

Resonance for Analog Recurrent Neural Network

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Abstract— Resonance, as a ubiquitous feature across many wave systems, is a natural candidate for analog computing in temporal signals. We demonstrate that resonance can be used to construct stable and scalable recurrent neural networks. By including resonators with different lifetimes, the computing system develops both short-term and long-term memories simultaneously.

Wave-based analog computing enjoys benefits of intrinsic parallelism and it can be extremely energy efficient compared to digital computing [1]. However, the transient nature of propagating waves makes it difficult to construct memory in the wave domain. Since memory is indispensable for computing in the temporal data, researchers have to resort to other means to realize the effect of memory such as optoelectronic conversion, routing through long waveguides and random internal feedback. In all these works, the memory is implicitly built into the complex structures, and physical intuition and interpretation are lacking. However, in the resonance system, we can include resonators with different lifetimes to realize both short-term and long-term memory. Here through a set of theoretical work, we propose resonance as a general form of memory to be used for complex temporal computing and advanced recurrent models such as LSTM. The findings here have broad impact and help to shape the future computing based on optical and acoustic waves.

A digital RNN consists of many artificial neurons with memories (Fig. 1(a)). One neuron often connects to many others. Similarly, one resonator can couple to many, providing a scalable way to construct large-scale analog computing system with memory (Fig. 1(b)). The coupling between resonators can be mediated through free space or waveguides. The coupling coefficients (e.g., connection weights) determine the function of computing. They will be trained in a similar way that neural networks are trained. The trained coefficients can be physically implemented, for example, by adjusting the distance between resonators.

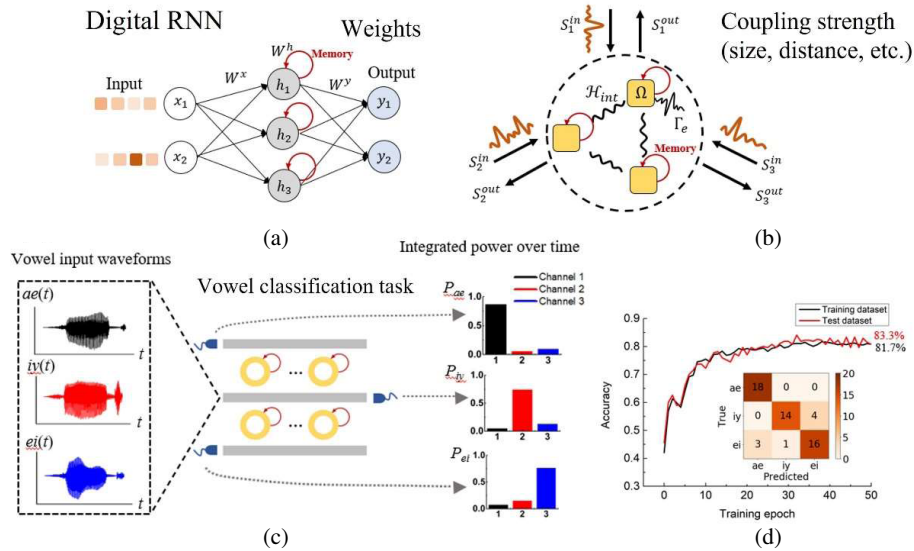


Figure 1: (a) Layout of a digital RNN. (b) Layout of a resonant recurrent network. (c) Raw audio waveforms of three spoken vowel classes and time-integrated power at each output channel. (d) Prediction accuracy over 50 training epochs.

Next, we demonstrate a specific example where we train acoustic resonators to recognize the vowels spoken by human. All computing is in the acoustic domain. The computing device contains three parallel acoustic waveguides that couple to two rows of whispering gallery resonators (Fig. 1(c)). Each row contains 60 resonators. The coupling between resonators is mediated through the waveguides. The trained resonance system can achieve an accuracy of 81.7% for the training dataset and 83.3% accuracy for the test dataset over 50 training epochs (Fig. 1(d)). The confusion matrix for the test data indicates that the resonance system can indeed perform vowel recognition. The time-integrated power at each waveguide demonstrates that the optimized resonant architecture can route most of the energy of the object vowel class to the correct channel.

The resonance system can be exploited for other challenging recurrent neural networks such as LSTM network. LSTM is explicitly designed to include both short-term and long-term memory. It incorporates cell states and gates such that events from the remote past can have current impacts. In the resonance system, we can include resonators with different lifetimes to accomplish short-term and long-term memory.

REFERENCES

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