj}}(t) - x_{\text{est}}(t), \quad (9)$$

which for simplicity depends on the posteriors only through the estimated location  $x_{\text{est}}(t)$  (Eq. 7). In practise, the change in position  $\pi(t)$  is translated into a discrete number of location classes  $\Delta l = \pi(t)/\Delta x$ , by a linear scaling because move increments  $\Delta x$  are assumed uniform. (We also restrict moves to at most 10 mm to prevent large jumps in position.)

After a move of  $\Delta l$  location classes, the location beliefs  $P(x_l | z_{1:t})$  should be kept aligned with the sensor by shifting the class probabilities by the number of classes moved

$$P(x_l | z_{1:t}) \leftarrow P(x_{l-\Delta l} | z_{1:t}) \text{ if } 1 \leq x_{l-\Delta l} \leq N_{\text{loc}}, \quad (10)$$

$$\text{else } P(x_l | z_{1:t}) \leftarrow P(x_1 | z_{1:t}) \text{ or } P(x_{N_{\text{loc}}} | z_{1:t}).$$

For simplicity, the (undetermined) probabilities shifted from outside the location range are assumed uniform and given by the existing probability at that extremity of the range (probabilities can then be renormalized to have unit sum).

5) *Offline and online validation*: Offline validation provides an analysis of localization accuracy and algorithm performance using cross-validation performed after data collection. Two sets of data, termed training and testing, are gathered for cross-validation. A Monte-Carlo method is then used to randomly select data from the testing set for analysis of localization accuracy based on likelihoods determined from the training set. Localization accuracy is quantified with the mean absolute error  $e_{\text{loc}}(x) = \langle |x - x_{\text{est}}| \rangle$  over all classified  $x_{\text{est}}$  location values with true location class  $x$ .

Online validation adds a physical confirmation of the method's performance during real-time robot operation. For online testing, the test data and robot are controlled in real-time using a closed loop between data capture and control, with localization based on likelihoods determined from the same training set used for offline testing. Online validation is applied to demonstrating tactile manipulation performance.

## IV. RESULTS

### A. Inspection of data

Data for the TacTip (Fig. 5) were collected while the sensor gradually rolled the test object (cylinder, 40 mm diameter) with a small (0.1 mm) lateral displacement to span a 80 mm location range over 800 incremental displacements. Contact features from the stimulus are encoded in the time-series response of each pin (colored on Fig. 5).

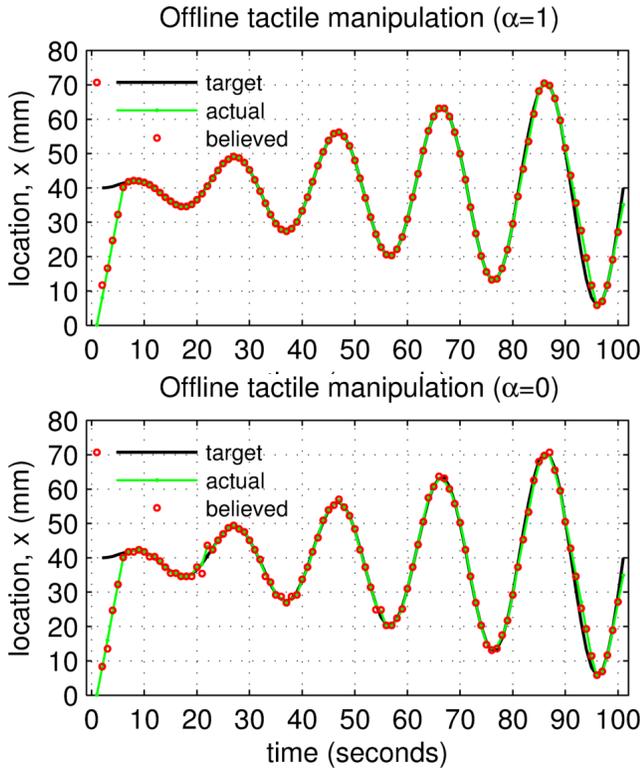


Fig. 7. Tactile manipulation in a simulated environment drawn from validation data. Performance for (A) recursive ( $\alpha = 1$ ) Bayesian inference; and (B) maximum likelihood estimation ( $\alpha = 0$ ). Target trajectories (black) are well tracked by the actual movements (green) and believed locations (red), with slightly better performance for the Bayesian method.

The most obvious effect of laterally displacing the sensor to roll the object was a change in the activation of tactile elements, permitting classification of where the cylinder is located relative to the TacTip. For example, in the pattern of  $s_x$  and  $s_y$  displacements (Figs 5A,B), the left-most locations activate the taxels plotted in blue on the left of the TacTip (*c.f.* Fig. 5), changing as the TacTip moves rightwards to the taxels plotted in red on the right.

### B. Offline localization accuracy

The localization accuracy of the TacTip is first assessed with an offline validation applied to single increments of data at locations  $x_l$  across the 80 mm range. Results are generated with an offline Monte Carlo procedure, repeatedly drawing from the test data (Sec. III-B.5) and determining location based on maximum likelihood estimation (Eq. 8).

The location error  $e_{loc}(x)$  varies strongly with test location (Fig. 6). The largest errors are  $e_{loc}(x) \gtrsim 5$  mm for glancing or no contacts near the extremities ( $x < 5$  mm and  $x > 65$  mm) of the range. The smallest location errors  $e_{loc}(x) \lesssim 0.5$  mm are in the central region (roughly  $5 \text{ mm} \leq x \leq 65 \text{ mm}$ ) when the sensor is fully in contact with the test cylinder. These results show that the roller can be accurately localized (to sub-millimeter acuity) while the fingertip makes good contact with the object.

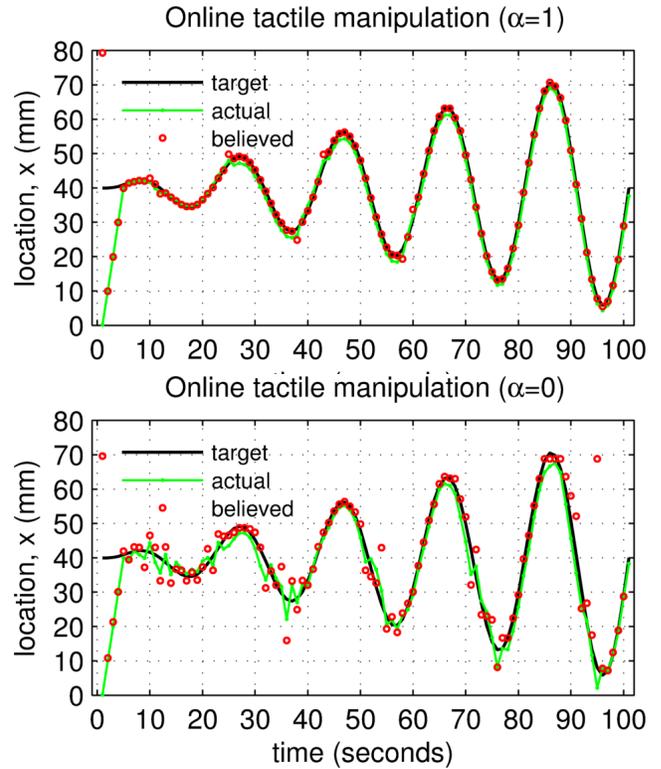


Fig. 8. Tactile manipulation in real-time on the robot. Panels are as in Fig. 7. With Bayesian inference, the target trajectories (black) are well tracked (green) according to the believed locations (red), with poorer but still approximate success for the maximum likelihood method.

### C. Validation of tactile manipulation

Validation of tactile manipulation capability was implemented by moving the cylinder along a target trajectory using only tactile data to control sensory location. For all experiments, we used a sinusoidal trajectory with linear increasing amplitude  $x_{traj}(t) = 0.4t \sin(2\pi t/20)$  with period 20 sec and amplitude 40 mm after 100 sec.

An initial offline testing of tactile manipulation capability was implemented using the training and test data sets to perform simulated manipulation of the cylinder. Data was sampled from the test set during the manipulation task according to the simulated location of the sensor. For both recursive Bayesian ( $\alpha = 1$ ) and maximum likelihood ( $\alpha = 0$ ) estimates of location, the simulated trajectory was successfully followed (Fig. 7). The Bayesian case (Fig. 7A) had near perfect accuracy, whereas the maximum likelihood case (Fig. 7B) had sub-millimeter deviations from the target trajectory, consistent with the offline estimate of localization error (Fig. 5). The superiority of the Bayesian approach is expected because evidence for location is integrated over the entire data history  $z_{1:t}$ , rather than just one increment  $z_t$ .

For online testing, the tactile manipulation was successfully performed in real-time, following the target trajectory similarly to offline validation but with less accuracy (Fig. 8). The recursive Bayesian method ( $\alpha = 1$ ) had near perfect accuracy with a couple of small deviations  $\lesssim 2$  mm near the beginning of the experiment (Fig. 8A); the maximum

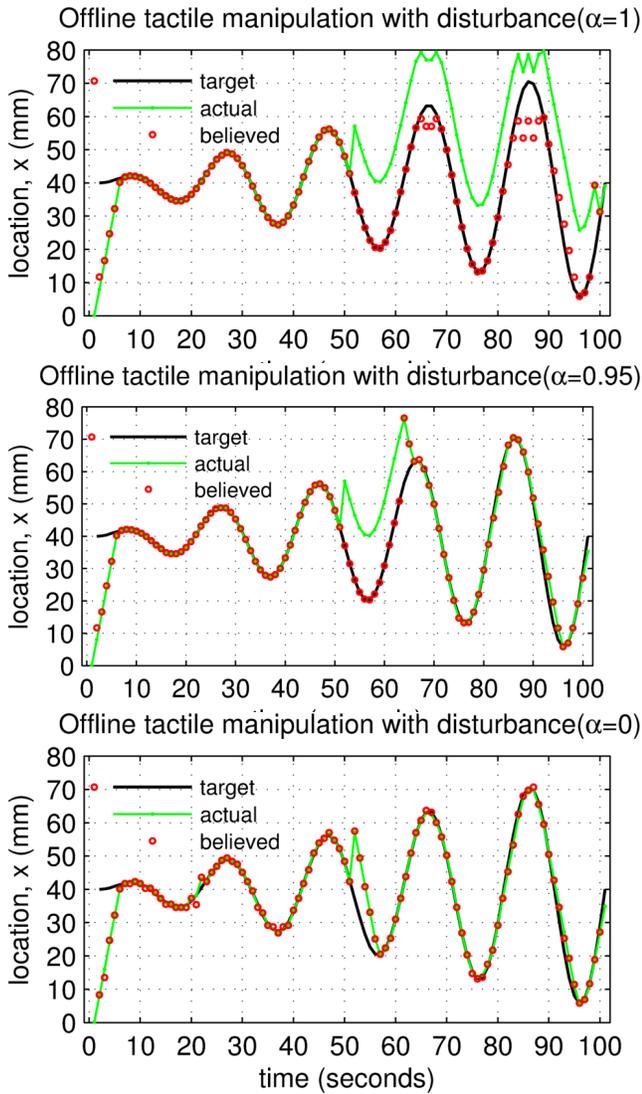


Fig. 9. Tactile manipulation in an offline environment with disturbance. Performance for (A) recursive ( $\alpha = 1$ ) Bayesian inference; (B) recursive ( $\alpha = 0.95$ ) inference with diminished priors; and (C) maximum likelihood estimation ( $\alpha = 0$ ). Only the methods with diminished priors and maximum likelihood can correct the disturbance, at the expense of reduced accuracy.

likelihood method ( $\alpha = 0$ ) was more inaccurate with deviations  $\sim 5$  mm over the entire trajectory (Fig. 8B).

The differences between offline and online testing are due to sources of noise in real-time on the robot not present in the pre-gathered test data. For example, move increments during gathering data are always  $\Delta x = 0.1$  mm, whereas increments during online testing can be up to  $\pm 10$  mm; and there may be other unknown differences between real-time operation and offline validation. This illustrates the importance of online validation for testing actual robot performance. The overall conclusion is that the recursive Bayesian method ( $\alpha = 1$ ) is superior to the maximum likelihood method ( $\alpha = 0$ ).

#### D. Tactile manipulation with a disturbance

To test the robustness of the tactile manipulation, the validation was repeated introducing an unknown disturbance into

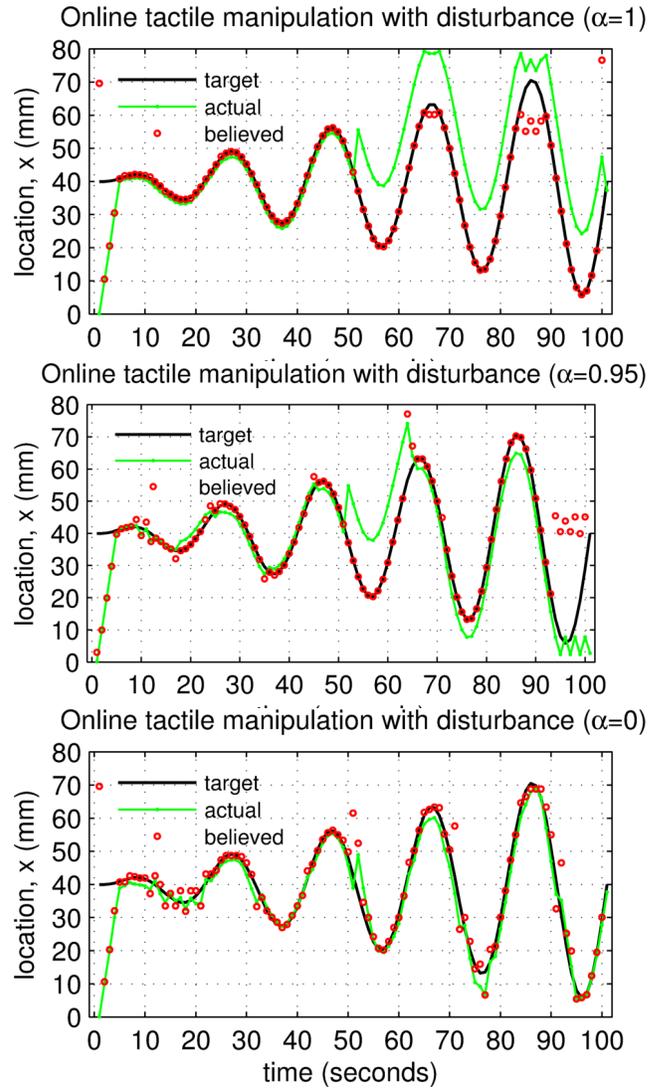


Fig. 10. Tactile manipulation in real-time on the robot with disturbance. Panels are as in Fig. 9. Only the methods with diminished priors and maximum likelihood can correct the disturbance, at the expense of accuracy deteriorating with lower  $\alpha$  before the disturbance.

the system. Midway through the trial (50 sec), the cylinder location was moved laterally by 20 mm. The effectiveness of the tactile manipulation to correct for this unknown movement by repositioning the cylinder back onto its target trajectory was then examined.

For offline testing, the tactile manipulation responded in different ways to the disturbance (Fig. 9) depending on the parameter  $\alpha$  from 1 down to 0 that represents a diminishing influence of past posteriors on current priors. The overall behavior was that the tactile manipulation responds more quickly to the disturbance as the value of  $\alpha$  is decreased. At  $\alpha = 1$ , the tactile manipulation completely ignores new sensory data that the location of the cylinder has moved, and consequently the trajectory after the disturbance is offset from the target trajectory (Fig. 9A). At  $\alpha = 0$ , the tactile manipulation responds immediately to the change in location of the cylinder and corrects onto the target trajectory

(Fig. 9C). For an intermediate value  $\alpha < 0.95$ , the tactile manipulation took  $\sim 10$  sec to realize the location had shifted, then corrects onto the target trajectory (Fig. 9B).

For online testing, the tactile manipulation responded to the disturbance similarly to the offline test (Fig. 10): for  $\alpha = 1$ , the trajectory after the disturbance was not corrected (Fig. 10A), for  $\alpha = 0.95$ , the trajectory after the disturbance was corrected after a delay of  $\sim 10$  sec (Fig. 10B), and for  $\alpha = 0$  the trajectory was corrected immediately (Fig. 10C). These improvements in ability to respond to change as  $\alpha$  decreases from 1 to 0, representing a diminishing effect of posteriors on priors, were accompanied by a deterioration of the accuracy of the tactile manipulation in following the trajectory, as observed in the previous section. There thus appears to be a trade-off between the responsiveness to unknown change and the manipulation accuracy when using tactile information to control object location.

## V. DISCUSSION

Biomimetic tactile manipulation based on active touch gives accurate control of rolling a cylinder with an artificial fingertip. Experiments were performed with a tactile fingertip (the TacTip) mounted as end-effector on an ABB robot arm, with which lateral movements could manipulate (roll) the cylinder from side-to-side. Location perception was achieved with decision making methods, giving sub-millimeter localization finer than the sensor resolution. In consequence, the tactile manipulation was performed at superresolved accuracy along a complex trajectory.

Subtleties were indicated under large (20 mm) disturbances of cylinder location during testing: the system has no ability to anticipate the disturbance, but can react to the sudden change in perceived object location. The capability of the tactile system to react to a change in object location was found to depend on the Bayesian update rule for the location belief during perceptual decision making. If the prior beliefs for estimating location are set equal to the posterior beliefs for the previous estimate, the system was not able to perceive sudden changes of location. This was because the prior beliefs had become sufficiently peaked late in the trial that new sensory evidence for location was ignored.

These problems with estimating object location could be addressed with a maximum likelihood procedure applied to just the present contact data (equivalently, the prior beliefs are considered flat). However, this solution came at the cost of reducing the accuracy of tactile manipulation. Therefore, we proposed an intermediate solution in which the prior beliefs are diminished by a power law relative to the posterior beliefs, giving moderately accurate performance that can respond to sudden changes in location. In general, there is a trade-off between responsiveness to unknown change and manipulation accuracy, to be set appropriately for the task.

We expect the trade-off between responsiveness to change and accuracy is a general aspect of tactile manipulation. The situation bears analogy with utilizing a Kalman filter to combine information for accurate control, which is linked with recent tactile manipulation methods based on classical

control theory [14] and particle filters [17]. Our expectation is that understanding the relation between these approaches and the biomimetic approach proposed here will help in solving the overall problem of attaining robust and general tactile manipulation in complex and uncertain environments

## REFERENCES

- [1] R. Bajcsy. Active perception. *Proceedings of the IEEE*, 76(8):966–1005, 1988.
- [2] J.J. Gibson. The senses considered as perceptual systems. 1966.
- [3] T.J. Prescott, M.E. Diamond, and A.M. Wing. Active touch sensing. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 366(1581):2989–2995, 2011.
- [4] N. Lepora. Active tactile perception. In *Scholarpedia of Touch*, pages 151–159. Atlantis Press, 2016.
- [5] C.M. Oddo, M. Controzzi, L. Beccai, C. Cipriani, and M.C. Carrozza. Roughness encoding for discrimination of surfaces in artificial active-touch. *IEEE Transactions on Robotics*, 27(3):522–533, 2011.
- [6] J.A. Fishel and G.E. Loeb. Bayesian exploration for intelligent identification of textures. *Frontiers in Neurobotics*, 6, 2012.
- [7] N.F. Lepora, U. Martinez-Hernandez, and T.J. Prescott. Active bayesian perception for simultaneous object localization and identification. In *Robotics: Science and Systems*, 2013.
- [8] N.F. Lepora, U. Martinez-Hernandez, and T.J. Prescott. Active touch for robust perception under position uncertainty. In *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, pages 3005–3010, 2013.
- [9] N.F. Lepora, U. Martinez-Hernandez, M. Evans, L. Natale, G. Metta, and T.J. Prescott. Tactile superresolution and biomimetic hyperacuity. *IEEE Transactions on Robotics*, 31(3):605–618, 2015.
- [10] N. Lepora and B. Ward-Cherrier. Superresolution with an optical tactile sensor. In *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, pages 2686–2691, 2015.
- [11] Z. Kappassov, J. Corrales, and V. Perdereau. Tactile sensing in dexterous robot hands - review. *Robotics and Autonomous Systems*, 74:195–220, 2015.
- [12] Z. Pezzementi, E. Plaku, C. Reyda, and G. Hager. Tactile-object recognition from appearance information. *IEEE Transactions on Robotics*, 27(3):473–487, 2011.
- [13] J. Romano, K. Hsiao, G. Niemeyer, S. Chitta, and K. Kuchenbecker. Human-inspired robotic grasp control with tactile sensing. *IEEE Transactions on Robotics*, 27(6):1067–1079, 2011.
- [14] H. Liu, K. Nguyen, V. Perdereau, J. Bimbo, J. Back, M. Godden, L. Seneviratne, and K. Althoefer. Finger contact sensing and the application in dexterous hand manipulation. *Autonomous Robots*, 39(1):25–41, 2015.
- [15] Q. Li, C. Schürmann, R. Haschke, and H. Ritter. A control framework for tactile servoing. In *Robotics: Science and Systems*, 2013.
- [16] H. Zhang and N. Chen. Control of contact via tactile sensing. *IEEE Transactions on Robotics and Automation*, 16(5):482–495, 2000.
- [17] M. Koval, N. Pollard, and S. Srinivasa. Pose estimation for planar contact manipulation with manifold particle filters. *The International Journal of Robotics Research*, pages 1–24, 2015.
- [18] H. van Hoof, T. Hermans, G. Neumann, and J. Peters. Learning robot in-hand manipulation with tactile features. In *Proc. IEEE-RAS 15th Int. Conf. on Humanoids*, pages 121–127, 2015.
- [19] B. Ward-Cherrier, L. Cramphorn, and N. Lepora. Tactile manipulation with a thumb integrated on the open-hand m2 gripper. *Robotics and Automation Letters, IEEE*, 1(1):169–175, 2016.
- [20] C. Chorley, C. Melhuish, T. Pipe, and J. Rossiter. Development of a tactile sensor based on biologically inspired edge encoding. In *Proc. Int. Conf. Adv. Robotics (ICAR)*, pages 1–6, 2009.
- [21] B. Winstone, G. Griffiths, T. Pipe, C. Melhuish, and J. Rossiter. Tactip-tactile fingertip device, texture analysis through optical tracking of skin features. In *Biomimetic and Biohybrid Systems*, pages 323–334. Springer, 2013.
- [22] T. Assaf, C. Roke, J. Rossiter, T. Pipe, and C. Melhuish. Seeing by touch: Evaluation of a soft biologically-inspired artificial fingertip in real-time active touch. *Sensors*, 14(2):2561–2577, 2014.
- [23] N.F. Lepora, C.W. Fox, M.H. Evans, M.E. Diamond, K. Gurney, and T.J. Prescott. Optimal decision-making in mammals: insights from a robot study of rodent texture discrimination. *Journal of The Royal Society Interface*, 9(72):1517–1528, 2012.