A Supramodal Vibrissa Tactile and Auditory Model for Texture Recognition

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Abstract. Audition and touch endow spectral processing abilities allowing texture recognition and discrimination. Rat whiskers sensory system exhibits, as the cochlea, resonance property decomposing the signal over frequencies. Moreover, there exists strong psychophysical and biological interactions between auditory and somatosensory corteces concerning texture analysis. Inspired by these similarities, this paper introduce a "supramodal" model allowing both vibrissa tactile and auditory texture recognition. Two gammatone based resonant filterbanks are used for cochlea and whiskers array modeling. Each filterbank is then linked to a feature extraction algorithm, inspired by data recorded in the rats barrel cortex, and finally to a multilayer perceptron. Results clearly show the ability of the model for texture recognition in both auditory and tactile tuning. Moreover, recent studies suggest that this resonance property plays a role in texture discrimination. Experiments presented here provide elements in the direction of this resonance hypothesis.

1 Introduction

Spectral information carried by the tactile and auditory systems is a primary cue used in cognitive tasks like speech or music perception in audition as well as surface or object recognition in touch. These abilities depend strongly on our perception of complex stimuli like surface textures through the skin or acoustic timbres through audition. Humans are able to discriminate textured surfaces by touch only, by auditory signals only and both touch and audition [1], with similar discrimination performance in each case.

Among the somatosensory systems, rat whiskers are capable of fine texture discrimination. By actively whisking their vibrissae, rats extract information about the spatial properties of a surface or object, including size, shape and texture [2][3]. Each vibrissa has a strong frequency tuning around a resonant frequency [4][5], allowing to increase the sensitivity of the vibrissa sensory system to an ecologically relevant range of low-amplitude, high-frequency stimuli [6]. The rat facial whiskers array allows the decomposition of the signal into an ensemble of components at different frequencies. There exist strong parallels between vibrissa tactile and auditory encoding. Inner hair cells - sensitive cells of the auditory system disposed along the basilar membrane of the cochlea - have also a strong frequency selectivity and decompose the auditory signal over resonant frequencies, from high frequencies in the cochlear base to low frequencies in the apex [7]. Thus, both cochlea and whiskers decompose a signal into frequency components, each sensory cell tuned to a particular resonant frequency. A tonotopic organization is found in the auditory pathway [7], especially in subcortical centers, as well as in the somatosensory pathway [8].

More recently, it has been shown that auditory and somatosensory systems interact in texture perception, both on psychophysical and biological levels (see [9] for a recent review). For example, Yau *et al.* [10] found a cross-sensory interference between auditory and touch temporal frequency channels in human: a touch-based texture discrimination task could be disturbed by a frequency-dependent auditory signal in a systematic manner. More precisely, given that the auditory system is specialized for spectral analysis, Yau *et al.* [11] recently suggested that spectral analysis of tactile signals is processed in the caudo-medial belt area, a region of the auditory cortex. They also proposed clear and testable predictions about underlying physiology.

This present contribution propose a same model for both vibrissa tactile and auditory texture recognition. In this way it can be characterized as supramodal. This work is inspired by the strong parallels between vibrissa and cochlea transduction in the one hand, and by crossmodal auditory and tactile interaction within texture discrimination in the other hand. We propose in Section 2 a whiskers array model based on a classical cochlear model using gammatone filterbank [12]. Each filterbank output is then plugged to a bioinspired multichannel feature extraction algorithm presented in Section 3. By estimating the instantaneous amplitude-frequency product of the signal, this algorithm is closely inspired by data recorded in the rat somatosensory cortex, which are supposed to be related to temporal frequency estimation [8]. Then, a multilayer perceptron is used to discriminate textures with this feature. Section 4 is devoted to the experimental part of this paper. A set of experiences are proposed in order to show texture classification skills for both tactile and auditory modalities with several sets of textures. A specific attention will be made to the influence of the resonance effect on the performance. Finally, a discussion about the results and there incidence is provided in Section 5.

2 Cochlear and whiskers array models

There exists several cochlear models in the literature. Some trying to reproduce internal (both active and passive) phenomena in the cochlea, *e.g.* basilar membrane elasticity or fluid mechanics [13]. In a more abstract level, the cochlea can be seen as a filterbank [14], decomposing the signal over frequency channels. One classical filterbank cochlear model is the gammatone auditory filterbank introduced by Patterson *et al.* in [12].

Rat whiskers have also been modeled, both with mathematical models and robotic implementations. Neimark *et al.* [4] proposed a model of vibrissa as a thin elastic beam, extended in [5], and have experimentally tested resonance-related predictions. These studies suggest to their author that whiskers resonance should be an important property for performing fine texture discrimination. Whiskered robotic sensors have also been developed for texture discrimination, both with real rat whiskers [15] or with artificial systems [16], [17]. Nevertheless, in spite of the similarities between cochlear and whiskers resonance properties, filterbank based whiskers modeling has not been investigated yet.

In one hand we briefly introduce gammatone filters and their use in a cochlea tuning. Because there exist fine parameters for human cochlea modeling which are not provided for rat cochlea, human parameters are used in this paper. On the second hand, we propose an adaptation of this cochlear model for modeling a rat whiskers array. The free C implementation of gammatone filters provided by Ma[3] is used in this paper.

2.1 Gammatone filterbank for cochlear modeling

Gammatone filters are well know to fit basilar membrane response to an impulse stimuli [12]. It appears that this is still similar for the movements of a vibrissa base [5]. In temporal domain, the impulse response of a gammatone filter is:

$$g(t) = at^{n-1}cos(2\pi f_c t + \phi)e^{-2\pi bt}. \tag{1}$$

Parameters of the filter are f_c, b and n: f_c is the center frequency of the filter, b determines the duration of the impulse response and thus the bandwidth of the filter, n is the order of the filter and largely determines the slope of the skirts. A gammatone of order 4 best fits human auditory filter shapes and is used in this paper. Slaney proposed in [18] a general formulation of the bandwidth of a 4^{th} order filter in function of the center frequency f_c, the asymptotic filter quality at large frequencies q_{ear} and the minimum bandwidth for low frequencies channels b_{min}. Glasberg and Moore [19] estimated these parameters from psychoacoustical human data and proposed $q_{ear} = 9.26$ and $b_{min} = 24.7$.

Moreover Slaney [18] addresses a solution for channel spacing along the frequency axis, assuming the number of channels n_c, the lowest and the highest center frequencies f_l and f_h are known. Transfer functions of a 50 channels gammatone filterbank tuned as cochlear model are plotted on Fig. 1(a). The human auditive frequency range were used ($f_l = 20$ Hz and $f_h = 20$ kHz) both with the Glasberg and Moore parameters.

2.2 Adaptations for whiskers array modeling

As we said above, the filterbank model of whiskers array is derived from the human cochlear one. It means that each vibrissa is represented by a well-tuned

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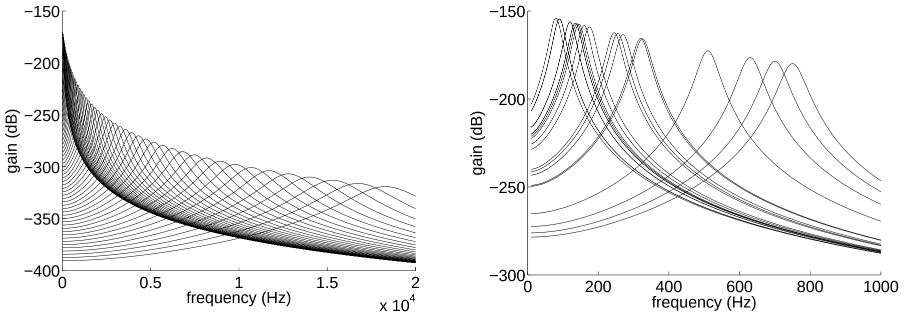
[3] Ma, N.: On efficient implementation of gammatone filters. http://www.dcs.shef.ac.uk/∼ning/resources/gammatone.



(a) Cochlear model

(b) Whiskers array model

Fig. 1. Transfer functions of the gammatone filterbanks. (a): cochlear model, 50 channels, $f_l = 20$ Hz, $f_h = 20$ kHz, $q_{ear} = 9.26$ and $b_{min} = 24.7$. (b): whisker array model, 20 vibrissae, center frequencies from [4], $q_{ear} = 35$ and $b_{min} = 15$.

gammatone filter. There are two strong arguments in favor of this approach for modeling whiskers. Firstly, it emphasis on the resonance phenomena which is understood as a key mechanism for temporal frequency perception and thus for texture discrimination. Secondly, gammatone filter and rat vibrissa have quite similar impulse responses [5].

The problem is now to adapt the whiskers model from the cochlea to fit as close as possible biomechanical properties of rat's whiskers. In [4], Neimark *et al.* provided the center frequencies of 20 vibrissa measured on a living rat. 5 vibrissa arcs are described, each composed of 4 whiskers. These values are used in order to fix the center frequency of each whisker gammatone filter. Andermann *et al.* [20] identified populations of neurons in the trigeminal ganglion and the primary somatosensory cortex of rats that respond to whisker vibrations only within a narrow band of frequencies centered at resonance. Nevertheless, to the best of our knowledge, there doesn't exist any experimental data directly concerning the bandwidth of whisker filters. Assuming the lack of data, we fixed $q_{ear} = 35$ and $b_{min} = 15$. These values provide a bandwidth from 111 Hz from low resonant whiskers to 233 Hz for high resonant ones (mean frequency is 145 Hz). In comparison with other existent models, this approach deals with simplicity and offers a functional view of vibrissa transcription mechanisms: as in the cochlear model, biomechanical details of whisker transduction are omitted. Obviously, the counterpart is a lack a biological fidelity. Transfer functions of the generated filters used as whiskers array model are showed in Fig. 1(b).

3 Feature extraction for texture discrimination

Model presented in the precedent section aim to reproduce basilar membrane and vibrissa motion in response to a stimuli. To serve as basis for feature extraction, a peak extractor algorithm is plugged to each filterbank channel output, mimicking the sensory nerve spike train activity. If the current sample is not a local extrema of the signal, its value is set to 0. 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 [21] 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.

In a previous work [16], we experienced texture discrimination on a whiskered robotic platform with a feature extraction algorithm inspired by data recorded in the rat’s barrel cortex, which estimates the instantaneous mean power of a multichannel spike train. Using an elastomer-based whiskers array [22], the robot was able to discriminate 8 different sandpapers with a mean performance above 90%.

Each rat’s whisker projects to a precise part of its somatosensory cortex, in a structure named “barrel cortex”. A barrel is a discrete neural structure that receives an input principally from a given whisker, with a little influence from neighboring ones [23]. Neuronal base of texture representation have been investigated in anesthetized rats’s barrel cortex [8]. By stimulating a whisker with a pure sinusoid fully described by its amplitude A and its frequency f and by recording the induced neural activity in the barrel cortex, it appears that the neural activity most probably encodes a quantity homogeneous to the product Af and called the equivalent noise level.

The feature extraction algorithm used in this paper estimates the instantaneous frequency f through the inverses of the time intervals between successive peaks. Thus the peak amplitude is multiplied by the estimate frequency and accumulates within a time window. In addition of this instantaneous mean power calculation, we also use in Section 4 both A and f alone as features for texture discrimination. These three feature extraction algorithms are summarized in Fig. 2.

4 Experiments

In order to demonstrate that the two models presented above are able to discriminate textures, several sets of experiences are proposed. The first one presents the texture discrimination skills, both in cochlear and whiskers tuning. The other ones are focusing on precise aspects of the model in order to illustrate the resonance effect and the whiskers bandwidth influence on the results. These experiments share the same data acquisition which is described before the results.

4.1 Experimental device

Sets of sandpapers are classically used in texture discrimination experiments on whiskers system. Neimark *et al.* [4] modeled a sandpaper in the frequency

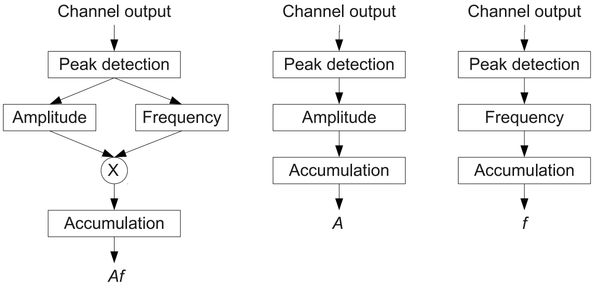


Fig. 2. Feature extraction algorithms for a single channel. From left to right: equivalent noise level estimation by Af product, amplitude A only, frequency f only. Accumulation is done over a constant time window.

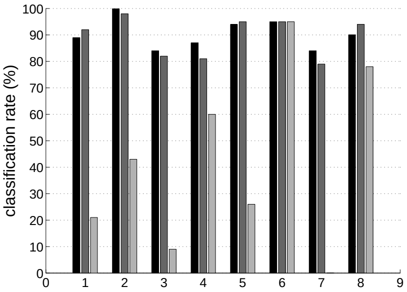
domain as a three peaks spectrum, with a dominant activity of low frequencies. According to this, a set of 8 textures is generated for each experiment (see Fig. 3). The lowest frequency peak is amplified to 6 dB whereas the two others are amplified to 3 dB. Other frequencies are attenuated to -3 dB. 40 seconds input files are generated with a sample frequency of 44100 Hz for the cochlea textures set and 5000 Hz for the whiskers set. Thus, each file is passed through its associate gammatone filterbank and feature extraction algorithms. The time window is set to 100 ms, which match the period of a typical rat whisking movement. For each texture 400 data vectors is computed, 300 for learning and 100 for testing. Vectors dimension is equal to the number of channels of their related filterbank and each vector contains values accumulated by the feature extraction algorithm over one time window.

Having thus obtained an input vector for each trial, we fed it into a simple three layer perceptron to perform supervised learning. The hidden layer had the same dimension than the input layer and the input vector. Obviously the output layer contains 8 neurons, one per texture. We used the FANN library [24] with the iRPROP training algorithm [25]. The final classification was done by a winner take all on the 8 output neurons.

4.2 Experimental results

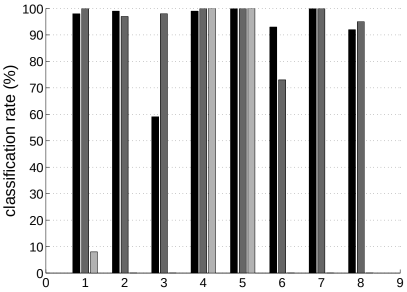
The first experiment presents the texture discrimination skills of the cochlear and whiskers array model described above. Filterbanks used are those showed in Fig. 1 and cover a frequency range between 20 Hz and 20 kHz for the cochlea and between 80 Hz and 800 Hz for whiskers. For each experience, the three feature extraction algorithms are compared over a set of 8 different textures. Classification results are presented in Fig. 3, both with the detailed spectral composition of the different textures. This experiment clearly shows the ability of the model for texture discrimination, with a mean classification rate near 90% for Af and A features. Moreover, it is shown that the f feature alone is irrelevant

Texture	Peak 1	Peak 2	Peak 3
1	250	420	710
2	100	200	500
3	90	350	800
4	200	350	800
5	250	500	600
6	65	250	600
7	90	600	800
8	150	550	850



(a) Whiskers model texture discrimination. Mean rate: $Af = 90.4\%$, $A = 89.5\%$ and $f = 41.5\%$

Texture	Peak 1	Peak 2	Peak 3
1	1000	3000	5000
2	100	1000	10000
3	500	2000	7000
4	150	3000	7000
5	200	10000	15000
6	300	5000	10000
7	500	1000	3000
8	200	1000	2000



(b) Cochlear model texture discrimination. Mean rate: $Af = 92.5\%$, $A = 95.4\%$ and $f = 26.0\%$

Fig. 3. Classification results for the model in cochlea tuning and whiskers array tuning, tested with 8 different textures. Left column: three peaks textures set used for discrimination, frequencies are given in Hz. Right column: classification rate for the 8 textures and the 3 features (Af in dark grey, A in pure grey and f in clear grey).

for texture discrimination: results are greater than the chance level (12.5% for 8 textures) but clearly under the amplitude based features (see Fig. 3 for details).

As showed in Fig. 4, where the comparison of the A and f features response to a pure sinus near the resonance frequency of the A4 vibrissa ($c_f = 630$ Hz) is provided, the f feature is sensitive to the resonance effect lesser than the A feature. The frequency based pattern becomes consequently less discriminative than the amplitude based pattern, that explains the irrelevance of the f feature for texture discrimination.

The major limitation of the gammatone based whiskers array model, as we said above, is the lack of biological data concerning the bandwidth of the filters. In the previous experiments, we used arbitrary fixed bandwidth values. Figure 5 shows the evolution of the mean classification rate in function of the whiskers filters mean bandwidth, from 5 Hz to 500 Hz. The same textures as in Fig. 3(a)

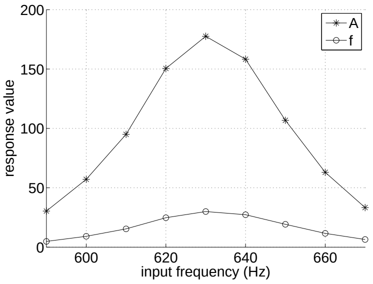


Fig. 4. Comparison of the A and f features response to a pure sinus near the resonance frequency of the A4 vibrissa ($c_f = 630$ Hz).

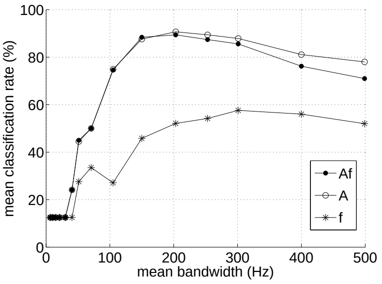
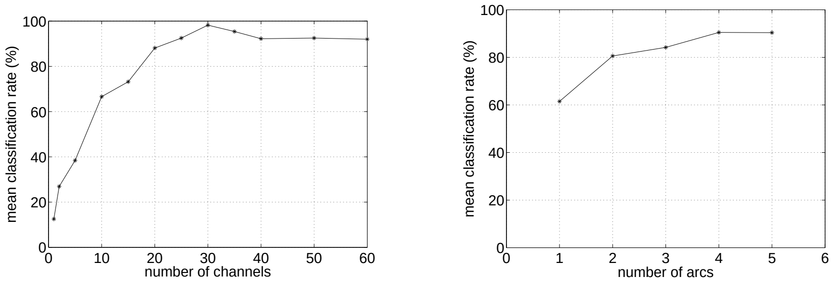


Fig. 5. Influence of the whiskers filters mean bandwidth on the classification rate. The set of 8 textures of Fig. 3(a) is used for the 3 features Af, A and f.



(a) Cochlear model

(b) Whiskers array model

Fig. 6. Influence of the number of filters on the mean classification rate of a set of textures. Input textures are the same as in Fig. 3. Af feature is used.

are used on the three features Af, A and f. Experimental results confirm those of Fig. 3(a) by showing the weak performance of the f feature alone. Moreover, one can observe that the model follows the same behavior for the three features: it doesn't work with minimal bandwidth value (the classification rate is equal to the chance level upon 30 Hz) but quickly rises the maximal classification rate for a mean bandwidth near 200 Hz for Af and A or near 300 Hz for f. Above this value, the mean performance is slowly decreasing.

The last experiment, presented in Fig. 6, tests the influence of the number of channels on the discrimination performance. Input textures were the same as previously (see Fig. 3) for both modalities and the equivalent noise level estimation Af was the only feature took into account. Nevertheless, due to morphological differences between the cochlea and a whiskers array, channel reduction is done by a different way. Thus, cochlear channels are disposed along a frequency range thanks to the Slaney channel spacing solution [18]: decreasing the number of channels will reduce the channel density but the same frequency range will be covered. Fig. 6(a) plots the evolution of the mean classification rate from 1 to 60 cochlear channels. In the other way, whiskers are organized in arcs over the rat's face [4], each arc containing whiskers with similar length and resonance properties. The channel reduction is done arc by arc following the length gradient from rostral arcs to caudal ones. Figure 6(b) plots the evolution of the mean classification rate from 1 to 5 arcs composing the whiskers array model. Results summarized on Fig. 6 show that the percentage of successful discrimination quickly rises with the number of channels and reaches values over 80% when 20 channels or 2 arcs at least are concerned. This result confirms previously obtained ones in [15], [16] about whiskers.

5 Discussion

Audition and touch endow spectral processing abilities allowing texture discrimination. Rat whiskers sensory system exhibits, as the cochlea, resonance property decomposing the signal over frequencies. Moreover, there exists strong psychophysical and biological interactions between auditory and somatosensory corteces concerning texture analysis. Inspired by these similarities, this paper proposes a vibrissa tactile model and auditory model sharing exactly the same mechanisms for texture recognition.

Based on gammatone filterbanks, cochlea and whiskers array models aim at reproducing the sensitive cell motion and offer a simple functional view of transduction. Nevertheless important aspects of transduction are omitted. Thus, active perception skills (such as damping adaptation or whisking movements in touch or cochlear adaptation in audition) are not modeled here, as well as mechanoreceptors, viewed as simple peak extractors. More specifically on the whiskers model, the lack of biological records about vibrissae bandwidth is a key problem for having precise parameters values. Moreover, by viewing the whiskers pad as a filterbank, we omit the spatial organization of vibrissae over the face and are only interested in its spectral organization, through the reproduction of the first order resonance frequency of whiskers.

Feature extraction used for texture discrimination is inspired by biological data recorded in the rat barrel cortex. Confirming previously obtained results on elastomer-based artificial whiskers [16], our results (Fig. 3) show that the Af feature allows fine texture discrimination in both artificial and simulated context. This finding is an argument in favor of the so-called kinetic signature hypothesis [8] which stands that each vibrissa encodes a specific signature of the touched surface in term of magnitude and temporal pattern. Nevertheless one can observe on Fig. 3 that the A feature alone have a very similar performance than Af, whereas the mean inter-peak frequency f is not able to fine texture recognition. The amplitude A reproduces the motion of the basilar membrane and the base of a vibrissa. Thus, when a filter resonates, its "motion" becomes more important and this activity is reflected by the A pattern. In the other way, the instantaneous frequency estimation f is not sharply sensitive to this resonance phenomena, as plotted in Fig. 4. From these findings we suggest that, by changing the A pattern over frequencies, the resonance property improves the discrimination skills of the model and thus its global performance. This suggestion is enhanced by the results presented in Fig. 4 and Fig. 6. Likewise, the fact that our results suggest that the texture discrimination capacities depends both on the number of channels and amplitude activity patterns seems to back up the resonance hypothesis [4]. This hypothesis stands that the self resonance property of the vibrissa plays a crucial role in vibration transduction and helps to enhance texture perception.

The whiskers array and cochlea model used in this paper provide a supramodal representation of the input signal. Although two distinct feature extractors are used in spite of a real crossmodal one as hypothesized in [11], this work is going in the direction of a multimodal integration of low-level fundamental sensory dimensions. Future work will be devoted to the implementation of this supramodal model on a robotic platform [26] in order to investigate crossmodal recognition of vibrissa tactile sensory signal and auditory signal produced by the contact of whiskers on a surface.

This paper shows that gammatone based filters, in spite of the lack of biomechanical precision, are suitable filters for texture discrimination. This kind of functional model may help in tactile transduction and neural spectral processing understanding by proposing a more abstract view of the transduction process and enhancing the resonant property.

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