LETTER

Predicting Properties of the Rat Somatosensory System by Sparse Coding

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Abstract **–** Many studies address how neurons in the barrel cortex of rats react to stimulation of the rat's whiskers. In this study we analyse how the statistical properties of whisker deflections from typical surfaces relate to the properties of neurons in the somatosensory system. We built an artificial whisker system to record realistic natural tactile data. An artificial whisker is moved about a set of surfaces of everyday objects. We analyse how simulated neurons can represent such stimuli in an optimally sparse fashion. These representations predict a number of interesting properties of neurons in the somatosensory system that have yet to be measured.

1. Introduction

Whiskers provide an important source of information to rats and other rodents [26]. Rats can, for example, distinguish surface properties (texture) purely on the basis of cues from their whiskers [7, 5]. They can furthermore use their whiskers to discriminate objects [4] based on their shape. As the rat explores its environment, its whiskers are moved over surfaces of various shape and texture. Neurons in the sensorimotor system thus need to transmit the relevant information to subsequent brain areas. The whisker deflections caused by these stimulations define the input to the rat's somatosensory system. Although a large number of studies analyse the electrophysiological properties of the barrel cortex [1, 17, 18], the relevant features of its input that should be transmitted by neurons have remained unknown.

Recent studies show a growing interest in the texture discrimination abilities of rats (for a review see [16]). Frequencies induced in the vibrissa hair are discussed as the relevant information used for this behaviour [19, 9]. Furthermore, it was shown that for an artificial whisker sensor, different textures could be discriminated analytically using power spectra [6].

In an emerging branch of neuroscience, optimal coding of natural scenes, it is studied in what respect neurons optimally encode natural stimuli. As animals grow up and evolve in a world of approximately constant properties, the properties of the brain should be well matched to the properties of the world [3]. Within this field, many studies address the properties of natural stimuli in the visual domain addressing the scaling behaviour of natural images [22] or the properties of higher order statistics using sparse coding [21, 20, 25]. Theses studies showed that many properties of the visual cortex can be understood as sparsely encoding the stimuli it typically encounters. A number of studies also address sparse coding in the auditory domain addressing the auditory nerve [14] or the primary auditory cortex [13]. Again these studies showed that many properties of the auditory system can be understood as sparsely encoding natural sounds.

Optimally sparse in these studies means that the neurons often have an activity close to zero and then sometimes have very high activity. Drawing upon this inspiration, we analyse the somatosensory system with similar methods. Sparseness has two distinct albeit related meanings: (1) At any point of time only a small number of neurons should be active (sparseness over the population). (2) Over the course of time each neuron should be active only rarely (sparseness over time). While the early explorations of sparseness often used definition 1, most modern studies use definition 2 as the implementation is typically a lot faster and in many cases the results are identical. There are a large number of discussed reasons why sparseness should be useful. Just to name two of them: (1) Sparseness ensures that information is transmitted using a minimal number of spikes emitted by the neurons and therefore results in a minimal energy consumption of the brain. (2) Sparse representations also maximise the independence between neural outputs and thus make recognition tasks easier for subsequent stages of cortical processing.

In this paper, we examine the statistics of natural stimuli to the somatosensory system. We thus examine if not only visual and auditory but also somatosensory stimuli can be understood as sparsely encoding typical stimuli. In analogy to the databases of natural images used for visual studies, we first need a database of natural whisker deflections. We thus built an artificial whisker system with a real rat whisker attached to a capacitor microphone. This set-up was described in previous papers [15, 8]. This extends previous robotics studies that used simple whisking devices measuring distances or contact only [10, 23, 11], but do not capture the rich information picked up by natural whiskers in a biologically plausible way. We collect whisker data by actively moving the whisker over a set of complex stimuli. The motion pattern of the whisker in this configuration closely matches the motion patterns of the whiskers in natural conditions (rough visual observation) and has similar movement frequency and the same shape.

We analyse if the neurons in the vibrissal system can be understood in terms of leading to sparse activity in response to these natural inputs. We represent the data coming from our artificial whisker system in the spectro-temporal domain to allow for a large class of spectrotemporal responses. Simulated neurons optimally coding for these data are analysed and generate predictions about neurons in the somatosensory system.

2. Hardware Design and Methods

This section describes the artificial whisker system we built and the responses we recorded in response to moving the whisker over natural surfaces. The desired artificial whisker should be functionally comparable to a natural rat whisker and therefore be sensitive to small amplitude deflections and fast oscillations. We investigated different designs, including piezo-electric crystals and small capacitor microphones. The influence of different whisker materials (metal wire, polyvinyl, human hair, rat whiskers) has also been compared [15]. Rat whiskers respond to a range of spatial frequencies and showed little oscillations. The most promising results were gained with a combination of the rat whisker with a capacitor microphone technique, which is described in the following subsection.

2.1. The Artificial Whisker System

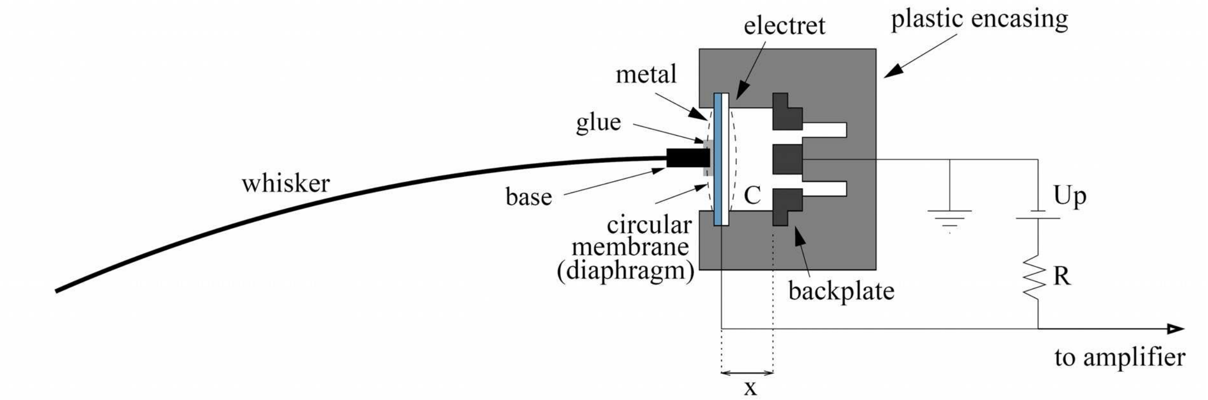

Figure 1. Basic schematic of the artificial whisker with an electret microphone picking up the oscillations and converting them into electrically measurable signals. The whisker is glued onto the membrane of the microphone. The deflection of the membrane is measured by the change of capacitance. The related change of voltage is fed into a preamplifier circuit.

We attached a rat whisker to the diaphragm of a capacitor microphone using cyanoacrylic superglue. Vibrations and displacement of the hair results in deformations of the microphone membrane. The resulting change in voltage is pre-amplified and digitally recorded. This technique allows us to measure fast oscillations of the whisker even if the amplitude is very low. The microphone with the rat whisker is attached to a servo motor to produce active whisking in a controlled way as described in the next section. A schematic drawing of the device is shown in figure 1, a picture of the artificial whisker system can be seen in figure 2.

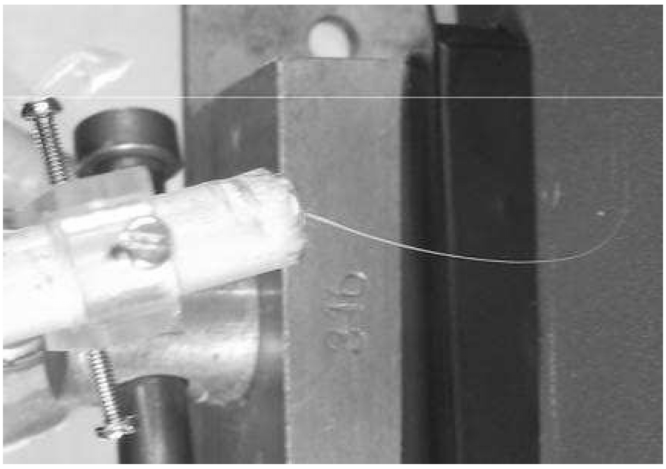

Figure 2. Image of the artificial whisker system used for recording the data.

2.2. The Deflections of the Artificial Whisker

We recorded deflections from a single whisker being automatically swept over different objects (sandpaper, leather, wool, etc.) with a servo motor turning back and forth at frequencies of either 1 Hz or 4 Hz. While this is a slow movement it is of the same order of magnitude as natural whisking of rats which is at about 8 Hz. Capacitance readings are sampled at 4000 Hz. In contrast to a previous study [8], the stimulation of the whisker was modelled on the active whisking behaviour of rats and mice. Previously, data was acquired either by manually sweeping the sensor across different surfaces or by stimulating the whisker by a rotating drum covered with sandpaper of varying roughness. In the first case, small variations in distance and speed could not be controlled and the whisker was not tilted as in natural whisking. The latter stimulation does not correspond to the biological reality and results in continuous, uniform stimulation. As some electrophysiological findings about differing responses in the whisker processing pathway suggest, this distinction might be highly relevant [24]. A typical trace of capacitance of the artificial whisker system can be seen in figure 3. It has eight signal peaks per second because of the forth and back movement.

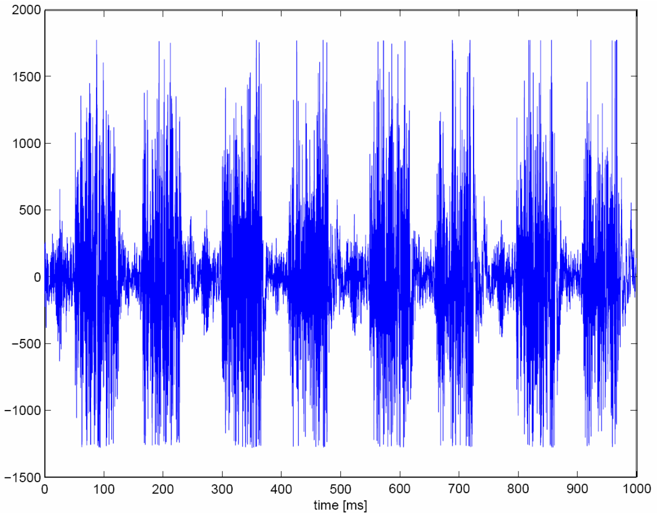

Figure 3. Capacitance trace measured by the artificial whisker system while whisking back and forth over an object.

3. Results

3.1. Representation in Spectrogram Space

Time varying data are conveniently analysed in spectrogram space, the space spanned by frequency and time. In this space both changes over time and over frequency are easily understood. This representation is particularly useful for the whisker system since rats are able to discriminate surfaces of different spatial frequencies [5]. It has also been shown analytically that the whisker oscillation frequencies elicited by different textures can be used to discriminate between different surfaces [6]. We thus present the input signals as spectrograms. The resolution on the tonotopic axis is 64 points, covering a frequency range from 1 to 512 Hz. In figure 4, three typical samples of such transformed whisker data can be seen. These spectrograms show that whisker deflections lead to a largely conserved frequency-time response.

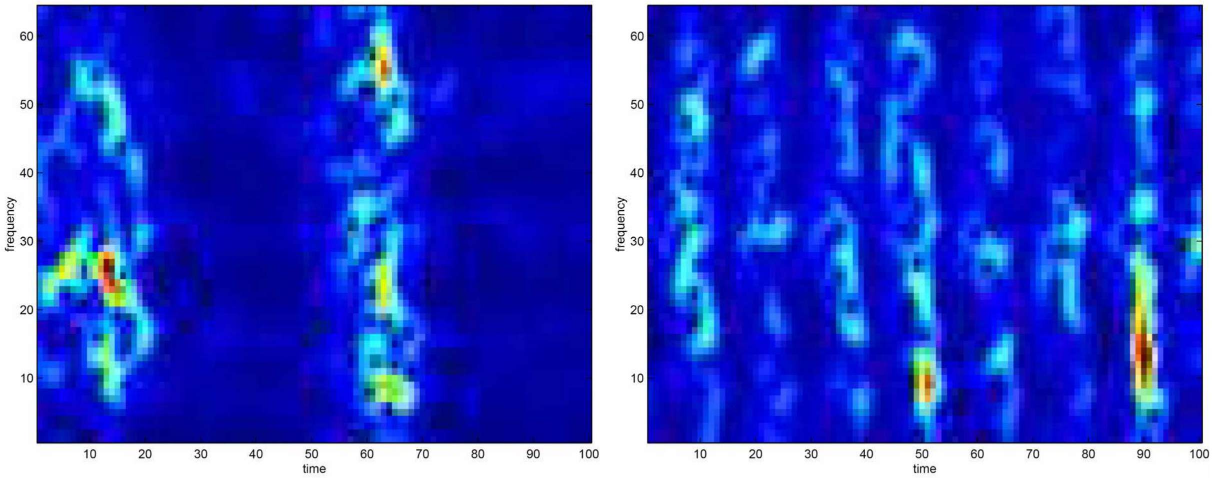

Figure 4. Sample spectrogram of whisker data (left: 1 Hz data, right: 4 Hz data). The frequency axis ranges from 1 Hz to 512 Hz while time runs from 0 to 1000 ms in steps of 10 ms. The colour codes for the intensity, red for high values and blue for low ones.

3.2. Principal Component Analysis

Neurons usually represent the properties of stimuli over a localised window of time. To analyse the properties of these stimuli we cut the spectrogram data in windows of 250 ms each, overlapping by 100 ms. The temporal resolution of these windows is 25 points. We subsequently assemble a set of 24360 samples of data spectrograms from a recording time of about 4 minutes.

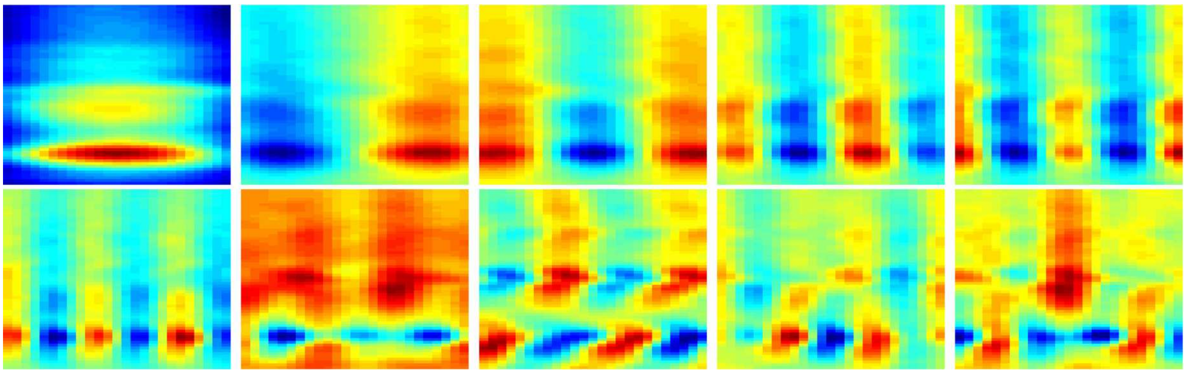

Figure 5. First 10 principal components of the spectrogram data. The PCA is applied to the whisker data in spectrogram space, using windows of 250 ms.

For the learning studies, the spectrograms are first compressed by a principal component analysis (PCA) using the first nP CA = 100 principal components (out of 25 × 64 = 1600). These components capture more than 96% of the variance. In Figure 5, the first 10 principal components of the spectrogram data are shown, sorted by the size of their corresponding Eigenvalues. The purpose of the PCA is merely the compression of the data. It does not significantly influence the results of the sparse coding described in the following subsection.

3.3. Sparse Coding and ICA

A set of 32 simulated neurons is trained to optimally code for the recorded dataset. The activity of the neurons is calculated as

$$A_i(t)= I(t)W_i(t),$$

where A_i is the activity of the neuron, W_i is the weight vector of the neuron i. I(t) is the input vector of length $n_{PCA} = 100$ shared by all neurons. This input vector itself again contains a representation of time as it encodes the whole spectrotemporal window. The weight vector of each neuron is optimised by scaled gradient descent to minimise the following loss function:

$$\Psi_{total} = \Psi_{cauchy} + \Psi_{std} + \Psi_{decorr} \quad \text{, with:}$$

- Cauchy: $\Psi_{couchy} = \frac{1}{n}\sum_i < \ln(1 + A_i(t)^2 >_t$,
  with $< \cdot >_t$ being the average over time t
- Standard deviation: $\Psi_{std} = \frac{1}{n}\sum_i (\sigma_{Ai} - 1)^2$
- Decorrelation: $\Psi_{decorr} = \frac{10\sum_{i,j} C_{ij}^2}{(n-2)(n-1)}$,
  with C = cov(A) being the n × n covariance matrix of A

ψ_{cauchy} is a function that favours sparse representations. The two other loss functions ensure the standard criterion used in Independent Component Analysis (ICA) and sparse coding studies that the output variances should be unitary and the output covariances should be vanishing. It can be shown (see [12]) that the decorrelation term is equivalent to minimising the reconstruction error for the original dataset, given a linear system and an overcomplete set of neurons.

3.4. Spectrotemporal Receptive Fields

Simulated neurons are optimised to sparsely encode naturally occurring whisker deflections. Figure 6 shows the general properties of the resulting spectrotemporal receptive fields. Out of 32 receptive fields, 18 are similar to plot A, 6 are similar to plot B, and there are some receptive fields looking like C, D, and E. Since ψ_{cauchy} is symmetric, the receptive fields can have positive or negative localisation features. Most of the analysed neurons are localised in time and frequency.

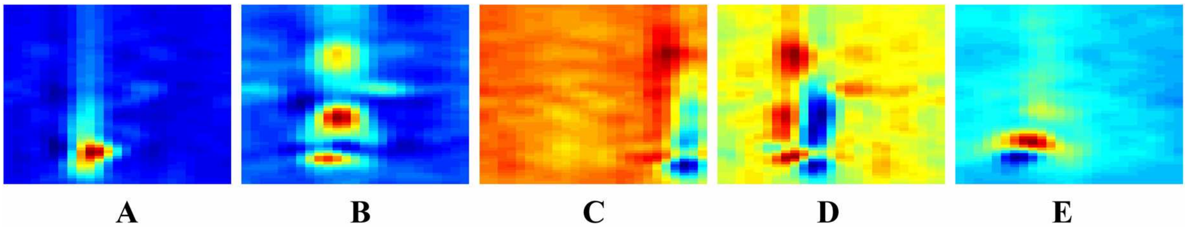

Figure 6. Five typical samples of colour-coded spectrotemporal receptive fields out of 32 neurons. y-axis: frequency (1 Hz to 512 Hz), x-axis: time (0 to 250 ms).

To further quantify this property, we introduce two measures of localisedness (figure 7). For the analysis, we calculate the average energy over time, and the frequency for each receptive field, respectively. We also measure the width of the maximum peak at half the peak value for time localisation, and the octaves log(fl /fh) for frequency localisation. More than 96% of the receptive fields have a localisation measure in time of less than 80 ms. This seems to be necessary for texture discrimination. Arabzadeh et al. [2] report that rats can distinguish textures already after an offset of 5−15 msec after stimulus onset. The receptive fields have a tuning width in frequency of less than one octave in 81% of the neurons. The cells coding for the data recorded for this research show significantly higher localisedness than cells coding for the sandpaper data (see [8]).

This is in analogy to sparse simulated neurons in the visual system that obtain localised receptive fields in space and orientation [21]. In addition to this, they are often tuned to changes or even modulations of the energy of the input over time, such as C and D in figure 6. This property might be useful for tactile texture recognition. We predict that in a similar setup for electrophysiological measurements, the somatosensory neurons should be tuned to both energy and frequency.

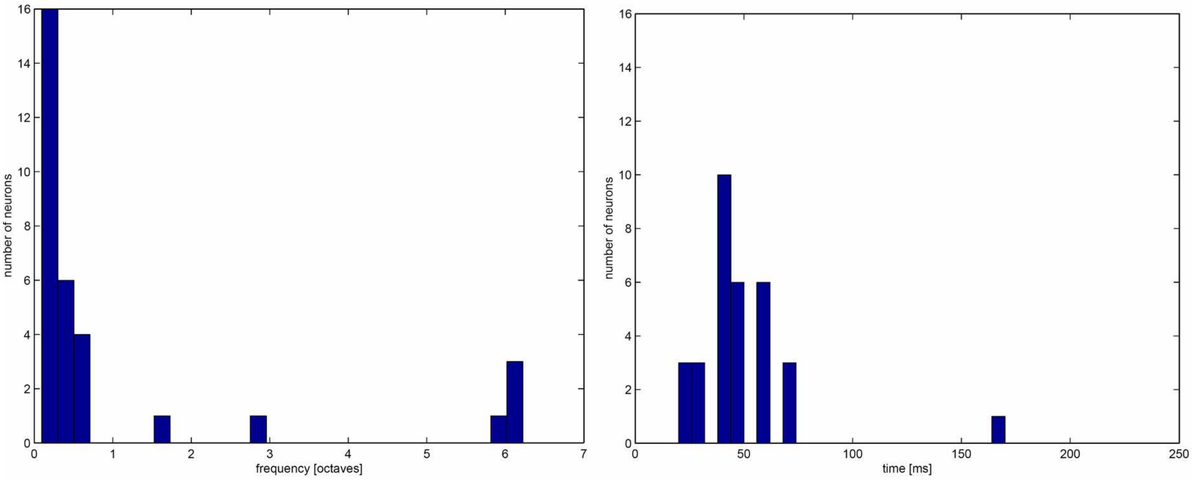

Figure 7. Histograms showing the localisedness of the spatiotemporal receptive fields for frequency in octaves (left figure) and for time in ms (right figure). The number of examined receptive fields is 32.

4. Discussion

We predicted properties of cells as they might be found in the somatosensory system of a rat by simulating neurons that receive input from an artificial whisker system and optimising their properties so that they exhibit optimally sparse response patterns.

There are two major assumptions that have to be considered: One is the choice of the preprocessing of the data. We decided to use spectrograms since data received from whiskers have very similar properties to auditory data with regards to their dimensionality and structure. It thus is likely that similar analysis methods should be used. It is up to date not known, what preprocessing is performed on the information travelling from the whisker follicle in rats to the barrel cortex. The other assumption is that the natural input is not assigned a class by any means of supervised learning, the clustering happens completely unsupervised on input data varying in material, speed of movement, frequencies, etc.

Our study shows that a pressure for sparse coding together with the chosen pre-processing would results in neurons that are typically localised both in time and in frequency. Modulations in time has been shown for neurons in the barrel cortex: A recent study by Arabzadeh et al. [2] has investigated neurons in the barrel cortex of rats and found no specifity for specific frequencies, but an encoding of the product of frequency and amplitude of the whisker movement. This seems to be in contradiction to our results, however, there are major differences between the two studies. The experiments described in [2] have been performed on anaesthetised rats without active whisking. Our experiments use active whisking frequencies of 1 or 4 Hz. Their stimulus to the whisker is a very controlled signal consisting of a single frequency presented as a sine wave each, we are presenting the whisker system with natural stimuli consisting of a whole range of frequencies. It is therefore impossible to directly compare the results, but further experiments are needed to elucidate the way by which the brain combines signals at different frequencies.

5. Future Work

The research described in this paper results in properties of simulated cells coding for natural whisker stimuli. In a next step, we will perform behavioural experiments on an artificial mouse robot. One of the advantages to use sparse coding in a robotic setup is the task independence of the sensory modality. Sparse models for the visual domain have already been applied successfully to biologically inspired sensorimotor tasks [27]. The receptive fields of the simulated neurons from our studies will be used to learn to discriminate different objects and textures. This will be based on the activation of a small number of neurons which are optimally tuned to the nature of the stimuli instead of using the original raw signal.

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