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Edge and plane classification with a biomimetic iCub fingertip sensor

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Abstract

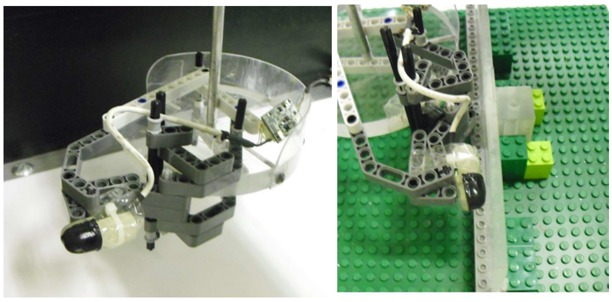
The exploration and interaction of humanoid robots with the environment through tactile sensing is an important task for achieving truly autonomous agents. Recently much research has been focused on the development of new technologies for tactile sensors and new methods for tactile exploration. Edge detection is one of the tasks required in robots and humanoids to explore and recognise objects. In this work we propose a method for edge and plane classification with a biomimetic iCub fingertip using a probabilistic approach. The iCub fingertip mounted on an xy-table robot is able to tap and collect the data from the surface and edge of a plastic wall. Using a maximum likelihood classifier the xy-table knows when the iCub fingertip has reached the edge of the object. The study presented here is also biologically inspired by the tactile exploration performed in animals.

Index Terms: tactile sensing, edge detection, probabilistic classification, biomimetic

1. Introduction

Nowadays most robots are equipped with haptic systems to improve their ability to interact with and learn from the environment. This is a required and important feature for humanoid robots in order to perform tasks safely. Haptics is considered as a perceptual system [1], which is mainly based on information provided by two types of sensing systems: proprioceptive sensing and extereoceptive sensing. Proprioceptive sensing detects body position, weight, and joints, whilst extereoceptive sensing refers to tactile sensing which provides physical properties of objects through physical contact [2].

Humans use the sense of touch, or tactile sensing, to explore their environment. Different predefined exploratory procedures (EPs) performed by humans with their hands and fingers allow them to recognise objects. The type of EP depends on the type of information required – for instance, sliding, pressure and contour following provide information about texture, hardness and shape respectively [3]. The way humans perform tactile sensing is considered as an active process rather than a passive one, because the movement of the hand and fingers is purposely guided to obtain more information. This process of tactile exploration is not only used by humans but is also present in the animal kingdom. Some examples of active tactile sensing are the antennae of insects and the whiskers (vibrissae) of rodents, which exhibit fascinating sensory capabilities [4]. For instance, antennae allow cockroaches to explore, detect objects and maintain their balance while climbing; rats are able to discriminate texture using their whiskers with high accuracy; seals can track fish using their whiskers, which are the most finely tuned in the animal kingdom.



(a) (b)

Figure 1: (a) iCub finger mounted on an *xy*-table robot to allow the movement of the finger across a plastic wall (b) to collect data from plane and edge.

Recent developments of haptic systems in robotics have allowed research in exploratory procedures inspired by the human and the animal kingdom. A three-fingered robotic hand has the capability to grasp through tactile sensing [5]. This robotic hand is able to recognise objects through the shape of the hand given by the joint angles. Another method for shape classification, using a robotic five-fingered hand, employs continuous rotational manipulation and pressure contact [6]. Texture recognition commonly is done by humans through a lateral motion or sliding EP. A robotic finger equipped with tactile sensors is able to recognise textures by sliding over materials [7], sliding either in vertical or horizontal direction. Hardness and texture recognition with a robotic hand is done with squeezing and tapping EPs [8]. This approach shows that the hardness can be measured based on the variation of joint angles while squeezing, and textures can be recognised through a tapping procedure analogous to the whisking performed by rats.

In this paper we consider tactile sensing with the iCub humanoid robot, which has recently been equipped with tactile sensors in its palm and fingers, allowing it to interact with the environment [9]. The iCub humanoid has 108 taxels (tactile elements) in total; 48 taxels in the palm and 12 taxels in each finger that respond to pressure when there is a contact. To analyse the tactile data from the iCub we employ recent advances in probabilistic perception methods inspired by tactile exploration in animals, especially rats [10, 11, 12]. In these developments, a maximum likelihood classifier (also called naive Bayes) was used for a variety of discrimination tasks, including texture, shape, position and velocity.

A key task in robotics that will be the focus of this study is to do object exploration by using edge detection through tactile sensing. Early research on edge detection has been influenced by digital image processing techniques. Low level tactile primitives have been proposed for a tactile sensor with an array of 10×16 taxels [13]. These primitives define an edge as a series of edge contacts. Another approach for edge detection uses a median filter which preserves edges and removes noise without blurring the edges [14]. In [15], image processing techniques are also applied using an edge detector which uses a threshold to remove noise. In order to obtain the location and orientation of the edge, an adaptive Hu transform is applied. Edge detection, location and orientation are obtained through the first three moments from the tactile image [16]. A new method for a low-resolution tactile sensor uses heuristics for edge detection [17]. This method has been designed for a 2×2 planar tactile sensor array.

This work presents an implementation of tapping exploratory procedure in a biomimetic robot based on the iCub fingertip applied to edge and plane detection. We apply a probabilistic method based on biologically-inspired tactile perception to perform the classification.

2. Methods

A. Tactile sensory system: iCub finger

For the experiments presented in this work, we used the tactile sensory system of the iCub humanoid. This humanoid resembles a child of 3 years old. It has 53 degrees of freedom and is equipped with digital cameras, gyroscopes, microphones and recently tactile sensors have been integrated in the forearm, palm and fingertips [18]. These tactile sensors allow the iCub humanoid to interact with the environment performing tasks safely e.g. exploring and grasping. Each fingertip has 12 contact pads called taxels, which are distributed in the base, sides and tip of the finger with a separation of about 4 mm between them. These taxels are built using a capacitive sensor technology that enables the fingers to respond to contact pressure. The measurements from the 12 taxels are sampled at 50 Hz. These measurements are digitised locally in the fingertip with a capacitive-to-digital converter (CDC) [19]. The result of the digitisation provides capacitive measurements in the range of 0 to 244, where 0 is for a maximum pressure in the fingertip and 244 is when there is no pressure. The data collected from the fingertip sensor are then passed through a drift compensation module, which converts the measurements to double precision.

B. Exploratory architecture: XY-table robot

To enable the iCub fingertip to move across a plastic wall for collecting data, it was mounted on an *xy*-table robot capable of achieving precise positioning (Figure 1). This platform enables the iCub finger to perform a tapping exploration procedure over *y* axis (vertically) whilst moving in *x* axis (horizontally). Also this platform allows the data to be collected systematically with precise movements in *x*-axis. The finger is mounted at an appropriate angle in order to have contact with most possible taxels. The *xy*-table robot moves the fingertip across appropriate regions of the stimulus to collect and store the pressure measurements from the taxels and the position for the fingertip. Figure 2 shows the two regions defined for collecting data: a 10 mm range for the plane and a 10 mm range for the edge. The *xy*-table robot performed a periodic movement across the *x*-axis of 1 mm spacing. This gave 10 taps for the plane stimulus and 10 taps for the edge stimulus.

This experiment was developed for two cases: first, moving

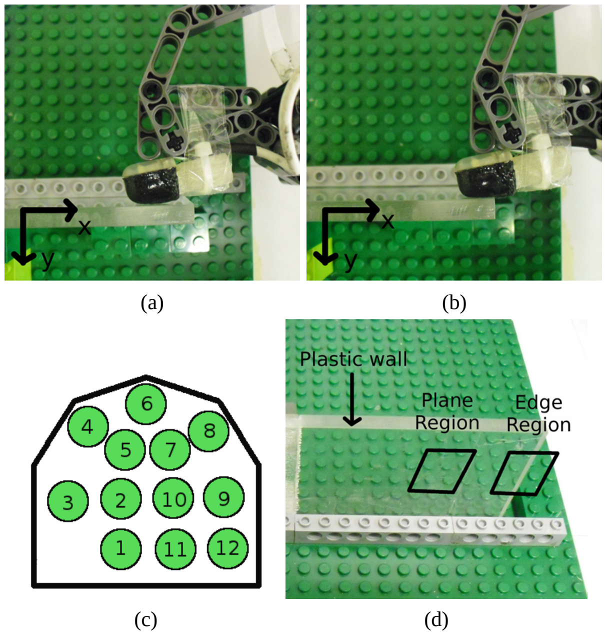


Figure 2: The iCub fingertip moved by the *xy*-table robot; *(a)* tapping in a plane region, *(b)* tapping in an edge region, *(c)* distribution of taxels in the iCub fingertip, *(d)* edge and plane regions. Note the positioning of the fingertip relative to the stimulus.

the iCub fingertip backwards (from base to tip), and second moving in lateral motion (from left to right). For the backward case, the iCub fingertip was first placed on the plane and then placed on the edge. In the lateral motion case, the iCub fingertip was first moved over plane and then returned to its initial position and started again over the plane region. There were collected 10 sets of data for the backward case and 6 sets for the lateral motion case. The first set of plane and edge data were used for the training phase and the remaining sets for testing.

C. Probabilistic classifier

Probabilistic techniques are the state of the art for robot performance under uncertainty [20]. The measurements are considered as being caused by the world with given probabilities. This study employs previous work on probabilistic classifiers used for tactile perception based on a maximum likelihood procedure [10, 12]. Equation 1 shows the accumulated log likelihoods estimator considering the measurements to be conditionally independent

$$\log P(x_1,\ldots,x_n|C_l) = \sum_{i=1}^{n} \log P(x_i|C_l) \qquad (1)$$

The log likelihoods $\log P(x_1,\ldots,x_n|C_l)$ are accumulated over n samples of data. The single sample log likelihoods $\log P(x_i|C_l)$ are estimated from the training data using histogram methods to determine the sampling distribution [12]. The decision-making for a choice of a class C_l which can be

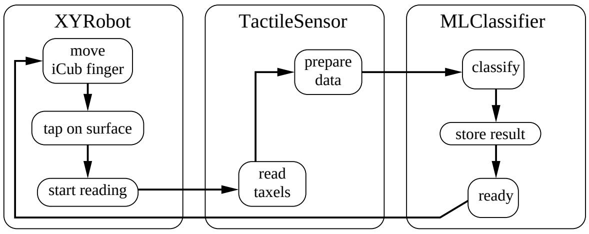


Figure 3: Interaction of modules in the experimental setup. Modules developed with C/C++ and YARP library to a straightforward implementation on the iCub humanoid.

an edge or plane is made through the maximum likelihood

$$\begin{aligned} C &= \arg\max_{C_l} P(x_1, \ldots, x_n | C_l) \\ &= \arg\max_{C_l} \left[\sum_{i=1}^{n} \log P(x_i | C_l) \right] \end{aligned} \quad (2)$$

where $\arg\max$ provides the maximum probability for a given dataset measurement from a edge or plane contact.

In this study there are two classes; *plane* and *edge*. The classifier takes as input the measurements from the 12 taxels of the iCub finger as a time series. The maximum probability calculated by equation 2 returns the class C for the current contact. In section 3, the training and testing phases for the classification are explained.

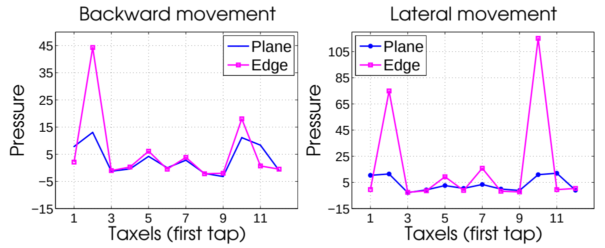
D. Experimental setup

For the experiments, several computational modules were used for control and classification: first, the *XYRobot* module for communication and control of the *xy*-table robot; second, the *TactileSensor* module for reading and preparing the measurements from taxels in the correct format to feed the classifier; and, third, the *MLClassifier* module to detect if the contact is over an edge or plane region. This experiment is based on the biomimetic iCub fingertip. However, the modules have been designed to be implemented straightforwardly on the iCub humanoid. Figure 3 shows the interaction between these modules.

3. Results

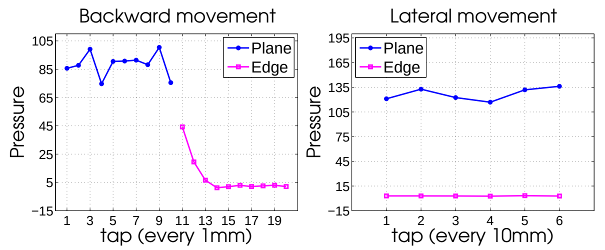
A. Training phase

The iCub finger was placed and adjusted to have enough pressure contact with the most possible taxels. The plane and edge regions were defined on a plastic wall of 6 cm×19.5 cm dimensions. A 10 mm region was defined for the plane class and a 10 mm region for the edge class. The iCub finger was configured to collect data at 50 Hz. A *drift compensation module* from the iCub repository was used to pre-process the data before classifying. For the training phase, two sets of data were collected: one for the plane and one for the edge. These datasets were taken from the first tap of the finger over the plastic wall. The datasets provided to the classifier had 12 dimensions from the number of taxels and were over 5 seconds (250 samples). Figure 4a shows the mean of pressure contact from the twelve taxels during the first tap on plane and edge regions. Similarly,



(a) (b)

Figure 4: Pressure contact of first tap over plane and edge; (a) backward movement, (b) lateral movement.



(a) (b)

Figure 5: Edge and plane detection in testing phase; (a) backward movement, (b) lateral movement.

the first tap for plane and edge in lateral movement is shown in Figure 4b. These datasets are the input for the classifier.

It can be seen that the pressure is higher for taxels 2 and 10 when the finger is on the edge for both backward and lateral movement, giving a discriminator for the edge from plane.

B. Edge and plane testing phase

Two scenarios were set up for edge and plane detection validation: (1) moving the finger backward and (2) moving laterally over the edge and plane regions. For scenarios 1 and 2, there were collected 20 and 12 datasets respectively. In scenario 1, the iCub finger moved across 20 mm; first 10 mm for plane and second 10 mm for edge. The taps were taken every 1 mm. Figure 5a shows the classification across the plane and edge for scenario 1 (backwards movement). It can be observed in the *x*-axis that the position of contact by the finger and the class (edge and plane) were well predicted. The first 10 taps correspond to the plane and the second 10 taps to the edge. A clear separation of the two classes is observed (Figure 5b).

For scenario 2, the iCub fingertip firstly moved over six different positions on the edge with a range of 60 mm with a tap every 10 mm. The same procedure was followed for the plane. In this case, the iCub finger was rotated manually to the vertical position to allow lateral movements. This manual rotation may cause systematic changes in the data collection procedure followed in scenario 1. However, good results were found for both edge and plane lateral movements. Figure 5b shows the classification in lateral motion. Similar to the backward movement, there is a clear separation of the two classes. Both, plane and edge are plotted in the same *x*-axis, since the taps were from same positions for the plane and edge.

Tables 1 and 2 show the confusion matrices for backward and lateral movements respectively. Both matrices present successful classification accuracy of 100%. Interestingly, for the scenario 2, even though the vertical rotation of the finger was done manually, a 100% of classification accuracy was achieved.

Table 1: *Classification of edge and plane for scenario 1.*

Class	Edge	Plane
Edge	100%	0
Plane	0	100%

Table 2: *Classification of edge and plane for scenario 2.*

Class	Edge	Plane
Edge	100%	0
Plane	0	100%

4. Conclusions

This work has been motivated by the study of tactile sensing capabilities in humans and animals which suggest probabilistic methods for perception. A biomimetic iCub fingertip that resembles the human fingertip was used for the experiments. This finger was mounted in an *xy* positioning robot to allow systematic movements in two dimensions. Different modules were developed to implement the architecture for communication, control, data acquisition and probabilistic classification.

It was demonstrated that a tapping exploratory procedure can successfully detect object features. A plane and edge region were defined for exploration and collecting data over a plastic wall. The platform developed allowed a systematic implementation of the experiments. The classification was performed in two scenarios: (1) the iCub finger moving backwards and (2) in lateral motion. For scenario 2, the experimental setup was changed manually by orienting the iCub fingertip to point in a vertical direction. For both cases the classification showed perfect results, in that the classification accuracies were 100%. The modules used in this work for the iCub finger were designed to be implemented straightforwardly on the iCub humanoid. As such, the results presented in this work are a first step towards studying and implementing exploratory procedures performed by humans and animals on humanoid robots.

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6. References

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