

Training a Spiking Neural Network using R-STDP to perform Autonomous Target Tracking on a Snake Car Robot

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September 23, 2018

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Contents

SNN and the Planar snake car model

- Spiking Neuronal Networks are promising for robotics
- **BUT** they can't be trained using gradient descend methods
- Snake-like robots are very mobile
- Simple planar snake robot with slithering gait model and wheels
- Highlevel controll using SNN

Task: Target Tracking

- Target Tracking

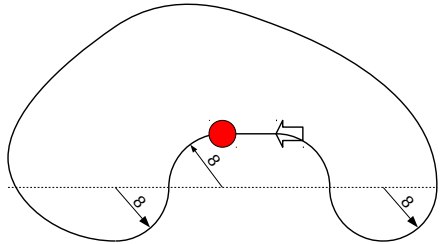


Figure 1: Target tracking SNN evaluation environment.

Task: Target Tracking

- Target Tracking
- Prevent collisions with walls

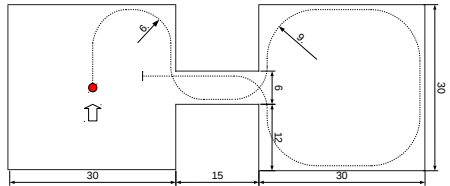


Figure 2: Evaluation environment

Target Following SNN

- Infrared image input 16×4 pixel resolution

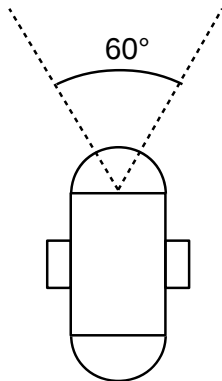


Figure 3: Infrared vision sensor

Target Following SNN

- Infrared image input 16×4 pixel resolution
- Image preprocessing

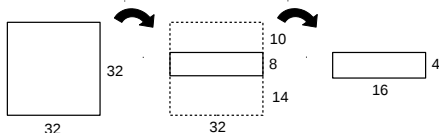


Figure 4: Image preprocessing in 3 steps

Target Following SNN

- Infrared image input 16×4 pixel resolution
- Image preprocessing
- 64 Poisson input neurons
- Feed forward architecture
- Left and Right LIF output Neurons

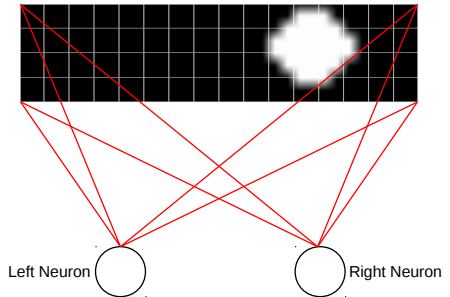


Figure 5: Target following SNN architecture

Target Following SNN cont.

- Output interpreted as angle

$$\text{decode}(n_{\text{spikes}}) = \frac{n_{\text{spikes}}}{n_{\text{max}}}$$

$$\alpha = \alpha_{\text{max}} (n_l - n_r)$$

$$\alpha_t = c\alpha + (1 - c)\alpha_{t-1}$$

Target Following SNN cont.

- Output interpreted as angle
- Reward depends on Angle between head module and target

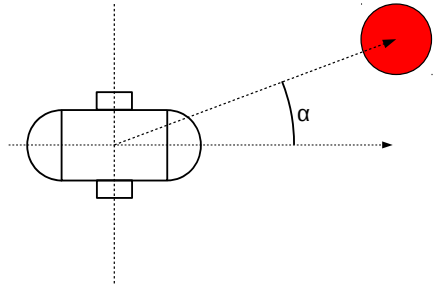


Figure 6: Angle between robot head module and target.

Target Following SNN cont.

- Output interpreted as angle
- Reward depends on Angle between head module and target
- Left and right neuron get the opposite rewards of each other

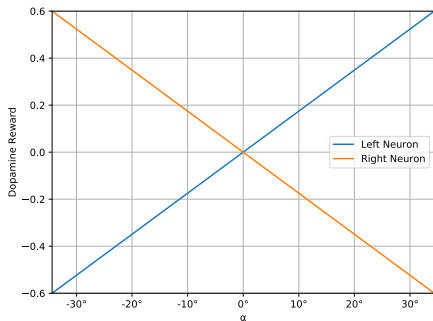


Figure 7: Target following reward function

Obstacle Avoidance SNN

- Four proximity sensors

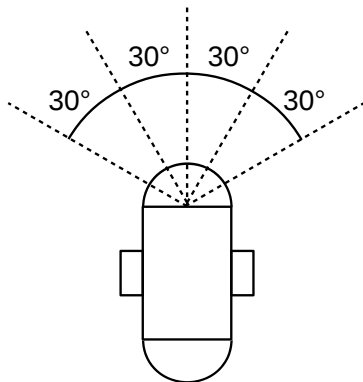


Figure 8: Proximity sensors

Obstacle Avoidance SNN

- Four proximity sensors
- Proximity data preprocessing
- Data in range $[0; 3]$
- Mapped to range $[0 : 1]$
- 0: No obstacle or at maximum distance
- 1: Close obstacle

Obstacle Avoidance SNN

- Four proximity sensors
- Proximity data preprocessing
- 4 Poisson input neurons
- Feed forward architecture
- Left and Right LIF output Neurons

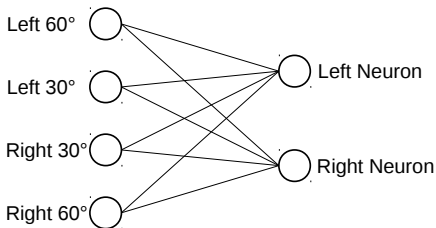


Figure 9: Obstacle avoidance SNN architecture

Obstacle Avoidance SNN cont.

- Output interpreted as angle

$$\text{decode} (n_{spikes}) = \frac{n_{spikes}}{n_{max}}$$

$$\alpha = \alpha_{max} (n_l - n_r)$$

$$\alpha_t = c\alpha + (1 - c) \alpha_{t-1}$$

Obstacle Avoidance SNN cont.

- Output interpreted as angle

$$\text{decode} (n_{spikes}) = \frac{n_{spikes}}{n_{max}}$$

$$\alpha = \alpha_{max} (n_l - n_r)$$

$$\alpha_t = c\alpha + (1 - c) \alpha_{t-1}$$

- Event based rewards on Episode failure
- Left and right neuron get the opposite rewards of each other
- 4 Reward cases, collision and target lost, obstacle left or right side

Training

- Training environments

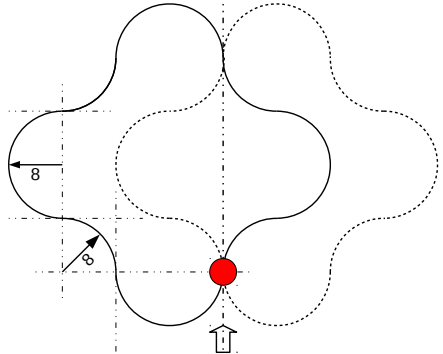


Figure 10: Target tracking SNN training path.

Training

- Training environments

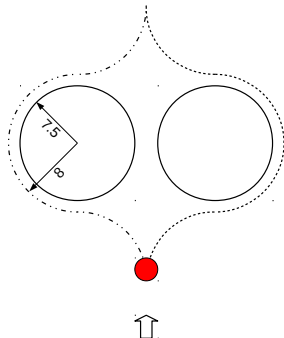


Figure 11: Obstacle avoidance SNN training path.

