TACTILE TEXTURE DISCRIMINATION IN THE ROBOT-RAT PSIKHARPAX

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Abstract: We endowed a whiskered robot with a simple algorithm allowing to discriminate textures. Its efficiency and robustness have been demonstrated using both a fixed head and a mobile platform. Comparatively to previous similar approaches, this system affords greater behavioral capacities and proves to be able to complement or supply vision in simple navigation tasks. The corresponding results suggest that the length and number of the whiskers involved play a role in texture discrimination. They also suggest that two hypotheses that are currently considered as mutually exclusive to explain texture recognition in rats - i.e., the "kinetic signature hypothesis" and the "resonance hypothesis" - may be, in fact, complementary.

1 INTRODUCTION

Touch is a very important sensory modality for many species of insects and mammals. For example, the whiskers of a rat are often compared to human fingertips in terms of their tactile - or haptic - ability. In particular, they make it possible to finely discriminate textures (Carvell and Simons, 1990; Guic-Robles et al., 1989) or objects (Brecht et al., 1997) and even to precisely determine an aperture width (Krupa et al., 2001). Biologists have studied rat whiskers for decades and know quite precisely the pathway from an individual vibrissa to the somatosensory cortex. One remarkable property of this haptic system is that whiskers project somatotopically to this part of the cortex, into a structure named "barrel cortex". A "barrel" is a discrete neural structure that receives an input principally from a given whisker, with little influence from neighboring whiskers (Petersen and Diamond, 2000). This relatively simple system, as compared to vision for example, facilitates the study of the neural coding scheme, as well as its use for perception and higher-level cognition.

Being simple, efficient and robust, whiskers should become popular in robotics (Hartmann, 2001) although few robots have been equipped with such devices in the past. The corresponding implementations were calling on various sensors ranging from the simplest binary switch to a very accurate bi-dimensional torque sensor. Brooks (1989), for example, used a simple sensor made of a metal shaft fixed on a push button, providing a very robust security sensor for a walking robot. Another implementation called upon probe whiskers made of a stem glued to a potentiometer with return springs and was used to evaluate the contour of an object (Russell, 1985). Even wind sensitive sensors have been designed (Chapman et al., 2000) allowing a robot to navigate through a labyrinth. Basically, this sensor was made of small springs surrounded by electric contacts and was able to detect the direction of the wind.

Recently, several artificial whisker systems have been used in robotics to discriminate textures. Whisker hairs of real rats, glued to capacitive sensors (electret microphone), served (Fend et al., 2003; Lungarella et al., 2002) to produce very precise haptic sensors, with an uni-dimensional measurement of dynamic signals. Using an active whisker array of such sensors mounted on a mobile robot, Fend et al. (2003) successfully discriminated a set of 11 textures. Kim and Möller (2004) tried both piezo and hall-effect sensors which, mounted in orthogonal pairs, provided a bi-dimensional measure of vibrissa deflection. Like capacitive sensors, piezo sensors cannot deliver static signals, but this can be achieved using an extra integrator circuit. With a data processing based on spectrum density, these authors were able to discriminate a set of 7 sandpapers. Likewise, Seth et al. (2004) performed texture discrimination using arrays of Flex sensors, which provided an unidimensional measure of curvature. Here, temporal differences between pairs of vibrissæ were fed into a barreloid system with spiking neurons. Finally, Fox et al. (2009) used two active whiskers with strain gage-based sensors mounted on a mobile robot. They explored different bioinspired methods of feature extraction and the implication of unconstrained whisker-texture contact on classification performance.

The work described herein contributes to the Psikharpax project (Meyer et al., 2005) which aims at designing a biomimetic artificial rat. Besides visual, auditory and vestibular sensors, the corresponding robotic platform is equipped with an original whisker system described elsewhere (N'Guyen et al., 2009). This system is intended to be used for texture discrimination and object recognition and, more generally, as an auxiliary or a substitute to vision. Its performance in texture discrimination is the subject of the present article.

2 SYSTEM DESCRIPTION

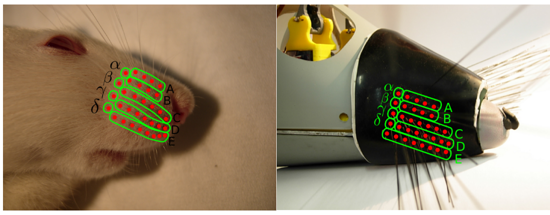

Figure 1: Comparison of whisker pads in a real rat and in our robot.

Insofar as the impact of the specific implementation of a rat's whisker system on its functionalities is currently unknown, we tried to design an artificial whisker system mimicking as much as possible the natural organization. Accordingly, our system (N'Guyen et al., 2009) is based on a simple, elastomer-based, artificial skin with two arrays of 33 vibrissæ and an arc/row organization (cf. Fig 1) and a whisker-length gradient (cf. Table 1) quite similar to those encountered in the rat.

Table 1: Vibrissæ arcs, with mean measured lengths in mm (in one adult *rattus norvegicus* specimen). Compared to those of a real rat, the robot's whiskers are approximately 6 times longer.

Arc	vibrissæ	rat	robot
1	$\alpha, \beta, \gamma, \delta$,E1	41.8	250
2	A1, B1, C1, D1, E2	37.2	200
3	A2, B2, C2, D2, E3	27.6	150
4	A3, B3, C3, D3, E4	20.6	120
5	A4, B4, C4, D4, E5	12.6	100
6	C5, D5, E6	8.33	90
7	C6, D6, E7		70
8	D7, E8		55

The deflection of each vibrissa is sampled in both its anteroposterior and dorsoventral axes, providing two 8-bit measurements at 1157Hz. However, orientation information being not necessary for texture discrimination, the two measures are normed ($\sqrt{x2+y2}$).

3 TEXTURE DISCRIMINATION

3.1 Feature Extraction

Neither the details of how a rat's brain actually encodes texture features, nor the exact nature of these features, are yet known. Arabzadeh et al. (2004) experienced different feature codings on both artificial and natural (in vivo) whiskers. Starting from the principle that a pure sinusoidal signal can be fully described by its amplitude A and its frequency f, they stimulated a rat's whiskers with various signals varying in amplitude and frequency. Then, recording the induced neural activity in the barrel cortex, they deduced that the neural activity most probably encodes a quantity homogeneous to the product Af. The generalized expression of this quantity to any natural signal is known as the "equivalent noise level (ENL)" (for more details see: (Arabzadeh et al., 2005)), which is usually used to measure sound power. This quantity can also be related to the more common "spectral centroïd" (Fox et al., 2009).
To compute the latter, instead of using a Fast Fourier Transform algorithm - of which no natural equivalent is known - we simply called upon a time domain "on-the-fly" estimate of the quantity $X\omega$. The corresponding algorithm (cf. Fig 2) can be compared to those used in auditory feature extraction, like ZCPA that is used for speech recognition (Ghitza, 1994; Kim et al., 1999; Sreenivas and Niederjohn, 1992). It

provides a quantity homogeneous to the ENL which we call the "Instantaneous Mean Power" or IMP feature.

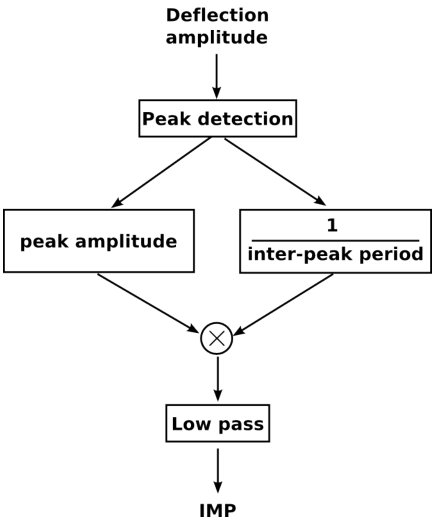

Figure 2: Feature extraction algorithm. "Peaks" are detected through the monitoring of the signal's derivative and frequencies are estimated through the inverses of the time intervals between successive peaks. Then, the peak amplitude is multiplied by the peak frequency, averaged within a time window.

This approach relies on the strong hypothesis that the peaks thus characterized provide enough information to describe a texture. Such hypothesis is reinforced by the fact that, when Licklider and Pollack (1948) assessed the effects of various signal distortions in human speech recognition, they found that "infinite clipping" - a treatment that only kept a signal's periodicity - did not prevent speech recognition in humans.

Be that as it may, the corresponding algorithm is very simple and computationally very cheap as it necessitates only one division per peak detection $(\frac{Peak\ amplitude}{Peak\ period})$ plus one addition (to compute the peak's period) at each time step. As for peak detection proper, it only entails one subtraction $(x_t - x_{t-1})$ and a comparison.

There are however possible limitations to the proposed algorithm. In particular, input data are drastically reduced by this procedure according to which a pure sinus input of frequency F and a triangle input of fondamental frequency F will lead to the same feature value although they obviously don't have the same spectrum. Likewise, turns out that amplitude modulations cannot be detected by a single vibrissa. Our hypothesis is that such limitations are alleviated by the fact that the natural filtering of vibrissæ, due to their intrinsic mechanical characteristics, decomposes complex signals along the pad in a manner similar to how the cochlea decomposes auditory signals.

3.2 Fixed Head Experiment

3.2.1 Experimental Appartus

At first, we tested this haptic system according to a relatively constrained fixed head experiment that consisted in sweeping a whisker pad over a set of eight sandpapers whose grits varied from P180 to P50 (cf. Fig 3). Sandpaper provide a complex random texture appropriate for this task and has been used on various experiment with real rats. Using this material, we performed qualitative experiments with humans that clearly indicated that the task of discriminating such textures by tactile contact only is a very difficult one, an observation also made by Hipp and coll. (2005) .

Figure 3: The texture set used for discrimination.

A vibrissa pad was fixed on the robot's head which could move in pan-tilt directions. The pan axis was at a fixed distance from the texture sample (cf. Fig 4) that was presented with a small amount of variability in position ($\sim \pm 1cm$) between each trial, with an appropriate angle to provide contact with a maximum number of whiskers.

For each texture, 400 experiments were made, 300 for learning and 100 for testing. The raw data (x and y deflections, 8 bits resolution sampled at 1157Hz) were normed ($\sqrt{x2+y2}$). For each vibrissa, this measure was fed into the feature extraction algorithm that output the IMP as one float value. Finally we summed these IMP values for each vibrissa during the sweep. Having thus obtained an input vector of 33 floats for each trial, we fed it into a simple multi layer perceptron (MLP) with 33 input neurons, 33 hidden layer neurons and 8 output neurons, to perform supervised learning. We used the FANN library (Nissen, 2003) with the iRPROP training algorithm (Igel and Hüskel, 2000). The final classification was done by a winner-take-all (WTA) on the 8 output neurons.

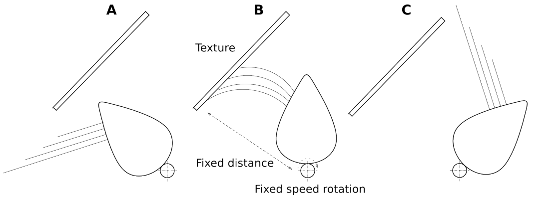

Figure 4: Schematic of the experimental protocol. A: start position, B: mid position, C: end position.

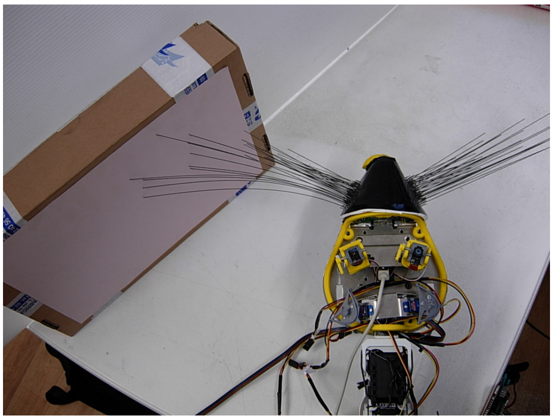

Figure 5: Top view of the experimental protocol.

3.2.2 Results

Table 2 gives the confusion matrices obtained on 100 test data. The mean performance is clearly above 90% (here the chance level is $\frac{1}{8} = 12.5\%$), which greatly improves the human aptitude at solving the same task.

Using the data thus acquired, we tested the influence of the number of vibrissæ on the classification performance. Starting with data obtained with one arc (Arc 1, 5 vibrissæ cf. Table 1), then with two arcs (Arc 1 + Arc 2, 10 vibrissæ) etc, up to the whole whisker pad, we assessed at each stage the quality of the discrimination. Results are summarized on

Table 2: Confusion matrix obtained for the 8 textures using IMP.

IMP	1	2	3	4	5	6	7	8
1	100	0	0	0	0	0	0	0
2	0	99	1	0	0	0	0	0
3	0	2	95	0	3	0	0	0
4	0	0	0	96	4	0	0	0
5	0	0	1	0	99	0	0	0
6	0	0	0	0	1	93	6	0
7	2	0	6	0	3	9	80	0
8	2	0	0	0	0	1	0	97

Figure 6. The percentage of successful discriminations is quickly rising with the number of vibrissae involved and reaches values comprised between 90 and 95% when three or more arcs (15 vibrissæ) are concerned. This result confirms previously obtained ones in (Fend et al., 2003; Hipp et al., 2006).

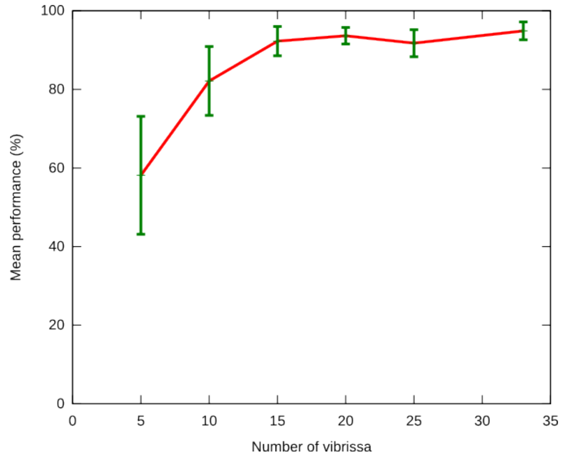

Figure 6: Mean performance (% of successful discriminations) obtained with IMP, over the number of vibrissæ involved.

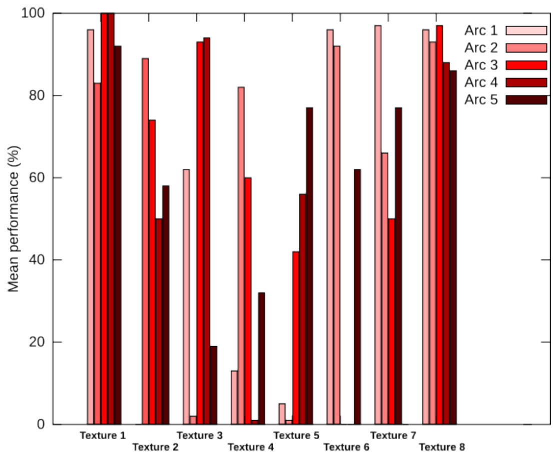

Figure 7: Mean performance obtained with IMP for the 5 longer arcs across the 8 textures.

When analyzing the performances obtained with a single arc (cf. Fig 7), one observes a great variability. Indeed, it seems that each arc separately performs better on a subset of the textures. For example, arc 2 is very bad at recognizing texture 5, but quite good with texture 6. This suggests that iso-length arcs complement each other and probably explains the increase in performance with the number of arcs involved.

The relative quality of these results demonstrates that the IMP is a suitable feature for texture recognition. However, as Fox et al. (2009) pointed out, the kind of fixed head task used so far is very different from that of a robot moving in an environment, where the distances and angles with which whiskers touch any texture are constantly varying. Therefore, to assess the robustness of the IMP, we also performed such a complementary experiment.

3.3 Mobile Robot Experimentation

3.3.1 Experimental Appartus

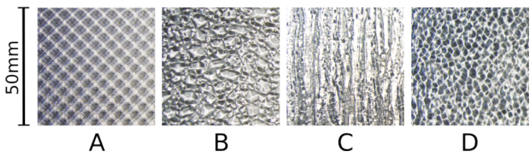

Figure 8: The four textures used in the mobile robot experiment. These textures were made of relief decorated plexiglass

In this experiment, a set of complex textures (cf. Fig 8) made of plexiglass were fixed on the sides of two small corridors (1m long). A different texture was assigned to each side of each corridor. The robot's task was to follow the walls in its environment, to enter a corridor if encountered, to recognize the textures on its sides, and to learn to turn left or right at the end of the corridor, depending on the left/right combination of the textures thus recognized. A main difference with the previous experiment was the "touch strategy". We previously swept whiskers on a texture by rotating the head, trying to maximize the number of whiskers in contact with the texture. Here, the whole robot was moving, the head didn't rotate and only a subset ($\sim$ 10 vibrissæ, the two longer arcs) of whiskers were actually touching the textures, from a varying distance.

To allow the robot to navigate in its environment using only its whiskers as sensory input, we developed a simple obstacle avoidance strategy. A distance information was first computed by taking into account the iso-length arcs. One minus the mean arc deflection was weighted by the mean within-arc vibrissa size. Thus, the more vibrissæ were bent, the smaller was the output distance. Repeating this computation for each arc, we obtained a value that decreased with the contact distance,

$$D = \frac{1}{N}\sum(1 - V_i) \times L_i \qquad (1)$$

V_i being the mean deflection of the i^{th} arc and L_i the mean length of the i^{th} arc. One can notice that the smaller whiskers - the most frontal ones - contribute less to this measure than the longer ones. This may seem counter intuitive as, when an object touches the small whiskers, it is probably closer than if it only touches the longer ones. But generally in the described task, when an object touches the smaller whiskers, it also touches the longer ones and the above weighting prevents an over-reaction. Moreover this method has shown a better stability in corridors, where a small variation of vibrissa deflection should provoke a small orientation reaction in order to make the corresponding trajectory as straight as possible. This centering strategy was an important component of the robot's behavior since the corridors were 35cm wide, while the robot's width was 25cm (including wheels) and the maximum whisker range was 50cm, leaving a small error margin for steady forward movement and whisker crack avoidance (cf. Fig 9). We controlled the robot through a speed vector V applied at the axis of the neck whose orientation component V_y was given by:

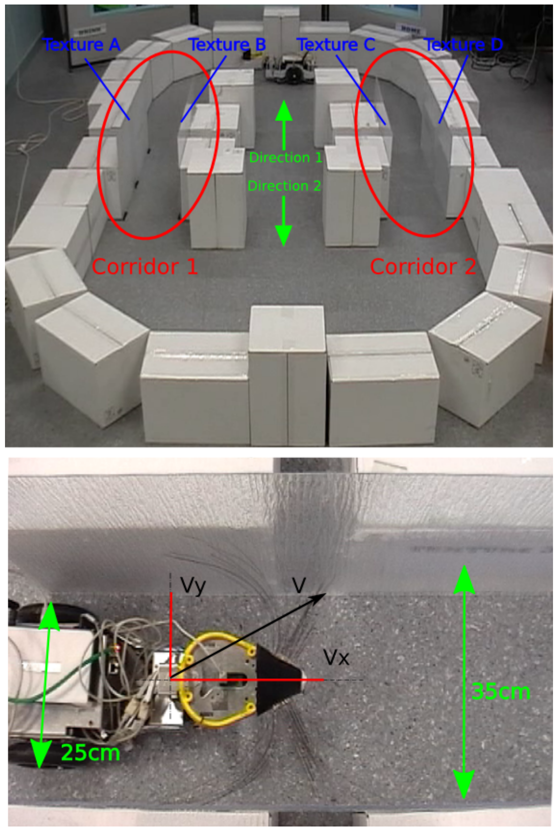

Figure 9: Robot environment showing the 2 corridors and direction convention used (Top). Robot inside a corridor, with dimensions and command vector (Bottom)

Table 3: Confusion matrix obtained for 20 runs for each corridor, in each direction.

Corridor-direction	1-1	1-2	2-1	2-2
1-1	75	15	10	0
1-2	0	100	0	0
2-1	15	0	85	0
2-2	0	15	0	85

$$V_y = (D_{left} - D_{right}) \times G \quad (2)$$

with the gain $G = 0.01$. V_x, the translation speed, was fixed to 10cm/s. This simple control produced an obstacle avoidance behavior, with a tendency to wall following. Additionally, this control produced a relatively stable corridor centering behavior - which was its principal objective. Finally, using D_{left} and D_{right} values, we could roughly determine the corridor's aperture size and trigger the learning/recognition procedure only when the robot was inside a corridor as determined by a distance threshold.

We first ran a series of 10 experiments for each corridor and each direction. We simply positioned the robot approximately in front of the corridor and recorded the IMP feature output at each time step within the corridor. We when fed 7 data runs to a MLP (2×33 neurons in the input layer, 2×33 neurons in the hidden layer and 4 neurons in the output layer), keeping the 3 others runs to test the learning result. A typical data run length was ~ 7000.

3.3.2 Results

Once the learning was completed, we ran four series of 20 additional experiments to evaluate the capacity of the robot to turn in the right direction at each end of each corridor. While the robot moved in a given corridor, in a given direction, we fed the smoothed (low pass filter) 2×33 IMP output to the previously learned MLP and computed the WTA on the output layer. By accumulating this winner value through the whole corridor, we obtained a mean decision vector which served to take the final decision (once again by a WTA). The corresponding results are summarized in Table 3. As expected, the trajectory stability played a role in performances as dithering in the corridor induced variations in the perceived vibrations. Most of the errors occurred when the robot's trajectories were unstable (lot of dithering).

We finally conducted qualitative experiments in the whole maze using the above described navigation rules. The maze was a round corner rectangle of 2.20m by 4.10m made of cardboard boxes with 2 corridors (cf. Fig 9). We added a simple hand cabled behavior consisting of turning left or right at the end of a corridor, depending on the recognized textures. The robot was initially positioned near the wall on the top of the maze with left or right orientations. Any other starting position could have been used with the limitation of avoiding a direct wall facing, as no "reversal" behavior was implemented. In these conditions, the robot succeeded to autonomously circulate around the maze, following either direction indicated by the textures on the corridor's sides. Several tours could be completed in a row thus demonstrating the efficiency of the robot's haptic system.

Figure 10 shows an example of the kind of trajectories obtained.

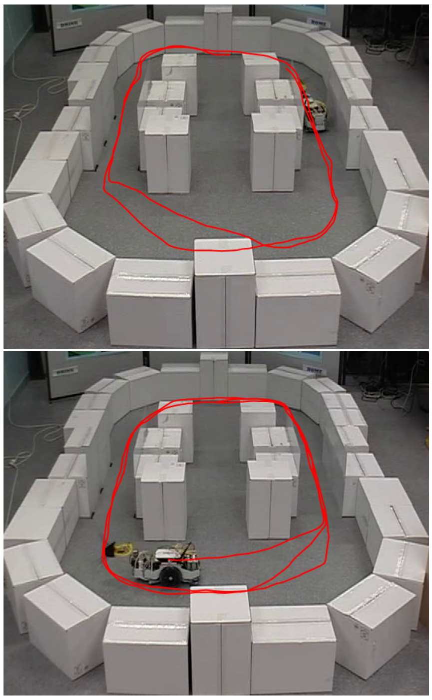

Figure 10: Typical trajectory of the robot into the maze. Top: left oriented start. Bottom: right oriented start.

4 DISCUSSION

If some research efforts have been devoted to texture discrimination in "fixed head" tasks (Fend et al., 2003; Lungarella et al., 2002; Kim, 2004; Fox et al., 2009), very few robots have been able to navigate and recognize tactile cues in a less constrained environment using whiskers. One such work was done using curvature sensors with two different types of surfaces that one may consider more as a "shapes" than as a

"textures", as they seem to induce a mere deflection sequence rather than a complex vibration (Seth et al., 2004). This robot could be conditioned to associate an aversive response with a given texture. A related work concerned a smooth versus rough discrimination task in an open arena and involved an active microphone-based whisker sensor with a natural rat's hair (Fend, 2005). Feature extraction called upon spectral analysis and lead to qualitatively good results. However, as the author concludes, such system could not be used to perform a more complex task without an improvement of its discriminatory capability and reliability. Finally, Fox et al. (2009) also obtained good results in a smooth/rough discrimination task on a mobile robot equipped with active whiskers using an "onset" feature. This "onset" feature is roughly the FFT magnitude within a short frequency band (2-3kHz) during the onset period of the whisker-texture contact (the first 12.8ms of the contact). Moreover, this feature is invariant to the relative position and orientation of whiskers and textures. Experimental conditions were slightly different from ours, as the texture position was chosen randomly and the robot didn't move while touching a texture.
None of these related approaches seems suitable for performing a more complex task than simply discriminating smooth versus rough textures. In contrast, the haptic system that has been described herein proved to be able to use texture discrimination to afford minimal navigation capacities in a complex environment. Such capacities could be used to complement vision in daylight conditions or to replace it in the dark.

With this haptic system, texture recognition is possible in both fixed and mobile robot conditions. This tends to indicate that, despite the underlying simple algorithm and the various approximations on which it relies, the IMP feature is robust.

Conversely, we already mentioned that the whisker orientations in our system is not always well suited. Indeed, our whiskers are oriented toward the front (cf. Fig 5), which occasionally prevents all the whiskers from touching a texture. Within a corridor, for instance, about 10 whiskers only were touching the walls. Additionally, our implementation sometimes entails brusque return jumps of some whiskers when they are stuck on a given surface, rather than a gentle sweeping, which makes their signals totally unreliable. Fortunately, this problem only occurs in corridors and with a minority of whiskers (usually the more dorsal and ventral ones) and thus the classifier can see it as mere noise. Obviously, a system in which the whisker orientation could be dynamically controlled - such as the one used in (Fox et al., 2009) - would be more adapted to alleviate this specific inconvenience and would be closer to the natural active whiskering system of rats.

Another remark concerns our feature extraction technique. We chose to design an algorithm that extracts an estimation of the amplitude-frequency product. This choice was based on a recent finding about how texture signals are encoded in a rat's brain (Arabzadeh et al., 2004). Using such a feature, we were able to perform fine texture discrimination. This finding is an argument in favor of the so-called "kinetic signature" hypothesis which stands that each vibrissa encodes a specific signature of the touched surface in term of magnitude and temporal pattern.

Likewise, the fact that our results suggest that the texture discrimination capacities depend both on the length and number of the involved whiskers, seems to back up the "resonance hypothesis" (Moore and Andermann, 2005; Neimark et al., 2003) which stands that the self resonance property of a vibrissa plays a crucial role in vibration transduction and, in some way, helps to enhance texture perception. The exact manner in which this resonance property is exploited in rats is still unclear, but it seems quite reasonable to think that a kind of signal filtering is involved. Additional experiments with the current system might help clarify this issue.

Be that as it may, already acquired results strongly suggest that two hypotheses that are currently considered as mutually exclusive to explain texture recognition in rats - i.e., the "kinetic signature hypothesis" and the "resonance hypothesis" - may be, in fact, complementary.

5 CONCLUSION

We endowed a whiskered robot with a simple algorithm allowing to discriminate textures. Its efficiency has been demonstrated using both a fixed head and a mobile robot. Comparatively to previous similar approaches, this system affords greater behavioral capacities and may complement or supply vision in simple navigation tasks. Future work will be devoted to demonstrating its ability to perform shape recognition. On a fundamental level, it will also be used to investigate the influence of whiskers resonance properties on texture transduction.

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