Whisker-Based Texture Discrimination on a Mobile Robot

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Abstract. Sensing in the dark is a useful but challenging task both for biological agents and robots. Rats and mice use whiskers for the active exploration of their environment. We have built a robot equipped with two active whisker arrays and tested whether they can provide reliable texture information. While it is relatively easy to classify data recorded at a specified distance and angle to the object, it is more challenging to achieve texture discrimination on a mobile robot. We used a standard neural network classifier to show that it is in principle possible to discriminate textures using whisker sensors even under real-world conditions.

1 Introduction

When light is dim or fading, tactile information becomes more and more important. In nature, many night-active animals such as rodents, cats or oppossums have developed an exquisite tactile organ, the whiskers. With their large mystacial whiskers, rats for example not only navigate to avoid obstacles, but they are also able to discriminate different textures and shapes [4]. Behavioral studies in rats have shown that their ability to discriminate surface structures with the whiskers is comparable to ours using our fingertips [11] [5]. Unravelling the information coding in the rat whisker system has recently attracted different researchers both from biology [18] [17] [3] [2] and from the field of robotics [10] [20] [22] [19] [15]. Theoretical studies have analyzed the properties of whisker vibrations [16] [9] [14] and their implications on neural coding and learning of simulated receptive fields [13] [12].

So far, tactile stimuli have largely been acquired by keeping parameters such as distance and orientation of the whiskers constant with respect to the texture (as in [20] [9]). Although it is reasonable to assume that animals can position their head appropriately, they are also able to discriminate textures from far away when forced to do so. One of the main differences between analyzing recorded data and using a behaving robot is that different parameters such as distance and angle towards the texture are not necessarily well defined. Thus, it is important to record data with different parameters and identify features significant for the discrimination of textures. Such features are necessary for the construction of a behaving system capable of showing discriminatory behavior comparable to a trained rat.

To our knowledge, so far only one study has conducted experiments on texture discrimination with a mobile robot [20]. In their experiment, the robot showed a wall

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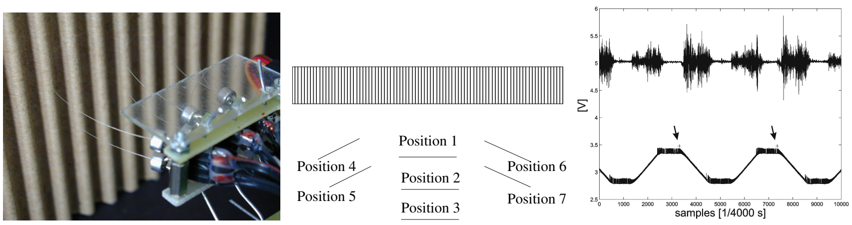
following behavior stimulating the whisker sensors by moving them across the wall. When a texture was encountered, the robot learned to avoid the wall based on the activity pattern of its neural network. Following the wall not only generates input, it also controls for the distance and angle at which a tactile pattern is sensed. The input to the neural system is thus more reliable and reproducible than at random orientations.

In the series of experiments presented in this paper, we want to consider a more general case, namely whether classification is possible even if a texture is explored from different angles and distances. Furthermore, the robot generates sensory stimulation not only by moving the whole body, but also by moving the whiskers actively. We have approached this question twofold: first, we recorded different textures from different angles and distances and trained a neural network to classify these textures. In a second series of experiments, we let a robot explore an environment equipped with different textures and trained a network with these self-acquired data. During a separate testing phase, the classification of the sensory input was recorded and evaluated.

2 Materials and Methods

The goal of this series of experiments was to assess the robustness and the discriminatory power of the whisker sensors under real-world circumstances. Detailed data analysis has been performed elsewhere [9]. We used a microphone-based whisker sensor with natural rat whiskers as described in [16]. A single whisker hair of approximately 5 cm is glued to a capacitor microphone. Mechanical stimulation is thus transduced to a deformation of the microphone membrane. The resulting signal is amplified and recorded by the computer. Six such whiskers are assembled in an array of two rows with three whiskers. They can be moved actively by one servo motor to perform a periodic synchronous sweep at a frequency of 1 Hz. The construction of the whisker array has been described in detail in [8].



(a) (b) (c)

Fig. 1. a) Photograph of the data collection setup with rough carton. The 6 whiskers of the artificial whisker array can be moved synchronously by one servo motor. The whiskerarray was placed at different distances and angles towards the texture. **b)** Schematic of the layout of the seven positions at which data was recorded with respect to the texture (indicated as a striped bar) **c)** Example of one sweep of raw data and the recorded motor signal. The borders between sweeps as extracted by the algorithm are marked with arrows.

2.1 Data Acquisition

We collected a dataset containing four different textures: 1) smooth metal, 2) sandpaper 400, 3) sandpaper 80 and 4) rough carton recorded at seven different positions (see figure 1(b)). At position 1, the base of the whisker sensor is at a distance of 2 cm from the texture. The positions in one column are each 1 cm apart. The whiskers were actively moved across the surface of the texture and the position of the servo motor was recorded simultaneously. Data acquisition was performed using a National Instruments Data Acquisition Card (DaqCard 6036E) at 4 kHz per channel.

For the robot experiments we used an open environment. Half of the surface was lined with a rough carton surface, the other half was left blank, displaying a smooth metallic surface.

2.2 Feature Extraction and Discrimination Capabilities of Recorded Data

Previously, we have shown that it is possible to generate texture specific signatures from power spectra of whisker signals (see [9]). Such a signature relied on several sweeps and covered frequencies up to 1 kHz. For a system behaving in real time, we sought to reduce the dimensionality of the input vector further. Three different preprocessing methods for feature extraction were tested: Spectrotemporal analysis, fourier transform convolved with a Blackman window of 70 data points (57 Hz) and raw data also convolved with a window of 57 Hz. In all three cases, the dimensionality was reduced to

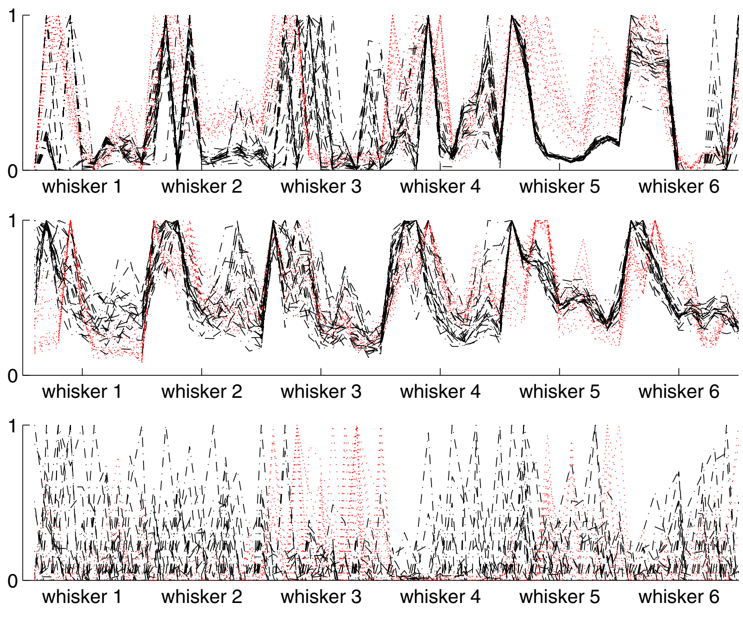


Fig. 2. Cumulated feature vectors of twenty sweeps in one position of texture 1 and texture 4. The dotted line indicates texture 1, dashed line texture 4. The preprocessing used was **Top row:** Smoothed raw data, **middle row:** fft and **bottom row:** PCA components after a spectrotemporal analysis.

10 values per whisker yielding a feature vector with 60 values. The raw data and the fourier transformed data were divided in 10 windows (the first 750 ms of each sweep and the frequencies between 1 and 1000 Hz) of 75 ms and 100 Hz respectively. Then the highest value of this window was passed as input to the network. Examples of 20 such input vectors of two different textures are shown in figure 2.

2.3 Training the Neural Network

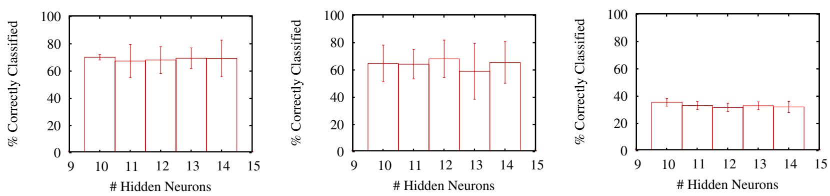
To identify and evaluate different features, a standard backpropagation network was used to classify previously recorded textures. Please note that the purpose of this experiment was not to postulate a specific biologically inspired architecture, but to evaluate the potential of the features used and the setup as a whole under real-world conditions. Any other statistical classification algorithm could have been used as well. Training was done using the Levenberg-Marquardt algorithm as implemented by the Matlab Neural Network Toolbox [1]. For all neural networks described in this paper, we trained ten runs with different random initializations and between 10 and 14 hidden layer neurons.

Since the whiskers were stimulated by actively sweeping over the surface, the proprioceptive signal from the motor identified the repeating elements. Multiple sweeps of the same texture were thus extracted from one continuous stream of input. One such sweep together with the motor signal is shown in figure 1(c). Together with the remaining five whiskers, this constitutes one sample of input for feature extraction and subsequent neural network training.

For each texture, one minute of data was recorded at seven different positions systematically varying the distance and angle of the whisker array with respect to the presented texture (figure 1(b)). A second set of data was recorded separately to be used for testing the network.

2.4 Evaluation of Network Performance

To test the classification and generalization, each trained network was simulated with the test data and a hit matrix (as in figure 4(a)) was computed by determining the output neuron responding most strongly and comparing it to the desired output neuron. From the hit matrix, the percentage of correctly classified samples was computed. After feature extraction using fourier transformation with subsequent dimensionality reduction



(a) (b) (c)

Fig. 3. Mean percentage of correctly classified samples using **a)** smoothed raw data and the ten highest values of each whiskers in blocks of 75 ms. **b)** FFT preprocessing **c)** spectrogram preprocessing with subsequent PCA.

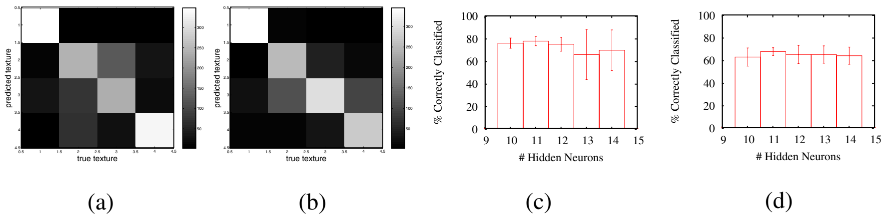


Fig. 4. Left Sample hit matrix on all recorded positions and textures with **a)** FFT preprocessing and **b)** smoothed raw data. The textures are from 1 to 4: smooth metal, sandpaper 400, sandpaper 80 and cardboard. **Right** Mean percentage of correctly classified test samples recorded with a mobile robot. **c)** Left whisker array and **d)** right whisker array. The textures to be discriminated were smooth metal vs. rough carton.

as well as the temporal analysis of the raw data, the neural network was able to classify not only the training set but also the test set (figure 3(a) and 3(b)). The best classification for raw data was 75 %, for spectral analysis (fft) it was 74 %. Usually, about one of the random initializations resulted in a network unable to classify the testdata above chance. This is the reason for the rather large errorbars in figure 3(b).

Figure 3(a), 3(b) and 3(c) show the mean number of correct responses for the three different types of feature extraction for 10 different random seeds and different numbers of hidden neurons. Spectrotemporal analysis followed by principal component analysis was not able to learn to discriminate the four textures, mean correct responses range between 25 % and 39 %.

Figures 4(a) and 4(b) show the hit matrices for the testdata with a sample neural network. Bright color indicates many entries. The bright diagonal shows that the network classified the textures correctly in most cases. More interesting is the interpretation of misclassifications: most mistakes occured for the two sandpapers (textures 2 and 3). Smooth metal and rough carton were rarely confused. The distinction between these two textures was especially clear between feature extraction using spectral analysis, therefore it was used in the robot experiments.

3 Classification of Data Recorded on a Mobile Robot

First tests with the robot were conducted using the same features and neural network structure as determined to be appropriate with recorded data. However, when the robot did not use any sensory feedback to adjust its position with respect to the encountered surface, often it did not get stimulation in more than two whiskers. Data recorded under such conditions did not result in successful classification (data not shown). Therefore, the whisker data was used to roughly position the robot such that at least four whiskers were stimulated.

For this behavior, the robot was equipped with a few motor primitives: It explored the environment while whisking actively for obstacles and explorable textures. Upon contact, the robot stopped and acquired a few whisks of data. Depending on this sensory input, it either logged data or repositioned slightly with a fixed turning behavior in order to achieve stimulation in at least four whiskers before acquiring data. The training signal necessary for the backpropagation algorithm was delivered manually. In unfortunate spots such as ambiguous corners, the robot was repositioned manually.

After a total of 150 encounters which were shared about equally between the two whisker arrays, the first 3/4 of the encounters of each side of the robot were used to train the neural network, the last fourth of encounters was used to test the performance. Please note that between every encounter, the robot moved for a minimum of 2.5 s including turning on the spot. This ensured that each instance of acquiring data was actually done at a new orienation and at a different spot. On average, the left whisker array classified correctly more often than the right whisker array. The mean values on the left side ranged between 65 to 76 % correctly classified samples with the best network classifying 85 % of the test samples correctly (figure 4). The right whisker array on average classified between 63 % and 67 % percent of the samples correctly. The maximum of correctly classified samples was 76 % (figure 4). The differences found between the two whisker arrays can depend on several factors which cannot be decided on the basis of the current experiments. Possibly, the quality of the whisker sensors varies. Another source of variation is that the robot acquires data on its own and thus it may be that one side accidentally records data more apt for classification.

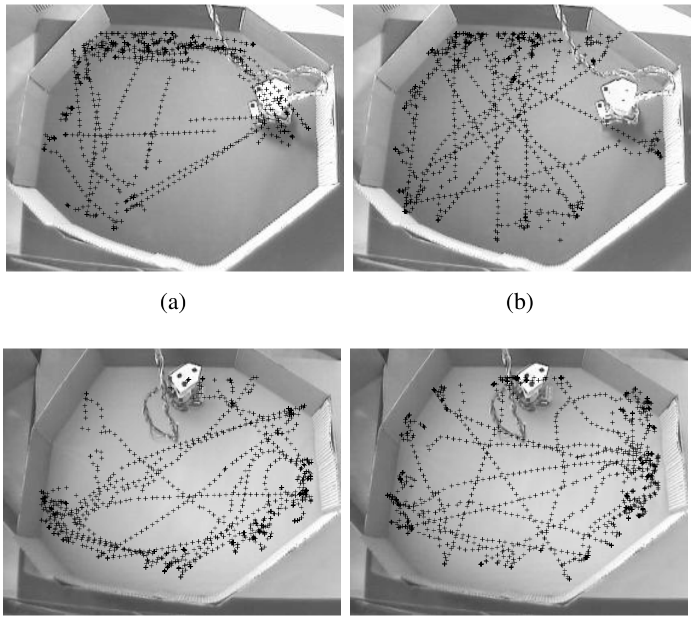
3.1 Behavioral Experiments with the Robot

The same neural network structure was used for the robot as was tested previously in the simulation described above. For each of the two whisker arrays with six whiskers a neural structure was created: this right and left hemisphere were fed with the signals from the respective whisker arrays and trained individually. During a behavioral testing phase, the previously trained robot explored the environment. Upon contact with a texture, it was palpated for 9 seconds of which five sweeps were used for classification. Depending on the resulting classification, the robot responded by turning by 30° or by 120° away from the texture. Given this behavior, we expect the robot to spend more time in that half of the arena, where the turning angle is smaller. The resulting trajectory should thus cover the respective part of the arena more closesly. To evaluate the robot performance, each run was recorded with an overhead camera and the robot was automatically tracked using the KLT library [21]. As a control condition, the robot behaved as described above, but instead of using sensory input for classification, the type of texture was supplied by the experimentor. Here, only slippage of the wheels or physical hindrance e.g. due to the cables can possibly induce deviation from a perfect behavior.

In the actual experiment, the robot classified whisker input with the neural networks trained as described above. To ensure that a behavioral pattern was actually induced by correct classifications and was not an artefact of the allocation of texture type and turning angle, this allocation was also switched.

3.2 Results of the Behavioral Experiments

In the control condition shown in figure 5(a) it is apparent that the robot spends much more time close to the smooth metal. It also reliably turns away from the carton. This is due to the different preprogrammed turning angles. Reversing the angles also reverses



(a) (b)

(c) (d)

Fig. 5. Trajectories of a single run. Each cross indicates the robot position during one frame of a consecutive image sequence. The background shows the actual robot arena with the robot as seen from an overhead camera. The bottom and the right wall are coated with rough carton, the upper and left walls are made of smooth metal. **Top row:** The robot turns from rough carton at a larger angle than from the texture classified as smooth metal. **a)** Classification supplied by the experimentor and **b)** classification according to sensory input. **Bottom row** The robot turns stronger from smooth metal (120° angle) than from rough carton. **c)** classification supplied by the experimentor and **d)** classification according to sensory input.

the overall impression (figure 5(c)). During the actual experiment, the classification depended solely on the sensory input acquired by actively whisking any surface encountered during exploration. Figure 5(b) shows such a run: the robot spends more time close to the metal coated walls. This is due to the lower angle with which it turns from the texture classified as metal. Larger turning angles can be seen well for encounters with the rough carton coated walls.

The same holds true when the turning angles are reversed (figures 5(c) and 5(d)). Here, the robot turns with a 30° angle from rough carton and with a 120° angle when palpating smooth metal.

4 Discussion and Future Work

Tactile discrimination based on whiskers is still a young research area. The experiments described above try to fathom the potential of artificial whiskers for haptic sensing both statically and on a robot. For this purpose, a standard classifier was used, namely a backpropagation network.

Since whiskers are potentially very interesting tactile sensors for robots, the main focus of the experiments was to assess how reliable whisker-based classification is without strict control of position and orientation. The results of neural network simulation of data recorded at different but defined positions are promising. Even with only few inputs and a standard preprocessing such as fourier transformation, classification of four different textures with about 70 % correctly recognized textures based on only one sweep has been achieved.

To test whether this would hold true for the continuous space of possible distances and orientations on a mobile robot, robotic experiments were conducted. In this series of experiments it became apparent that it is more difficult to achieve classification behavior under real world conditions. Firstly, sensory feedback based on whisker input had to be introduced to avoid active exploration in situations when only one or two whiskers touched the surface. Having limited the range of possible positions to those, where at least four of six whiskers were activated, test data could be classified to some extend, but not without mistakes.

Based on these results, a lot of experiments can be proposed. For example, we want to test the whisker-based texture discrimination of the robot in a behavioral task comparable to experiments on rats. We have already built a maze with variable number of arms. The robot should be able to chose specific arms based on textural information at the walls of each arm. For this task it will probably be necessary to improve the reliability and the discriminatory capability of the system. While we cannot exclude that the preprocessing chosen for these experiments is not optimal, we believe that to achieve more reliable classification sensory-motor coordination might be used on two levels. Firstly, feedback from the whiskers could be used adaptively to orient the body of the robot appropriately with respect to the texture. Rats for example are reported to prefer a distance of 2 cm from their whiskers to an object or texture [7]. Secondly, the whisking behavior itself could be influenced by sensory feedback. Varying the speed or amplitude of whisking could possibly help to resolve ambiguities. Again, there is evidence from behavioral rat studies that the whisking frequency is not always the same but might be varied from one whisking cycle to the next [6]. Most probably, both proper orientation and adapted active exploration are crucial for fine texture discrimination and thus complement the stereotyped active exploration that was investigated in this paper.

In addition to behavior exclusively based on whiskers, the robot is already equipped with an omnidirectional camera. This opens up the possibility of investigating behavior based on two different sensory modalities.

5 Conclusion

In this paper, we have shown that it is possible to classify tactile data of different textures acquired with artificial whiskers. In a first series of experiments, we have shown that four textures consisting of a smooth metallic surface, two different sandpapers and rough carton can be classified even when the position of the whiskers with respect to the texture is varied considerably. This result is a prerequisite for using the sensor on a robot without highly precise position control. In a second series of experiments, a mobile robot was used to acquire data in an open environment with walls of different tactile quality. Here, the positions of the robot with respect to the wall were not specified but only limited loosely. Our experiments have shown that classification is not entirely reliable under real-world conditions. However, given sufficient data, a rough discrimination has been achieved. In the future we will use more biologically inspired sensory processing and sensory-motor feedback to refine the tactile capabilities.

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