Many-routes hypothesis of fear conditioning: A dynamical reservoir based approach

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1. Abstract

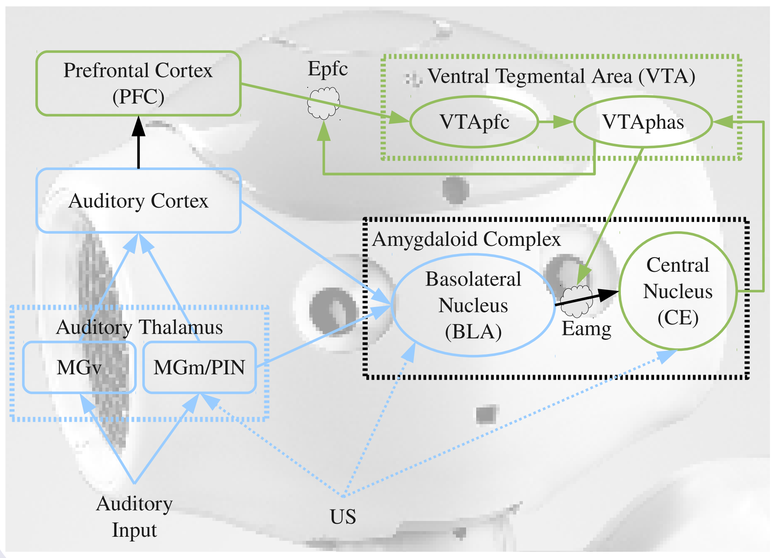
Classical fear conditioning has experienced a growing interest over the last decade. Fear learning mechanisms are a simple and robust learning paradigm that involves sensory and motor areas. We believe that a deeper study of these mechanisms will contribute not only to a better understanding of fear conditioning but also to the development of future robot generations.

2. System Overview

Here, we present a biologically motivated model of auditory cue conditioning. The model includes the known thalamic and auditory cortex routes plus reward learning based on phasic dynamics of dopamine.

We aim to develop a biologically plausible architecture able to run on a real humanoid robot. Our architecture is based on a reward prediction error model presented by Lowe, et al. 2009 [3]. We included three bio-plausible pathways to the amygdala, including the auditory thalamus, auditory cortex and prefrontal cortex (PFC).

Applications of this learning mechanism may be used in artificial self-protective systems, to predict both appetitive and aversive behavioral outcomes.



3. Methods

We developed a neural architecture for reward prediction learning. This architecture processes analog auditory input (single tones) in a time-averaged manner. A tone is selected *(CS)* and paired with an US signal. Light blue modules are layers of a feedforward neural network based on Armony's model [1]. The PFC module is modeled as the dynamical reservoir of an *"echo state network" (ESN)*. VTA_{pfc} is the readout layer of the ESN. E_{pfc} and E_{amg} are connection weights that are modified in real time using a Hebbian learning rule and an eligibility trace, based on Lowe's model [3].

Light blue modules activation use both a squashing function (ramp $[0, 1]$) and a winner-take-all algorithm. The winner unit inhibits laterally "loser" units.

Weights are updated using the Hebb-Stent rule [1]. Weight updates are computed as follows and then normalized:

$$W'_{ji} = \begin{cases} W_{ji} + \epsilon a_i a_j, a_j > \overline{a} \\ W_{ji} \quad \text{, otherwise} \end{cases}$$

Light green modules use a squashing function (ramp $[0, 1]$, denoted as f), except VTA_{phas} that uses a ramp $[-1, 1]$ denoted as g. Internal units in the PFC are updated as described in [2], but only allowing activation values between $[0, 1]$.

$$VTA_{phas} = g(CE - VTA_{pfc})$$

E_{pfc} and E_{amg} are computed as follows:

$$E_k = max(\text{incoming signal}, \Omega E_k(t-1))$$

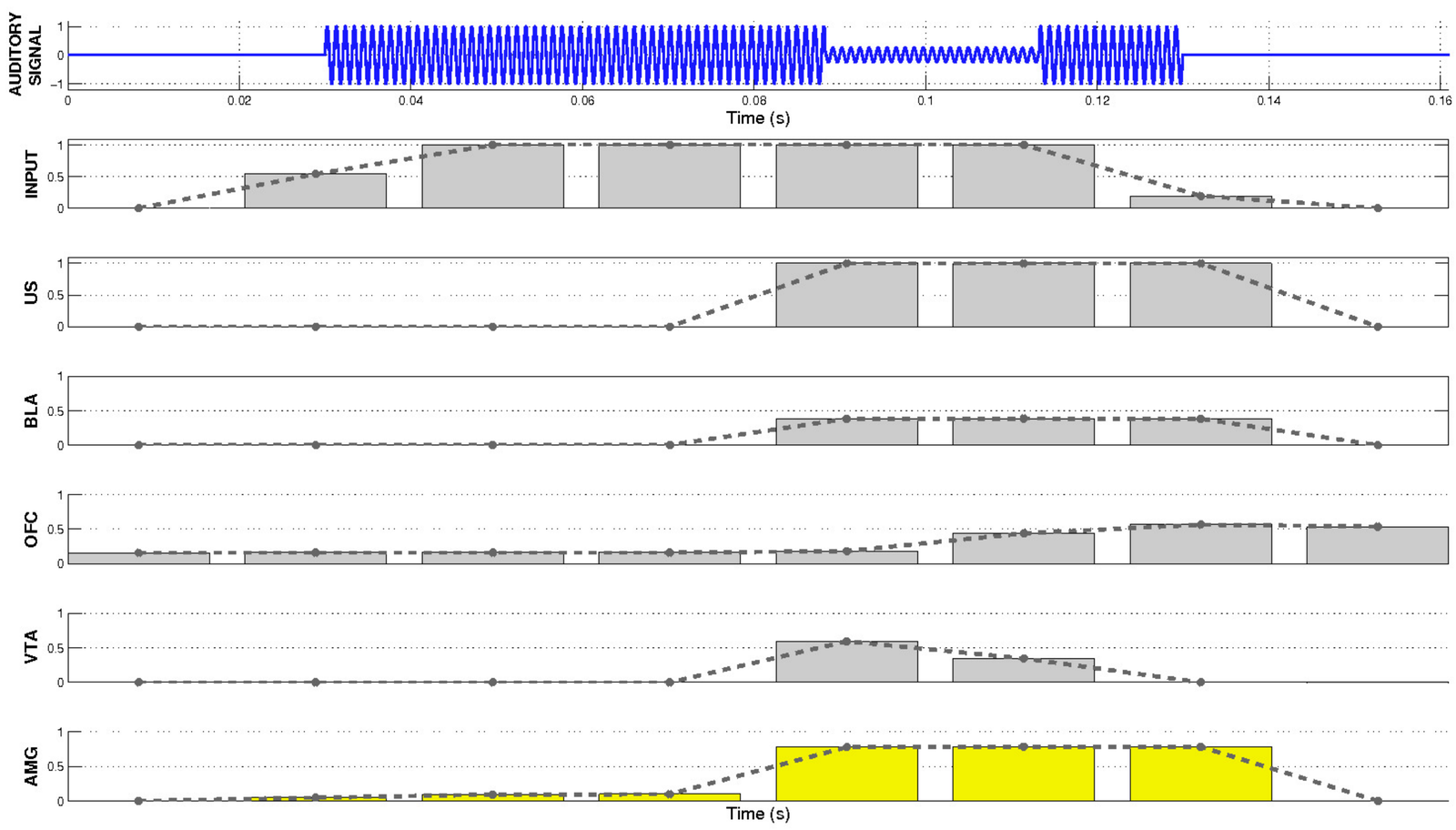
The ESN readout weight updates W_{pfc} and W_{amg} is done as follows. In both cases the upper equation applies when $VTA_{phas} <= 0$

$$W_{pfc_i} = \begin{cases} f(W_{pfc_i}(t-1) + \kappa VTA_{phas} PFC_i) \\ f(W_{pfc_i}(t-1) + \kappa VTA_{phas} PFC_i E_{pfc}) \end{cases}$$

$$W_{amg} = \begin{cases} f(W_{amg}(t-1) + \eta VTA_{phas} E_{amg}(US == 0)) \\ f(W_{amg}(t-1) + \eta VTA_{phas} E_{amg} CE) \end{cases}$$

Decay constant $\Omega = 0.9$, learning rate $\eta = 0.075$ and $\kappa = 0.1$ For all equations time dependence "(t)" was omitted and it is just indicated when is different from the current time step.

4. Experimental Results



The figure shows the avg. output of different modules in 20 ms time windows [1]. From the top: the blue curve represents the analog input signal modulated in amplitude (for clarity a signal of lower frequency is shown). 2nd row shows the neuron activation sensitive to the given frequency. 3rd row shows the US signal. 4th avg. output of the BLA. 5th OFC output. 6th VTAphas output. Last in yellow the response of the CE module.

After the conditioning phase the system was able to trigger (CE output) a reserved anticipatory response. The response strengthens when the US is presented. The architecture is able to discriminate between different frequencies. However, we observed an undesired low activation for frequencies close to the CS frequency, which vanishes for distal frequencies (approx. 1 octave away).

5. Conclusion

One of the limitation of the system is the limited anticipatory response of the system. We believe that a larger readout (VTA module) may play a key role improving the model in that respect. Improvements in the amygdaloid complex module are also required.

As part of future work, we would like to improve the implementation of all different modules, moving towards a more **biological plausible** implementation of them. Besides we would like to improve the architecture to process more complex auditory signals such as **spoken words**. We are thinking of including coarse visual input to finally test the architecture on a **real humanoid robot**.

References

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