Modelling the Auditory System: Preprocessing and Associative Memories using Spiking Neurons

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Abstract

We implemented a model of the auditory system incorporating the cochlea, the cochlear nucleus, the inferior colliculus and the primary auditory cortex. For the simulation of the cochlea gammaton filters are used. The other areas are simulated by neural networks consisting of leaky integrate and fire neurons. The peripheral processing in the cochlear nucleus and the inferior colliculus is modelled by special neural networks for pitch processing and the primary auditory cortex is implemented as an associative memory. Binaural interactions are not considered in the model.

The results bear resemblance to biological findings. For the inferior colliculus and the primary auditory cortex we get a tonotopic/periodotopic map, which can be found in the human brain. By using this map we can detect and separate vowels in the primary auditory cortex.

Key words: peripheral auditory system, primary auditory cortex, periodicity pitch processing, associative memory

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1 Introduction

The auditory system is a complex part of the brain where acoustic signals pass several different nuclei before entering the cortex. Some of the functions of these nuclei have become clearer in recent years but others are still widely unkown. To find out more about the auditory system it is helpful to simulate those parts for which physiological knowledge and some functional ideas exist. Then we can compare the results to biological findings and may also arrive at some theses about the less well understood parts of the auditory system. To do this we implemented a model consisting of the major parts of the auditory system for pattern recognition:

- The outer ear is modeled by standard low cost microphones.
- The cochlea is modeled by a gammatone filter bank.
- The cochlear nucleus and the inferior colliculus are modeled using a variation of a biologically motivated periodicity pitch processing neural network [4].
- The primary acoustic cortex is modeled by an associative memory which was previously used successfully for the visual system [3].

As input to the system and for learning synaptic connections in the associative memory vowels were used.

2 The Model

2.1 Signal recording and filtering (outer ear and cochlea)

The vowels were spoken by one male and recorded using a standard low cost microphone and a standard PC soundcard. We then used a gammaton filter bank [6] with 50 filters from 360 Hz to 3580 Hz.

2.2 Periodicity pitch processing (cochlear nucleus and inferior colliculus)

The neurons are modeled as simple leaky integrate and fire neurons [7]. In order to model the peripheric auditory system we implemented a variation of the periodicity pitch processing model introduced by Langner [4]. Our variation generates similar results but without the comb filter behaviour of [4]. The output of the model is a two dimensional tonotopic map similar to a map found in the inferior colliculus of the cat [2]. The map is realized by 50×50 coincidence neurons which are tuned to AM signals. On this map carrier and modulation frequency are mapped orthogonally. Each coincidence neuron receives input from three different sources (see Fig. 1): One oscillator circuit (modeling parts of the cochlear nucleus) and two integrating neurons - one inhibitory and one excitatory integrator. Both are synchronized to the input signal using a trigger neuron, which also activates the oscillator. Each coincidence neuron requires independent integrators, thus we implemented a total of $2 \times 50 \times 50$ integrators (similiar for the trigger and oscillator neurons).

When an amplitude modulated signal is applied to this network the trigger neuron fires phase-locked to the modulation frequency, thus the oscillator generates short spike trains, which are also synchronized with the modulation frequency. When the trigger neuron fires, the integrators are reset by the integstop neuron, which initiates a new integration cycle of the input. Input is

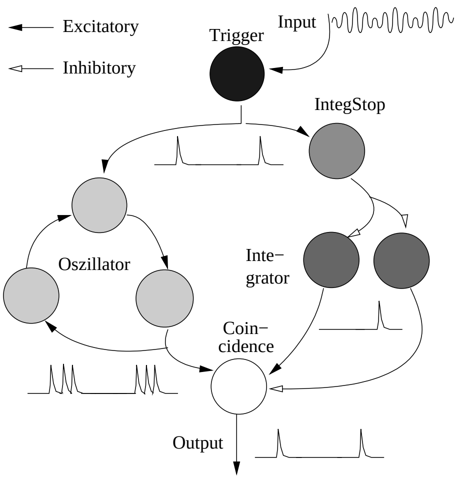

Fig. 1. The modified model. This model is replicated 2500 times to obtain a map of 50 × 50 coincidence neurons. A coincidence neuron fires if (and only if) the delay from the integrators matches the periodicity of the input signal. The comb filter behaviour of the original model [4] is suppressed by spontanous activity of the integrators, because input from the *inhibitory* integrator is stronger than from the excitatory integrator.

integrated and the integrators fire as soon as the thresholds are crossed. Transmission delays are chosen such that the spike from the inhibitory integrator reaches the coincidence neuron shortly after the spike from the excitatory integrator. This allows firing of a coincidence neuron if input from the oscillator neuron is synchronized with input from the (excitatory) integrator. This happens when the modulation frequency matches the time delay introduced by the integrators. Thus the coincidence neuron will only fire under this circumstances. This modulation frequency is called best modulation frequency (BMF). In the original model proposed by Langner [4] the coincidence neuron would also fire if the modulation frequency is the BMF multiplied with an integer. This generates a comb filter like behavior which can sometimes be found at the onset of signals in animals, but is disturbing, if not suppressed in time. Our variation replaces only the original integrator and the flip/flop circuit by the integstop and the two integrators. The rest of the model remains the same. In our version the comb filter behaviour [5] is suppressed since the integrators keep firing spontanously after the first spike and therefore the coincidence neuron is inhibited until the next trigger spike resets the integrators.

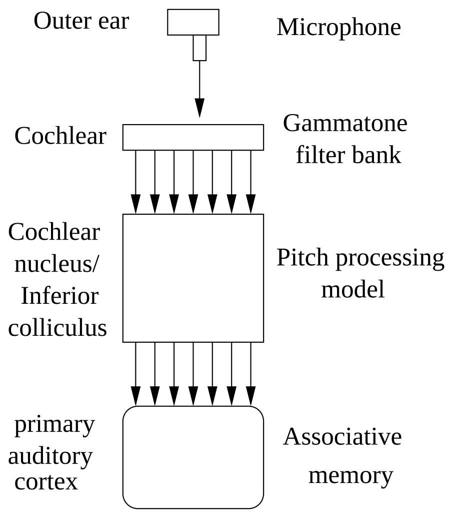

Fig. 2. The complete model. The inscription on the left side stands for the biological areas involved. On the right side the corresponding technical implementations are listed.

So the modulation frequency is extracted using the delays from the integrators and the coincidence neurons whereas the carrier frequency is extracted earlier by the gammatone filter bank.

2.3 Associative memory (primary auditory cortex)

The associative memory (size 40×40) is implemented using three neuron populations similar to [3]. The coincidence neurons deliver input to the associative memory by a topographical connection. So the associative memory is also tonotopically organized (as found in the human cortex [1]). We used five vowels ([a:],[e:],[i:],[o:],[u:] - pronounced German) spoken by a male speaker to generate the patterns stored in the associative memory. The patterns were derived from the spike rates of the concidence neurons when stimulating with the vowels. By applying a threshold on the rate maps one binary pattern (size 50) for each vowel is obtained. After storing the patterns we started simulations of the complete model.

Fig. 3. Spike activity (white patches indicate high spike rates) in the coincidence map (modeling the inferior colliculus). The ordinate represents the carrier frequency (from 360 Hz to 3580 Hz), the abscissa the periodicity pitch (from about 30 Hz to 400 Hz). Since the [o:] was spoken with higher pitch, the activity is more to the right than the [a:] (spoken with lower pitch). The formant frequencies can be determined by the ordinate position of the activity spots: For the [a:] the activity corresponds to 990 Hz/1500 Hz, for the [o:] 490 Hz/860 Hz.

3 Results

In Fig. 3 the summed activity of the concidence neurons is displayed for two vowels. The maps illustrate pitch and formant frequencies of the vowels. The [o:] was spoken with higher pitch, so the activity is more to the right compared to the [a:] where the pitch was lower.

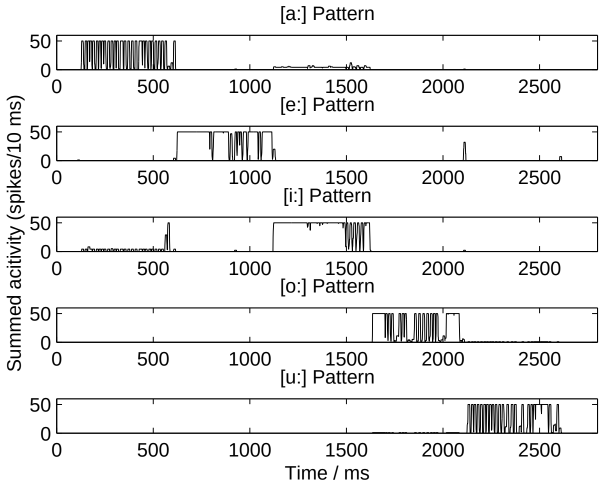

Fig. 4. Summed spike activity (vs. time) in the associative memory (primary auditory cortex) when stimulated with single vowels in a sequence. Each plot corresponds to 50 neurons representing one certain vowel.

In order to simulate a detection task vowels were applied to the system in a sequence, one vowel after the other. The activity in the associative memory was recorded by counting the spikes of the neurons corresponding to each vowels representation (Fig. 4). The results show, that the neuronal assemblies coressponding to the applied vowel in the associative memory became activ.

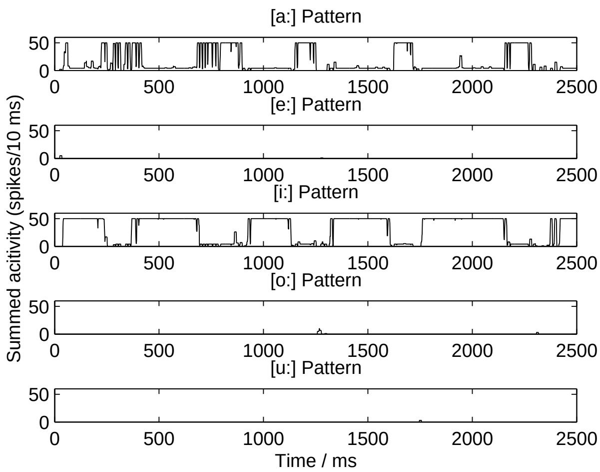

Fig. 5. Results that could be observed when two vowels ([a:] and [i:]) were applied simultaneously.

In a second experiment we stimulated with a superposition of [a:] and [i:]. The results show that most of the time the system attends to one of the two vowels, alternateing between [a:] and [i:] (Fig. 5). In some cases the neurons corresponding to both vowels were active.

4 Conclusion

We implemented parts of the auditory system using biologically motivated models and spiking neurons. The performed simulations proved that the implemented system is able to detect and separate vowels and the results indicated closeness to biological findings.

Our modified variant of Langner's model [4] extracted both periodicity and formant frequency of the vowels (see Fig. 3). So the biologically motivated model extracts useful information of the applied input.

The associative memory was able to detect which vowel was used as input. It was even able to separate two simultaneously applied vowels. Both tasks would be more difficult, if all vowels were spoken with the same pitch, whereas some of the vowels used here could be distinguished using the pitch periodicity, not only the formant frequencies (for example the [a:] and the [o:]).

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References

[1] G. Langner, M. Sams, P. Heil, H. Schulze. Frequency and periodicity are represented in orthogonal maps in the human auditory cortex: evidence from magnetoencephalography. *J. Comp. Physiol.*, 181:665–676, 1997.

[2] G. Langner, Schreiner C.E. Periodicity coding in the inferior colliculus of the cat I. Neuronal mechanisms. *Journal of Neurophysiology*, 60:1799–1822, 1988.

[3] A. Knoblauch and G. Palm. Pattern separation and synchronization in spiking associative memories and visual areas. *Neural Networks*, 14:763–780, 2001.

[4] G. Langner. Temporal processing of pitch in the auditory system. *Journal of New Music Research*, 26:116–132, 1997.

[5] M. Borst, G. Langner, G. Palm. A biologically motivated neural network for phase extraction from complex sounds. *Biological Cybernetics*, submitted.

[6] M. Slanley. Auditory toolbox. *Apple Computer, Inc. Advanced Technology Group*, 1993-1994.

[7] R.J. MacGregor. *Neural and Brain Modeling.* Academic Press, San Diego, 1987.