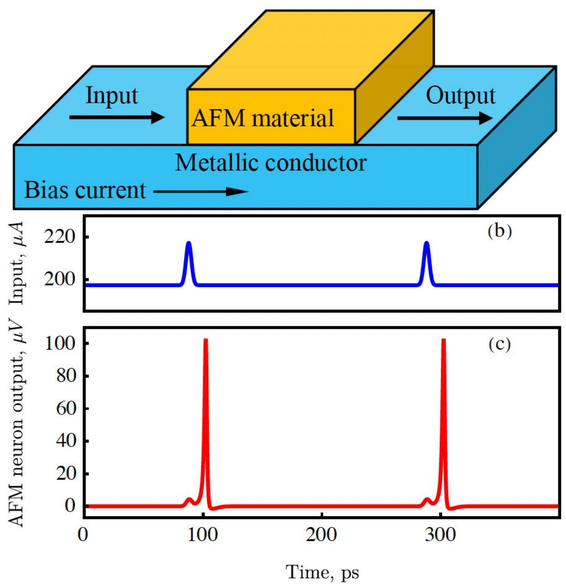
Antiferromagnetic Artificial Neurons: A Platform for Neuromorphic Computing and Physiological Modeling

Lily Quach[1], Hannah Bradley[2], Steven Louis, Ph.D.[3], Vasyl Tyberkevych, Ph.D.[2]

1. Oakland University William Beaumont School of Medicine
2. Department of Physics, Oakland University
3. Department of Electrical and Computer Engineering, Oakland University

Abstract

A foundational understanding of how biological neuronal networks function could prove instrumental for refined clinical applications and treatments. Spiking artificial neurons emulate action potentials of biological neurons, and are the foundation for enhanced, energy-efficient neuromorphic computing systems. Antiferromagnetic (AFM) materials are the framework for such spiking artificial neurons. The innate effective inertia and dual magnetization of AFM materials provides propensity for simulating biological neurons. AFM neurons consist of nanometer sized nitric oxide mounted on platinum. When an electrical current flows through the platinum, it can elicit the rotation of the AFM magnetization and generate a voltage spike that behaves like an action potential in a biological neuron. We have developed a mathematical model that describes the voltage spike with a differential equation and a simulation software to simulate biological characteristics such as response latency, refractory periods, inhibition, and interconnectivity.
Compared to slower modern computational speeds, AFM neurons operate with a rapid spike duration of the order of a picosecond and minimal power consumption of about 10−3 pJ per synaptic operation.
Intrinsic AFM qualities allow neurons to form networks and dynamically modeling biological neural circuitry to improve efficiency of artificial intelligence.[3, 6, 7, 10, 13]



(a)This illustrates the architectural framework of an AFM neuron. AFM material (NiO) is mounted onto a metallic conductor, through which electrical current will flow. (b) Input current is graphed: Bias current ~198 μA; with 18μA input impulses just before 100 ps and 300 ps. (c) AFM-produced output spikes (~100μV) result from impulses at 100 and 300 ps 18μA. [1, 2, 5, 7, 11, 12, 13, 14]

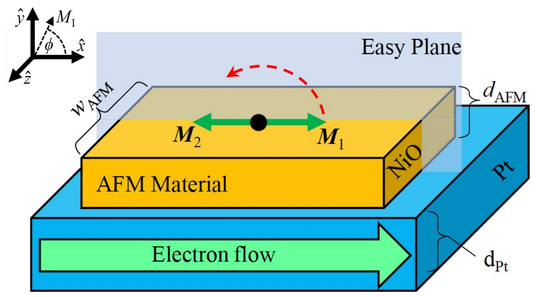
Introduction

Artificial Intelligence (AI) has shown to enhance efficacy of healthcare through streamlining diagnoses and improving clinical outcomes. It has been trained for image recognition and data processing of skin cancers, radiographs, and beyond. While AI and machine learning is seemingly quintessential across society, its effectiveness is compromised by three main limitations: immense computing power, costly operations, and suboptimal performance speeds. It has been demonstrated that the human brain capacity operates with an efficiency that is orders of magnitudes greater than that of computers. This has brought profound attention to the structure, topography, and interconnections of the human brain.

Foundational understanding, simulation, and modeling of biological neuronal networks could prove instrumental for refined application of AI in clinical softwares and treatments. As such, we have developed an artificial neuron that uses antiferromagnetic (AFM) auto-oscillators to produce ultra-fast voltage spikes as a response to external stimulation. AFM neurons have many features that not only closely resembling biological neurons, but also operate with faster speeds and lower energy consumption compared to state-of-the-art computers available today. Dynamic modeling of biological neural circuitry with AFM neurons can propel technology in medicine to augment the degree, efficacy, and quality of healthcare.

[2, 3, 4, 7, 12, 13]

Methods and Physics of Operation

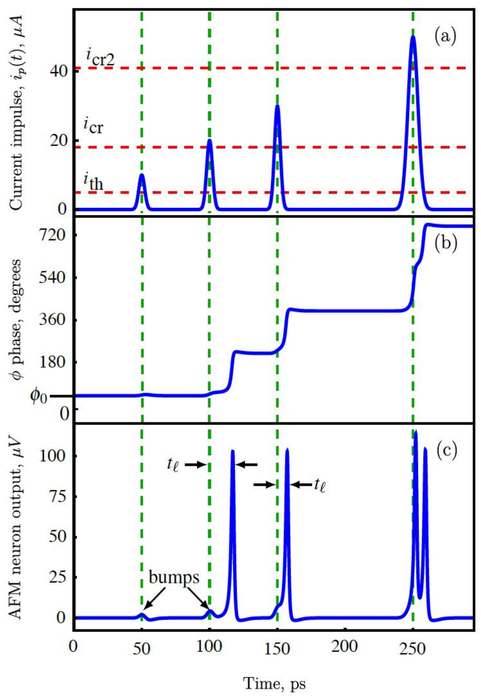


The physical schematic for the AFM architecture was established to be feasible, inexpensive, energy-efficient, dynamic, and compact.

- AFM material: Nitric Oxide--cost-efficient and anisotropic.
- Electrical Conductor: Platinum– high spin-orbit coupling.[1, 3, 6, 7, 13]

Neuron Equation (AFM Input Equation)

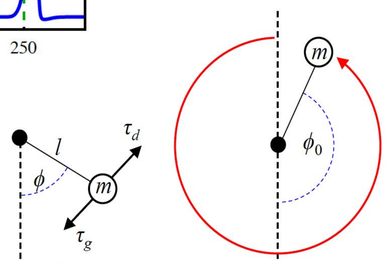
$$\frac{1}{\omega_{ex}}\ddot{\phi} + \alpha\dot{\phi} + \frac{\omega_e}{2}\sin 2\phi = \sigma I$$



Numerical simulations were run through Mathmatica to demonstrate an AFM neuron generating spikes.
(a) input currents
Critical Impulse is required to elicit a spike. This is comparable to a biological neuronal threshold for AP firing.
(b)degrees of magnet rotation
(c)voltage output
Latency Period exhibited[7,13]

The AFM neuron is mathematically modeled after a simple pendulum system with an applied torque. Velocity around this axis is dictated by 3 factors:

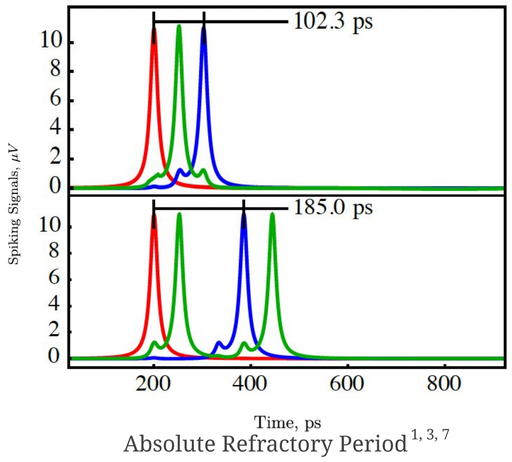
1. Moment of inertia
2. Friction
3. Gravitational potential.



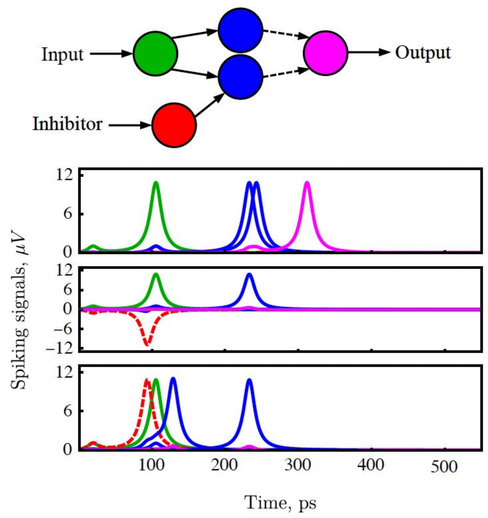
$$I_m\ddot{\phi} + b\dot{\phi} + mgl\sin\phi = \tau_d$$

Motion Equation

The sum of these three is the Spin Transfer Torque (STT), which represents the current provided to the AFM neuron, directly modeling AFM spiking activity.[7,13]

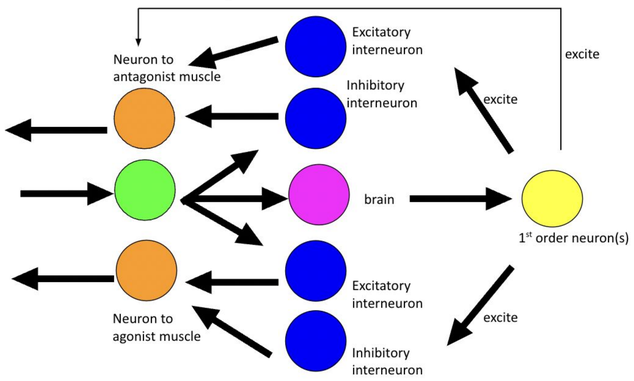


Absolute Refractory Period[1, 3, 7]



Negative inhibition, positive inhibition, and interconnectivity[2,3,7]

Extended Modeling: Withdrawal Reflex and Override



Results and Conclusion

AFM spiking simulations demonstrate three things: firstly, AFM neurons are capable of accurately modeling the functionality and characteristics of biological neuron including response latency, refractory periods, and inhibition, which arise from an effective internal inertia. Secondly, our AFM artificial neuron model overcomes current AI limitations with its state-of-the-art speed of conduction, inexpensive and compact architecture, and minimal computational energy. Thirdly, this study develops a platform to perform further studies of neural circuitry such as physiological reflexes simulations, and training for robust diagnoses.

References

Bibliography
1.Abu-Hassan K, Taylor JD, Morris PG, et al. Optimal solid state neurons. *Nature Communications*. 2019;10(1):5309. doi:https://doi.org/10.1038/s41467-019-13177-3
2.Al-Antari MA. Artificial Intelligence for Medical Diagnostics—Existing and Future AI Technology! *Diagnostics*. 2023;13(4):688. doi:https://doi.org/10.3390/diagnostics13040688
3.Aleksandr Kurenkov, Samik DuttaGupta, Zhang C, Shunsuke Fukami, Horio Y, Ohno H. Artificial Neuron and Synapse Realized in an Antiferromagnet/Ferromagnet Heterostructure Using Dynamics of Spin–Orbit Torque Switching. 2019;31(23):1900636-1900636. doi:https://doi.org/10.1002/adma.201900636
4.Amisha, Malik P, Pathania M, Rathaur V. Overview of artificial intelligence in medicine. *Journal of Family Medicine and Primary Care*. 2019;8(7):2328. doi:https://doi.org/10.4103/jfmpc.jfmpc_440_19
5.Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. *Artificial Intelligence in Healthcare*. Published online June 26, 2020:25-60. doi:https://doi.org/10.1016/B978-0-12-818438-7.00002-2
6.Akinola OG, Hu X, Bennett C, Marinella MJ, Friedman JH, T. Paul Chow. Three-terminal magnetic tunnel junction synapse circuits showing spike-timing-dependent plasticity. *Journal of Physics D: Applied Physics*. 2019;52(49):49LT01-49LT01. doi:https://doi.org/10.1088/1361-6463/ab4157
7.Bradley H, Louis S, Trevillian C, et al. Artificial neurons based on antiferromagnetic auto-oscillators as a platform for neuromorphic computing. *arXiv:220806565 [cond-mat]*. Published online August 17, 2022. https://arxiv.org/abs/2208.06565
8.Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. *Nature*. 2017;542(7639):115-118. doi:https://doi.org/10.1038/nature21056
9.Greenfield D. Artificial Intelligence in Medicine: Applications, implications, and limitations. Science in the News. Published June 19, 2019. https://sitn.hms.harvard.edu/flash/2019/artificial-intelligence-in-medicine-applications-implications-and-limitations/
10.Hall K, Fitall E. Artificial Intelligence and Diagnostic Errors. *psnetahrqgov*. Published online January 31, 2020. https://psnet.ahrq.gov/perspective/artificial-intelligence-and-diagnostic-errors
11.Lakhani P, Sundaram B. Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks. *Radiology*. 2017;284(2):574-582. doi:https://doi.org/10.1148/radiol.2017162326
12.LeCun Y, Bengio Y, Hinton G. Deep Learning. *Nature*. 2015;521(7553):436-444. doi:https://doi.org/10.1038/nature14539
13.Lobo JL, Del Ser J, Bifet A, Kasabov N. Spiking Neural Networks and online learning: An overview and perspectives. *Neural Networks*. 2020;121:88-100. doi:https://doi.org/10.1016/j.neunet.2019.09.004
14.Rosado B. Accuracy of Computer Diagnosis of Melanoma. *Archives of Dermatology*. 2003;139(3):361. doi:https://doi.org/10.1001/archderm.139.3.361

sdesigned by FPPT.