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A novel spiking neural network of receptive field encoding with groups of neurons decision

Key words: Tempotron; Receptive field; Difference of Gaussian (DoG); Flip invariance; Rotation invariance

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Motivation

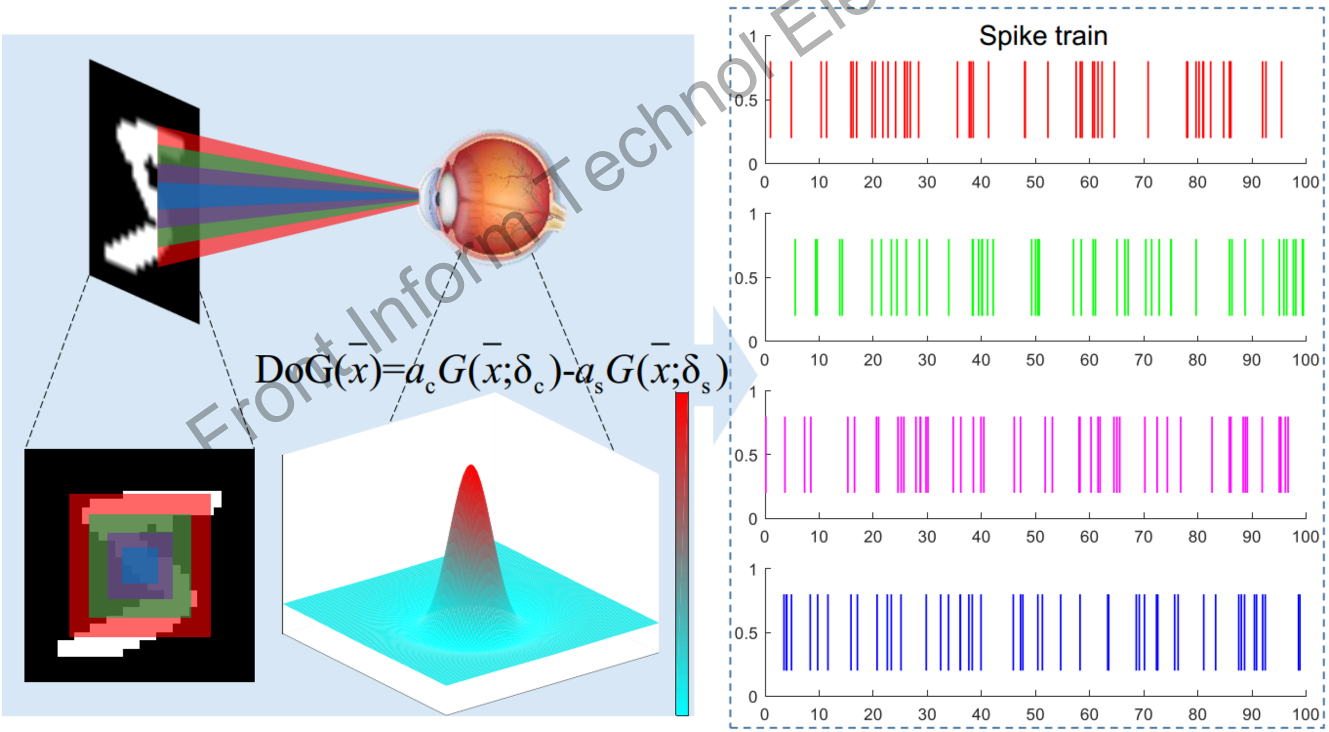
- A lot of ANNs can do classification well; however, it is difficult to construct these networks, and the training cost is high. We need an effective structure that is closer to a biological neural network.
- Although we do not know how to convert stimulus signals into spike trains in biology until now, a suitable encoding is needed for SNN.
- For the human, we can identify objects no matter whether it is flipped or rotated, and we can learn a new concept from a few samples.

Main idea

- Using receptive field to encode spike trains from images
- Randomly selecting partial spikes as inputs for each neuron to approach the absolute refractory period of the neuron
- Using groups of neurons to make decisions

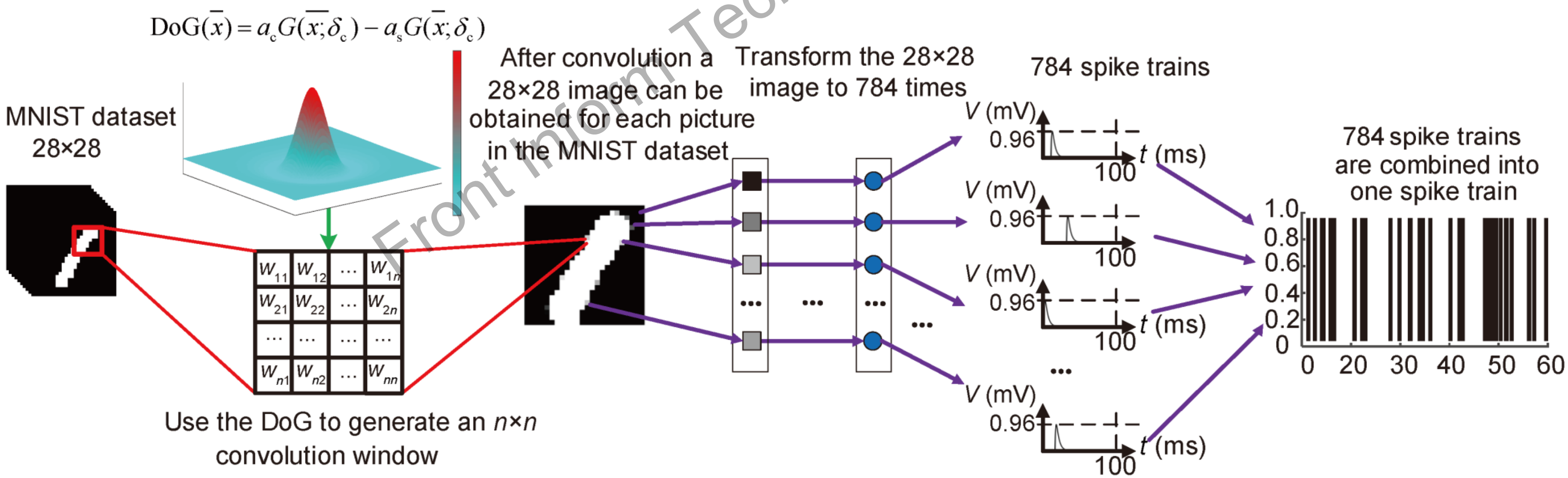
Method

- Receptive field model of DoG in encoding. When choosing different sizes of vision windows, different spike trains will be generated.



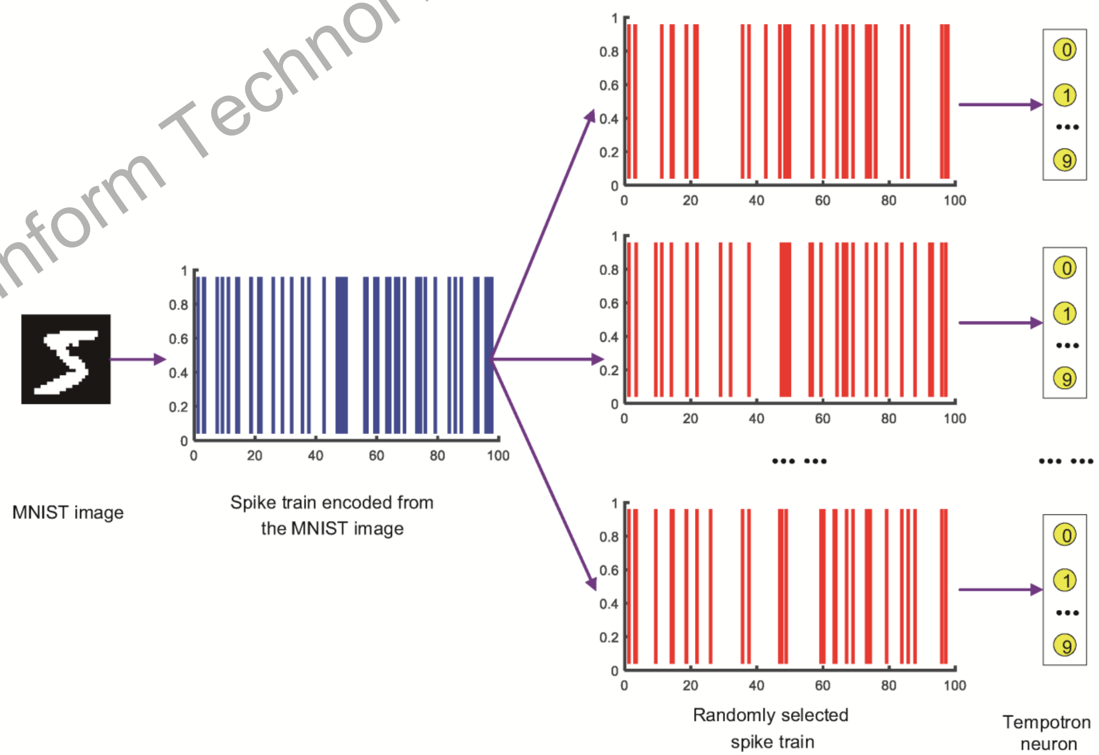
Method

- The encoding process of MNIST with a receptive field of DoG. A 28x28 picture of MNIST is convoluted with padding by an *nxn* vision window generated by the DoG model, and then the pixels of the convolution image are mapped to a fixed time window to compose a spike train including 28x28 spikes.



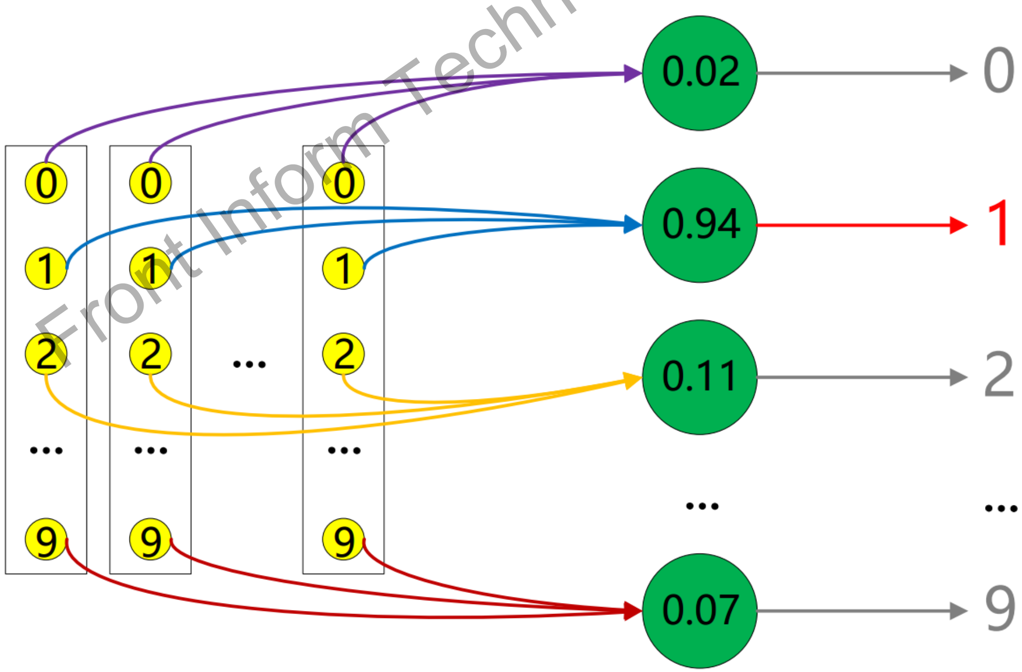
Method

- The images of MNIST are first encoded into spike trains and then several sub-spike trains are generated by randomly selecting ratio *p* from the original spike trains. The randomly selected spike train will be inputted into 10 Tempotron neurons, which represent 10 classes of handwritten digits.



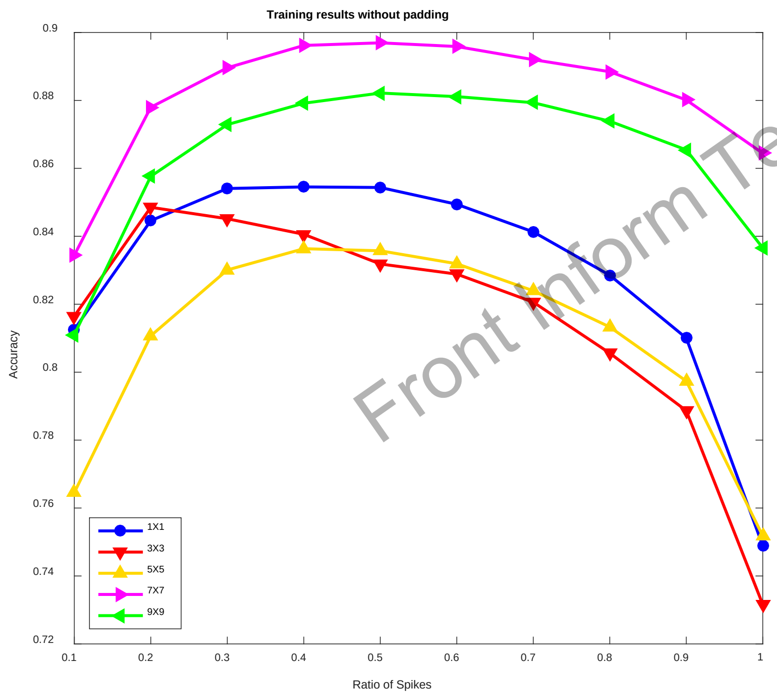
Method

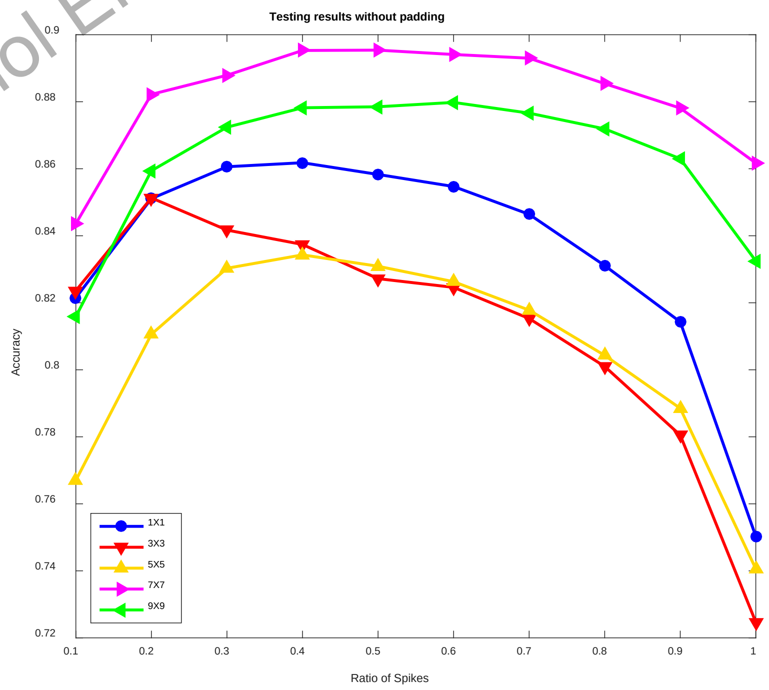
- The outputs of multiple groups of neurons are counted in the readout stage. The classification result is given based on the statistic result. The input image belongs to the class where the neuron has the largest count number.



Major results

- The accuracy of training and test results with vision windows of different sizes *n* and different ratios *p* of randomly selected spikes of MD-SNN on MNIST.





Major results

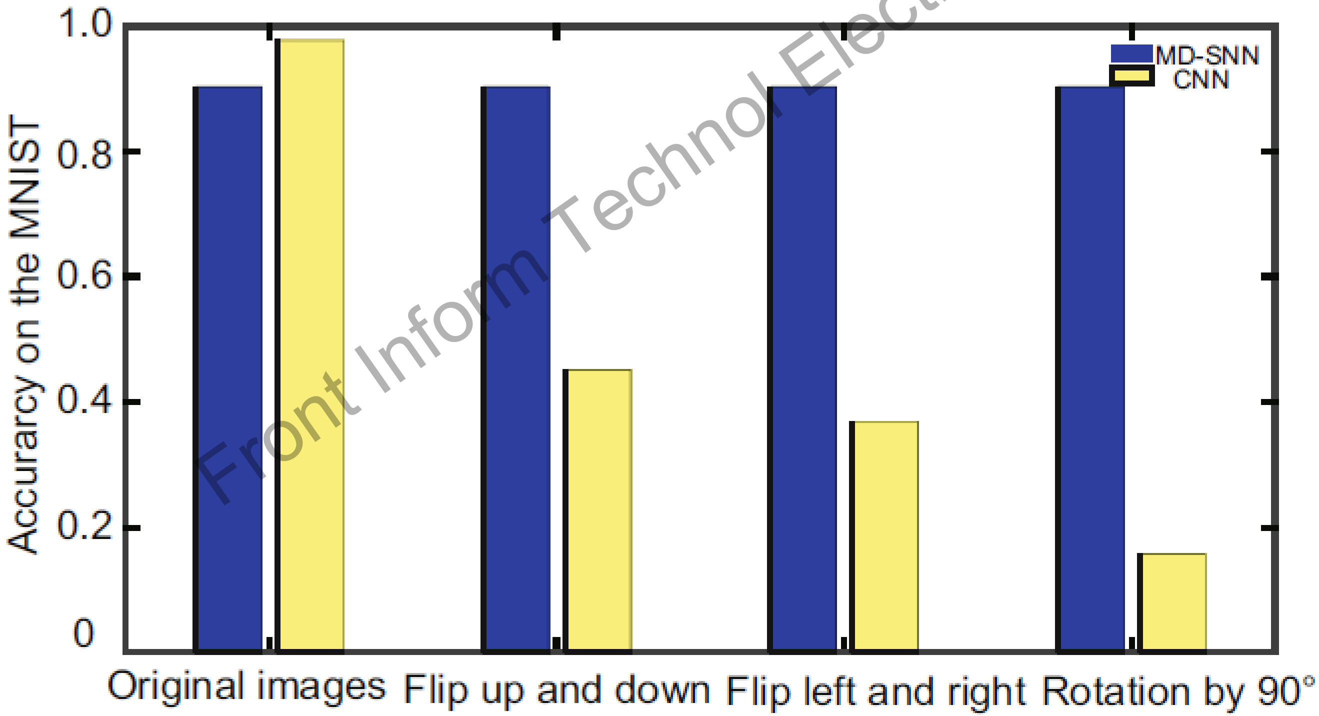
- Comparison between different SNNs on MNIST dataset classification

Table 2 Comparison between different SNNs on MNIST dataset classification

Structure	Unsupervised/Supervised	Accuracy
Minimal SNN (Tavanaei and Maida, 2015)	Supervised	75.93%
Spiking RBM (Merolla et al., 2011)	Supervised	89.00%
Dendritic neurons (Hussain et al., 2014)	Supervised	90.30%
MD-SNN (our method)	Supervised	90.44%

Major results

- Comparison of flip invariance and rotation between MD-SNN and CNN.



Major results

- The accuracy comparison between MD-SNN and CNN with training sets of different sizes

Training set size	MD-SNN	CNN
200	61.42%	9.80%
500	73.84%	9.82%
1000	80.15%	10.28%
2000	85.22%	14.92%
5000	88.02%	68.02%
10000	89.05%	77.87%
60000	90.44%	98.19%

Conclusions

- The size of receptive field influences classification results significantly.
- Considering the neuronal refractory period in the SNN model, using group neurons in the learning layer could greatly reduce the training time, effectively reduce the possibility of overfitting, and improve the accuracy by 8.77%.
- Compared with other SNN methods, MD-SNN achieves a better classification; compared with the convolution neural network, MD-SNN maintains flip and rotation invariance and is more suitable for small sample learning.