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Design of k -space Magnon Dynamics by Machine Learning

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We demonstrate the application of machine learning techniques to the design of magnonic neuromorphic devices. Specifically, we show that these techniques are applicable not only to inverse-design propagating waves but to engineer the modal dynamics of nanomagnets in such a way that these magnets solve basic classification tasks.

Index Terms—Machine learning, backpropagation, k -space computing, normal modes model, vowel classification

I. INTRODUCTION

NEUROMORPHIC COMPUTING HARDWARE is usually imagined as network of spatially separated neurons. The neurons take a number of inputs, generate a weighted a superposition of them, and after applying a nonlinear function to these superposition, the neural output is processed by further layers. This is a natural approach if the network is realized as an electrical circuit.

When neuromorphic computing functions are realized by a dynamical physical system (such as a magnonic system) then one may imagine a computing model that is very different from this neuron-based picture. For example, nonlinear wave-interference may be used for neuromorphic computing primitives: in this case propagating waves play the role of interconnections and amplitude-dependent nonlinearities in the medium substitute the neuron nonlinearities [1].

Another approach, which we explore in detail here, assigns the neural functions to oscillatory modes of a nanomagnet [2] [3]. The information is processed by the time dynamics of the modal amplitudes. In this device two signals are applied simultaneously to the magnet: the time dependent input signal and a time-dependent programming signal. The output of the computation is represented by the amplitude of the normal modes. Rather than forming a network in the real space, computation takes place in the wavevector-space (k -space).

While substantially different from traditional neural networks, the k -space neural net can be trained using the same gradient-based learning methods that determine the weights of standard neural networks.

II. BACKPROPAGATION IN REAL SPACE AND k -SPACE

Machine learning on a dynamic system is efficiently performed through the BPTT (Backpropagation through time) method. In this procedure the ordinary differential equations (ODEs) that describe the system are first solved by some time-marching procedure (such as the Runge Kutta method) and all the intermediate results are saved. Following this forward solution, a backward differentiation step is performed, when the derivative of a so-called loss function is calculated with

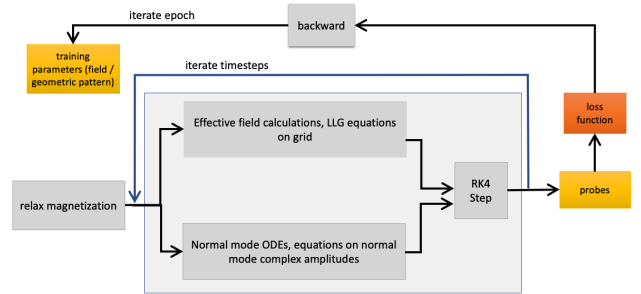


Fig. 1. Schematics of the backpropagation-based machine learning, applied to micromagnetics. The micromagnetic model can either be based on real-space magnetization dynamics (LLG equations) or a normal mode-based description.

respect to some physical parameters of the system. Subsequently, a gradient-based optimization step is performed that adjusts the physical parameters in the direction that minimizes the loss function. This can be done by software widely used in the machine learning community, such as Pytorch that we have used. The schematics of how micromagnetic ODEs are integrated into Pytorch is sketched in Fig. 1.

Spintorch is a machine-learning enabled micromagnetic simulator [1] that implements this procedure on the solution of the Landau-Lifshitz-Gilbert (LLG) ODE. If the loss function describes a waveform-classification task than Spintorch designs a magnonic system that performs this classification via magnon interference.

Instead of solving the LLG equation, magnetization dynamics can be treated by a normal mode description, where instead of the discretized \mathbf{M} distribution, the time evolution of $a_i(t)$ mode amplitudes is determined. This method is well applicable so small-size magnetic structures where magnetization dynamics can be accurately described as a superposition of a (typically) smaller number of eigenmodes (see Fig. 2).

Normal mode description [3] offers several benefits over the LLG-based solution. Significantly fewer equations must be solved, which makes the learning procedure much more efficient. In addition, the number of relevant normal modes corresponds to the degrees of freedom of this system and

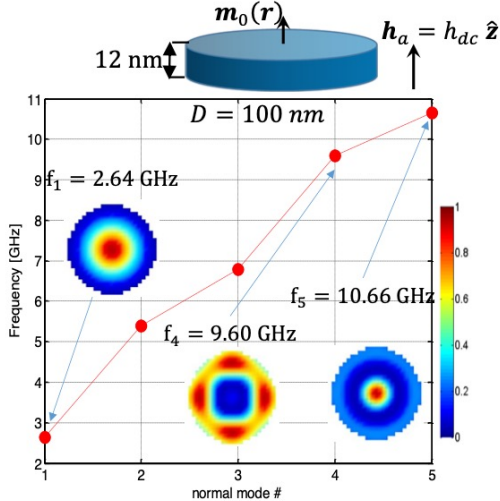


Fig. 2. Normal modes in a nanoscale Permalloy magnet. The disk is magnetized out of plane and excited by an in-plane rf field. The first five eigenmodes are taken into account in the calculation, and the spatial profile of three of them are illustrated.

eventually to the amount of nodes in a functionally equivalent neural network.

The effectiveness of the normal modes approach has been demonstrated for systems of nano- and micro-scale systems relevant for magnonics and spintronics [3].

Normal modes can be efficiently determined by using frequency-domain micromagnetic methods [2] appropriately implemented for large-scale computations. This calculation along with evaluation of couplings between modes can be performed once for all for a given geometry, but the normal mode description remains valid for arbitrary (small-amplitude) RF field excitations which are relevant for applications [3].

III. CONTROL OF MODAL AMPLITUDES

If the \mathbf{M}_0 initial magnetization of a nanomagnet is close to its equilibrium state, and there is no external field, mode amplitudes evolve independently from each other and decay toward a $a_i = 0$ equilibrium state. Higher modal amplitudes and externally applied RF fields bring the modes into coupling with each other. The modes are all-to-all coupled by the physics, realizing a high-interconnection neural network.

Training on the network is performed via the BPTT algorithm, following the schematics of Fig 1. Training the programming field effectively programs the coupling weights. The parameters of the external field waveform are optimized toward minimizing the loss function.

IV. CLASSIFICATION EXAMPLES

We tested our algorithm on widely applied classification algorithm: vowel recognition and character recognition on a subset of the MNIST database. The nanomagnet and the fields are shown in Fig. 2

Vowel recognition was performed by applying the formants of vowels as input to the magnet. Three dominant formants were applied with equal amplitudes, alongside a programming signal. The programming signal was a simple sinusoidal waveform with its amplitude and frequency being the trained

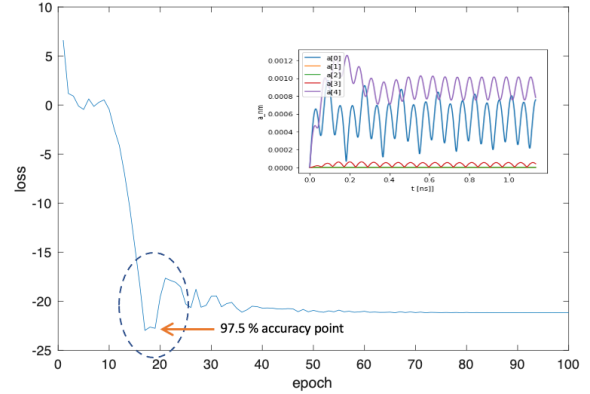


Fig. 3. Loss curve for formant-based learning - a high success rate achieved in less than 20 steps. The time evolution of the vowel amplitudes is shown in the inset.

parameters. The output of the classification algorithm was the a_4 mode amplitude its high or below-threshold amplitude distinguished between the two vowels.

We found that in this simple test case, a 97.5 percent classification accuracy was achievable - that is, the network properly characterized all but one the 40 vowels in the training set. This accuracy was reached in 18 training epochs (see Fig. 3).

It is worthwhile to note that that there are other approaches toward applying nanomagnets for neuromorphic computation, such as using them as a reservoir [4]. In this case reservoir training is not required but a linear classifier is necessary after read-out.

V. CONCLUSION AND OUTLOOK

In this paper we explored how machine learning techniques can be used to program magnetization dynamics to perform a desired function. Such techniques were recently explored for propagating waves, but to our knowledge our work is the first to engineer the coupling of standing-wave modes toward computing functions.

VI. ACKNOWLEDGEMENTS

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