Material computing based on physicochemical dynamics toward neuromorphic hardware implementation

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Mimicking brain function by nanomaterials is an innovative approach for an effective information processing system. Reservoir computing (RC), a kind of artificial neural network, is an attractive learning method with low power consumption and fast calculation because weight update was carried out at only readout between reservoir layer and output layer. Owing to this advantage, reservoir layer can utilize even dynamic physical behaviors. Robust nonlinearity and memory properties are needed to use the material as an RC device. To achieve the requirement, we propose to utilize a highly conductive material network containing nonlinear-conduction regions.

Firstly, we will introduce the sulfonated polyaniline (SPAN) network. SPAN is expected as a polaron conduction material [1] and generates ionic conduction, including charging an electric double layer and ionic diffusion under high humidity. The rich dynamic output behavior with wide variations for each electrode improved the RC performance, such as 90 % waveform task accuracy and the spoken-digit classification with 60-70 % accuracy by only 12 outputs.[2]

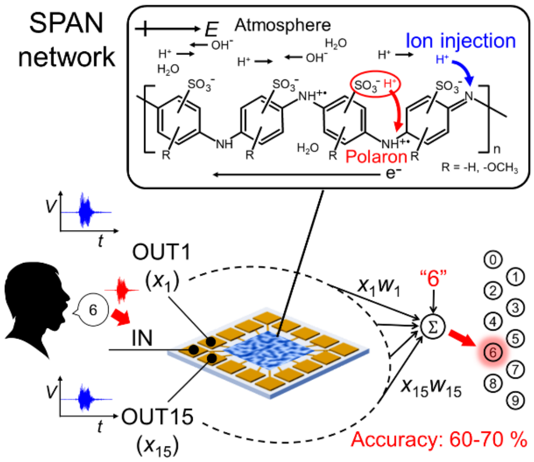

Fig.1 Schematics of spoken-digit classification with SPAN network.

We will also introduce various other nanomaterials, such as carbon nanotubes/polyoxometalate (SWNT/POM) [3,4,5], Ag/Ag_2S nanoparticle [6], and Ag_2Se nanowires [7], as RCs for waveform generation task, tactile-sensing object recognition, etc., including the correlation between material properties and reservoir performance. Finally, current challenges and future prospects of material-based RC devices will be discussed.

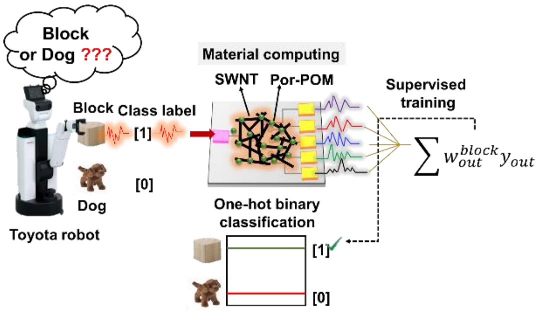

Fig.2 Schematics of tactile-sensing object recognition with SWNT/POM network.

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References

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