A neurocomputational amygdala model of auditory fear conditioning: A hybrid system approach

Nicolás Navarro-Guerrero
Robert Lowe and Stefan Wermter
University of Hamburg
Dept. of Informatics, Knowledge Technology

http://www.informatik.uni-hamburg.de/WTM/

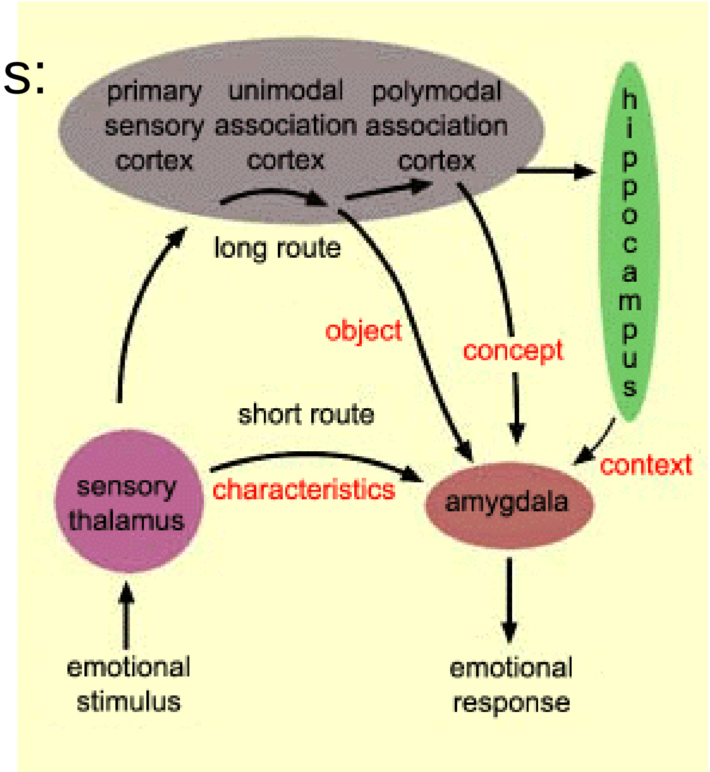
June 11, 2012

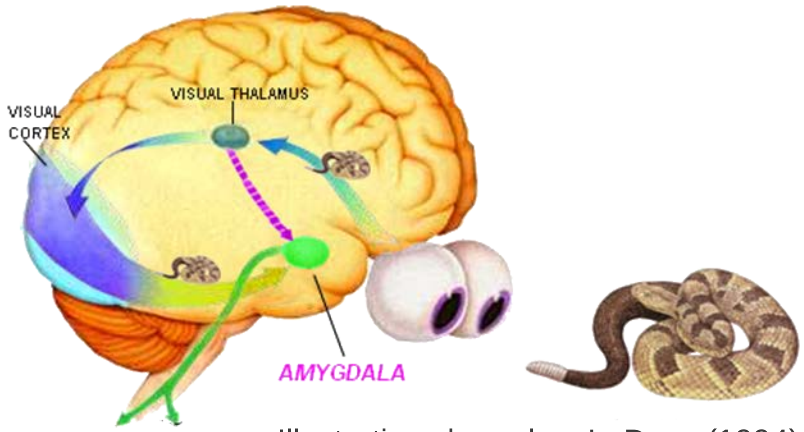
Fear circuits in the brain

Amygdala - attributing a value to appetitive and aversive situations

Learning to fear threats in the environment is:

- highly adaptive
- allows anticipation and
- organization of appropriate defensive behaviors, attention, etc.





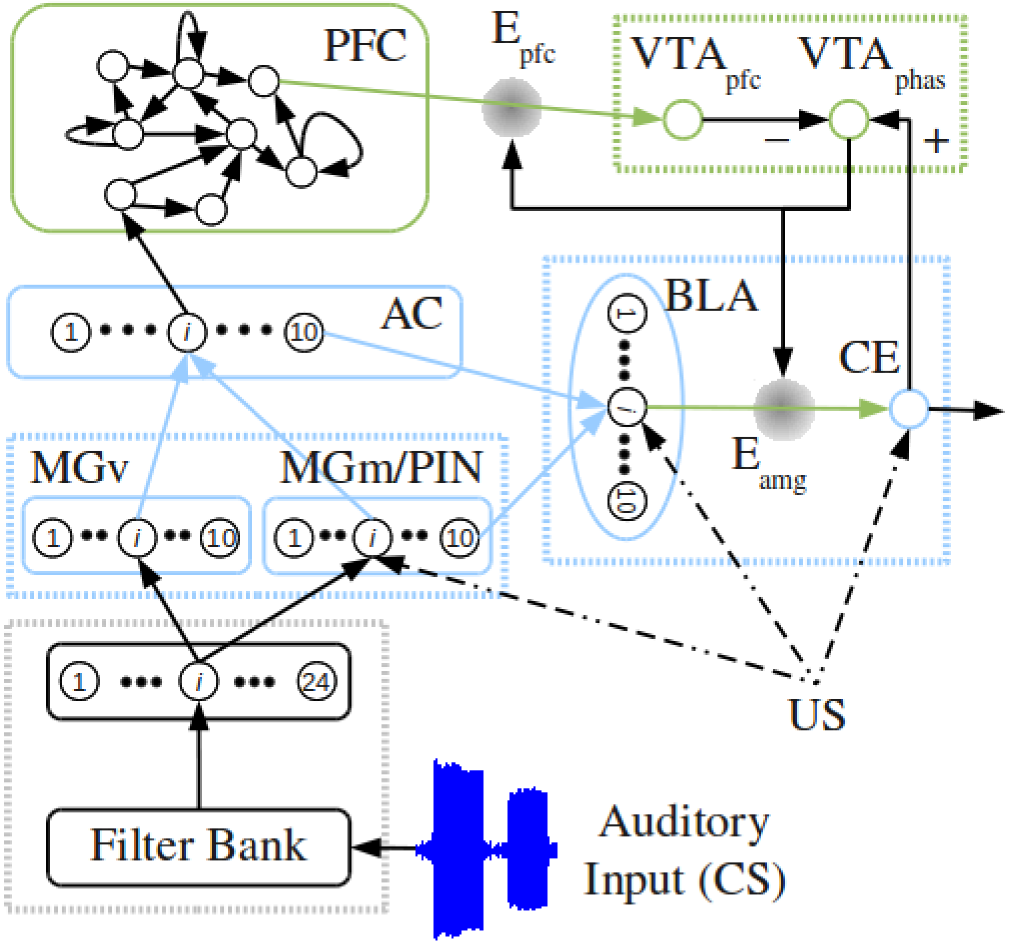
Illustrations based on LeDoux (1994) Emotion, Memory, and the Brain. Scientific American.

A computational architecture for fear conditioning dynamics

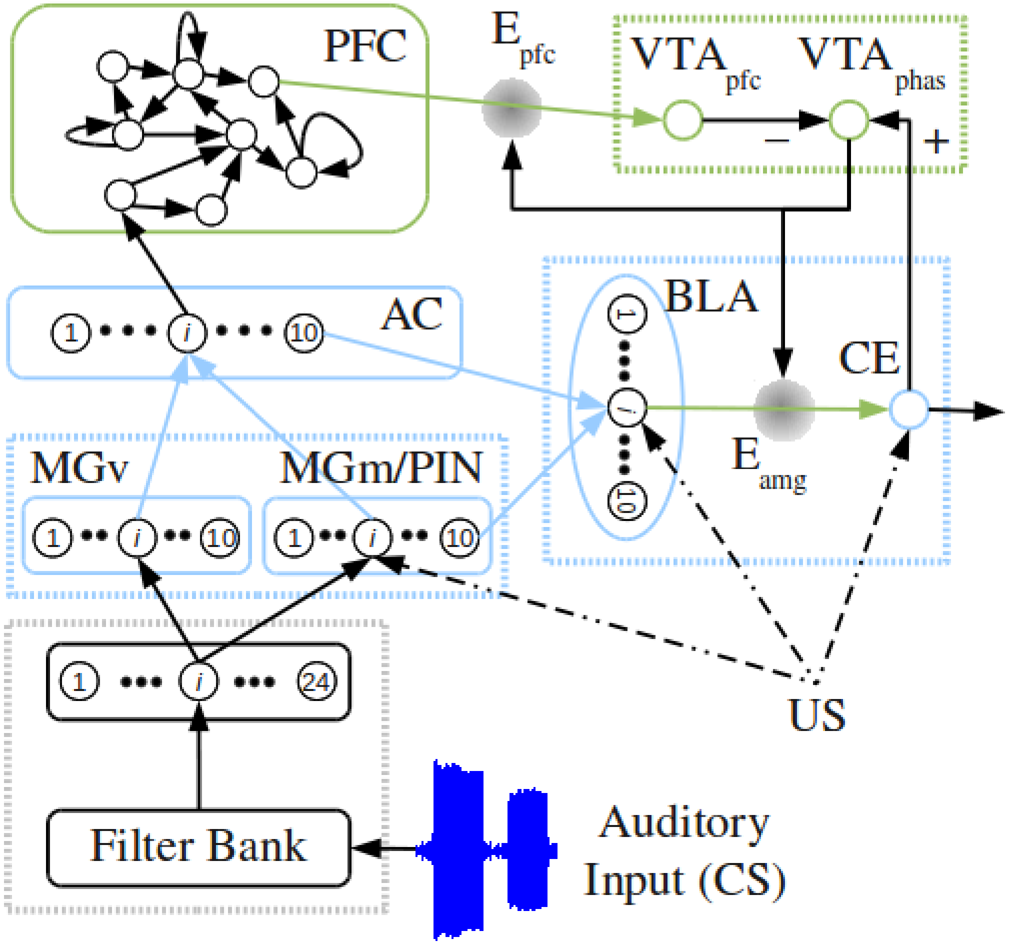
Pape, H.-C. and Pare, D. (2010). Plastic synaptic networks of the amygdala for the acquisition, expression, and extinction of conditioned fear. Physiological reviews, 90(2):419-463.

Armony, J. L., Servan-Schreiber, D., Cohen, J. D., and LeDoux, J. E. (1995). An anatomically constrained neural network model of fear conditioning. Behavioral neuroscience, 109(2):246-257.

Lowe, R., Mannella, F., Ziemke, T., and Baldassarre, G. (2011). Modelling coordination of learning systems: A reservoir systems approach to dopamine modulated pavlovian conditioning. Advances in Artificial Life. Darwin Meets von Neumann. 10th European Conference on Artificial Life (ECAL), vol. 5777 of Lecture Notes in Computer Science, pages 410-417, Berlin, Heidelberg. Springer-Verlag.



A computational architecture for fear conditioning dynamics - Implementation



$$a_{win} = f\left(\sum_{j\in S} a_j \cdot w_{ji}\right)$$

Lateral inhibition

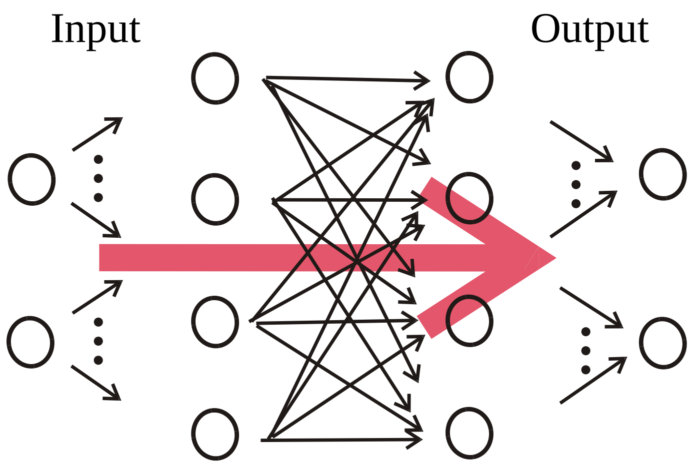
$$a_i = f\left(\sum_{j\in S} a_j \cdot w_{ji} - \mu_r \cdot a_{win}\right)$$

Weights update – Hebb-Stent Rule

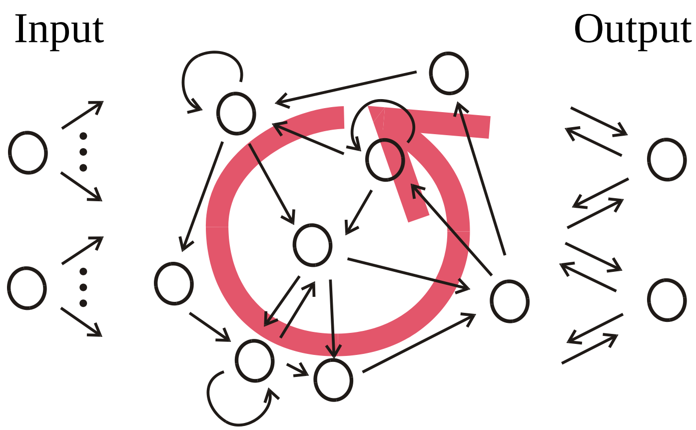
$$w'_{ji} = \begin{cases} w_{ji}(t-1) + \epsilon \cdot a_i \cdot a_j, & \text{if } a_j > \bar{a} \\ w_{ji}(t-1), & \text{otherwise,} \end{cases}$$

$$w_{ji} = \frac{w'_{ji}}{\sum_{j\in S} w'_{ji}},$$

Feedforward- vs. recurrent NN



- connections only "from left to right", no connection cycle
- activation is fed forward from input to output through "hidden layers"
- no memory



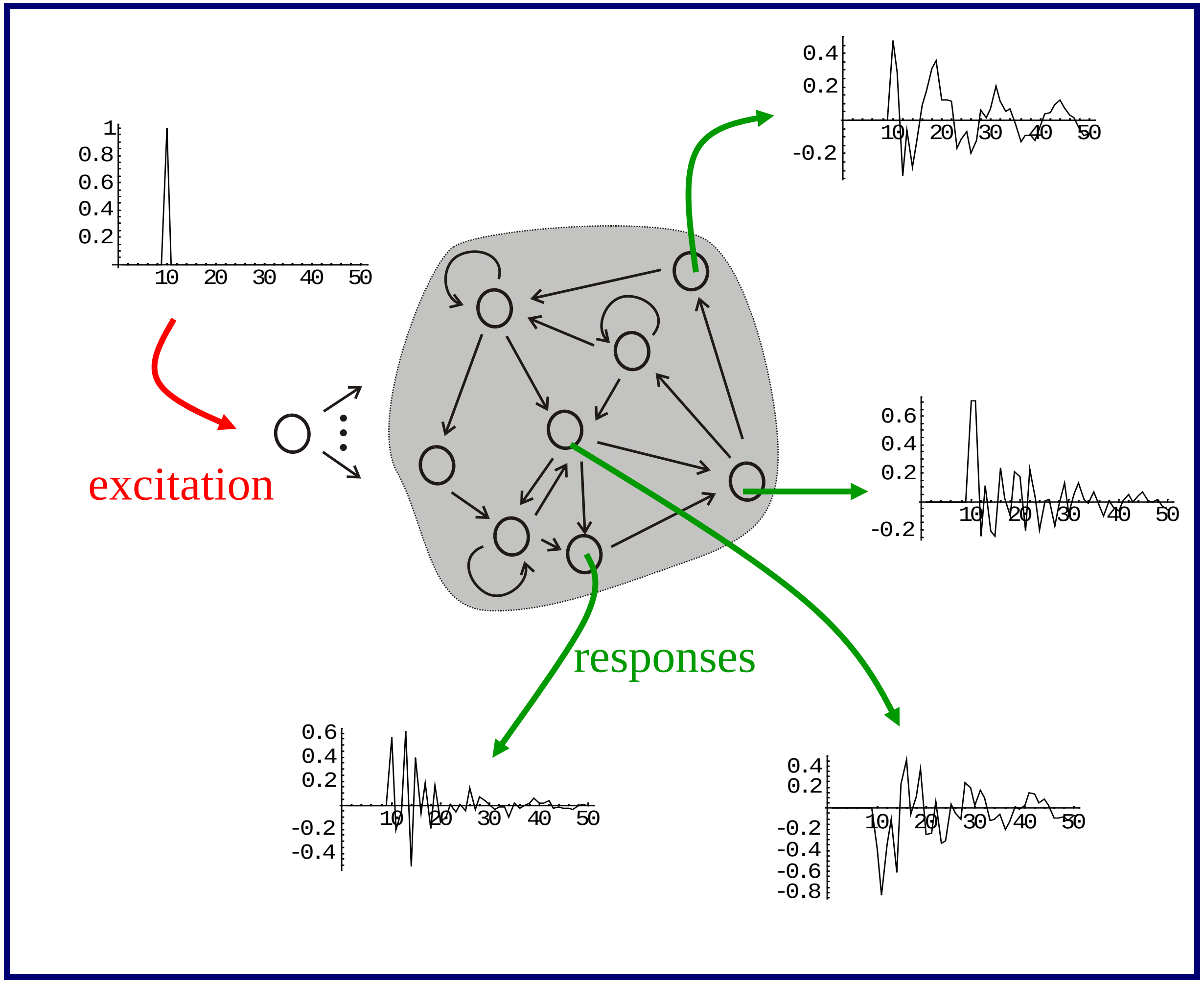
- at least one connection cycle
- activation can "reverberate", persist even with no input
- system with memory

Rich excited dynamics

Unit impulse responses should vary greatly.

Achieve this by, e.g.,

- inhomogeneous connectivity
- random weights
- different time constants



Notation and Update Rules

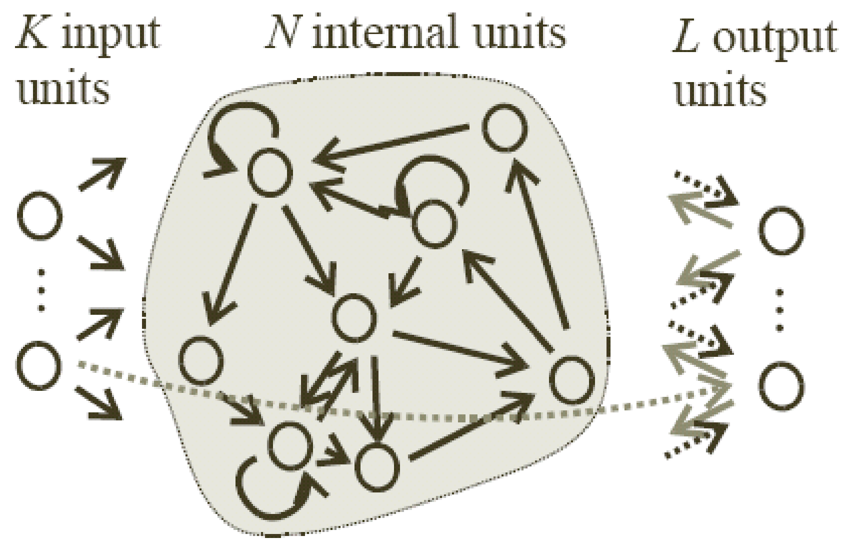
$$u(n) = (u_1(n),\ldots,u_K(n))'$$

$$x(n) = (x_1(n),\ldots,x_N(n))'$$

$$y(n) = (y_1(n),\ldots,y_L(n))'$$

$$W^{in} = (w_{ij}^{in}), W = (w_{ij}),$$

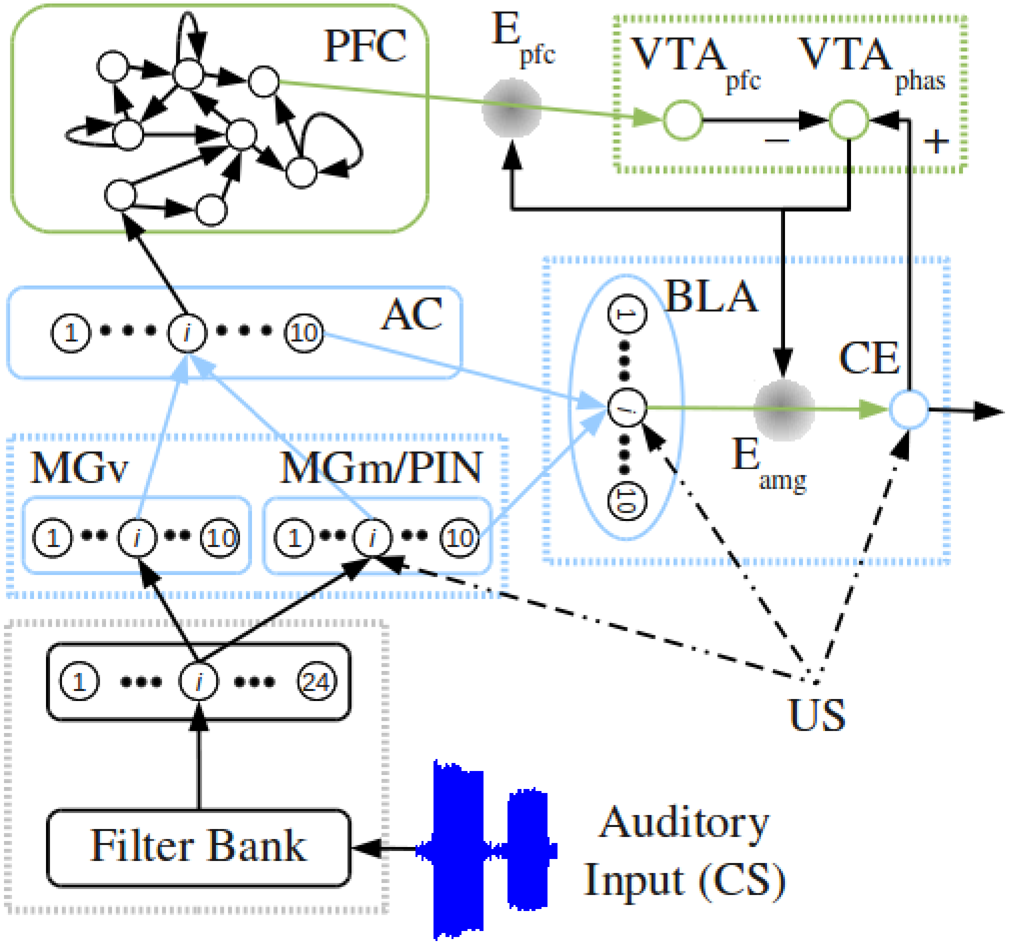
$$W^{out} = (w_{ij}^{out}), W^{back} = (w_{ij}^{back})$$



$$x(n+1) = f(W^{in}u(n+1) + Wx(n) + W^{back}y(n))$$

$$y(n+1) = f^{out}(W^{out}(u(n+1), x(n+1), y(n))$$

A computational architecture for fear conditioning dynamics - Implementation

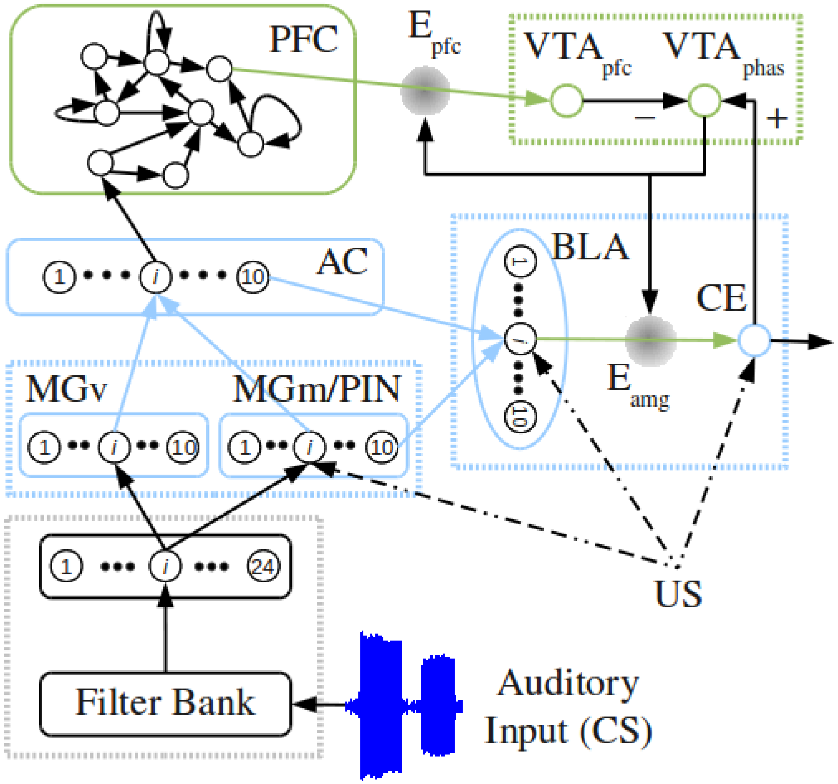


$$VTA_{phas} = g\left(CE - VTA_{pfc}\right)$$

$$CE = f\left(US \cdot w_{us} + \sum_i BLA_i \cdot w_{bla_i}\right)$$

$$E_k = max\left[\text{incoming signal}, \Omega \cdot E_k(t-1)\right]$$

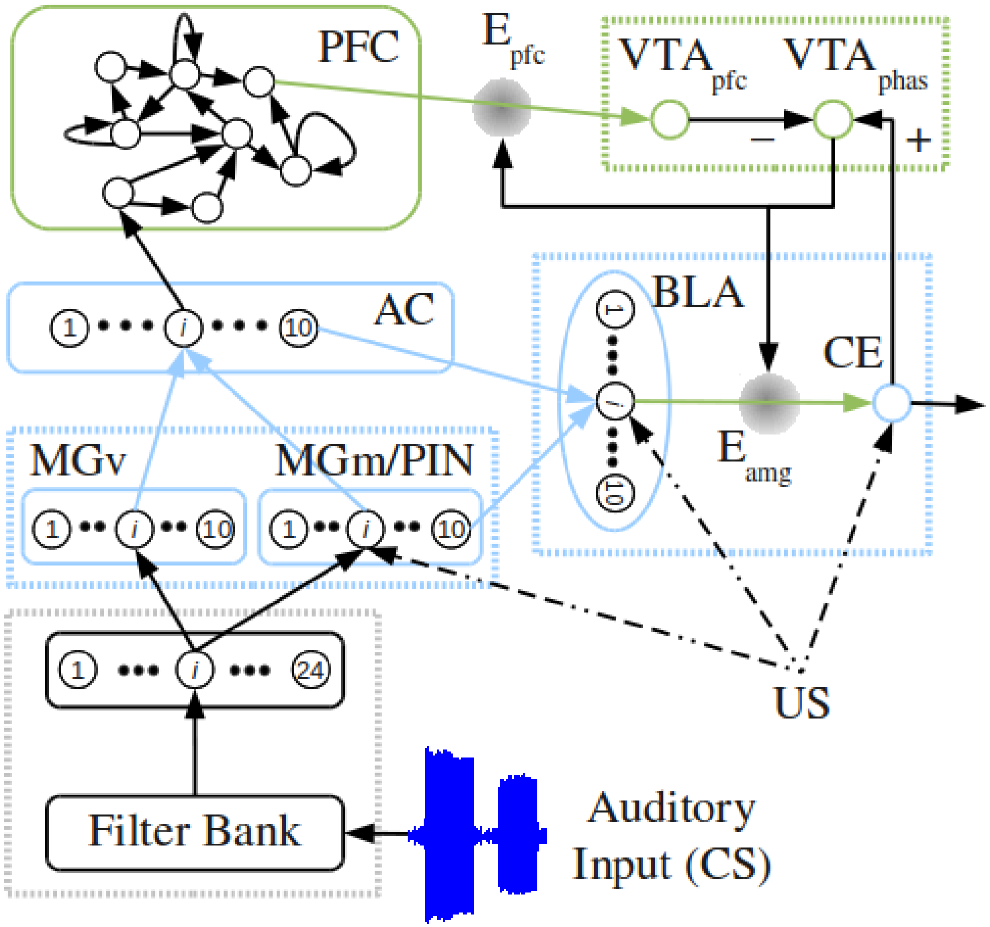
A computational architecture for fear conditioning dynamics - Implementation

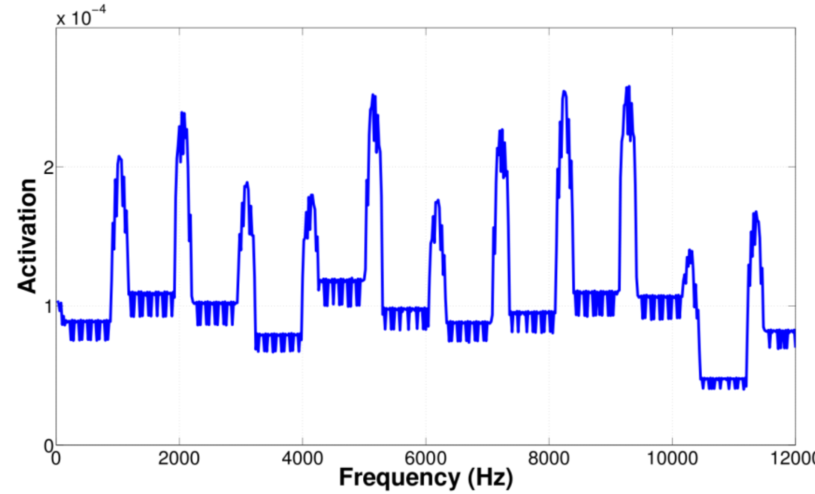


$$w_{pfc_i} = \begin{cases} f\left(w_{pfc_i}(t-1) + \kappa \cdot VTA_{phas} \cdot E_{pfc}(t-1) \cdot PFC_i\right), & \text{if } VTA_{phas} \geq 0 \\ f\left(w_{pfc_i}(t-1) + \kappa \cdot VTA_{phas} \cdot PFC_i\right), & \text{if } VTA_{phas} < 0 \end{cases}$$

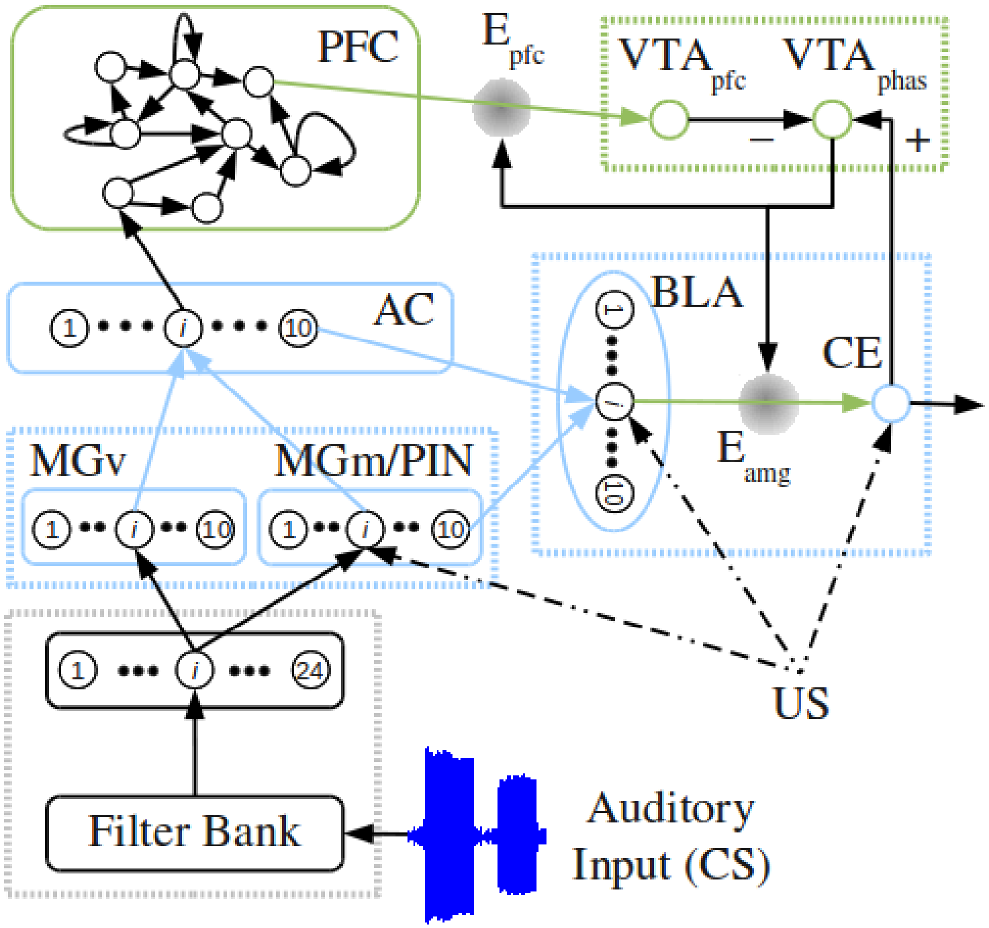
$$w_{bla_i} = \begin{cases} f\left(w_{bla_i}(t-1) + \eta \cdot VTA_{phas} \cdot E_{amg} \cdot CE\right), & \text{if } VTA_{phas} \geq 0 \\ f\left(w_{bla_i}(t-1) + \eta \cdot VTA_{phas} \cdot E_{amg}\right), & \text{if } VTA_{phas} < 0 \text{ and } US = 0 \end{cases}$$

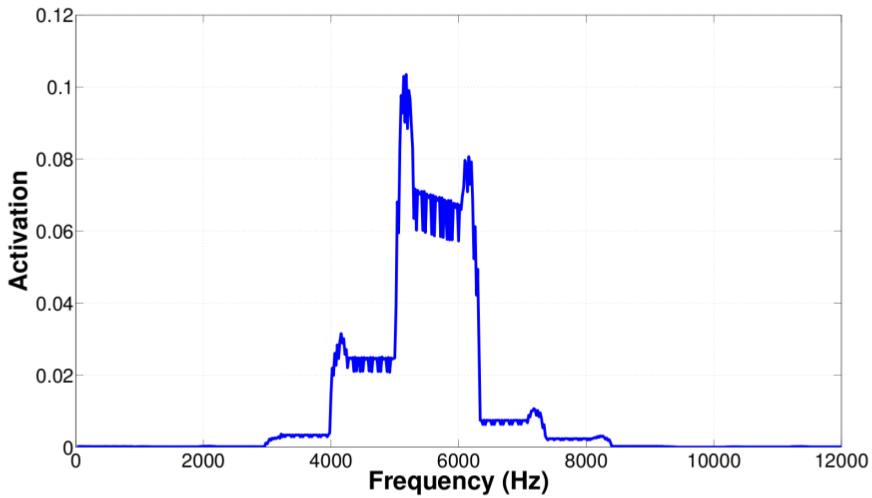
Receptive fields before conditioning



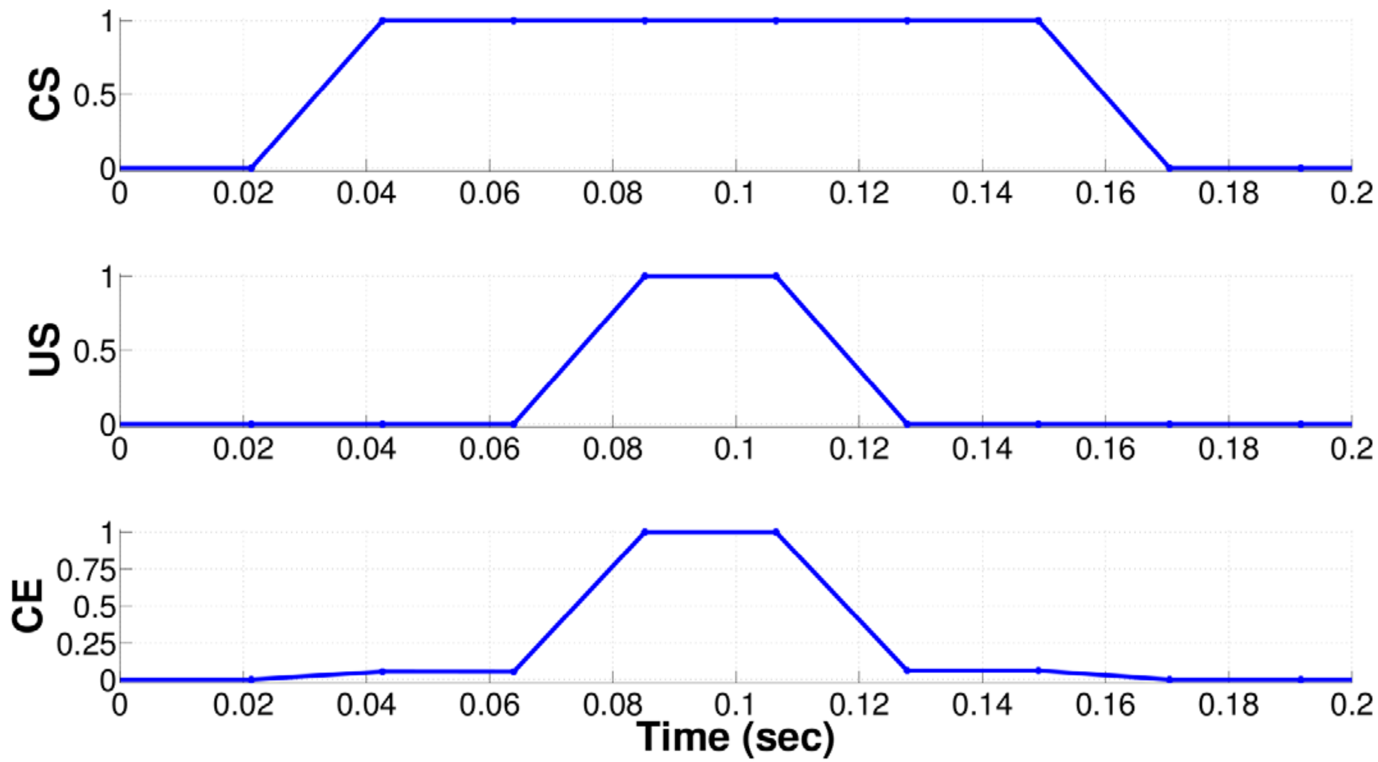


Receptive fields after conditioning





Activation profile after conditioning



Discussion

- Quick association of CS and US with good frequency discrimination.

Shortcomings

- PFC-VTA circuit reacts slowly. A different online weight update strategy is needed.

Future work

- Real-world testing
- Improve implementation of auditory pathway and CE module
- Add a recurrent network in the amygdala to store fear memories?

Intended test scenarios: Home-like environment

The End

Thank you for your attention.

Literature:

- J. L. Armony, D. Servan-Schreiber, J. D. Cohen, and J. E. LeDoux, “An anatomically constrained neural network model of fear conditioning,” Behavioral neuroscience, vol. 109, no. 2, pp. 246–257, 1995.
- R. Lowe, F. Mannella, T. Ziemke, and G. Baldassarre, “Modelling coordination of learning systems: A reservoir systems approach to dopamine modulated pavlovian conditioning,” in Advances in Artificial Life. Darwin Meets von Neumann. 10th European Conference on Artificial Life (ECAL), ser. Lecture Notes in Computer Science, vol. 5777. Berlin, Heidelberg: Springer-Verlag, 2011, pp. 410–417.
- H. Jaeger, “Tutorial on training recurrent neural networks, covering BPPT, RTRL, EKF and the “echo state network” approach,” Fraunhofer Institute for Autonomous Intelligent Systems (AIS), Tech. Rep. 159, 2002.