Reservoir Computing Using Dynamics of Micropattern Cultured Neural Networks

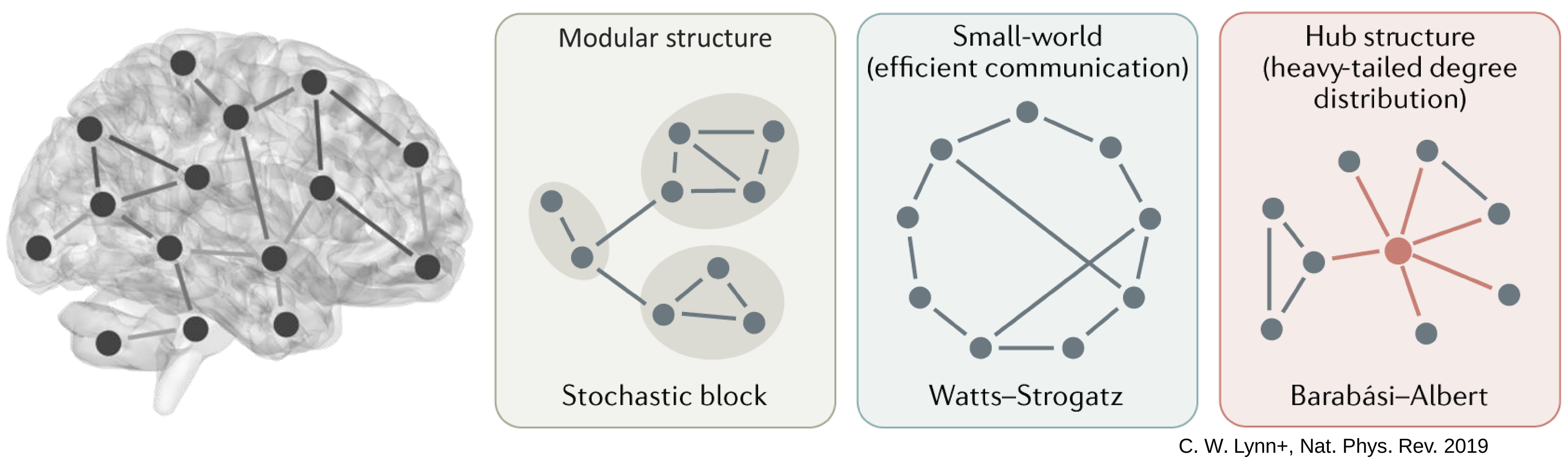
T. Sumi[1,2], H. Yamamoto[1], K. Ito[1,2], Y. Katori[3], S. Sato[1], A. Hirano-Iwata[1,2,4]

[1]RIEC, Tohoku Univ., [2] Graduate School of Biomedical Engineering, Tohoku Univ., [3]Future Univ. of Hakodate, [4]WPI-AIMR, Tohoku Univ. Japan

Introduction

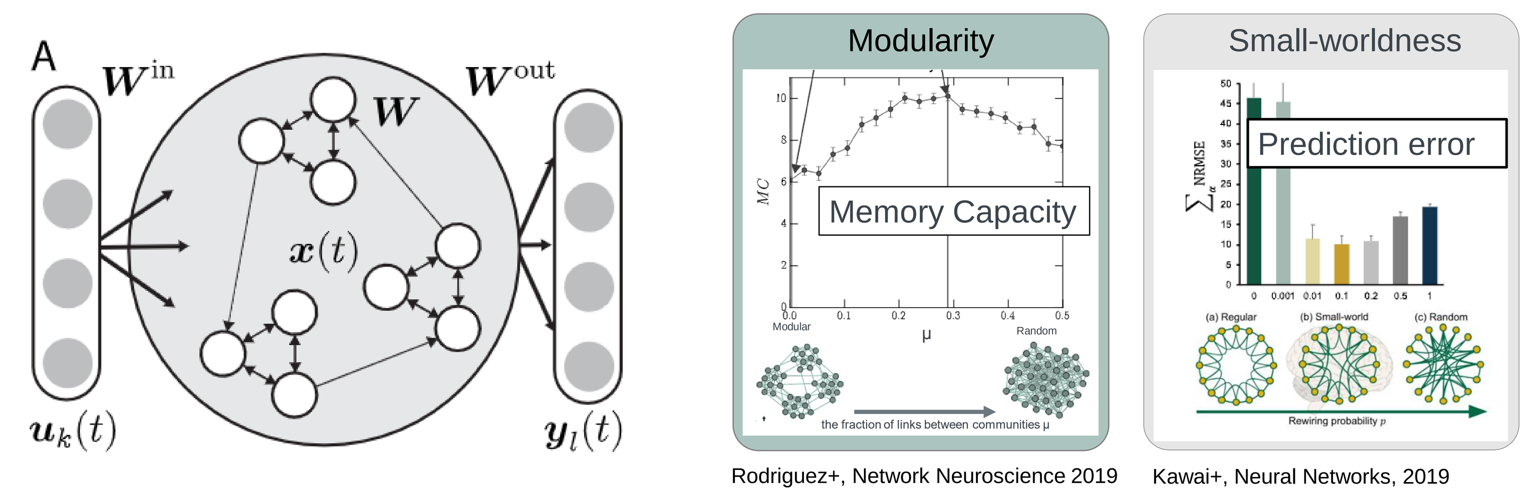
Investigation of the brain connectome revealed that brain has several non-random structures. Modular structure is especially important since it appear at different scale in the brain and has a small-worldness by its nature

How do these non-random structures facilitate information processing in the brain?



A beneficial tool to investigate the effect of network structure on performance of information processing is reservoir computing

Theoretical models predicted that the non-random network structure increases performance in reservoir computing (memory capacity, time-series prediction



How the modular architecture integrates with the living neurons to characterize the function of biological neuronal networks (BNNs)

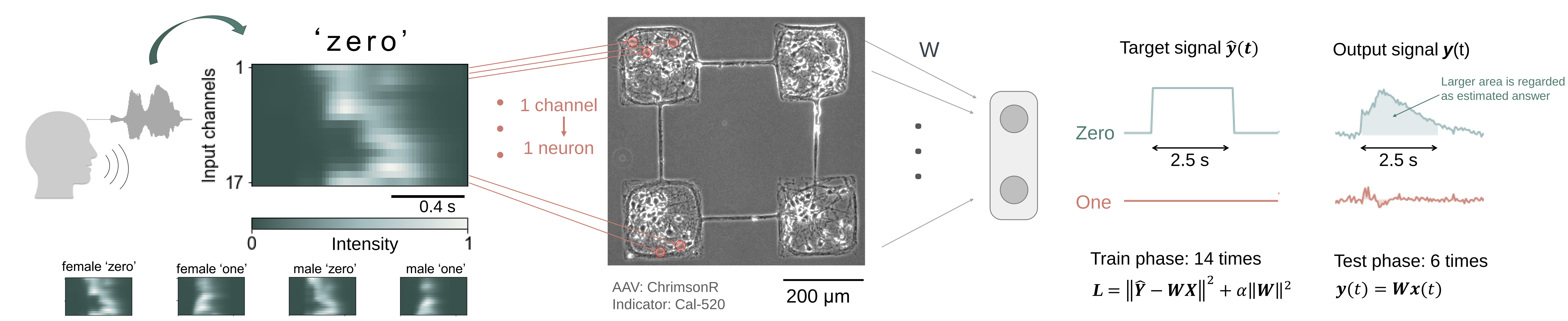
Experimental

Signal was converted to spectrogram using Lyon Cochlear model

The diameter of circular light d is: d = intensity × 25 μm

modular BNN

W is updated by ridge regression in training phase
60 (15 per module) neurons were used for readout



Train phase: 14 times

$$L = \|\hat{Y} - WX\|^2 + \alpha\|W\|^2$$

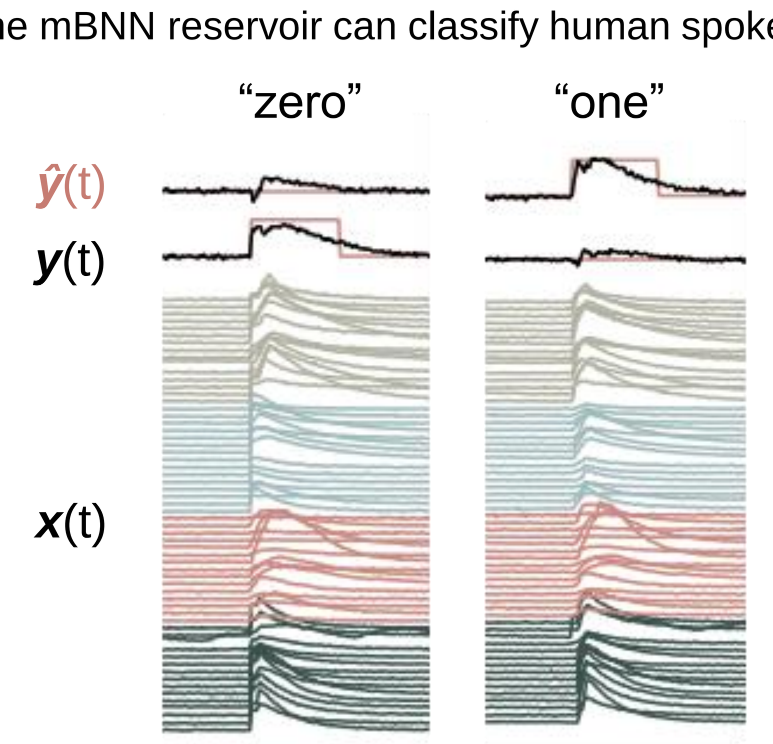
Test phase: 6 times

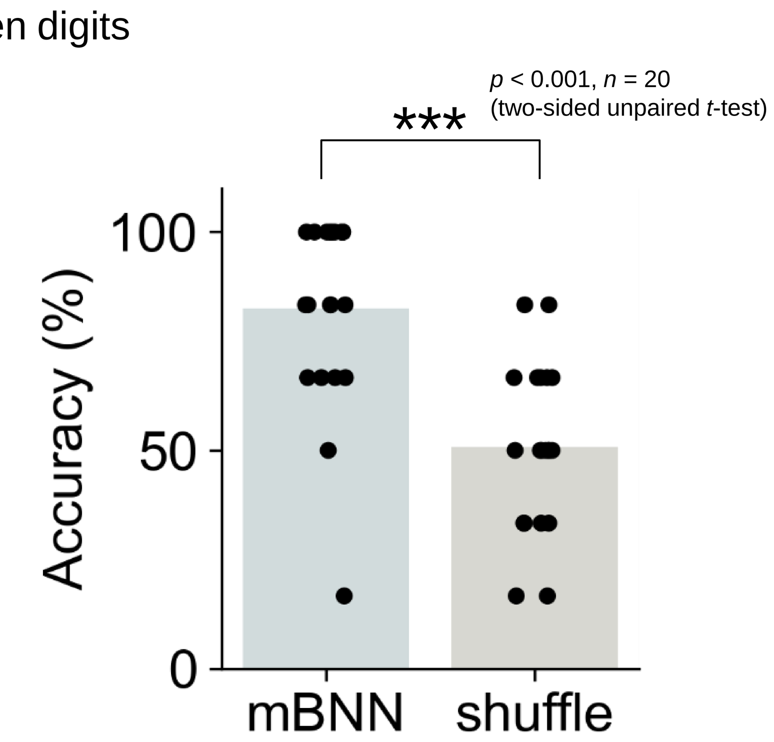
$$y(t) = Wx(t)$$

Results & Discussion

1. Neuronal States and Classification Accuracy

The mean accuracy was 82.5 ± 21.9% (mean ± SD, n = 20)
The value was significantly higher than that obtained from label-shuffled null models
The mBNN reservoir can classify human spoken digits





2. Distance Analysis of Neuronal States

$$D_{pq} = \langle d_{pq}(t)\rangle_t = \langle \|p(t) - q(t)\|_2\rangle_t$$

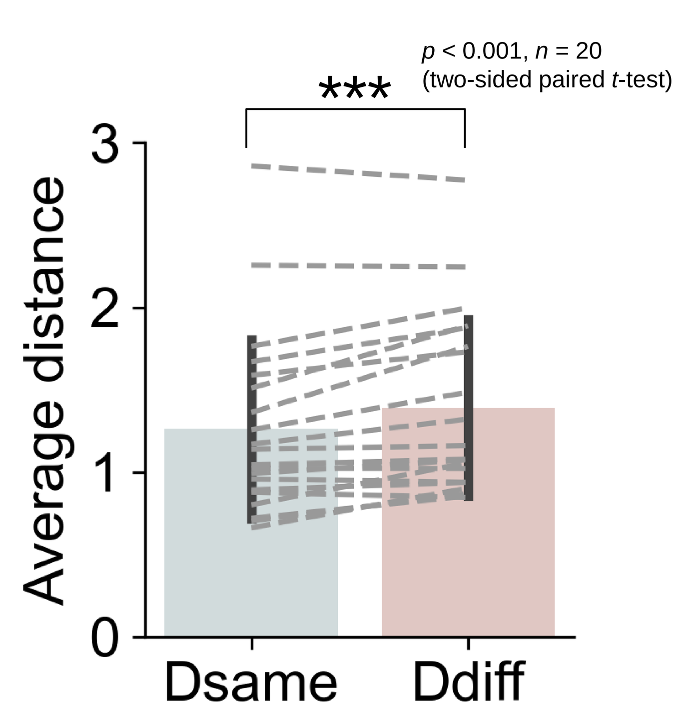
$\|\cdot\|_2$: L2 norm , $\langle\cdot\rangle_t$ temporal average

$D_{\mathrm{same}} = \langle D_{pq}\rangle$ (same input classes)

$D_{\mathrm{diff}} = \langle D_{pq}\rangle$ (differnt input classes)

Most samples of D_{diff} were lager than D_{same}

Such a separation is considered to be responsible for its decodability by linear classifiers

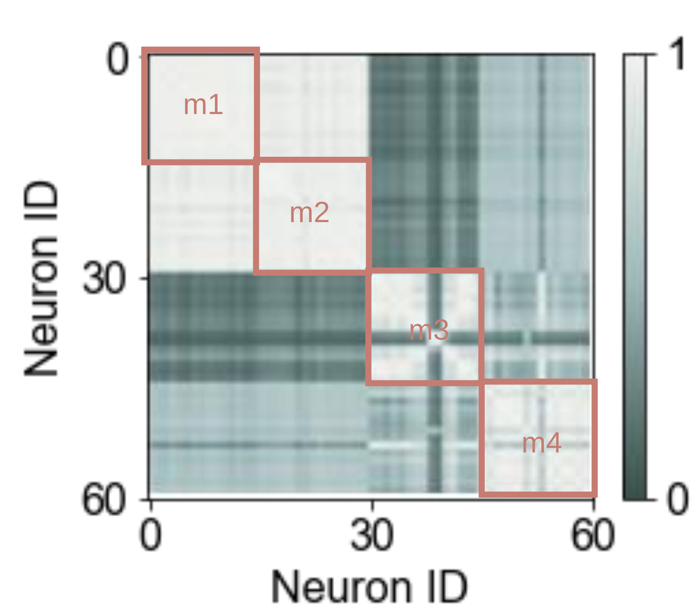


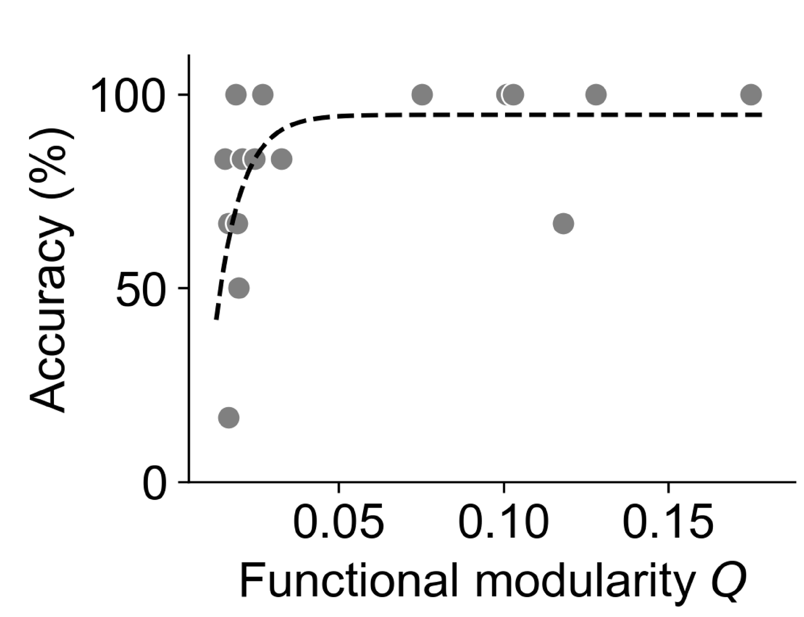
3. Classification Accuracy vs Modularity

Large variability was in Q < 0.05
Most modular networks (Q > 0.05)
exhibited an accuracy of 100%.
Functional modularity is beneficial for classifications

Modularity $Q = \frac{1}{2M}\sum_{ij}\left(r_{ij} - \frac{k_i k_j}{2M}\right)\delta(m_i, m_j)$

$M = \frac{1}{2}\sum_{ij} r_{ij}$, $k_i = \sum_j r_{ij}$, δ = Kronecker delta, and m_i is the module containing neuron i.



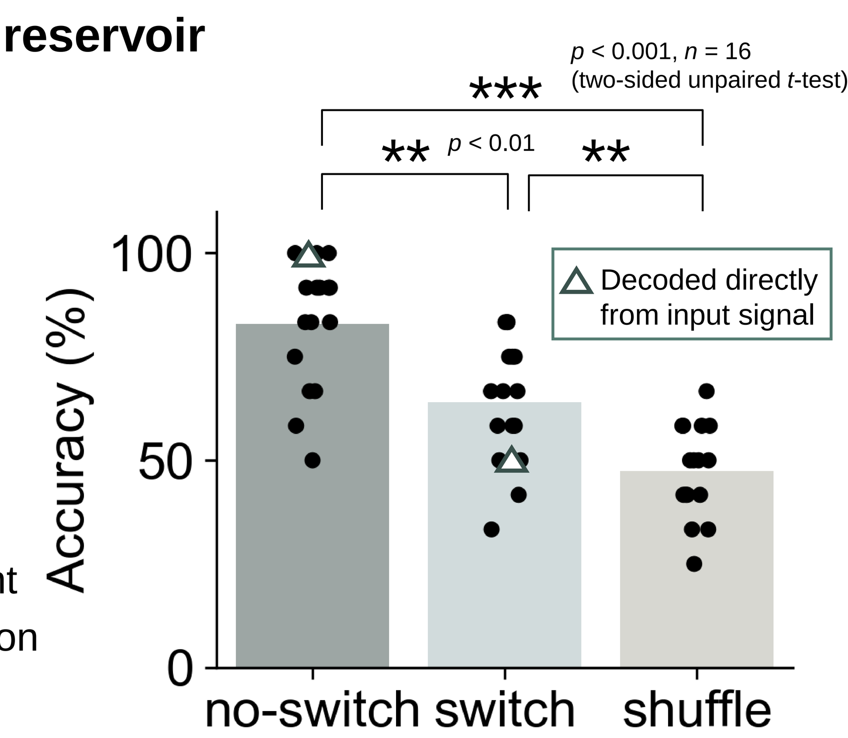


4. Generalization ability of mBNN reservoir

We explored computing unique to mBNN reservoir, focusing on generalization
The speaker was switched in training and testing phase

Mean accuracies were 82.8% and 64.1%
When input was directly decoded, the accuracies were 100% and 50%

The characteristic of BNN such as inherent noise intrinsically improve the generalization capability, although the performance for same signals decreases



paper link

conclusion

The mBNN can classify the time-series signals, and functional modularity is beneficial for classifications
Signal transformation by the mBNN provides the ability to generalize the spoken digits with the reservoir