



# Sensory Feedback Cancellation: Developing Resonator Networks to Mimic *A. leptorhynchus*'s Cerebellar Processing of Sensory Feedback

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**Abstract.** Sensory feedback allows animals to read, react, and adapt to an environment. However, the sensory information received by the body could become overwhelming, thus overloading the brain. Yet, animals are able to process all this information by canceling redundant signals from their surroundings. One species in which this phenomenon has been explored is the *Apteronotus leptorhynchus* (brown ghost knife fish), a small electric fish that generates a bioelectric field. Sensory signals from electrical sensing organs are passed through granular cerebellar cells, which then feedback onto the primary sensory neurons to cancel low-frequency components of the sensory information. This enables the canceling of redundant sensory information and noise and makes downstream networks more sensitive to changes in sensory input. In this preliminary study, we take the first step of replicating this functionality using a series of neural resonators. Each resonator has a unique preferred frequency and then should feed back onto the sensory signal with a frequency-specific phase delay. Our resonator is a neural “differentiator” from our prior work, which amplifies frequencies up to the cutoff frequency of the network. We propose how sensory feedback cancellation could be incorporated into bioinspired robot control.

**Keywords:** Resonator · Synthetic Nervous System-toolbox · Functional Subnetwork Approach · Cerebellum · Ghost Knife Fish

## 1 Introduction

Neural systems perform functions that can inspire engineered systems. Cerebellar networks are particularly interesting in that regards and we focus here on a circuit in which feedback input allows to filter out redundant sensory signals. More specifically, we draw inspiration from the parallel fiber feedback onto primary sensory neurons in gymnotid fish [1]. These fish are exposed to continuous inputs of sensory signals, including self-generated signals (e.g. from movement) or from nearby fish. The low frequency and redundant signals are particularly inconvenient because they can interfere with their capacity to perceive important novel signals by masking them [2]. To cope with these noisy background signals, their sensory system has a mechanism to filter redundant low-frequency signals without filtering novel important signals.

This mechanism relies on a feedback pathway through granular cerebellar cells that provides a canceling signal to subtract the redundant noise in the primary sensory neurons [3]. To generate this canceling signal, the feedback pathway consists of a delay line with frequency-tuned channels [1] that returns a copy of the sensory input. The synapses between the feedback and the primary sensory neurons (parallel fibers onto ELL pyramidal cells) are plastic and therefore only the fibers with the correct delay for a given input frequency remain strong. This feedback input is thereby shaped into a negative image of the redundant sensory input. A key aspect of this mechanism is the presence of frequency-specific channels [1] which must rely on a resonance mechanism to be selective to specific frequencies. In this paper, we create a realistic neural circuit that could underly the frequency-tuned resonator that could be present in the feedback pathway described above.

In particular, we seek to capture the functionality of these feedback-canceling mechanisms mathematically without the complexity of detailed biological modeling (e.g., specific ion channels). Because we plan to incorporate them into a real-time robot controller, we use simple neural models that can be simulated rapidly. Furthermore, because we wish to understand how the network functions, we use models that are tractable to analyze. For this reason, we are creating our model using the Synthetic Nervous System (SNS) framework [4] and implementing it with the SNS-Toolbox Python library [5].

In this preliminary study, we simulate the response of a number of neural “resonator” circuits. Multiple resonators were constructed because the system we draw inspiration from the electrosensory system- relies on multiple frequency-specific cerebellar channels to provide feedback independently different frequencies [1]. We apply a series of sinusoidal inputs of varying frequencies to each network in order to generate its frequency response spectrum. Each circuit is tuned differently to have a different resonant frequency, replicating the functionality of the parallel fibers in the cerebellum. We show that as an ensemble, the activity of these resonators reflects the frequency of the incoming signal. This preliminary result supports our plans for future work, in which each resonator will feed back onto the incoming signal with a specific phase delay in order to cancel components of the input signal.

## 2 Materials and Methods

Using the SNS-Toolbox library [5] in Python, we developed six resonators each containing three non-spiking neurons: one fast-responding one slow-acting, and one postsynaptic neuron (Fig. 2). The fast and slow-acting neurons make an excitatory and inhibitory synapse connection, respectively, to the postsynaptic neuron. For the neurons in the neural network, the dynamics are as follows:

$$C_m \cdot \frac{dV}{dt} = -G_m \cdot (V - E_r) + I_b + I_{syn} + I_{ext} \quad (1)$$

where  $C_m$  is the membrane capacitance,  $G_m$  is the membrane conductance,  $V$  is the voltage,  $E_r$  is the resting potential,  $I_b$  is the bias current,  $I_{syn}$  is the synaptic current, and  $I_{ext}$  is the external current. With the voltage, and currents already being set values we can alter the resting potential and the membrane capacitance. Our resting potential

value was set to 0 so our current is changed. The values for the membrane capacitance for each neuron can be found in Table 1. The synapse is what allows our network to differentiate the incoming signal and just as the neuron, the SNS-Toolbox has built-in synapse dynamics which are defined by the equations,

$$G = G_{\max} \cdot \max(0, \min(1, U_{pre}/R)) \quad (2)$$

$$I_{syn} = G \cdot (E_{rev} - U_{post}) \quad (3)$$

where  $G$  is the conductance,  $G_{\max}$  is the max conductance,  $U_{pre}$  is the presynaptic voltage or the membrane potential of the presynaptic neuron relative to its rest potential (i.e.,  $U = V - E_r$ ),  $R$  is the expected range of fluctuation in the membrane voltage,  $E_{rev}$  is the reversal potential relative to the postsynaptic neuron's rest potential, and  $U_{post}$  is the postsynaptic neuron's membrane potential. Changing the reversal potential of the synapse allows us to define the role of the synapse, e.g., excitatory ( $E_{rev} > 0$ ) or inhibitory ( $E_{rev} \leq 0$ ).

The SNS-toolbox simulates the network response using the Forward Euler method,

$$y(t_0 + n\Delta t) \approx y(t_0) + \sum_{i=0}^{n-1} f(t_0 + i\Delta t) \Delta t$$

where  $t_0$  is the initial time,  $n$  is the number of timesteps at which to calculate the response,  $\Delta t$  is the time step, which we set at 0.1 ms. Using this we can update and observe the responses of our system in terms of time. For further implementation see [Nourse et al. 2023].

## 2.1 Functional Subnetwork Approach to Creating a Resonator

To create a network that functions as a differentiator, we pass the input current signal through two neurons with different time constants in parallel. The neuron with the shorter time constant is called the “fast” neuron, and that with the longer time constant is called the “slow” neuron. Then, the fast neuron excites the network's third, output neuron and the slow neuron inhibits the output neuron. As shown previously, the output neuron's voltage reflects the rate of change of the input current [4]. For an appreciable output voltage, the time constant of the slow neuron needs to be substantially longer than that of the fast neuron. The resulting network performs as a high-pass filter because rapidly changing inputs depolarize the fast neuron before the slow neuron can respond, temporarily activating the output neuron.

However, one aspect of this network that was not addressed in previous work is that every neuron in the network is a low-pass filter, itself. Therefore, the differentiator network really functions as a band-pass filter: When the input changes slowly, both the fast and slow neurons are activated at the same rate and the network output is 0; when the input changes rapidly, neither the fast nor the slow neuron are activated and the network output is 0; when the input changes at the appropriate rate, the fast neuron is activated before the slow neuron and the output is temporarily positive. Because the network has a frequency at which its output is greatest, we call this network a “resonator”.

The fast neuron in each resonator possesses a small membrane capacitance value with 5 nF being the smallest and increasing by 5 nF per resonator up to 30 nF. For the slow neurons, the membrane capacitance must be much larger than the fast-acting neuron, so each neuron’s membrane capacitance is 10 times more than the fast neuron’s (Table 1). We can calculate the time constants for every pair of neurons by using the equation,

$$\tau = \frac{C_m}{G_m}, \quad (4)$$

where  $\tau$  is the time constant,  $C_m$  is the membrane capacitance, and  $G_m$  is the membrane conductance, which we set to  $1 \mu S$  (or  $(M\Omega)^{-1}$ ). Setting  $G_m = 1 \mu S$  makes each neuron’s time constant equivalent to its membrane capacitance (Table 1).

**Table 1.** Each resonator’s fast and slow time constants

Resonator	Fast time constant	Slow time constant
Resonator 1	5 ms	50 ms
Resonator 2	10 ms	100 ms
Resonator 3	15 ms	150 ms
Resonator 4	20 ms	200 ms
Resonator 5	25 ms	250 ms
Resonator 6	30 ms	300 ms

To determine the frequency response of each network and ensure that these “differentiators” possess a resonant frequency as expected, the neurons were excited with an input current with the shape of a sine wave with frequencies ranging from  $10^{-5}$  to  $10^{31}$  kHz. This frequency range was chosen to characterize the resonator responses over their most sensitive frequencies.

Finally, to obtain the resonant frequencies of each resonator, the gain (i.e., the ratio of the output neuron’s voltage to the input current) was needed. The gain was procured by taking the peak of the amplitude of the response in the frame of,

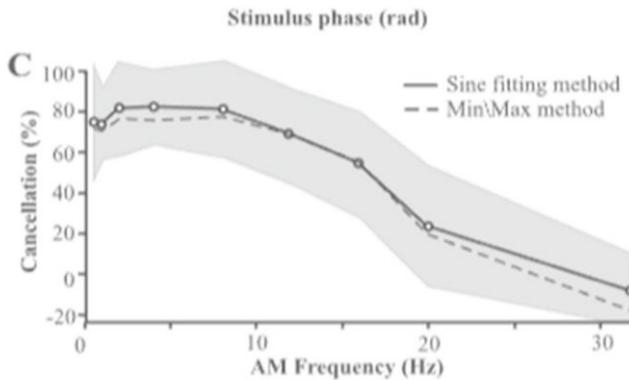
$$t > (c - 1) \cdot \tau_L, \quad (5)$$

where  $t$  is the amount of time the input current is being applied,  $c$  is the number of cycles of the current stimulus, and  $\tau_L$  is the longest neuron time constant in the network. This was to ensure that the simulated network’s response had achieved a steady state. The number of cycles for testing was 15 and the longest time constant was 300 ms.

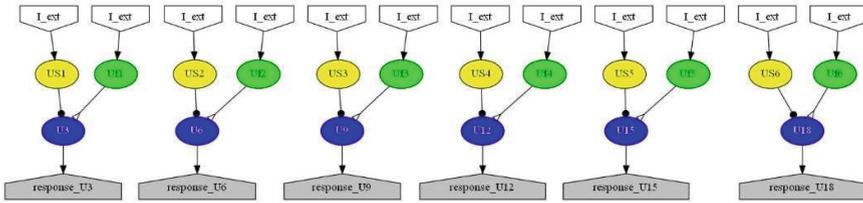
Lastly, to simulate the response of a parallel fiber in response to continuous sensory feedback, e.g., as a fish moves through different environments, we tested how the resonators would respond to a current that changes its frequency during one of its cycles.

### 3 Results

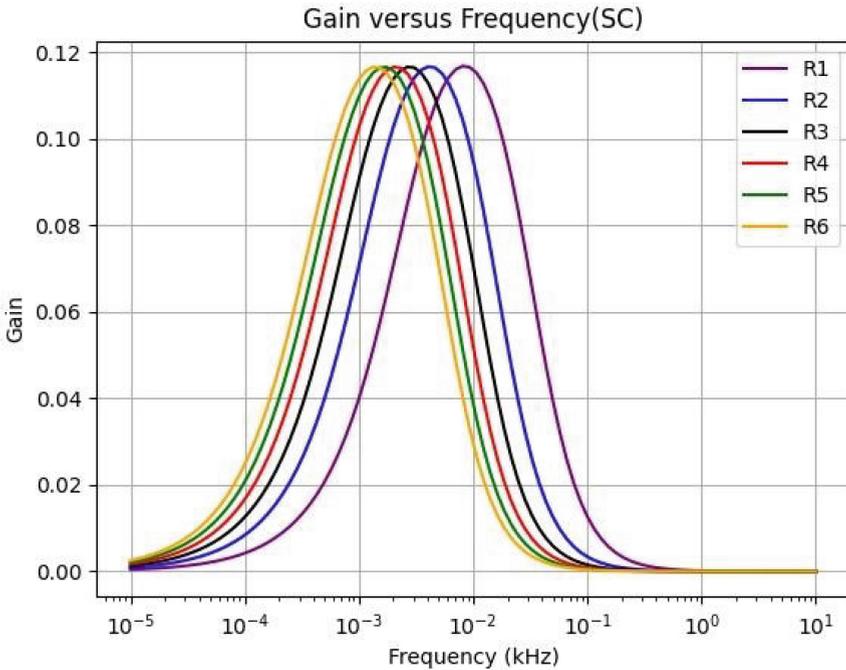
The resonant frequency for each resonator was found (Fig. 3). They are represented as the peak of the amplitude from each resonator’s response curve. All the values for the resonant frequencies are very small (Table 2). This tells us that the resonators do not have resonance outside the range of the frequencies that we want our system to respond to which can range from 0 to 30 Hz (Fig. 1).



**Fig. 1.** “Cancellation of the stimulus-response due to feedback as a function of stimulus frequency”. Using the “Sine Fitting method” reveals the resemblance the shape of the stimulus-response has to a sine wave when given the same frequency [1].



**Fig. 2.** Configuration of the resonator(s). Each resonator has its respective time constants for its fast and slow-acting neurons. The time constants increase from left to right.

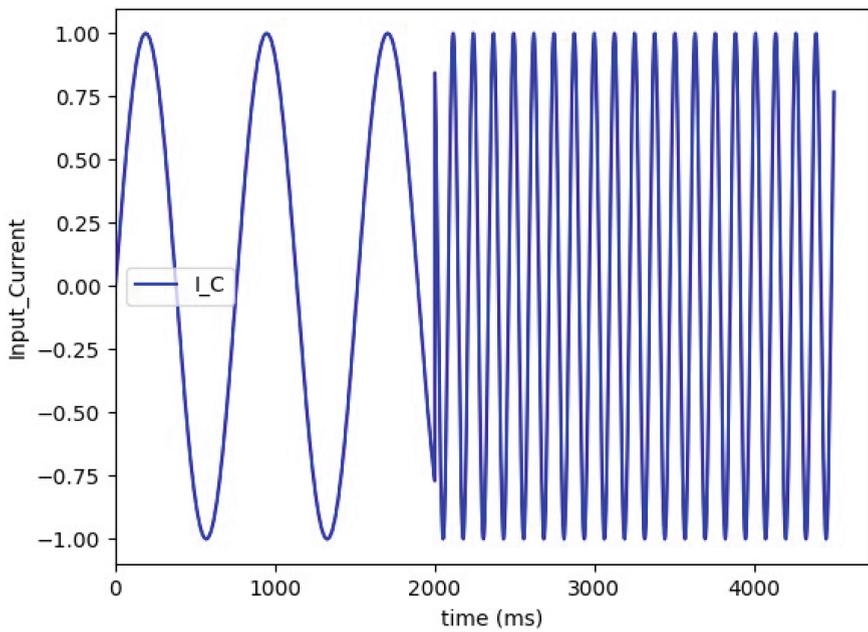


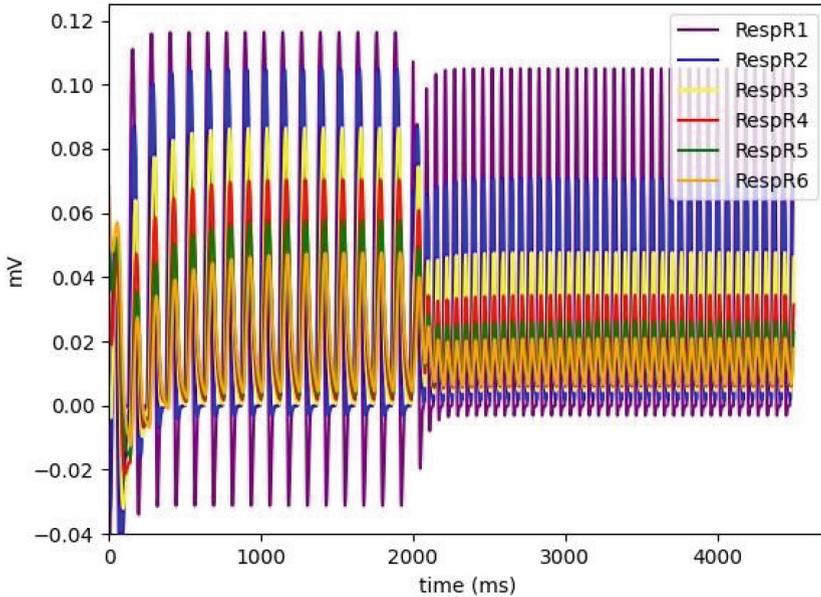
**Fig. 3.** The resonator’s frequency response spectrum. Each peak represents the resonant frequency to which each resonator responds.

Being able to see how our system responds to a change in frequency is crucial. So, to mimic the sudden shift in the frequencies of the signal, we increase our input current frequency partway through the simulation (Fig. 4). The system is responding as expected of our differentiator. The frequency shift can be seen by the decrease in the amplitude of resonators 4, 5, and 6 and the increase in the voltage values for resonators 1, 2, and 3 (Fig. 5). This has let us confirm that when the frequency is within the range of the resonant frequencies the response of the resonator changes accordingly (i.e., the change seen in resonator 3’s response). These changes can also be seen clearer when plotted as a bar graph (Fig. 6).

**Table 2.** Resonators resonant frequencies associated gain from constant sine wave input.

Resonator(s)	Gain	Resonant frequencies
Resonator 1	$1.16 \times 10^{-1}$ dB	8.11 Hz
Resonator 2	$1.16 \times 10^{-1}$ dB	4.04 Hz
Resonator 3	$1.16 \times 10^{-1}$ dB	2.66 Hz
Resonator 4	$1.16 \times 10^{-1}$ dB	2.01 Hz
Resonator 5	$1.16 \times 10^{-1}$ dB	1.75 Hz
Resonator 6	$1.16 \times 10^{-1}$ dB	1.32 Hz

**Fig. 4.** The sinusoidal input that changes its frequency mid-period.

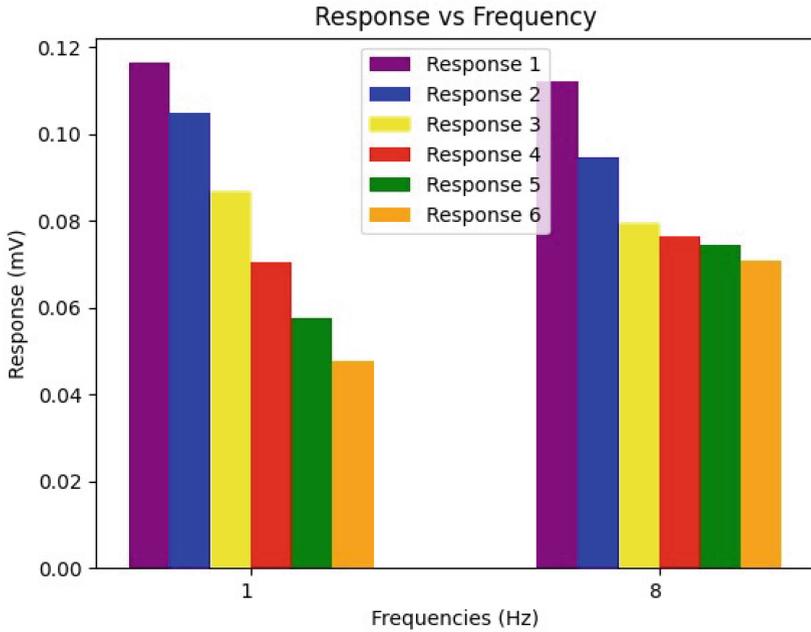


**Fig. 5.** The resonators’ response to a sinusoidal wave that had its frequency changed mid-cycle.

## 4 Discussion

To abstract the way in which parallel fibers in the brown ghost knife fish’s cerebellum cancel “expected” sensory feedback and apply it to a bioinspired robot control system, we created a series of resonators, each of which had a unique resonant frequency. In this preliminary investigation, we designed the resonator as a differentiator because the network functions as a high-pass filter, but every neuron in the network functions as a lowpass filter, resulting in a preferred frequency at which the response has the greatest [4]. As expected, each resonator in the group has a unique response to the input. The activity of the ensemble corresponds to the frequency of the input. In the future, we will extend the model such that each resonator inhibits the input with a unique synaptic delay, replicating some features of the parallel fibers in the cerebellum [1]. We will also test our system in more complex scenarios such as using noisy inputs with multiple-frequency components since the inputs we used for our preliminary work were an unnoisy, single-frequency sinusoid.

We anticipate that canceling redundant sensory information in this way will enable a robot to focus on novel, unexpected sensory stimuli. Such stimuli could be self-generated. In a ghost knife fish, moving the tail or the presence of another fish will alter the electrical feedback it receives in a way that can be predicted [6] and the feedback needs to adapt its prediction as these redundant signals change. Analogously, the movement of our robots can activate sensors along the leg that are intended to measure contact forces with the ground but can also be fooled by vibrations of the leg [7]. This results in temporary “false positive” detections of ground contact. We plan to build on this preliminary model to



**Fig. 6.** The resonators' response to a sinusoidal wave that had its frequency changed mid-cycle. Displays the changes between the maximum value of the original frequency and the maximum value after it has been altered.

predict the force feedback in response to the movement of the legs and cancel unwanted force feedback, which may eliminate false positives.

Canceling redundant sensory information may also make the robot more aware of changes in the environment. If it is already predicting forces in response to motion as described in the previous paragraph, it should be able to detect some environmental changes, e.g., walking from pavement onto ice. Canceling the expected force feedback from walking on pavement may make small changes in force feedback more apparent. Such changes in the environment could then trigger autonomous changes in robot behavior, e.g., trotting across firm ground but walking carefully over ice.

We hypothesize that a robot may learn to distinguish these scenarios through unsupervised learning mechanisms, in which it “clusters” similar sensory experiences together and applies the same behavior in response to similar experiences. We believe that canceling redundant sensory feedback as performed by parallel fibers in the cerebellum will facilitate such learning in the future. Also, we expect our system to function as an artificial cerebellum for the robot, integrating the sensory information received from an environment. We want to observe different factors that could help with real-time adaptation. We plan to look at joint angles, strain measurements, touch, and any other physical alterations the robot experiences externally from the environment that generates sensory

information that can be measured. This would allow the robot to eventually discern the difference between falling off a cliff or trudging through water.

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