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Research Letter

Toward remote and secure authentication: Disambiguation of magnetic microwire signatures using neural networks

Akshar Varma, Khoury College of Computer Sciences, Northeastern University, Boston, MA, USA
Xiaoyu Zhang, Department of Mechanical and Industrial Engineering, Northeastern University, Boston, MA, USA
Brian Lejeune, Department of Chemical Engineering, Northeastern University, Boston, MA, USA
Laura Cebada Almagro, Department of Materials Physics, Complutense University of Madrid, Madrid, Spain
Rafael P. del Real, Instituto de Ciencia de Materiales de Madrid, Cantoblanco, Madrid, Spain; Instituto de Magnetismo Aplicado, Universidad Complutense de Madrid-ADIF, Madrid, Spain
Pilar Marin, Department of Materials Physics, Complutense University of Madrid, Madrid, Spain; Instituto de Magnetismo Aplicado, Universidad Complutense de Madrid-ADIF, Madrid, Spain
Ogheneyunume Fitchorova, The George J. Kostas Research Institute for Homeland Security, Northeastern University, Burlington, MA, USA; KRI at Northeastern University, LLC, Burlington, MA, USA; Department of Electrical and Computer Engineering, Northeastern University, Boston, MA, USA
Laura H. Lewis, Department of Mechanical and Industrial Engineering, Northeastern University, Boston, MA, USA; Department of Chemical Engineering, Northeastern University, Boston, MA, USA; The George J. Kostas Research Institute for Homeland Security, Northeastern University, Burlington, MA, USA
Ravi Sundaram, Khoury College of Computer Sciences, Northeastern University, Boston, MA, USA

Address all correspondence to Akshar Varma at **varma.ak@northeastern.edu**

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Abstract

Secure and high-throughput authentication systems require materials with uniquely identifiable responses that can be remotely detected and rapidly disambiguated. To this end, complex electromagnetic responses from arrangements of amorphous ferromagnetic microwires were analyzed using machine learning. These novel materials deliver maximal spectral dispersion when the frequency of incident electromagnetic radiation matches the microwire resonance. Utilizing data obtained from 225 unique microwire arrangements, a neural network reproduced the response distribution of unseen data to a confidence level of 90%, with a mean square error less than 0.01. This favorable performance affirms the potential of magnetic microwires for use in tags for secure article surveillance systems.

Introduction

Secure, high-throughput, and contactless tracking of assets is an enormous challenge for supply chain management as well as for monitoring and controlling illicit transactions involving counterfeit currency and documents, pirated goods, and substandard/falsified pharmaceuticals.[1,2] It is clear that sustained advances in materials, devices, and data handling are needed to address this complex and escalating issue. While radio-frequency identification (RFID) technologies, including chipless RFID,[3] can satisfy some of these requirements, their expanded deployment remains constrained by cost, physical size, and difficulties associated with storing sufficient data to uniquely identify the signatures of extremely large numbers of individual objects. At their essence, these identification systems consist of an electromagnetic (EM)-active tag, a transmitter to deliver interrogating incident EM radiation to the tag, and a receiver to detect and analyze the subsequently emitted EM signal. Although increased complexity in the received EM signals, or spectra, provides a larger portfolio of potentially unique tag signatures, at the same time it greatly increases the challenge of disambiguating these signals and validating the objects of interest.

To address this imperative, a system encompassing creation, interrogation, and disambiguation of complex electromagnetic signatures is described here. Signals emitted from EM-active "tags" comprising specified arrangements of unique micron-scaled magnetic objects—amorphous magnetic microwires—were analyzed using machine learning in the form of neural networks.[4] Results reported here were obtained from a surprisingly small number (225) of measurements, and these results confirmed parameterized learning of the response function to successfully reproduce training and testing set data to a commendable confidence level in excess of 90%. In this manner, a proof-of-concept demonstration has been achieved, allowing contemplation of strategies to refine the parameter space and physical configuration of the magnetic tags for improved performance and applicability.

The uniqueness of this current work is derived from the application and integration of three typically separate knowledge domains—advanced magnetic materials,[5] machine learning,[6] and information theory[7]—to address a complex systems challenge. Below we briefly elaborate on the novelty and significance of combining these three disciplinary arenas. As an innovative composite material, glass-coated magnetic microwires have the ability to modulate reflection or transmission of microwave (GHz) EM radiation incident on their surface, with maximum dispersion achieved when the incident frequency is matched to the microwire antenna resonance frequency. The emitted microwire signal is very sensitive to details of chemical composition as well as to environmental parameters (including ambient magnetic field, strain, and temperature).[8,9] Further, the response of a multiwire ensemble is influenced by the number, length, and proximity of the constituent wires.[10,11] Overall this abundance of controllable parameters provides an immense and highly versatile palette of variables and conditions to realize unique tracking "tags" comprised of magnetic microwires. The high-fidelity reproduction by a neural network of the electromagnetic response of these magnetic microwire arrays allows us to envision simulating a variety of materials compositions in conjunction with physical configurations, to efficiently explore and survey a much larger tag space.[12,13] It is notable that our neural networks achieve good performance with training dataset sizes on the order of a few hundreds, while machine learning and especially neural networks typically require dataset sizes on the order of 10,000 to a few million; this aspect is noted within the materials science community as well.[14] With the tag modeled as a neural network, we are now in a position to innovate on the neural network architecture front to create efficient encoder and decoder for tags.[15,16] In follow-on preliminary work,[17] we leverage the proof-of-concept described in this paper to create a general technique for creating a practical tagging system from any scanning technology employing a novel autoencoder-based neural network architecture.

Materials and methods

Magnetic microwires and their response

Amorphous glass-coated ferromagnetic microwires derive their very high sensitivity to applied magnetic fields[18–20] from interplay between their atomic and magnetic structures.[21] In addition to ultrasoft magnetic behavior (coercivity $H_C \sim 0.2$ Oe), these materials can exhibit a giant magnetoimpedance (GMI) effect or a ferromagnetic resonance (FMR) effect;[22–24] in the absence of applied electric current, this phenomenon is referred to as the "antenna effect."[22–24] Here, investigation is focused on the antenna effect response of amorphous magnetic microwires comprising of an amorphous metallic ferromagnetic core (typical radius 10–20 microns) covered by uniform borosilicate glass (i.e., pyrex) coating of approximately 20–30 microns in thickness. The microwires of this study were procured from Microfir Tehnologii Industriale Ltd. (Moldova) with a consistent composition of $(Co_{0.94}Fe_{0.06})_{75}Si_{10}B_{15}$ and an outer wire diameter of 75–100 microns. Data were collected from configurations of parallel wire arrays (array specifics provided in the following section) that were mounted on a piece of dielectric plastic film and secured with clear adhesive tape.

The initial neural network computational analyses were performed on 225 separate and unique measurements (*aka* configurational response pairs) of the antenna effect response collected from the glass-coated amorphous magnetic microwires arranged in a variety of configurations as tags. The microwire arrays were assessed in the frequency domain in the range 1–4 GHz using two double-ridged guide horn antennas (ETS-LINDGREN model 3115) as an emitter and a receiver; these were spaced 1.2 m apart to ensure a far-field configuration. The antennas were connected to a programmable network analyzer (Agilent E8362B PNA Series Network Analyzer). The microwire arrays were oriented perpendicular to the midline connecting the two antennas, perpendicular to the direction of the incident EM waves. After open-air calibration, the scattering parameters S_{21}, which quantify in decibels (dB) the ratio of the emitting antenna power (P_1) to the receiving antenna power (P_2), were determined according to Equation 1:

$$S_{21} = 20 \cdot \log_{10} \frac{P_2}{P_1} \tag{1}$$

The resultant EM scattering information was collected in the frequency domain where the measured S_{21} scattering coefficient presents a minimum.

Neural network architecture and training

Using the data collected as described above, a neural-network-based machine learning model[4,25] was developed and optimized to predict the S_{21} response generated by a given configuration of magnetic microwires. The microwire configurations used to generate signals were initially defined using three features: (a) the length of the microwires (either 3, 4, or 8 cm), (b) the number of the microwires (between 1 and 16), and (c) the separation between microwires (ranging from 0.4 to 20 cm). The response of a particular configuration was represented by a 200-dimensional vector of dB values denoting the S_{21} response, with each dB value corresponding to fixed, linearly separated frequencies in the 1–4 GHz range.

These three features describing the microwire configurations were input into the neural network model with a single hidden layer of 1000 artificial neurons with rectified linear unit (ReLU) activations.[26,27] In the field of neural networks, the term "neurons" refer to an operation that performs a weighted sum of all the inputs, with the weights being parameters that are optimized using training data. Batch normalization[28] was applied to the hidden layer before the output layer produced an output of a 200-dimensional vector designed to match the recorded S_{21} response. The model was trained on Mean Square Error (MSE) loss using the popular ADAM optimizer,[29] with a learning rate hyperparameter value of 1e−3 and a L2 regularization[30] hyperparameter value of 1e−6 for up to 2000 epochs. The MSE represents a statistical assessment of the validity of the model and is the average of the square of the differences between the target dB values and predicted dB values, which is minimized during the training phase. From the total 225 (configuration, response) pairs that were initially studied, a randomly chosen selection of 202 measurements (90% of the total number) was used for training the neural network model, while the remaining 23 measurements (10% of the total number) were employed as "unseen" data to evaluate the model's performance. This 90-10 split was performed 10 times to quantify the error associated with the random splitting of the training and testing data.

Results and discussion

Initial outcomes

The neural network favorably reproduced the response distribution of unseen data to a confidence level of 90%, with a quite favorable mean square error less than 0.01. The model outcomes are provided in the first two columns of Table I that contain the MSE values resulting from both the training and testing phases. Corresponding plots of the actual and the predicted responses obtained from a selection of the unseen microwire configurations are provided in Fig. 1. Good agreement between the actual data and the predicted data is visually evident, and is anticipated to improve further as more configurational response pairs are analyzed by this neural network model. The high quality of the predictions, as obtained from only 202 separate spectral response measurements, is very noteworthy as conventional machine learning wisdom indicates that thousands of images are typically necessary for achievement of good predictions.[31]

Calibrating the neural network model for new environments

To evaluate the performance of the model in evaluating microwire array data collected in new environments arising from altered measurement conditions, effects of calibrating, or fine-tuning, the neural network was investigated using a small subset of the additional measurements (referred to as the calibration set). Of particular note are the differences in how well shielded the measurement apparatus were to the ambient magnetic fields and temperatures, allowing us to understand our model's performance in more real-life environments as opposed to a shielded lab environment. In the absence of this calibration step, the performance of the original neural network applied to the additional data obtained in a new environment was noted to degrade; that is, model predictions of the microwire array response measured in a new environment resulted in greatly increased MSE values (see Table I, Column 3). To perform this fine-tuning, the original neural network model was trained using this calibration set

Table I. Resultant mean square error (MSE) values and corresponding error in magnetic microwire transmission coefficient responses (S_{21}).

Original training MSE value	Original testing MSE value	Testing MSE value of original model applied to data obtained in a new environment	Testing MSE value of fine-tuned model applied to data in a new environment
0.002 ± 0.0005	0.0075 ± 0.0007	0.02 ± 0.009	0.008 ± 0.0006

The neural network model was developed from 202 randomly chosen training measurements and was tested on 23 unseen measurements. The final two columns in this Table denote the performance of the neural network in the new environment (a different measurement condition) both without and with calibration/fine-tuning.

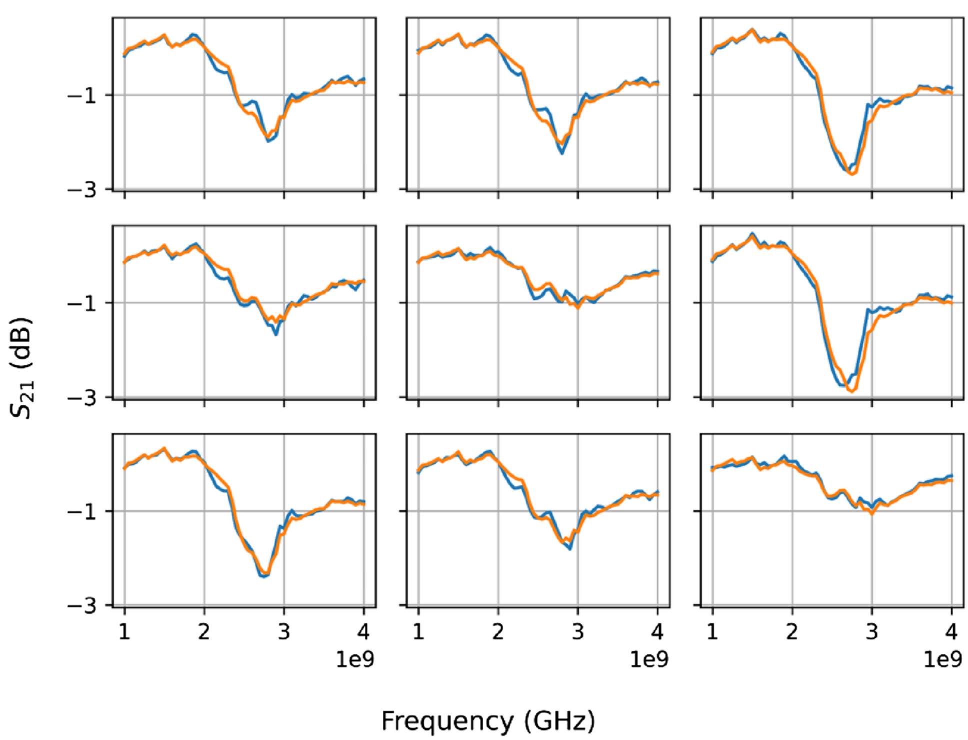

Figure 1. Actual responses (blue traces) and predicted responses (orange traces) for the scattering coefficient data (S_{21}) originating from various unseen magnetic microwire tag configurations.

for up to 2000 epochs, as was conducted earlier, with the other training hyper-parameters kept fixed as described in the previous section. It was found that calibration sets consisting of as few as 30 additional measurements (compared to the 202 measurements required for the initial training activity) were sufficient to enable the model to detect nuances of responses to the new environment and improve the MSE values, restoring them back to their original low levels (see Table I, Column 4). Note that quantification of error in the MSE values, arising from random selection of the original training data or the calibration set, is obtained from 10 repetitions of the fine-tuning step, each conducted with a different random calibration set. This allows us to average out fluctuations in the results due to the randomness in the neural network training process, and we report the observed fluctuations as a confidence interval around the average MSE values.

Analyzing the sensitivity of machine learning models

Once the models were able to accurately predict responses obtained from various magnetic microwire tag configurations and adapt to changing environments, the sensitivity of the machine learning models to differences in these configurations was investigated. That is, it was desired to determine the smallest change in response that the machine learning model could correctly accommodate. This aspect was investigated by acquiring and analyzing new datasets that probed three additional microwire configuration features. The first additional feature was the angle θ between the wire orientation and line connecting the antennas; this feature tracked in-plane changes in the direction of the emitted EM wave. The remaining two additional features, expressed as two-dimensional x and y coordinates, tracked the in-plane position of the microwire relative to the midline position between the emitter and receiver antennas. The x-shift described the distance that the wires were displaced along the direct transmitter/receiver line (closer to/farther away from the antennas). The y-shift was perpendicular to the x-shift.

Preliminary observations indicate that the spectral predictions returned by the machine learning models are poor when the angle θ is changed from its original value of zero degrees. We hypothesize that these poor results are due to the response changing as the wires move away from being perpendicular to the direction of the electromagnetic wave propagation. The machine learning models, in turn, could not compensate for this change in the nature of the response. The spectral predictions of the machine learning models are better for the x-shift; however, even with respect to that feature, the MSE values were worse than those reported in previous sections. While the reasons underlying these results are not clear at the current time, it is believed that they may have their origins in details of the detected response in near-field versus far-field conditions. In contrast, spectra produced from the y-shift is easy for the model to predict, with MSE values in the same range as the results depicted in Table I. In fact, significant differences in responses produced by microwire arrays that have been shifted only in the y-direction are quite distinguishable.

Conclusions

Successful prediction (< 0.01 mean squared error (MSE), within 90% confidence level) of "unseen" high-frequency electromagnetic responses measured from 2D arrays of amorphous ferromagnetic microwires was achieved using neural network-based machine learning. These results, obtained from a surprisingly small number (225) measurements, were extended using an additional 30 measurements to fine-tune the model for improved robustness to varied environments.

This work combines magnetic materials science, specifically the electromagnetic response of amorphous magnetic microwires, with machine learning techniques for training neural networks to faithfully reproduce the microwire GHz antenna responses with high fidelity. We demonstrate that with the carefully chosen neural network architectures and clean data, it is possible to achieve good performance using very few measurements compared to what is considered the norm in neural network literature.[31] Interpreting the results of the machine learning model to improve the physical understanding of the properties of magnetic microwire signatures is part of ongoing and future work. Considering the overall abundance of controllable parameters enabled by the magnetic microwires, we have an immense and highly versatile palette of variables and conditions to realize unique tracking "tags." Combined with the high-fidelity reproduction by a neural network of the electromagnetic response of these magnetic microwire arrays allows us to envision simulating a variety of materials compositions alongside varying physical configurations of these materials, to efficiently capture and understand large scale tag spaces.[12,13] Our results allow us to model tags using a neural network, which allow innovative neural network architectures to create efficient encoder and decoder for tags to and from their electromagnetic responses.[15,16] In follow-on preliminary work,[17] by employing a novel autoencoder architecture along with concepts from information theory, we leverage the proof-of-concept described in this paper to create a general algorithm for creating a practical tagging system from any scanning technology.

These proof-of-concept results are but the necessary first step in a novel approach toward the eventual goal of hidden machine-readable authentication of objects (equipment, medical and pharmaceutical products, materials, documents, currency, etc.). We note that the security of supply chains in the USA is a market estimated to be over a billion dollars in size in 2021 and growing at a CAGR greater than 5%. Our approach and architecture are very general. With any scanning technology modeled as a deep network, we envision a cyber-physical system—the cyber half constitutes the brains exploring and organizing the tag space, while the physical robotic half constitutes the brawn, creating and validating actual physical tags, and the two work in close coordination to create an efficient and practically usable tag system.

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Data availability

The authors will not make data used for training the neural network models available since they are part of an IP disclosure.

Code availability

The code used for analysis will be made available on request.

Declarations

Conflict of interest

The authors have no conflicts of interest.

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