RF signal classification in hardware with an RF spintronic neural network

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Extracting information from radiofrequency (RF) signals using artificial neural networks at low energy cost is a critical need for a wide range of applications. Here we show how to leverage the intrinsic dynamics of spintronic nanodevices called magnetic tunnel junctions to process multiple analogue RF inputs in parallel and perform synaptic operations. Furthermore, we achieve classification of RF signals with experimental data from magnetic tunnel junctions as neurons and synapses, with the same accuracy as an equivalent software neural network. These results are a key step for embedded radiofrequency artificial intelligence.

Introduction

Making sense of radiofrequency (RF) signals is key to a wide range of applications, from connected objects and radars to gesture sensing and biomedical devices. For many signal classification tasks, for instance emitter type identification, artificial neural networks have proven to perform better than standard methods and prove superior robustness to noise and defects. Running neural network on conventional computing hardware consumes high amounts of time and energy, which limits the possibility to equip embedded system with such capability. This issue is amplified in the case of RF signals, because they require signal digitization before being processed by the neural network.

A promising path to reduce the energy consumption of artificial intelligence is to build physical neural networks using emerging technology. For this goal, spintronic nanodevices have key advantages, including their multifunctionality, fast dynamics, small size, low power consumption, high cyclability, high reliability and CMOS compatibility. Furthermore, the high-speed dynamics of spintronic devices provides them key features for the emission, reception and processing of RF signals. Several studies have shown their potential for building hardware neural networks. In particular, it was recently proposed to use the flagship devices of spintronics, magnetic tunnel junctions (MTJs) as synapses for RF signals.

Here we show how MTJs can process multiple RF inputs in parallel. Then we perform extreme learning on analogue RF signals, using RF MTJs both as synapses and neurons. We experimentally classify RF signals encoding a four-pixel image, into three classes with over 99% accuracy, as good as the equivalent software network. Our hardware neural network opens the path to embedded RF artificial intelligence.
Analogue processing of multiple radiofrequency signals in parallel

We leverage the intrinsic fast dynamics of nanodevices called magnetic tunnel junctions (MTJs) to natively process analog RF signals. These devices are nanopillars of two ferromagnetic layers separated by a tunnel barrier. When an RF current is injected into an MTJ, as depicted in Figure 1, the magnetization of one layer enters in resonance with the input signal and by magnetoresistive effect a direct voltage is generated\(^3\). This effect, called spin-diode, is frequency selective: the output voltage is only generated when the input signal is close to the resonance frequency of the device. Figure 1, depicts how four MTJs of different resonance frequencies process the 100 MHz to 700 MHz spectrum. All four devices are from a material stack of SiO\(_2\) // 5 Ta / 50 CuN / 5 Ta / 50 CuN / 5 Ta / 5 Ru / 6 IrMn / 2.0 Co\(_{70}\)Fe\(_{30}\) / 0.7 Ru / 2.6 Co\(_{40}\)Fe\(_{40}\)B\(_{20}\) / MgO / 2.0 Co\(_{40}\)Fe\(_{40}\)B\(_{20}\) / 0.5 Ta / 7 NiFe / 10 Ta / 30 CuN / 7 Ru, where thicknesses are indicated in nm, and have different diameters from 250 nm to 450 nm. The typical resistance area product of the devices is 8 Ωµm\(^2\). Using individual magnetic fields, we can fine tune the frequencies of the devices.

Each MTJ can perform synaptic operations on analog RF signals. Indeed, the output dc voltage \(V_i\) is proportional to the input RF power \(P_i\) injected in the device and can be expressed as:

\[
V_i = P_i \times w_i (f_i^{RF} - f_i^{res})
\]

Where \(f_i^{RF}\) and \(f_i^{res}\) are the input and resonance frequencies respectively. The input frequencies are \(f_i^{RF} = 160\) MHz, \(f_i^{RF} = 310\) MHz, \(f_i^{RF} = 400\) MHz and \(f_i^{RF} = 524\) MHz. The synaptic weights \(w_i\) can thus be tuned through the resonance frequencies of the
devices. Each column of Figure 2 demonstrates the synaptic operation for one of the four MTJs. The top row shows how the output dc voltage is proportional to the input RF power, with a proportionality factor (i.e., synaptic weight) that is controlled by the magnetic field (i.e., the resonance frequency) and can be set both to positive and negative value. In order to have a significant output, for each MTJ we chose an input frequency close to its resonance. The bottom row compares the experimental voltage to the expected voltage for a perfect synaptic operation. We obtain a high accuracy (root-mean-square errors of 2.5%, 6.3%, 7.7% and 5.6% of the range for each MTJs respectively), which demonstrates the synaptic operations on single signal inputs.

Figure 2. (a-b-c-d) Synaptic multiplication: rectified DC voltage versus RF power, for different magnetic fields (colors). The dots are measurements while the dashed lines are linear fits. (e-f-g-h) Accuracy of the operation: measured voltage (dots) versus the ideal voltage (solid line). The magnetic fields are, from yellow to purple: (a) 370 mT, 360 mT and 350 mT, (b) 320 mT, 310 mT and 300 mT, (c) 460 mT, 450 mT, 440 mT and 430 mT, (d) 410 mT, 400 mT, 390 mT and 380 mT.

In applications, RF signals are composed of several frequencies. As a consequence, we now send the sum of the four RF inputs to all MTJs, as schematized in Figure 3(a). Each MTJ simultaneously processes the four RF signals. The resulting output dc voltage of each MTJ is:

\[ V_i = \sum_{k \text{ inputs}} P_k \times w_{ik} (f_k^{RF} - f_i^{res}) \]

Were \( P_k \) and \( f_k^{RF} \) are the power and frequency of each RF input signal. Figures 3(b-c-d-e) show the measured voltage versus ideal expected voltage for each device, for all input power and synaptic weight combinations. The ideal voltages were computed using the synaptic weights from the responses to individual RF inputs. The fact that there is a good agreement (8.0%, 6.5%, 8.3% and 6.6% respectively) between the measured and ideal voltages demonstrates the ability of the MTJs to linearly sum RF signals and function as synapses even when they receive several RF inputs simultaneously.
In neural networks, the output of synapses connecting to a neuron are summed before a non-linear activation function is applied by the neuron\textsuperscript{31}. Therefore, we sum the outputs of the four MTJs. The resulting voltage is expressed as:

\[
V = \sum_{i} V_i = \sum_{i} \sum_{k} P_k \times w_{ik}(f_{k}^{RF} - f_{i}^{res})
\]

\[
V = \sum_{k} P_k \times W_k
\]

The total voltage is a weighted sum of the input powers by tunable weights, as desired. Each synaptic weight \(W_k\) is encoded by all MTJs, although the main contribution comes from the device whose resonance frequency is closest to the input frequency. Figure 3(f) shows that there is a good agreement (the root-mean-square error is 4.4 % of the range) between the measured and expected voltages. We observe that the agreement is better for the sum of all outputs than for the individual devices outputs. This is because errors on the individual voltages are averaged out through the sum. As only the result of the sum is meaningful for the neural network, this is promising for the scalability of the system. These results demonstrate that arrays of MTJs can process multiple RF inputs simultaneously, over a wide frequency range in parallel.

![Figure 3](image)

Figure 3. (a) Schematic of each MTJ receiving four RF inputs. (b-c-d-e) Measured voltage (dots) versus expected voltage (solid line). For each plot, all combinations of input powers (from 1 to 11 \(\mu\)W by 2 \(\mu\)W steps) and weights values where measured. (f) Measured voltage (dots) versus expected voltage (solid line) for the sum. All combination of the four sets of powers and weights were measured.

**Classification of RF signals with experiments**

We now use these experimental results to perform RF signal classification with a neural network. We compose a dataset of analogue RF signals as follows. Each sample of the dataset is a four-pixel image, as the ones shown in Figure 4. Each pixel corresponds to a frequency \(f_{i}^{RF} = 160 \text{ MHz}, f_{i}^{RF} = 310 \text{ MHz}, f_{i}^{RF} = 400 \text{ MHz} \text{ and } f_{i}^{RF} = 524 \text{ MHz}\) and the intensity of the pixel is encoded by the RF power at that frequency. For each class of the dataset, two pixels are chosen to be “on” while the two remaining are “off”. We chose three classes, shown in Figure 4. We assign the powers 1 and 3 \(\mu\)W to the “off” pixels and 7 and 9 \(\mu\)W to the “on” pixels. Having different possible values for on and off emulates noise.
In order to classify these signals, we use a neural network method called extreme learning\textsuperscript{28,29}, depicted in Figure 4. In extreme learning, there are two fully connected layers of synaptic weights, separated by one layer of neurons. Similar to reservoir computing, the first layer of weights $W^{(1)}$ is random and not trained. The second layer of weights $W^{(2)}$ is trained by a simple matrix inversion. The class of the signal is the output with the highest value. The equation of the network is:

$$y = W^{(2)} \times a(W^{(1)} \times P)$$

Where $y$ is the output vector, $a$ is the activation function of the neurons and $P$ is the input vector of powers. The weights of the second layer are chosen as:

$$W^{(2)} = \hat{y}_{all} \times \mathcal{F}(a(W^{(1)} \times P_{all}))$$

Where $P_{all}$ is the matrix of all input vectors in the dataset, $\hat{y}_{all}$ is the matrix of all target outputs in the dataset and $\mathcal{F}$ is the pseudo-inverse function.

We compose the first fully connected layer using the experimental weighted sums. By using all combinations of measured weights of the four MTJs (i.e. of the weights shown in Figure 2), we obtain 144 pseudo-random sets of weights. The results of the 144 MAC operations are injected into MTJ neurons. These MTJs are used as neurons as in\textsuperscript{23}, where the non-linear relationship between their output RF power and input DC current serves as activation function. We implement 144 activation functions with two MTJ devices. The two MTJs are measured under different conditions so to vary their activation function and thus mimic device to device variability: using dc current injection in a strip line above the device we generate a different local Oersted field for each neuron.

![Figure 4. Schematic of classification using extreme learning.](image)
equivalent software network, where the first layer is composed of ideal weighted sums with weights extracted from the experiment, and the neurons are conventional rectified linear units. We perform 100 runs, with 4 randomly chosen samples per class for the training set, and 20 randomly chosen samples per class for the test set. We obtain 100 % accuracy (i.e. proportion of correctly classified samples) for the training set, both for the experimental network and for the equivalent software network. For the test set we obtain 99.7 % for the experimental network and 96.2 % for the equivalent software network, with standard deviations of 0.9 % and 7.2 % respectively. If we complexify the task by having six classes (all possible combinations of two chosen pixels in the image), the test accuracy becomes 93.2 % for the experimental network and 94.9 % for the equivalent software network, with standard deviations of 3.6 % and 5.2 % respectively. Figure 5 shows the corresponding confusion matrices for both tasks. These results demonstrate that a network composed of RF MTJs as synapses and neurons can classify raw analogue RF signals, as well as a software network.

![Confusion matrix for the classification of RF signals, both for the purely software network and for the network using experimental data.](image)

**Conclusions**

We have leveraged the dynamics of magnetic tunnel junctions to perform synaptic operations, and performed weighted sums on several analogue RF signals in parallel. By choosing the materials, shape and size of the devices, their frequency can be engineered from 50 MHz to 50 GHz\textsuperscript{32}. As a consequence, an array of magnetic tunnel junctions could process RF signals over this whole frequency range in parallel, without digitization. This removes the need of multiple local oscillators or high-speed ADCs\textsuperscript{33}. Using RF MTJs both as synapses and as neurons, we compose a neural network and demonstrate classification of RF signals with the same accuracy as the equivalent software network. These results open the path towards large neural networks able to perform artificial intelligence tasks on raw RF signals, without digitization, at low energy cost and small size.
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