Biomimetic Functions with Magnetic Tunnel Junction-Based Networks: Target Anticipative Tracking and Multisensory Information Integration

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Abstract: A population coding strategy based on superparamagnetic tunnel junctions (SMTJs) is a natural platform to implement the brain-inspired unconventional probabilistic computing. Continuous attractor neural networks (CANNs) consisting of SMTJs are applied for anticipative tracking of target motion and multisensory information integration with a decentralized structure. Using the head direction motion, we show the anticipative tracking of a SMTJs-based CANN, and its dynamics can be theoretically described by a group of travelling line. The results reveal the connection improves the performance and can be greatly reduced by SMTJs. The strategy with multiple independent CANNs also presents high price performance in anticipative tracking of high-dimensional motions. Besides, using the head direction inference combining different sensory information, we demonstrate our proposed model has a wide range of network parameters and its performance is better than the standard Bayesian inference. The model is very robust against the different sources of noise, the different breakdowns of module and the diversity of magnetic components.

1. Random magnetization reversal in SMTJ

Thermally induced stochastic magnetization reversal in MTJ has been reached nanosecond scale experimentally.

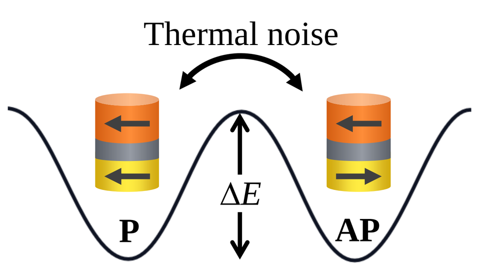

Fig. 1 Schematic diagram of principle. SMTJ is composed of fixed layer, tunnel barrier and free layer.

2.1. The model for anticipative target tracking

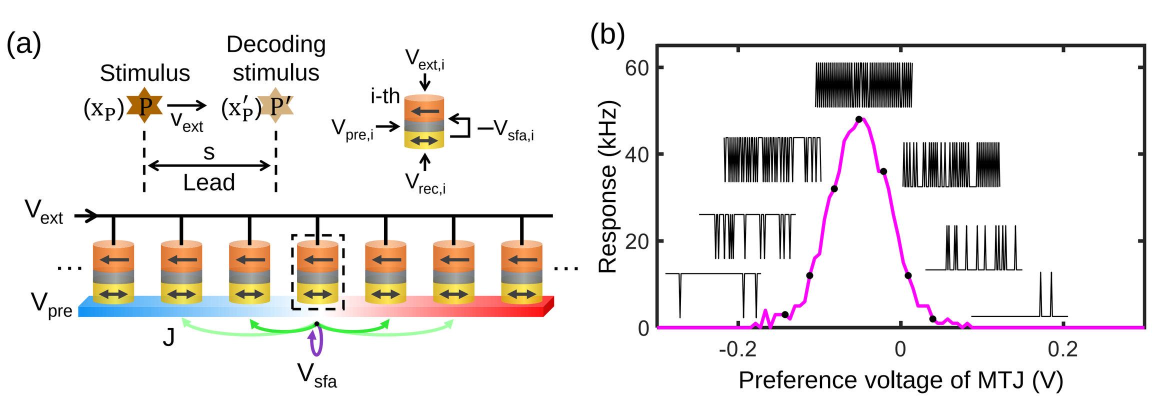

Fig. 2 (a) The structure of CANN with SMTJs for the anticipative tracking. (b) Responses of the network.

2.2. The anticipative tracking behaviour

- Predicted displacement proportional to velocity.

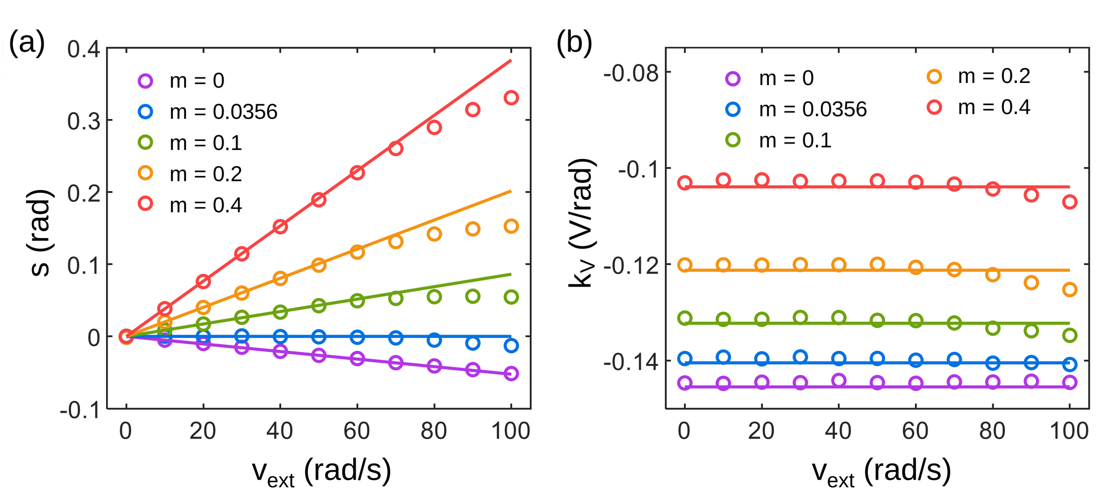

Fig. 3 Effects of network parameters on the anticipative tracking. Hollow circles and solid lines represent the simulation and theoretical results respectively.

2.3. High-dimensional anticipative tracking

- High price performance.

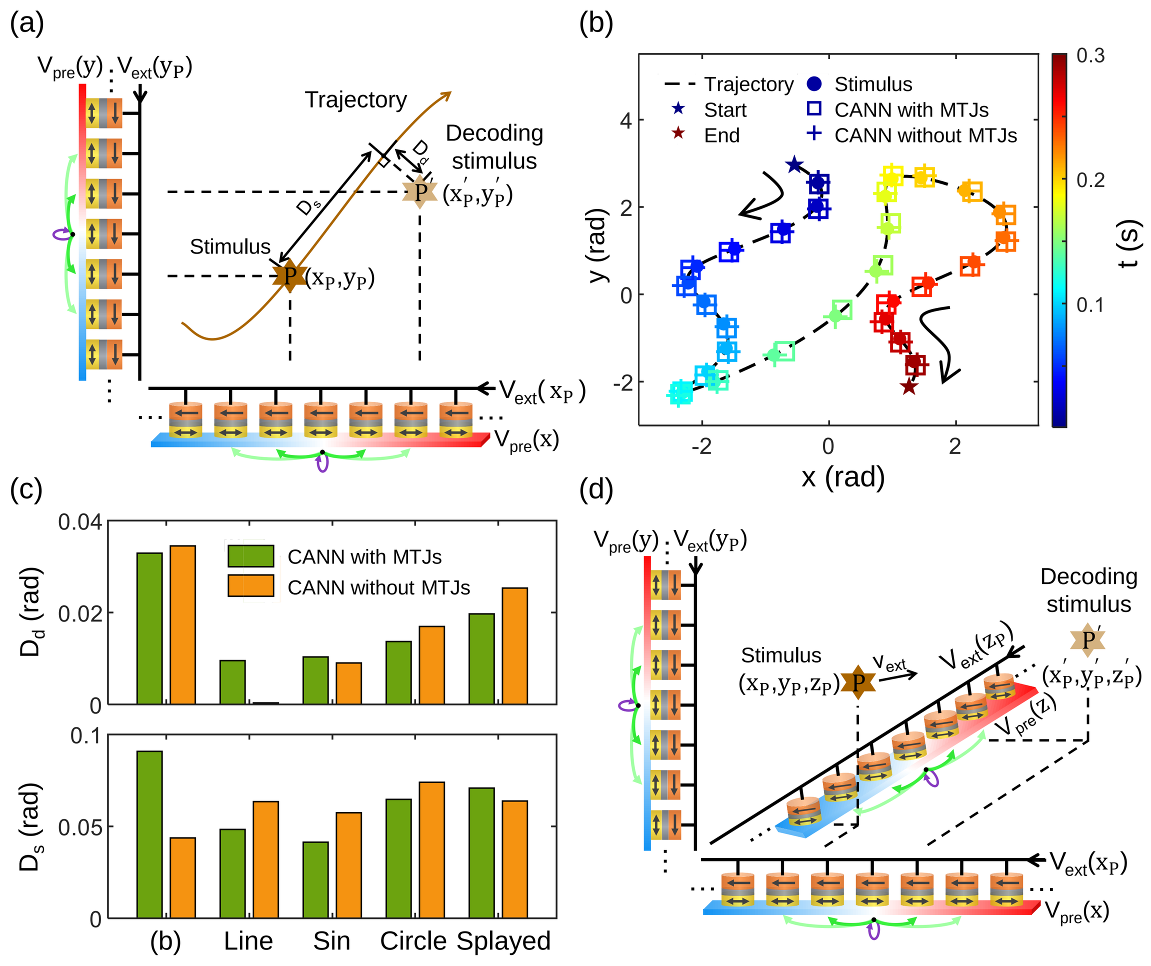

Fig. 4 Anticipative tracking of 2D (3D) target movements with two (three) independent CANNs consisting of SMTJs.

3.1. The model for information integration

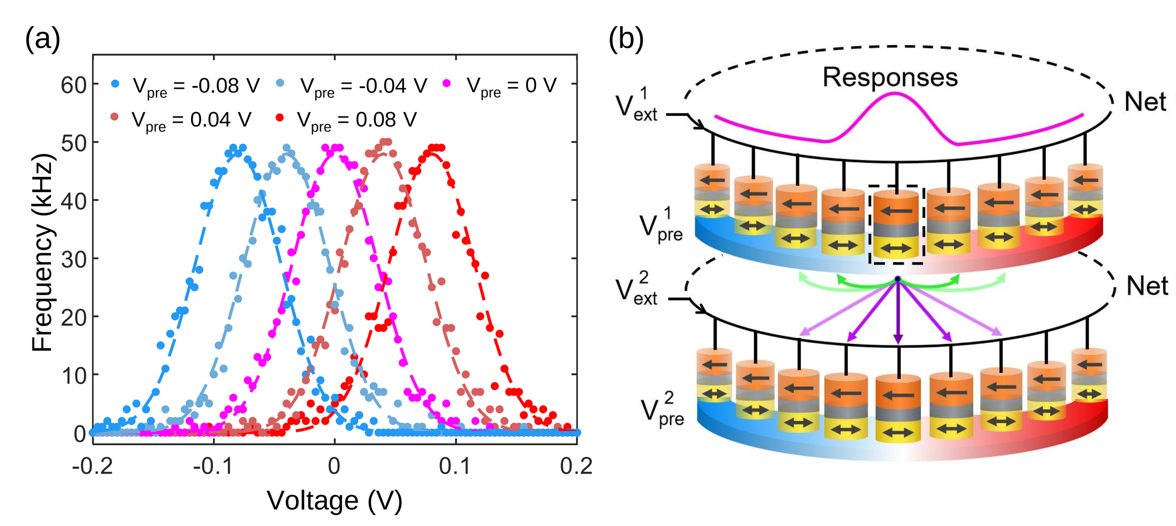

Fig. 5 (a) Network structure for decentralized model. (b) Magnetization switching frequency for SMTJ as functions of voltage for different bias voltages.

3.2. The role of recurrent connections in a CANN

- Memorizing the stimulus information.
(After the stimulus disappears, holding a bell-shaped response with the gravity center around the external stimulus)
- Improving the accuracy of encoding.
(the reduction of network estimation's variance and deviation)

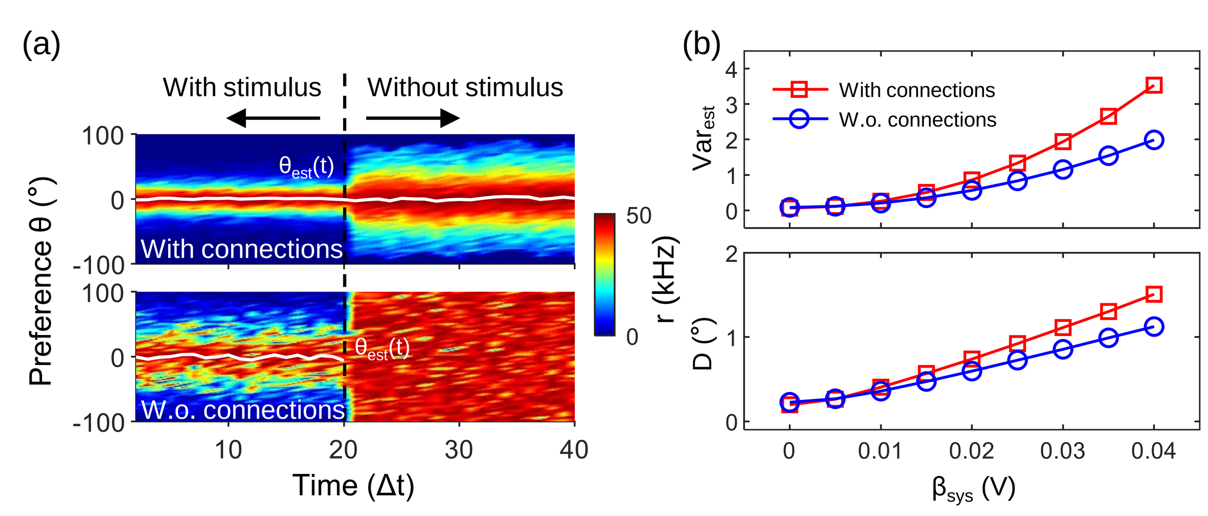

Fig. 6 (a) Population activities of a CANN with and without stimulus. (b) The deviation of the network estimation from the real stimulus and the variance of the network estimation as functions of the system noise strength.

3.3. The role of reciprocal connections in CANNs

- Significant suppression of the system and input noises.
- The reccurrent connection has little effect on the input noise

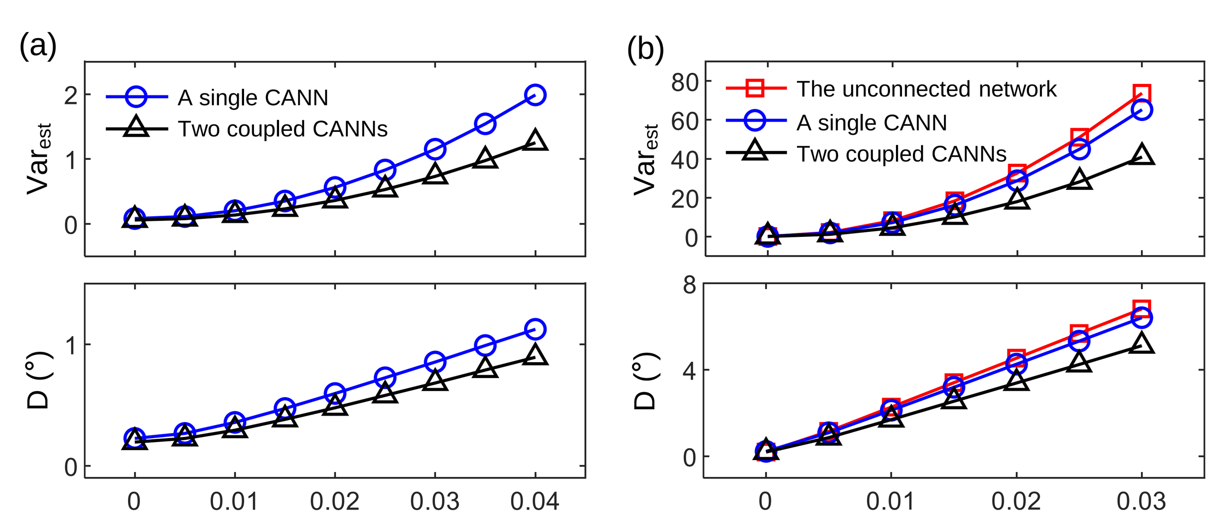

Fig. 7 The deviation of the network estimation from the real stimulus and the variance of the network estimation as functions of the noise strength, (b) the input noise strength and (c) the system noise strength.

3.4. Network's responses and estimation

- Improving the accuracy of integrated information.
(the reduction of network estimation's variance)

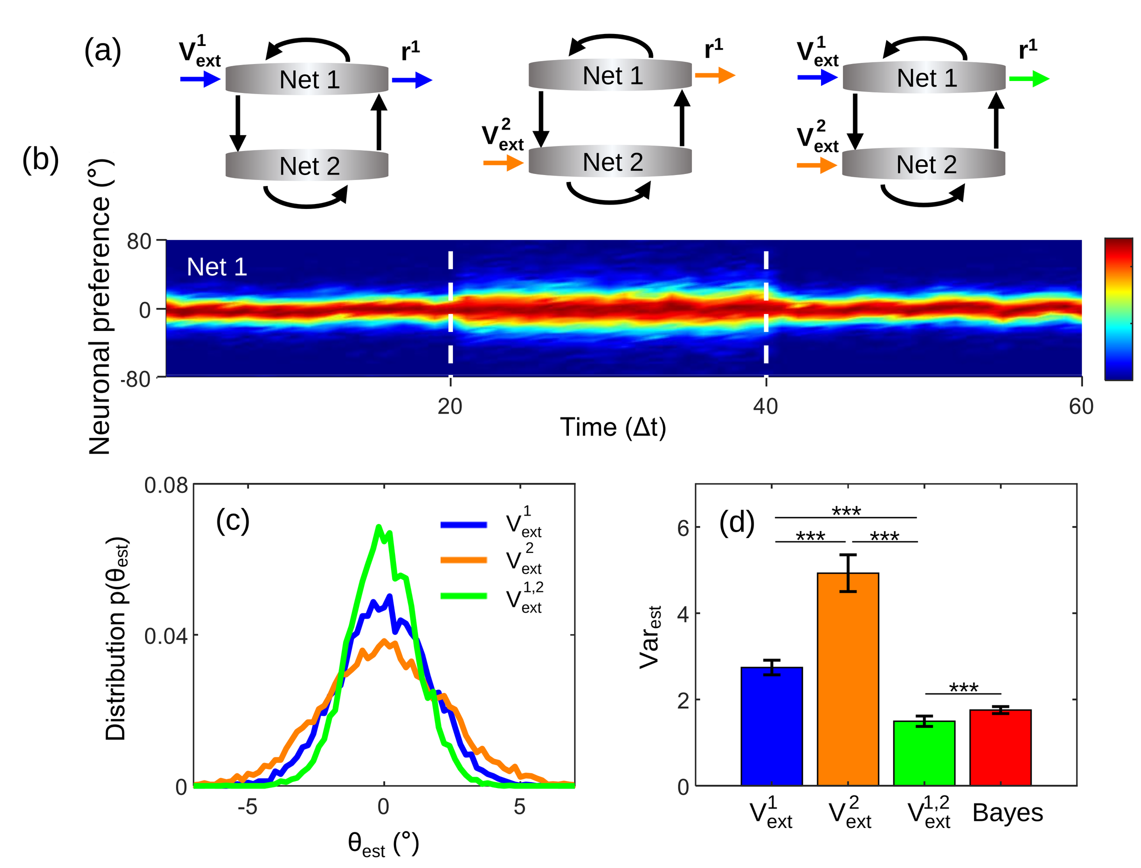

Fig. 8 (a) Schematic diagram of the three stimulus conditions applied to the system. (b) Population activities of network 1 for the three input conditions in a temporal order. (c) Distribution of the extracted position. (d) The mean variance obtained using the estimation of network 1.

3.5. Decentralized multi-information integration

- Robust information integration in module failures.
(The variance of the network estimates is slightly lower than that of Bayesian inference)

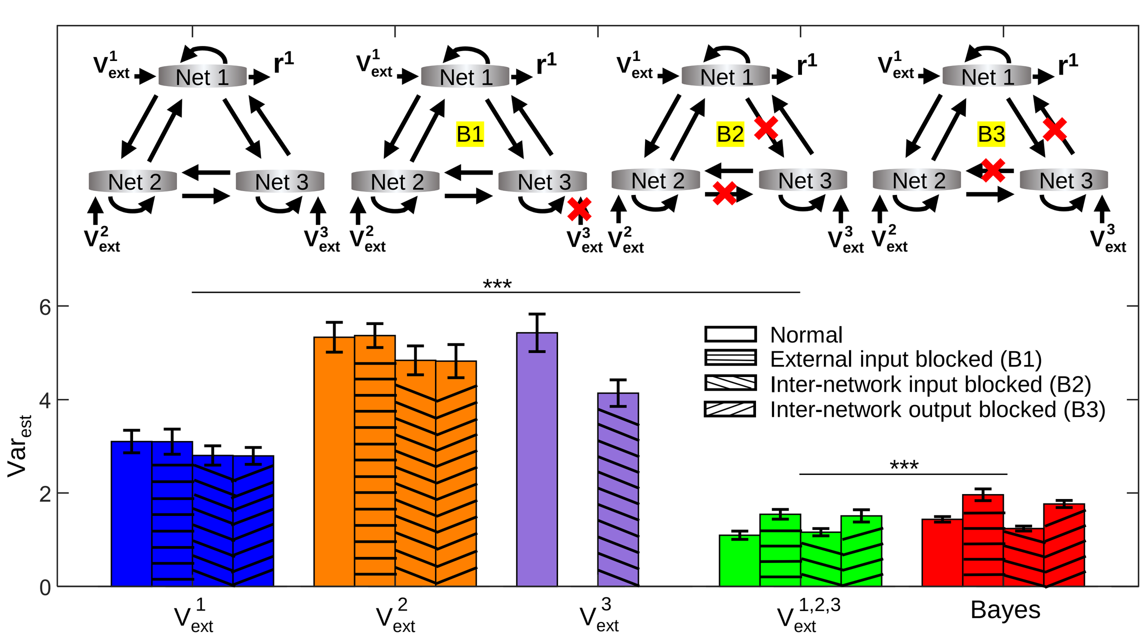

Fig. 9 Top insets illustrate the system consisting of three CANNs. The bottom histograms show the calculated average variance from network 1 under the four input conditions shown in top insets.

4. Reference

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