

# A Neurorobotic Model of Learning to Shake a Rattle

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## I. INTRODUCTION

Reward-modulated Hebbian learning is a biologically plausible neural learning mechanism that has been previously applied to a variety of learning tasks. For example, recent work used reward-modulated spike timing dependent plasticity (STDP) to help explain how infants learn to produce syllabic babbling [1]. This project attempts to extend this learning mechanism to a new domain of infant motor development, shaking a rattle. The experiment transduces neural spike trains to adjust frequency of sinusoidal movement around a robotic arm's articulation point. Reinforcement given when the volume, defined as the root mean square (RMS) amplitude, of sound made by a rattle attached to the robot arm exceeded the mean RMS of recent trials.

## II. METHODS

The robotic arm was constructed from 3D printed components on a PVC frame. Movement is controlled by a HiTEC HS-311 servo and Arduino microcontroller (Fig. 1). The Arduino waits for serial commands from MATLAB, using ArduinoIO [4]. A Bright Starts Rattle & Shake Barbell rattle was attached to one end of the arm and a counterweight was attached to the other

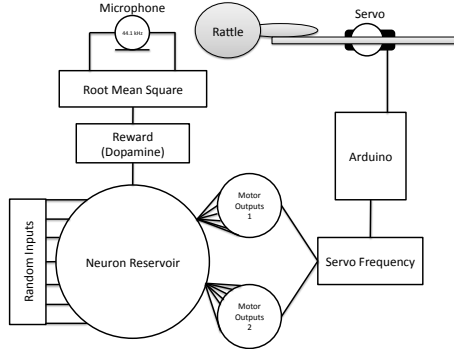


Fig 1: The robotic arm (left). Schematic of the electronic and neural system (right).

The neural network consisted of a reservoir of 1000 Izhikevich spiking neurons (800 excitatory, 200 inhibitory) with 100 randomly assigned synaptic connections outgoing from each neuron to other reservoir neurons [3], plus two motor output sinks with 50 motor neurons each. 100 excitatory reservoir neurons were fully connected to all the motor output neurons. After each second of simulated neural activity, the total number of spikes in each output group during the previous 900 ms were counted. The first group of output neurons preferred no movement and the second group preferred high frequency movement. The frequency,  $f$ , of the arm's back-and-forth movement was a scaled average of the two motor neuron groups' movement preferences, weighted by their spike counts (scaling parameters were chosen based on pilot experiments):

$$f = 10 \cdot \frac{14 \cdot \text{group 2 spike count}}{\text{group 1 spike count} + \text{group 2 spike count}} - 140 + 7.$$

The servo's target position,  $y$ , was then calculated according to:

$$y = 25 \sin\left(\frac{f\pi x}{180}\right) + 120,$$

where a  $y$  of 0 corresponded to the rattle being at the topmost point and 180 corresponded to it being at the bottommost point.  $x$  increased in increments of 1 from 1 to 100. Upon every increment of  $x$ ,  $y$  was sent to the Arduino microcontroller, and the MATLAB control was paused for .03 s before making the next increment. During the arm movement, sound was recorded from the internal microphone of the MacBook Pro controlling the simulations. The laptop was positioned with the microphone near the location of the rattle. Root mean square amplitude (RMS) of the sound was calculated:

$$RMS = \sqrt{\frac{\sum_{t=1}^T A^2(t)}{T}},$$

where  $A$  is the audio waveform,  $t$  are the samples in the audio recording time series, and  $T$  is the total number of samples. Each sound was 3.3 s and the audio sampling rate was 44.1 kHz. Although the servo contributed some sound to the RMS value, pilot explorations indicated that rattle shaking reliably led to larger amplitude sounds being superimposed on those servo-generated sounds. If RMS was greater than the average RMS of the previous 10 trials, the model was rewarded, which corresponded to a

spike in DA. The presence of DA increased the magnitude of STDP. Learning via DA-modulated STDP took place only at connections between the reservoir and the output motor neurons; all connections within the reservoir remained static at randomly initialized values.

We performed 10 runs of the model, each lasting 300 simulated seconds. For each run, we also ran a yoked control model, which had independent random weight initializations and random inputs, but had rewards corresponding to one of the 10 RMS-reinforced runs. The RMS-reinforced and yoked control runs were interleaved. Both the arm apparatus and computer were securely mounted to a desk and remained so for all runs. Runs took place in an unoccupied room to minimize environmental noise, although sounds from air vents, a refrigerator, automatic blinds, and computers were present.

### III. RESULTS

Fig. 2 a and b show the servo control parameter,  $f$ , and the resulting RMS for Run 4 and its yoked control. Over time, the RMS-reinforced run shows increasing RMS as well as increasing  $f$ ; these change little for the yoked control. Fig. 2 c shows a linear model of the changes in RMS across all the RMS-reinforced and the yoked control runs. A linear mixed effects model indicated that RMS-reinforced models had significantly higher RMS values than the yoked control models,  $\beta = -0.73$ ,  $p < .001$ , and increasing simulation time corresponded to higher RMS,  $\beta = .26$ ,  $p < .001$ , where  $\beta$  is the standardized regression coefficient. There was a significant interaction between simulation time and simulation type, with the RMS-reinforced simulations increasing RMS more than the yoked control simulations,  $\beta = -0.20$ ,  $p < .001$ . Fig. 3 d shows the relationship between  $f$  and RMS. Higher frequencies produce louder volumes, though there is a ceiling effect beginning at around  $f > 12$ .

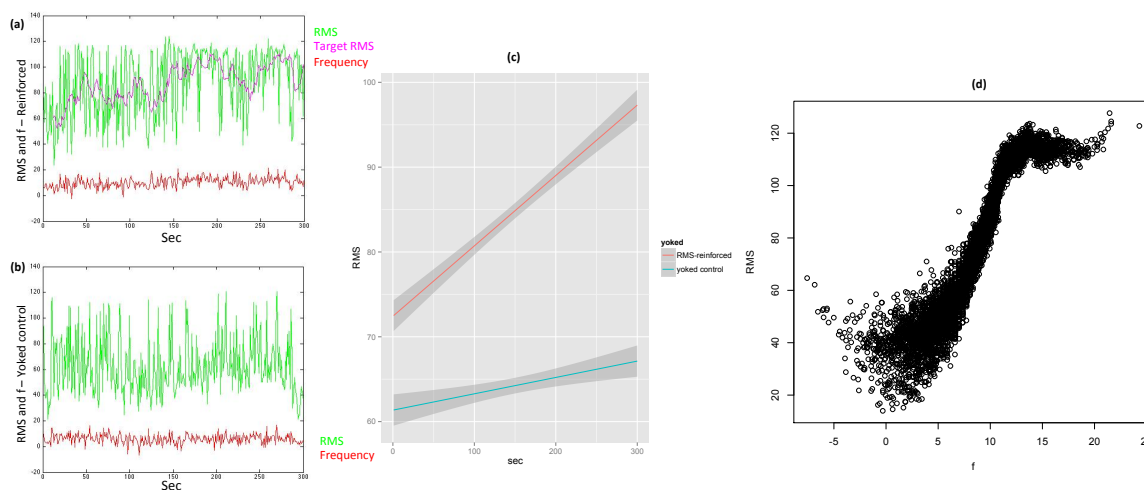


Fig 2: Run 4's (a) and its yoked control's (b) control frequency and RMS data. (c) Linear model of the change in RMS over time for reinforced vs yoked runs. (d) The relationship between  $f$  and RMS.

### IV. CONCLUSIONS AND FUTURE DIRECTIONS

We presented an initial model of infant rhythmic rattle shaking. Frequency oscillatory movement by a robotic arm was controlled by a spiking neural network; high sound amplitude led to immediate dopamine reward, increasing the network's STDP learning rate. Sound amplitude increased over time compared to yoked control simulations. Future research should explore whether the form of movement can be itself learned rather than assuming oscillatory movement, and movement dynamics should be compared to human data. Variations in the neural network architecture, such as biologically plausible architectures where dopamine reflects reward prediction error, would also be good to explore. Other models of auditory processing and of intrinsic reward, e.g. using more sophisticated notions of auditory saliency or taking into account the formation of auditory-motor correspondences should also be explored. Finally, future work should aim to combine models of rhythmic vocal development and rhythmic limb movement development, to help account for the close relationship between the two in human infancy [5,6,7].

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