Single Neuron Dynamics —
Models Linking Theory and Experiment

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Intensity invariance in a primary auditory interneuron
7. INTENSITY INVARIANCE IN AN AUDITORY INTERNEURON

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Cover: The cricket *Gryllus campestris* (drawn by Uta Grünert).

7.1 Introduction

The adaptation models derived in chapter 4 assume that the input is applied directly to the spike generator. The auditory receptor neurons of locusts approximately satisfy this assumption and the adaptation models describe their response properties well, as shown in the previous chapter. Here, the models are tested on the AN1, a first order interneuron of the auditory system of crickets. The response properties of the AN1 are similar to the response properties of the auditory receptor neurons which have direct connections to the AN1 (Hennig, 1988). The question is whether the adaptation models are still capable to describe the activity of this interneuron, or whether the transformation of the stimulus by the receptor cells, the synapses, and the dendritic tree exhibits an additional dynamics
which cannot be described by the models. For that purpose, extracellular recordings of the AN1 were performed in the cricket *Teleogryllus oceanicus*.

The calling song of this cricket species can last for minutes or even hours. The structure of these songs is determined by the duration of syllables and pauses, which are of the order of magnitude of 10–100 ms. Crickets recognize their conspecific partners based on these fast patterns (Hennig & Weber, 1997).

Auditory receptor afferents project into the prothoracic ganglion (Esch et al., 1980), where they connect to several interneurons directly (Hennig, 1988). From the ascending interneurons the AN1 is most sensitive. In addition, the AN1 is a bottleneck for the information transmission about the received calling songs to the brain (Schildberger & Hörner, 1988). The auditory system of the cricket is sketched in Fig. 7.1.

On condition that one of the adaptation models from chapter 4 explains the response properties of the AN1, the signal-transmission properties of this interneuron can be analyzed quantitatively. The high-pass properties of adaptation would support to compensate for varying intensities of the calling songs perceived from different distances.
7.2 Methods

All experiments were performed by R. Matthias Hennig, Berlin.

Animals

Laboratory-reared *T. oceanicus* females were used in all experiments.

Preparation

Both pairs of wings and the meso- and metathoracic legs were removed and the animal was fixed ventral side uppermost to a platform. The prothoracic legs with the ears were waxed to pins at the coxae and the tarsi in a normal walking position. The ventral nerve cord was cut at both sides of the prothoracic ganglion in order to reduce background activity from ascending and descending neurons. See Hennig (1988) for a more detailed description.

Recordings

Extracellular hook-electrode recordings were made from the connectives between the prothoracic and subesophageal ganglia that also contain the axons of the AN1 and of the AN2, another ascending auditory interneuron. The electrodes were electrically isolated with a vaseline – mineral oil mixture. Two tungsten wires were used as electrodes in differential mode. The voltage trace was digitized with an AD-board (National instruments: AT-MIO-16E-1 using 12 bit) at 10 kHz sampling rate and stored on disk. Spikes were detected offline using Labview software (National Instruments). For the AN1 every event with its peak in an appropriate voltage range was counted as a spike. Spikes less than 2.8 ms apart from the preceeding spike were discarded to minimize background activity. Interspike intervals shorter than 2.8 ms very likely originate from the detection of spikes from other neurons, since previously reported firing frequencies of the AN1 were below the corresponding maximum of 357 Hz (Schildberger & Hörner, 1988). Occasionally high activity in the connectives caused by breathing of the animal induced a strong increase in detected spikes probably not due to AN1- or stimulus related activity. Such spike trains were discarded from the analysis. The recordings were necessarily noisy, since the AN1 is a small neuron in the large connective, which contains axons of more than 1000 cells. Furthermore, the activity of the AN2 may mask the AN1 activity with its larger spikes, especially at high intensities. As illustrated in Fig. 7.2 B the interspike-interval distribution of the background activity is close to an exponential distribution, which is expected for a Poisson spike train (Dayan & Abbott, 2001). The time courses of the firing frequency averaged from up to 25 repetitions of the same stimulus still were very noisy (see Fig. 7.2 and Fig. 7.3 for examples).

Out of 24 cells *n* = 13 cells were used for the analysis. The remaining cells were excluded since either the background activity of the recording was above 50 Hz or the onset *f*-*I*-curves (see below) were not stable throughout the experiment. The background activity before stimulus onset of the cells included into the analysis was still above 30 Hz.
Figure 7.2: Response of an AN1 to constant stimulation. The left column (A & C) shows the mean firing frequency of a cell evoked by stimulation with a sound wave of constant amplitude and carrier frequency 4.5 kHz as indicated by the bottom bar. The spikes evoked by 22 repetitions of the same stimulus were used to calculate the averaged time course of the firing frequency. The corresponding interspike-interval histograms (right column, B & D) are compared with the one of a Poisson spike-train of equal ring rate and refractory period (2.8 ms) (solid line).

A The extracellularly recorded response to a stimulus intensity of $I = 33$ dB SPL. The activity is most probably due to the detection of spikes not originating from the AN1. B Most of the interspike intervals are in the tail of the corresponding exponential distribution of a Poisson spike-train. The coefficient of variation (standard deviation of the interspike intervals divided by their mean) is $CV = 0.75$. C At a sound level of $I = 54$ dB SPL the cell clearly responds with a firing frequency of about 170 Hz. It decays back to 100 Hz with a time constant of $\tau_{\text{eff}} = 166$ ms. D The interspike-interval histogram now has a distinct peak between 5 and 10 ms, but still has a CV of 0.7. The tail of the distribution probably originates from failures of the detection of AN1-spikes.

**Stimulation**

The recording setup was lined with sound-absorbing foam to reduce echos. An advantage of the extracellular recordings is that the recording chamber is free of large obstacles like a micro-manipulator, which further enhances the quality of the sound stimulation. The stimuli were multiplicated analogically with a carrier sine-wave of frequency 4.5 kHz, which corresponds to the calling song of *T. oceanicus* and is at the same time the best frequency of the AN1 (Hennig, 1988). Rectangular and step-like stimuli had rise and fall times of 2 ms. Stimuli were presented frontal by a dynamical loudspeaker at a distance of 50 cm.

**$f$-$I$-curves**

The onset and steady-state $f$-$I$-curves, $f_0(I)$ and $f_\infty(I)$, are important to characterize spike-frequency adaptation (see chapter 4). Both $f$-$I$-curves were measured once at the
beginning and once at the end of an experiment. Rectangular stimuli of 500 ms duration were applied at intensities every 3 dB from 30 to 93 dB SPL. Each stimulus was repeated 25 times, the pauses between the stimuli were 1.5 s long. Single spike trains were discarded in order to control for the quality of the recording, if their mean firing frequency during 100 ms before stimulus onset was greater than the mean firing frequency of the 25 trials in this interval plus 1.8-times the standard deviation. The time course of the firing frequency was calculated every millisecond as the trial-averaged inverse interspike interval (equation (5.5) on page 105). The maxima of the time courses smoothed with a rectangular 30 ms averaging window were taken for the onset $f$-$I$-curve (see Fig. 7.3 for such smoothed ring frequencies). For the steady-state $f$-$I$-curve the mean firing frequencies from 350 to 450 ms after stimulus onset were calculated directly from the interspike intervals in this range. In order to obtain the effective time constant of spike-frequency adaptation a single exponential function was fitted into the data (Fig. 7.2 C).

The resulting $f$-$I$-curves were fitted by a rectified hyperbolic tangent

$$f(I) = \begin{cases} f_{\text{min}} + (f_{\text{max}} - f_{\text{min}}) \tanh(k(I - I_{\text{th}})) & ; \quad I > I_{\text{th}} \\ f_{\text{min}} & ; \quad I \leq I_{\text{th}}. \end{cases}$$

The spontaneous activity for sub-threshold stimuli $f_{\text{min}}$ was set to the average value of all sub-threshold steady-state responses. The “maximum firing frequency” $f_{\text{max}}$ was set to the average over three data points around the one with the largest measured firing frequency. The threshold intensity $I_{\text{th}}$ was set to the intensity of the largest intensity point.
7.2 METHODS

D

I

dynamic range

steady state

f

¥

I

onset

f

0

I

I

dB SPL

80

70

60

50

40

30

I

th

f/Hz

300 ms

onset \( f_0(I) \)

steady state \( f_\infty(I) \)

dynamic range

\[ f_0 \]

\[ \tau_{\text{eff}} \]

\[ f_\infty \]

\[ \Delta I \]

Figure 7.4: \( f-I \)-CURVES OF AN AN1. From the firing frequencies evoked by constant stimuli in Fig. 7.3 the onset and the steady-state \( f-I \)-curve, \( f_0(I) \) and \( f_\infty(I) \), were constructed. The open circles denote the mean values of the firing frequency and the error bars the standard error of the mean \( (n = 22) \). The inset shows the time course of the firing frequency evoked by a constant stimulus of \( I = 63 \) dB SPL. The initial peak response \( f_0 \) approximately resembles the properties of the unadapted neuron. The fitted lines concentrate on the dynamic range of the \( f-I \)-curves and neglect the decrease of the onset \( f-I \)-curve \( f_0(I) \) at high sound levels (above 70 dB). The dynamic range \( \Delta I \) of the onset \( f-I \)-curve is marked by the horizontal arrow and is defined as the intensity \( I_{75} \) that evoked 75% of the maximum response minus the threshold intensity \( I_{th} \). The high firing frequencies of the onset \( f-I \)-curve data below threshold \( I_{th} \) are an effect of noise, since they are measured as the peak response of the smoothed time course of the firing frequency (compare with Fig. 7.3). That evoked less than 10% of \( f_{\text{max}} - f_{\text{min}} \) above \( f_{\text{min}} \) of the steady-state response. The remaining slope factor \( k \) was fitted using the Levenberg-Marquardt method as described in Press et al. (1992). Data up to the maximum response were used for the fit. Thus, the observed decrease of the firing frequency at high intensities was neglected (Fig. 7.4). The slope \( s \) of the \( f-I \)-curve at threshold \( I_{th} \) is given by

\[
    s = \left. \frac{df}{dI} \right|_{I=I_{th}^+} = k(f_{\text{max}} - f_{\text{min}}) .
\]

The adapted \( f-I \)-curves were measured as described in Fig. 7.5 to further specify the adaptation properties. With a 500 ms stimulus the neuron was adapted to some background intensity \( I_b \). Then the onset response to a different intensity was tested by a subsequent 100 ms stimulus and the cell was adapted back to \( I_b \) during the following 300 ms. This was repeated for 12 different test intensities every 3 dB. Five background intensities were used: \( I_b = 35, 47, 59, 71 \) and 83 dB SPL. The average firing frequencies over the first half of the test stimuli were used to construct the adapted \( f-I \)-curves. Again, (7.1) was used as a parameterization of the adapted \( f-I \)-curves. \( f_{\text{min}} \) and \( k \) were taken from the previously measured onset \( f-I \)-curve. \( f_{\text{max}} \) was set to the average of all the data points at
Figure 7.5: Measuring an adapted f-I-curve. A The stimulus used to measure the adapted f-I-curve for the neuron adapted to $I_b = 71$ dB SPL. During the first 500 ms the neuron was adapted to the background intensity $I_b$. Then with a louder stimulus (100 ms, $I = 86$ dB SPL) the response of the adapted neuron to this intensity was tested. Again the neuron was adapted to $I_b$ and the response to a lower intensity ($I = 53$ dB SPL) was tested. This procedure was repeated for different test intensities in an alternating order. The entire stimulus was 4.8 s long and tested for 12 different intensities (every 3 dB). B The 18 spike trains evoked by such a stimulus. C The time course of the firing frequency calculated from the spike trains. Note that the response is delayed for about 10 ms due to latency of the entire system. The mean values of the responses during 50 ms after onset of the test stimuli plus latency (dots) were used for constructing the adapted f-I-curve (see Fig. 7.7 lower left panel). The horizontal line marks the averaged steady-state response to the background intensity.

the highest intensities measured whose firing frequency decreased with intensity. Finally, $I_{th}$ was fitted to the data.

**White-noise stimuli and pulse patterns**

To investigate the dynamics of adaptation and to test the adaptation model, the responses to different Gaussian white-noise stimuli and pulse patterns were recorded. Each stimulus was repeated 25 times. The 8 different white-noise stimuli had cut-off frequencies of 50, 100, 200 and 400 Hz, standard deviations of 4 and 6 dB, and a duration of 1000 ms. They
Table 7.1: Properties of f-I-curves of the AN1.

<table>
<thead>
<tr>
<th>f-I-curve</th>
<th>$f_{\text{min}}$ (Hz)</th>
<th>$f_{\text{max}}$ (Hz)</th>
<th>$I_{\text{th}}$ (dB SPL)</th>
<th>$I_{90}$ (dB SPL)</th>
<th>$\Delta I$ (dB)</th>
<th>$s$ (Hz/dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>onset</td>
<td>32 ± 14</td>
<td>200 ± 23</td>
<td>42 ± 6</td>
<td>61 ± 5</td>
<td>12.4 ± 3.0</td>
<td>13.8 ± 3.3</td>
</tr>
<tr>
<td>steady-state</td>
<td>32 ± 14</td>
<td>107 ± 17</td>
<td>42 ± 6</td>
<td>73 ± 7</td>
<td>20.1 ± 5.6</td>
<td>3.8 ± 1.1</td>
</tr>
</tbody>
</table>

The table summarizes averaged values of $n = 26$ f-I-curves measured in 13 animals. The minimum and maximum firing frequencies, $f_{\text{min}}$ and $f_{\text{max}}$, and the threshold $I_{\text{th}}$ correspond to the parameter in (7.1). Note that both $f_{\text{min}}$ and $I_{\text{th}}$ are equal for the onset and steady-state f-I-curve by definition. The initial slope of the f-I-curves is given by (7.2). The intensity where the f-I-curve reaches 90% of its maximum value is $I_{90}$. The dynamic range of the f-I-curves, $\Delta I$, is the intensity of 75% maximum firing frequency minus $I_{\text{th}}$. $s$ is the initial slope (7.2) of the f-I-curves.

were first presented at 80 dB SPL and then at 90 and 70 dB SPL (peak intensities, which is three times the standard deviation of the stimuli above their mean).

All pulse patterns had a duty cycle of 50% (duration of the syllable as compared to the period), were about 500 ms long and were presented at 80 dB SPL. The durations of syllables and pauses used were 5, 8, 10, 15, 20, 30, 40, and 60 ms.

Between those measurements 10 onset f-I-curves were measured to monitor the stability of the sensitivity of the cell. For this purpose stimuli of 100 ms duration and intensities ranging from 30 to 93 dB SPL in steps of 3 dB were repeated 10 times spaced by pauses of 300 ms duration. The resulting firing frequencies were smoothed with a 30 ms averaging window. From the maximum values the onset f-I-curves were constructed.

Adaptation model

To model the time course of the AN1-response to the white-noise and pulse stimuli, the following phenomenological model was used:

\[
\begin{align*}
    f(t) &= \frac{f_0(I - A)}{1 + \gamma_0 A} \\
    \tau_{\text{eff}} \dot{A} &= \frac{I - f_0^{-1}(f_\infty(I))}{1 + \gamma f_\infty(I)} - A,
\end{align*}
\]

where $s_0$ is the slope of the onset f-I-curve as defined by (7.2). The model (7.3) is the transducer-adaptation model (4.27) extended by a linear $\gamma f$-term from equation (4.34). The first equation is adopted from the linearized equation for the f-I-curve (4.42) to account for the compression of the adapted f-I-curves as observed in the experiments. Note, that the steady-state f-I-curve of this model is only for $\gamma = 0$ identical to $f_\infty(I)$. For the f-I-curves the parameterization given by (7.1) was used. The measured adapted f-I-curves revealed a value of about 0.002 for $\gamma$ (Fig. 7.8). See discussion for more details about the model.

With the filter (6.8) (page 121) derived from the non-leaky phase-oscillator (3.2) the firing frequency from the model (7.3) was smoothened. The resulting firing frequency $v(t)$ was compared with the experimentally measured firing frequency $f_{\text{exp}}(t)$. The prediction error $p.e.$ (6.9) from page 121 is the mean squared difference $\sigma_{\text{diff}}$ of the experimentally...
measured firing frequency $f_{\text{exp}}$ to the firing frequency of the model $v$ related to the variance $\sigma_{\text{exp}}^2$ of $f_{\text{exp}}$.

The standard deviation $\sigma_{\text{exp}}$ of the firing frequency $f_{\text{exp}}$ is a measure for the modulation depth of the response $f_{\text{exp}}$ of the neuron. It was used to quantify the intensity invariance of the response $f_{\text{exp}}$ to different white-noise stimuli.

In order to assess the prediction error of the model for firing frequencies evoked by pulse-patterns as stimuli, the dependence of the modulation depth $\sigma_{\text{exp}}$ on the length of the syllables and pauses of the pulse patterns used as stimuli is of importance. The basic effect is that during the pauses of duration $\Delta t$ between the pulses the firing frequency equals $1/\Delta t$ if a spike occurred right at the end of the preceding syllable and the following spike occurred right at the beginning of the succeeding syllable. Thus, the firing frequency measured between the syllables increases with decreasing duration of the pauses. The corresponding modulation depth of the firing frequency can be estimated roughly as follows. Assume the neuron to fire during a syllable of the same duration $\Delta t$ as the pauses with a firing frequency $f_s$. The firing frequency between the pauses equals approximately $1/\Delta t$ as just discussed. Both the syllables and pauses have the same duration $\Delta t$ and the resulting standard deviation of the firing frequency is then

$$\sigma_{\text{exp}} \approx \frac{1}{2} \left( f_s - \frac{1}{\Delta t} \right). \quad (7.4)$$

### 7.3 Results

The data from $n = 13$ cells were included in the following analysis. The data shown in the figures are all from the same cell. Its parameters are close to the averaged results as summarized in tab. 7.1.
Figure 7.7: ADAPTED f-I-CURVES. With the procedure described in Fig. 7.5 the adapted f-I-curves for different background intensities $I_b$ were measured. Four such curves are shown in comparison with the onset and steady-state f-I-curves from Fig. 7.4. The filled circles denote the mean of the firing frequency and the error bars the corresponding standard errors ($n = 18$). With increasing background intensity $I_b$ these f-I-curves are shifted to higher input intensities. Furthermore their saturation value decreases dramatically and their slope seems to decrease, too. The adapted f-I-curves should cross the stead-state f-I-curve at the background intensity $I_b$. However, the adapted f-I-curves are always slightly below. This may be attributed to the very long stimulus used for measuring the adapted f-I-curves, during which a slower type of adaptation further desensitizes the neuron.

Spike-frequency adaptation

An example of the time courses of the firing frequencies evoked by stimuli of 500 ms duration and different intensities is shown in Fig. 7.3. Their properties are summarized in the f-I-curves and adaptation time-constants shown in Fig. 7.4 and 7.6, respectively. The data of the peak responses form the onset f-I-curve $f_0(I)$, and the steady-state firing frequencies result in the steady-state f-I-curve $f_\infty(I)$. On average (see tab. 7.1) both f-I-curves have their threshold at $I_{th} = 42$ dB SPL. The onset f-I-curves raise approximately linearly with a slope of 14 Hz/dB for about $\Delta I = 12$ dB. At $I_{90} = 61$ dB SPL they reach 90% of their maximum response of $f_{\text{max}} = 200$ Hz. The maximum firing frequency of the steady-state f-I-curves $f_{\text{max}} = 107$ Hz is about half of the onset firing frequency ($f_0/f_\infty = 1.9 \pm 0.2$). The corresponding percentage of adaptation $F_{\text{adap}} = \frac{f_0-f_\infty}{f_0}$ (Wang, 1998) is 46 ± 6%. The dynamic range of the steady-state f-I-curves over $\Delta I = 20$ dB is nearly twice as large as the one of the onset f-I-curves, resulting in a slope, which is almost a
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Figure 7.8: Compression of adapted $f$-$I$-curves. From the data of the adapted $f$-$I$-curves shown in Fig. 7.7 the compression factor as the ratio of the adapted to the unadapted $f$-$I$-curve $f_0(I,A)/f_0(I)$ in dependence on the state of adaptation $A$ was calculated. In order to obtain a value for $\gamma$ needed for the model (7.3), these data were fitted with the compression factor $1/(1 + \gamma_0 A)$ of the phenomenological adaptation model (7.3) (solid line). Note that this function is bounded to one at $A = 0$. The data revealed $\gamma \approx 0.002$ for most of the cells.

quarter ($1/3.7$) of the one of the onset $f$-$I$-curves (tab. 7.1). At around 80 dB SPL the data of the onset $f$-$I$-curves decrease again by about several ten Hertz, which very likely can be attributed to the masking of spikes by the AN2.

The effective time constants $\tau_{\text{eff}}$ of adaptation obtained from the data are very variable, as can be seen in Fig. 7.6, probably due to the noisiness of the data. However, the mean time constant calculated from the averaged time constants of each single cell is nevertheless determined relatively precisely as $\tau_{\text{eff}} = 141 \pm 23$ ms.

In 9 cells the adapted $f$-$I$-curves were successfully measured. The adapted $f$-$I$-curves of one cell are shown in Fig. 7.7 (see Fig. 7.5 for the stimulus used). What can be clearly seen in all measurements is the shift of these $f$-$I$-curves to higher input intensities, even beyond the saturation of the onset $f$-$I$-curve (see Fig. 7.7, lower right panel: $I_b = 83$ dB). The maximum possible shift as the difference between the threshold of the adapted $f$-$I$-curve measured for the largest background intensity and the threshold of the onset $f$-$I$-curve is quite large. On average this difference was $33 \pm 8$ dB and a maximum shift of 45 dB was observed in two cells. This capability of the AN1 to shift its $f$-$I$-curve by more than about 40 dB is the reason for the intensity invariance of its response as discussed below.

The maximum firing frequency of the adapted $f$-$I$-curves drops with increasing background intensity to the one of the steady-state $f$-$I$-curve. Whether this results from an overall compression of the adapted $f$-$I$-curves, or whether it is the consequence of a saturating input, cannot be decided from the data. A compression of the $f$-$I$-curves implies a decreasing slope within the dynamic range, while a saturating input leaves the slope untouched. However, especially at high background intensities $I_b$ only three data points determine the slope. The fits in Fig. 7.7 are shifted and scaled versions of the onset $f$-$I$-curve, but an unchanged slope fits the data, too (not shown). From the compression of the adapted $f$-$I$-curves a value of 0.002 for the factor $\gamma$ in the model (7.3) was obtained as illustrated in Fig. 7.8.
**Intensity invariance**

Adaptation can shift the $f$-$I$-curve of the AN1 over a wide range of more than 30 dB. This suggests that the time course of the firing frequency is almost invariant of the mean intensity of the stimulus. Thus, the modulation depth of the firing frequency evoked by a fluctuating stimulus is expected to be approximately independent of the mean intensity of the stimulus. If the AN1 would not adapt, i.e. the stimuli would be transmitted via the onset $f$-$I$-curve, a stimulus fluctuating for example between 70 and 90 dB would cause a constant firing frequency of about 200 Hz, since it is completely above the dynamic range of the onset $f$-$I$-curve. The resulting modulation depth would be close to zero.

This was tested with the white-noise stimuli. In four out of thirteen cells they were successfully applied at three different peak intensities of $I = 70$, 80, and 90 dB SPL as shown in Fig. 7.9 for one particular example. After the neuron was adapted to these stimuli (after about 200 ms), the modulation depths of the evoked firing frequencies were very similar, showing that all three stimuli used the whole dynamic range of the cell.

In Fig. 7.10 this phenomenon is quantified. The modulation depth was calculated as the standard deviation of the firing frequency from 200 ms to 950 ms after stimulus onset. Each value was related to the corresponding stimulus at 70 dB SPL. These relative modulation depths were averaged for each stimulus over the four cells and are shown in the figure. The values are in the range from 80 to 110 %, thus confirming the observation made in Fig. 7.9 that due to spike-frequency adaptation the responses to stimuli of different intensities are similar.
**Figure 7.10: Relative modulation depths for different intensities.** In four cells Gaussian white-noise stimuli were measured successfully at three different peak intensities ($I = 70, 80,$ and $90 \text{ dB SPL}$, for clarity the data points are jittered around the corresponding intensity). Shown are the averaged modulation depths (standard deviation of the firing frequency from 200 ms to 950 ms after stimulus onset) evoked by the different white-noise stimuli as compared to the one at $I = 70 \text{ dB SPL}$. The cut-off frequencies of the stimuli were $f_c = 50, 100, 200,$ and $400 \text{ Hz}$ as indicated. Open symbols denote stimuli with standard deviation $\sigma = 4 \text{ dB}$, filled symbols such with $\sigma = 6 \text{ dB}$. On average the standard deviation of the relative modulation depths at $80$ and $90 \text{ dB SPL}$ was $14\%$.

**Performance of the adaptation model**

After measuring the $f-I$-curves and adaptation time constant of a cell the parameters of the phenomenological model (7.3) are completely defined. The predicted time course of the model for different Gaussian white-noise stimuli and pulse patterns was compared with experimental data. Two typical examples are shown in Fig. 7.11. A model without adaptation, which just mapped the stimulus through the neuron’s onset $f_I$-curve, predicted the experimentally measured firing frequency much worse (not shown).

In Fig. 7.12 the performance of the model is analyzed quantitatively for the different stimuli. The firing frequency evoked by slow stimuli with a cut-off frequency of $f_c = 50$ and $100 \text{ Hz}$ are better predicted by the model than the response to fast stimuli with $f_c = 200$ and $400 \text{ Hz}$. In addition, the prediction error for the slow stimuli increases with intensity, while for the fast stimuli it slightly decreases.

The firing frequency evoked by pulse patterns with long syllables ($\geq 30 \text{ ms}$) is predicted very well (Fig. 7.13). With decreasing duration of the syllables the prediction error increases. However, the absolute deviation $\sigma_{\text{diff}}$ of the measured firing frequency from the prediction is nearly independent of syllable duration, but the modulation depth $\sigma_{\text{exp}}$ of the AN1 response decreases dramatically and becomes even smaller than the deviation $\sigma_{\text{diff}}$. The decrease of the modulation depth $\sigma_{\text{exp}}$ can be mainly explained by the increasing firing frequency during the pauses due to decreasing duration of the pauses. The graph of the function (7.4), which is a rough sketch of this consideration, is close to the data for durations of the syllables and pauses greater than $10 \text{ ms}$. This simple model fails at shorter syllables, since then only one ore two spikes occur during a syllable and the assumption of a constant firing frequency during the whole syllable is no longer valid.
Figure 7.11: Performance of the Adaptation Model. Shown is the firing frequency measured experimentally and that predicted from the adaptation model (7.3) for two stimuli applied at 70 dB SPL peak intensity. Superimposed on the stimulus-trace is the threshold of the adapted $f-I$-curve, i.e. $I_{th} + A$. Only parts of the stimulus above this line are transmitted. A Gaussian white-noise stimulus with a cut-off frequency of 100 Hz and standard deviation 6 dB. After onset of the stimulus the neuron adapts to a steady-state value which remains nearly unchanged throughout the whole stimulus. This is due to the high cut-off frequency compared to the adaptation time constant. The fast fluctuations do not affect the state of adaptation. The root mean squared difference $\sigma_{\text{diff}}$ of the measured and predicted firing frequency was 28 Hz, resulting in a prediction error of 47 %. Without adaptation included into the model ($A(t) = 0 \forall t$) the prediction error is 513 %. B A pulse pattern with 30 ms pulses and 30 ms pauses. The cell does not completely recover from adaptation during the pauses. Therefore the mean state of adaptation increases during the stimulus. This helps to suppress the enhanced activity of the neuron during the first pause (arrow). The decay of the response during the pulses is due to the decrease of the saturation value of the adapted $f-I$-curves. The prediction error was 15 % (59 % for a model without adaptation) at an absolute error of $\sigma_{\text{diff}} = 22$ Hz. The firing frequency during the first pause is usually larger than during the following pauses and is not reproduced by the model (arrow). The peaks in the firing frequency evoked by every second pulse are most likely caused by noise, since this systematic effect was not observed in the recordings of other cells.
**Figure 7.12:** Model performance for white-noise stimuli. The prediction error of the model for the different types of Gaussian white-noise stimuli in dependence on the peak intensity $I$ averaged over $n = 13$ cells. Open symbols denote stimuli with standard deviation $\sigma = 3$ dB, filled symbols such with $\sigma = 6$ dB. The cut-off frequencies of the noise stimuli were as indicated. The averaged absolute deviation $\sigma_{\text{diff}}$ of the prediction from the measured response was 26 Hz.

**Figure 7.13:** Model performance for pulse patterns. The mean dependence of the prediction error of the model (7.3) on syllable length is shown ($n = 13$ cells). For comparison the standard deviation of the experimentally measured firing frequency $\sigma_{\text{exp}}$, and the root mean squared difference $\sigma_{\text{diff}}$ to the model prediction are plotted (right axis). While the deviation $\sigma_{\text{diff}}$ is approximately constant, the modulation depth $\sigma_{\text{exp}}$ of the measured firing frequency decreases with decreasing syllable length. The corresponding dashed line is the function (7.4) for $f_s = 145$ Hz. This function assumes a firing frequency $f_s$ during the syllables and a maximum firing frequency of $1/\Delta t$ during the pauses. For syllable durations longer than about 10 ms it explains the decrease of the standard modulation of the firing frequency quite well.
Transfer function

For the dynamic range of the $f$-$I$-curves the transfer function for the firing frequency of the AN1 can be calculated by means of (4.53) as shown in Fig. 7.14. Frequency components of the stimulus above 2 Hz are transmitted with a high gain of about 14 Hz/dB through the shifted onset $f$-$I$-curve $f_0(I - A)$. Very slow components below 0.5 Hz and the mean are transmitted only with a gain of about 4 Hz/dB. Note, that the gain in this linear approximation is given by the slopes of the onset and the steady-state $f$-$I$-curves, not by their maximum values (tab. 7.1).

7.4 Discussion

Measuring $f$-$I$-curves with 500 ms stimuli and a high resolution of intensities requires long and stable recordings. With 25 repetitions of each stimulus the measurement of a single $f$-$I$-curve lasted about twenty minutes. Then adapted $f$-$I$-curves at five different background intensities (twelve minutes), Gaussian white-noise stimuli at three different intensities (twenty minutes), pulse patterns (seven minutes) and ten $f$-$I$-curves with 100 ms stimuli (each two minutes) were measured. Testing all these stimuli in one cell lasted at least one and a half hour. For this reason extracellular recordings were performed, which allowed routinely such long lasting recordings. Since the AN1 is a small neuron, intracellular recordings of this duration are nearly impossible. The penetration with a microelectrode could also damage the AN1, which may change the properties of the neuron. Extracellular recordings disturb the AN1 much less. However, the detection of the AN1 spikes from the extracellular signal was not perfect as mentioned already in the methods section. In the absence of any stimulation there was a high background activity of about 30 Hz. Such a high spontaneous activity was usually not observed in intracellular recordings (Hennig, 1988). The long tail of the interspike-interval histograms indicate that some AN1 spikes were not detected. One reason for such failures is the masking of AN1 spikes...
by the larger spikes of the AN2. It is much less sensitive compared to the AN1, so that this masking effect plays a role at high stimulus intensities only. This masking effect is therefore probably the reason for the decrease of the onset $f$-$I$-curve of the AN1 at intensities above 79 dB SPL (Fig. 7.4). Nevertheless, the resulting firing frequencies were clearly correlated to the stimulation and in good agreement with previous intracellular recordings (Hennig, 1988; Horseman & Huber, 1994a).

Properties of $f$-$I$-curves

Horseman & Huber (1994b) measured $f$-$I$-curves of the AN1 in another cricket species (*Gryllus bimaculatus*) as the number of spikes per chirp consisting of four syllables and pauses with a duration of 20 ms. They reported a similar threshold slightly above 40 dB SPL. However, their $f$-$I$-curve rose slowly until it saturated above 80 dB at approximately 200 Hz. Since the stimulus was composed of 20 ms short syllables, in principle their $f$-$I$-curve should be very close to the onset $f$-$I$-curve. However, due to the presentation of four syllables in a chirp, there is a likely effect of the steady-state $f$-$I$-curve that leads to the less steeper and wider dynamic range compared to the onset $f$-$I$-curve from *T. oceanicus* of this study.

Possible mechanisms for spike-frequency adaptation

Several mechanism may explain the strong adaptation in AN1. First, it can reflect the adaptation of the receptor neurons. Second, the synapses of the receptors to the AN1 may adapt. Both possibilities are of the category transducer adaptation introduced in chapter 4. Third, the AN1 may exhibit encoder adaptation due to intrinsic slow ionic currents. Fourth, there is the possibility of inhibitory inputs (Stumpner, 1998), either as an additional feed-forward input or as recurrent inhibition.

Encoder and transducer adaptation can be differentiated based on (1) the dependence of the effective time constant of adaptation on input intensity, and (2) the shift of the adapted $f$-$I$-curves in comparison with the intensity where the onset $f$-$I$-curve saturates.

(1) The time constants of adaptation measured in the AN1 scatter strongly. Thus, they do not allow to make any statement about their dependence on input intensity (Fig. 7.6), and no statement about the type of adaptation is possible (recall Fig. 4.11).

(2) The onset $f$-$I$-curve clearly saturates. This is a strong sign of a saturating transducer process to the AN1. As shown in Fig. 4.8 encoder adaptation for such onset $f$-$I$-curves cannot be the reason for a shift of the adapted $f$-$I$-curve beyond the saturation of the onset $f$-$I$-curve. Since once the conductance mediating the stimulus is saturated, stronger inputs do not make any difference for the neuron. Therefore, intrinsic mechanisms like encoder adaptation cannot influence the point of saturation. Thus, the main contribution of the adaptation observed in the AN1 is of the category transducer adaptation, provided saturation of its onset $f$-$I$-curve indeed reflects the saturation of the transduction of its input.

This transducer adaptation can be evoked by the adaptation in the receptor neurons as it is the case in locusts (chapter 6), by depressing synapses, and by additional slow feed-forward inhibitory input. There are several hints for an inhibitory input via the Omega-neuron, a local auditory interneuron, but this inhibition acts on a much shorter time scale than the adaptation observed here (Schildberger & Hörner, 1988; Horseman & Huber,
1994a).

It cannot be ruled out that in addition to the transducer adaptation there is also a contribution of encoder adaptation. For adaptation on time scales of several seconds, a calcium dependent adaptation mechanism may be the reason (Sobel & Tank, 1994). This type of adaptation could also explain that the adapted $f-I$-curves measured with stimuli of nearly five seconds duration resemble the state of the neuron which is less sensitive than expected from the fast adaptation investigated here (Fig. 7.7).

The last possibility is some recurrent inhibitory input. As well as encoder adaptation its strength depends on the firing frequency of the AN1. Thus, it can have only a minor contribution on the AN1’s adaptation, too.

**Receptor neurons**

The AN1 receives direct input from the auditory receptor neurons (Hennig, 1988). Since the main contribution to the observed spike-frequency adaptation in the AN1 arises very likely from an already adapting input, the receptor neurons are possible candidates as a source of this adaptation.

Imaizumi & Pollack (2001) analyzed extensively the $f-I$-curves of auditory receptor neurons in *T. oceanicus*. The $f-I$-curves they measured reflect mainly the onset $f-I$-curves, since their stimuli were 30 ms long. The dynamic ranges of the receptor neurons with best frequencies around 4.5 kHz cover approximately 15 to 35 dB, which is about twice the dynamic range of the AN1 onset $f-I$-curve measured here. The thresholds of the receptor neurons are distributed between about 35 and 80 dB SPL. This range agrees with the possible shift of the adapted $f-I$-curve in the AN1 from 42 to about 80 dB SPL. Similar properties of receptor cells were observed in the cricket *G. bimaculatus* (Oldfield et al., 1986).

To my knowledge no data exist about adaptation of auditory receptor neurons of crickets. However, since receptor cells of grasshoppers and crickets are part of chordotonal organs that occur as serial homologous in the segments of Orthopteran insects, the principal properties of the receptor cells in crickets and locusts are expected to be similar. Indeed, the onset $f-I$-curves measured by Imaizumi & Pollack (2001) in *T. oceanicus* are similar to the onset $f-I$-curves of grasshoppers (chapter 6). Thus, the adaptation properties of auditory receptor cells in both taxa can be assumed to be similar. Adaptation in receptor neurons of locusts shifts their $f-I$-curve only over a range of about 10 dB, while the AN1 uses a range of at least 40 dB. Future modeling studies have to show whether a simple linear summation of the receptor cell responses is sufficient to describe these adaptation properties of the AN1, or whether more sophisticated computations take place in the AN1. Such a study may show how the AN1 pools the response of receptor neurons with different sensitivities in order to achieve the observed intensity invariance.

**Intensity invariance**

Slow adaptation over several seconds in auditory interneurons was already observed in the omega neuron of crickets and bush-crickets (Pollack, 1988; Römer & Krusch, 2000). In these studies the forward masking effect of adaptation was emphasized, i.e. the suppression of less intense stimuli by a preceding louder one. In this study, adaptation on a much shorter time scale of about 100 ms and its implications for intensity invariance
was investigated. The observed range of the shift of the \( f-I \)-curve over more than 40 dB is the reason for the intensity invariance. Since the AN1 in crickets is probably the main carrier of information about calling songs to the brain, the data suggest that the cricket should hardly perceive slow changes in sound intensity. Interestingly, phonotactic orientation towards calling songs stimuli measured on a locomotion compensator also showed constant values at intensities for 50–80 dB in this species (R. Hennig 2001, personal communication). Thus, the adaptation properties of the AN1 correspond well in threshold and range of adaptation to the behavior (see also Doolan & Pollack, 1985, for similar measurements). However, the intensity invariance in the AN1 is not perfect, since the steady-state \( f-I \)-curve does not vanish and the saturation level of the adapted \( f-I \)-curves decreases with increasing mean intensity.

**Pulse patterns**

Calling songs of crickets are composed of syllables separated by pauses, which are repeated many times. The period of these patterns in *T. oceanicus* is between 10 and 100 ms long (Hennig & Weber, 1997). Due to adaptation the firing frequency evoked by the syllables is reduced (Fig. 7.11 B). However, to be able to resolve short syllables or even the sub-structure of the syllables, high firing frequencies are needed, since only fluctuations of the input which are slower than about half of the firing frequency can be transmitted as discussed in chapter 3. In order to estimate the firing frequency evoked by a syllable, in the following the state of adaptation right at the beginning of the syllable is calculated. Let \( \Delta t_s \) and \( \Delta t_p \) be the duration of the syllables and the pauses, respectively, and \( A(\infty)(I) \) the steady-state value of the adaptation \( A \) evoked by the intensity \( I \) of the syllables. During the pauses \( A(\infty) \) is assumed to be zero. Then, in the steady state the state of adaptation \( A_0 \) right at the beginning of a syllable is

\[
A_0 = A(\infty)(I) \frac{1 - e^{-\Delta t_s/\tau_{eff}}}{e^{\Delta t_p/\tau_{eff}} - e^{-\Delta t_s/\tau_{eff}}},
\]

where \( \tau_{eff} \) is the effective adaptation time-constant. The dependence of this function on the duration of the pause \( \Delta t_p \) is illustrated in Fig. 7.15 A. Only for pauses much longer than the adaptation time-constant the neuron recovers completely from adaptation resulting in \( A_0 \approx 0 \). If both syllables and pauses are very short, \( A_0/A(\infty)(I) \) equals the duty cycle.

The neuron adapts completely to its steady-state \( f-I \)-curve \( f(\infty)(I) \), if it is stimulated with a constant intensity \( I \) without interruption. To a pulse pattern it adapts less, as quantified by (7.5). Thus, the response to the syllable is greater than the steady-state response \( f(\infty)(I) \). The response is only limited by the saturation level of the corresponding adapted \( f-I \)-curve. The higher values the steady-state \( f-I \)-curve has, the higher the firing frequency during the syllables has to be. This is important to resolve pulse patterns with short periods. With a spike frequency of \( f = 50 \) Hz, for example, the minimum period is \( 1/50\text{Hz} = 20 \) ms. Every syllable evokes just one spike. To resolve shorter syllables, a higher firing frequency is needed. As illustrated in Fig. 7.15 B pulse patterns applied at 10 dB above threshold already evoke firing frequencies of more than 100 Hz, thus allowing to detect syllables down to 5 ms duration (duty cycle 50 %). This lower limit of detectable syllable durations is in good agreement with results of both temporal modulation transfer functions measured in the AN1 and behavioral studies (R.M. Hennig (2001), personal communication). The saturation frequency of the AN1 steady-state \( f-I \)-curve of
about 100 Hz ensures this resolution over a wide range of intensities. Note that the corresponding periods are a lower bound of the capability of the AN1 to transmit the structure of the pulse pattern, if no assumptions about the stimulus are made.

**Adaptation model**

Due to the properties of the observed $f$-$I$-curves in the AN1, the adaptation model (7.3) was chosen. In addition to the shift of the onset $f$-$I$-curve $f_0(I - A)$ it is scaled down appropriately by the denominator $1 + \gamma_0 A$. It is not possible to model the compression by a multiplicative term on the state of adaptation $A$ similarly as for encoder adaptation (4.22), since such a term does not affect the saturation level. The dynamics of the state of adaptation $A$ is driven solely by the input as it is required for any kind of transducer adaptation.

The overall performance of the model (7.3) is quite well. However, there are some deviations between the modeled and the measured firing frequencies, which can be seen in all comparisons. First, the initial response is underestimated by the model. It is determined by the maximum frequency of the unadapted $f$-$I$-curve $f_0(I)$. The procedure of calculating the maximum frequency $f_{\text{max}}$ included two averaging processes. The time course of the firing frequency was smoothed with a 30 ms running average, and values at three intensities were averaged to get $f_{\text{max}}$. In addition, at high intensities AN2 spikes mask the AN1 response. Thus, the maximum value of the unadapted $f$-$I$-curve used to model the firing frequency is very likely too small. Second, peaks of the firing frequency throughout the response to white-noise stimuli are much weaker in the prediction of the model. In addition to the too small maximum value of the unadapted $f$-$I$-curve an underestimation of the slope of the adapted $f$-$I$-curve could be the reason for that phenomenon. From the data of the adapted $f$-$I$-curves as in Fig. 7.7 it is not clear, however, whether adaptation compresses their initial slope. If this slope would be independent of adaptation, then the model (7.3), which compresses it, produces smaller responses. Third, the

![Figure 7.15: Adaptation to Repeated Pulses](image)
activity evoked by the pulse patterns continued after the syllables into the pauses during the first approximately 100 ms after stimulus onset (arrow in Fig. 7.11 B). This after discharge is not reproduced by the model. It is a phenomenon which also can be observed in receptor neurons of bush crickets (Schütze, 1995). Therefore it originates probably from the transduction of the sound waves into changes of the membrane conductance.

Altogether, the slow dynamics of spike-frequency adaptation of the AN1 can be explained by the model (7.3) of transducer adaptation. Thus, all processes preceding the generation of spikes in the AN1 (transduction of the sound wave, adaptation of the receptor cells, synaptic transmission to the AN1, integration on the dendritic tree) are captured sufficiently by the single first-order differential equation of the model. All deviations of the model from the real firing frequency arise on a faster time scale and therefore have to be attributed to the faster dynamics of the spike generator. However, due to the noisiness of the data it is not possible to check different models for the generation of spikes as proposed in chapter 3.

7.5 Summary

- Spike-frequency adaptation in the AN1, an ascending primary auditory interneuron, was studied in the Australian cricket *Teleogryllus oceanicus*.
- The dynamic range of its onset $f$-$I$-curve is about 12 dB wide. Adaptation shifts the $f$-$I$-curve over a range of more than 40 dB. The adaptation time constant is on average 140 ms.
- Due to this adaptation the AN1 response is approximately invariant of intensity on slow time scales $> 500$ ms, which is in good agreement with phonotactic behavior of this species.
- The non-vanishing steady-state $f$-$I$-curve forces the firing frequency evoked by pulse patterns to be at least 100 Hz. This makes it possible to resolve pulse patterns with periods down to less than 10 ms.
- The dynamics of adaptation in the AN1 can be described well by a phenomenological model of transducer adaptation, taking the decreasing saturation level into account.