A SPIKE-BASED MODEL OF BINAURAL SOUND LOCALIZATION

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This paper describes a spike-based model of binaural sound localization using interaural time differences (ITDs). To handle the problem of temporal coding and to facilitate a hardware implementation all neurons are simulated by a spike response model, which includes postsynaptic potentials (PSPs) and a refractory period. A winner-take-all (WTA) network selects the dominant source from the representation of the sound's angles of incidences, and can be biased by a multisensory support. We use simulations on real audio data to investigate the function and the practical application of the system.

1 Introduction

Sound localization is an important function for spatial hearing of human beings and animals. Many investigations and models of auditory perception exist from neurobiology to psychoacoustics [5, 2, 3]. But although we could imagine numerous applications in robotics, videoconferencing and speech recognition only a few working examples are known. When we implemented demonstration software for a mobile robot we noticed one reason for this: the computational demands of digital simulations are extremely high, but special hardware solutions of certain auditory processing tasks are rare. Therefore we strive for a mixed analog-digital VLSI implementation, and use the experiences with software simulations on application-relevant audio data. Our work is related to Lazzaro's neuromorphic auditory localization system [12], but follows a more pragmatic approach.

We assume, that ITD analysis provides a sufficient cue to many localization tasks. In our simulations, we use digital algorithms for the preprocessing and coincidence detection within spike patterns, as well as a uniform spiking neuron in all other parts of the model. One motivation to use spikes is, that a temporal resolution in the range of microseconds is required for the ITD detection. On the other hand, spike patterns can be considered as a consistent way of signal coding which enables a merging of features from different modalities [11].

Figure 1 sketches the system architecture. In the current simulations 16 parallel frequency bands, delivering a spatial resolution of 65 azimuthal angles are computed, whereby the system is simply scalable to practical demands or constraints of the VLSI design. Several stages of the model contribute to localization:

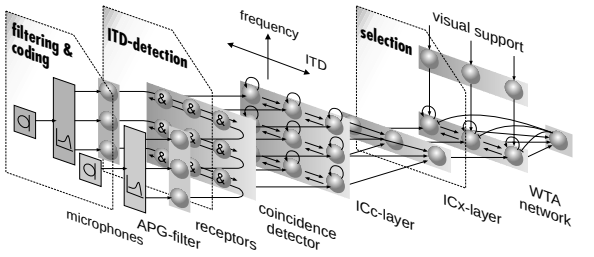

Figure 1. System architecture, composed of the localization model and a following selection mechanism.

1. Filtering and spike coding: The analog signals from two microphones are filtered by a cochlear model (all–pole–gammatone filter) and coded into spikes (receptors).

2. ITD detection: For every frequency channel the spike patterns from left and right are cross–correlated (coincidence detector). The resulting pattern is stored and postprocessed (ICc layer) and finaly projected to a nontonotopic representation (ICx layer) of the azimuthal locations of sound sources in the acoustic scene.

3. Selection: As the result of a WTA process on auditory and visual input only one direction will be dominant in the final representation.

2 Neuron model

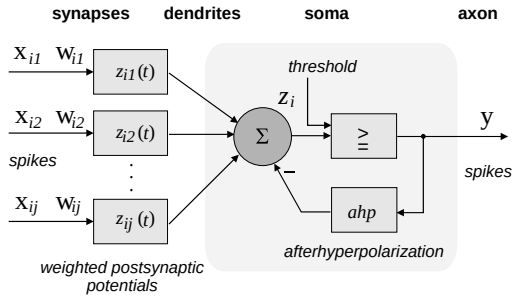

Figure 2. Neuron model

The neuron model (figure 2) is a spike response model inspired by Gerstner's work [6], and takes up fundamental properties of biological cells: the spatial and temporal integration of stimuli via postsynaptic potentials (PSP) in the dendritic tree, the generation of an action potential when reaching a threshold, and the effect of diminished sensitivity during a period of refraction. An absolute refractory period and axonal delays are not contained. To describe the impulse response of a synapse, we chose the so called α–function $f_\alpha(t) = \frac{t}{\tau} e^{1-\frac{t}{\tau}}$, the afterhyperpolarization (AHP) follows a simple exponential fading function. The combination of these potentials results in a biological plausible behavior (figure 3), which is more complex than the performance of leaky integrate-and-fire models.

To facilitate the current hardware implementation of the neuron model in analog VLSI [8] an exponential decaying PSP function was tested. In the context of our ITD based localization system this simplification seems not to affect the networks dynamic seriously, although we cannot give an analytical description of the potentials within the recurrent network structure.

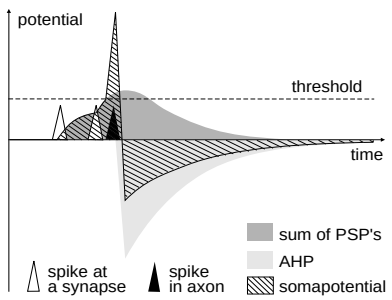

Figure 3. Interpretation of the potentials

3 Components of the system

3.1 Filtering and spike coding

The preprocessing generates an auditory nerve–like spike pattern from the analog acoustic input signals. The first step is the frequency analysis in the cochlea as the basis for the tonotopic organization of the auditory pathways. Lazzaro's neuromorphic model [12] contains silicon cochleas with 62 output channels to process the analog input directly. In our simulation the task is solved by a cochlear model using an all–pole gammatone (APG) filter cascade [13]. With respect to the broadband tuning in the auditory nuclei that are involved in ITD detection [5] we calculate 16 logarithmically arranged channels in the relevant frequency range from 100 Hz to 2.5 kHz from the digitalized microphone signals.

The output of the filter corresponds to the mechanical properties of the cochlear basilar membrane, and has to be transformed into a neural response, the specific timing of spike trains in the auditory nerve. This spike coding is realized by a receptor model, simulating the interaction of inner hair cells and ganglion cells. Since their firing is connected with the movement cycles of the basilar membrane, the resulting spike pattern shows the effect of *phase locking* on the acoustic stimulus. The degree of phase locking depends on the refractory properties of the receptor. In figure 4 the APG filter output and the binary spike response of the receptor model (phase–locked up to approx. 2 kHz) are depicted.

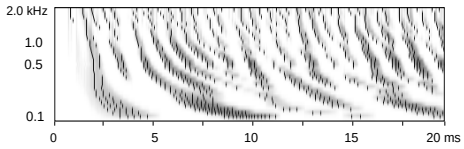

Figure 4. Analog response of the APG filter cascade to a noise burst and primary spike coding.

An important difference between an analog silicon and a digital model is the matching of the left and the right cochlea – only digital cochleas can be exactly identical. In an analog cochlea a time delay between the same output channels occurs even on identical input signals. Further we notice the difference between Lazzaro's time-continuous analog model (a spike can occur at any time) and a digital time-discrete simulation (a spike can occur only at discrete times). In the digital realization the maximal temporal deviation depends on the sampling frequency, which finally influences the azimuthal resolution and localization error of the model.

3.2 Localization

Coincidence detection

If a sound source is not located exactly in the medial-sagittal plane its position will cause a time difference between the correlated spike patterns in the left and right auditory nerve. According to Jeffress' coincidence model [9] and neurophysiological findings [4] the evaluation of ITD effects is realized by counter propagating axonal delay lines. Coincidence cells, located at different positions along the axons, generate spikes if they receive a simultaneous stimulation from the left and the right hemisphere. Because of the different time delays depending on the length of the propagating fibers, each cell becomes sensitive for a certain ITD. In this way, the temporal information of ITD is transformed into a place code, represented in the spatial distribution of activity in the neural structure.

Numerous extensions have been proposed to the coincidence model of Jeffress, e.g. the suppression of ambiguous responses by a contralateral inhibition [3], the selforganization in the coincidence sensitivity of the cells by Hebbian learning [7] and the usage of bipolar dendrites [1]. In our model a simple abstraction of the function is sufficient — we use a digital delay line and AND gates, which causes a discretization of the angles. Because the maximal delay in the structure must correspond between the model and the real world, the model parameters length N of the delay line and sampling frequency f_s are connected with the physical parameters base distance b of the 'ears' and sonic speed c of the environment by $N = \lfloor f_s \cdot b/c \rfloor$. Using f_s=44.1 kHz, b= 0.25m and c=343 m/s the model can detect $2 \cdot N + 1$=65 directions.

ICc layer

In the midbrain of birds and mammals ITDs like other auditory features are projected into the Inferior Colliculus (IC), before a further feature extraction and mechanisms of selection and attention take place. One possibility to illustrate the feature representation in this auditory nucleus is to describe the formation of maps. These maps of different orientations in the 3-dimensional structure of the central IC display the neural sensitivity to several features, e.g. the tonotopic organization, modulation frequencies or ITDs [5]. In our model characteristic frequencies (CF) and characteristic delays (CD) are mapped onto a neural field (figure 5 left).

Lateral synaptic connections between ITD-sensitive columns of this field and selfexciting feedback loops are used for a manipulation of the represented feature (figure 5 right). Primarily we introduced this synaptic structure to achieve a sharpened feature representation by lateral inhibited receptive fields. However, it turned out that the spatial resolution of the binary coincidence detection and the sharpness of its response was already sufficient for almost all localization tasks. In the opposite to a lateral inhibition, smoothed patterns caused by excitation of the cells' immediate neighbors prevents jitter effects in the response of the discrete coincidence detector. In addition the overall spike activity increases, which results in a more robust behavior of the WTA layer.

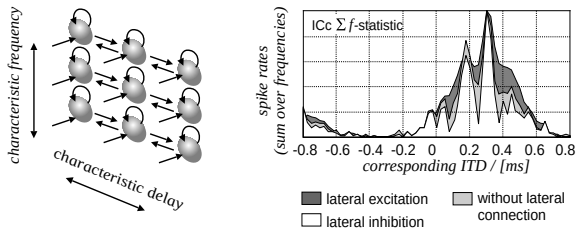

Figure 5. Left: Formation of a 2-dimensional map representing the tonotopy and characteristic delays. Right: The lateral interconnections cause a sharpening or smoothing of the ITD-feature.

Especially in the case of a sharpened response, caused by lateral inhibition, a periodical component of the detected ITD feature can be observed. Since the coincidence detection is similar to the calculation of the cross-correlation of periodical signals its result is just as periodical.

ICx layer

In the context of localization it is the striking feature of tonotopy to distinguish ITDs from ambiguous phase differences by a recombination of frequency bands. Phase differences are located at different positions in the ITD map, depending on the characteristic frequencies. In a convergent projection from many frequency bands they produce a diffuse activation. The position of the detected ITD is independent from the tonotopic organization and gives rise to a less ambiguous feature (figure 6).

The idea of a summation of the tonotopic response is strongly supported by findings in the IC of the barn owl, where ambiguous activations of single highfrequency bands of the central IC, but a definite response in the nontonotopic extern IC could be observed [12].

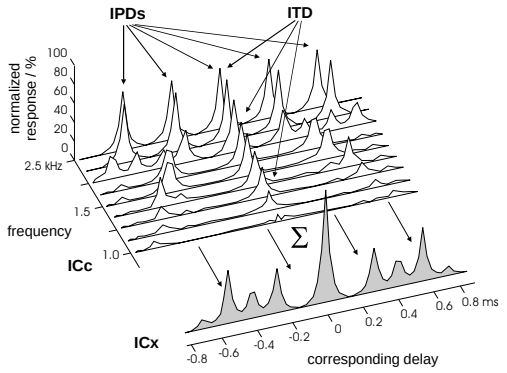

Figure 6. The combination of the tonotopic distributed response of the ICc in a onedimensional ICx-model enables to distinguish ITD from phase differences (IPDs).

While Lazzaro combined the function of the ICx layer and the competition between ITDs in one analog WTA layer, in our experiments with the spike-based WTA and a multisensory input the separation of the functions to different layers has advantages. The WTA network is stimulated by a maximum spike frequency of just one row of neurons which is independent of the frequency of the acoustic stimulus and limits the dynamic range of the tonotopic distributed feature. This results in a very robust WTA performance.

3.3 Selection

The response of the one-dimensional ICx model often is disarranged by several disturbances like interferences with other sources, echos, or ambiguities which could not yet be suppressed. Modeling attentive auditory perception we need to simulate a focusing mechanism, selecting a dominant ITD in the representation of competing features.

Findings about cortico-thalamic feedback loops, mechanisms of efferent, inhibitory control and lateral interactions between neurons of the thalamic nuclei [5] suggest the application of winner-take-all (WTA) networks to solve this problem. Our model uses a structure containing lateral and self excitation (like the IC feature map) and an interneuron which integrates the instantaneous activity of the net and generates recurrent inhibition to all cells. In the resulting WTA process only a single region of dominant feature representation can maintain activity [10].

For the application to dynamic acoustic scenes the selection network should be capable to move the focus of attention to a new sound source. This effect called strong WTA behavior [10] can be achieved by a suitable global inhibition, in particular since we are interested in a decaying WTA activity in the case of silence.

Usually, the attentive perception, especially the localization of objects, has a multimodal character. Various projections from the somatosensory and visual system can be found at the level of the thalamic nuclei [5]. To model an abstract *visual support* to the auditory localization, we first consider where the combination of the two modalities might take place. Since visual features have no interrelations with characteristic frequencies, the first stage for a visual-auditory integration might be the nontonotopic, extern IC. In our system visual information, like the detected skin color of a speaker, is interpreted as the direction of an object of interest. Next we had to decide, whether multiple peaks in the visual inputs are allowed or a single location as the result of a preceding selection process is required. In the sense of an efferent support, only one direction is supported at a time. The actual inclusion of the support is finally realized via additional inputs to the WTA neurons. This is a very simple approach, because it assumes, that the auditory and visual coordinates are already aligned.

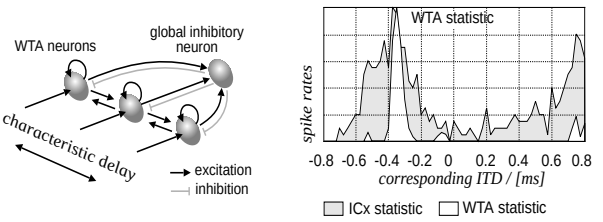

Figure 7. Left: Structure of the WTA network. Right: Result of the selection process.

4 Simulations and results

Up to now we are using *offline* simulation to investigate the behavior of the model on recorded data and *online* experimensts to demonstrate the basic function of the system directly coupled to real world inputs. Eventually, the aspired VLSI-implementation enables a *real-time* application to demonstrate the full function of the model embedded in the real world.

4.1 Offline simulation

The localization system was tested offline with data recorded in an open environment including background noise but only little echo effects. Narrow and broadband sounds, including numerous speech

signals, were recorded by 2 microphones (omnidirectional characteristic, base distance b=0.25m).

The localization of single sources was comparatively simple and robust – the directions of all tested broadband sounds were determined correctly. Figure 8 illustrates the focusing to a moving source, emitting pink noise. While the ICx layer displays a diffuse activation and disturbances, the capability of the WTA network to detect a dominant ITD leads to a clear feature representation. The focus stays stable, even if the sound source is moving, which is an important feature of the strong WTA dynamics (figure 8).

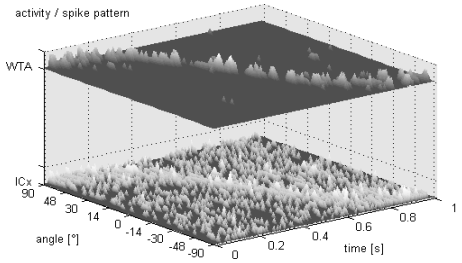

Figure 8. Model behavior for a moving source emitting pink noise. Visualization of the ICx output (bottom) and the activity of the WTA neurons (top).

If multiple sources are present in the acoustical scene, the requirements to the localization system change considerably. Because of interferences between periodical sound components, the dominance of a certain source has to be caused by its intensity or broader spectral constitution. The experiment shown in figure 9 demonstrates, how the focus of attention is shifted from a narrowband sound toward a voice stimulus.

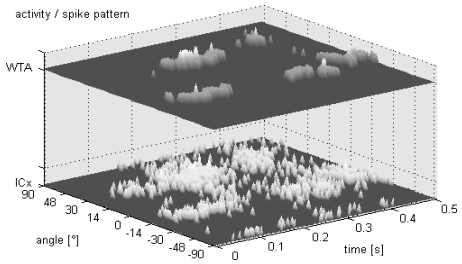

Figure 9. Localization of a narrow band signal and a human call setting in after 100 ms.

Finally the effect of simulated external support to the WTA process is shown. The system is able to bridge short breaks in the acoustic signal or keep the focus on a nondominant source (figure 10).

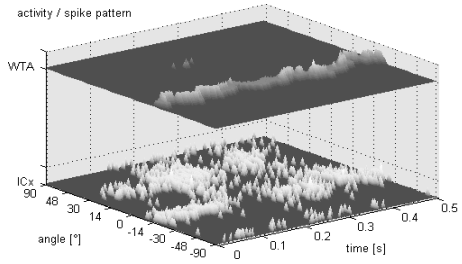

Figure 10. Repetition of the previous experiment, with external support to the narrow-band signal.

4.2 Online simulation

To demonstrate the performance of the localization system in an indoor environment on our mobile robot we implemented a simplified version without the ICc and WTA layers in C++. Because the synchronous simulation is still not real-time capable and acoustic problems occur in rooms, we use only a short block of samples from the signal's onset to estimate the direction of a sound source. The simulation is fast enough to trigger a turn-reflex of the robot's vision head and showed robust results on hand-claps and similiar signals. However, the application of the selection part of the model should deliver interesting improvements: In offline experiments we noticed, that the WTA process is able to focus on a sound source in about 10ms – often unaffected by the first echos reaching the microphones. For most broadband signals, this time is longer then the arrival of a first wavefront, which has been considered as the longest part of reverberate signals one can localize. But only if a voiced sound hit the room's resonance frequency (in our recordings resonances build up after 30ms) the focus of the WTA layer may be shifted apperently to a random position of an interference (figure 11).

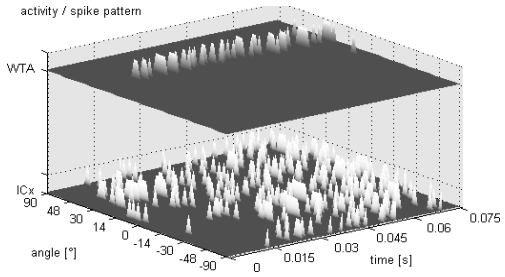

Figure 11. Onset selection in reverberate environment.

This way, although it was not our intention, we can model major aspects of the precedence effect – the dominance of the original sound event up against it's echos. Adding a simple onset detector and with the

constraint of a comparatively quiet enviroment, the introduced model is a suitible tool to localize command words under reverberate indoor conditions.

We still have no solution which fulfils a real-time simulation of the model, but are convinced, that for robotics applications a mixed analog-digital hardware implementation is a promising approach. The design of a VLSI chip containing the delay line structure and one layer of neurons is in progress [8]. In this concept we intend to use available cochlea chips for preprocessing, realize biological plausible time constants, and solve the inter-chip communication.

5 Conclusion

Comprising our experiments, the presented model yields convincing results in open enviroments. Ambiguities and disturbances in the ITD representation at the level of the IC are successfully suppressed by the WTA process. Thereby the simulation of the spike-based selection model proved to be uncomplicated – the limited dynamic range of a spike coded WTA input enables a robust operation of the network.

While testing the system in complex acoustic situations it turned out that an ITD-dependent differentiation between multiple sources, as a typical application of the model, has to be based on a sequential detection and selection of ITDs (see figure 9). Applying an external support, the focusing on a nondominant source could be observed, as long as its original phase information was present. Because the ITD feature is locked on the phase of the signal, the localization fails if interferences occur between voiced sounds. Thus, even a realtime capable hardware solution will require an onset detector to deliver reasonable results.

The experiences of the software simulations crucial influenced the design process of a mixed analog-digital hardware system, which VLSI implementation is currently in progress. In particular the usage of real world data and tests on robot systems are important to understand the problem and the model in details hidden to purely theoretical investigations.

References

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