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Temperature-dependent reservoir computing with granular vortex magnetic tunnel junctions

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Granular vortex-based magnetic tunnel junctions (GV-MTJs) provide a promising hardware platform for physical reservoir computing by combining nonlinear magnetodynamics, intrinsic short-term memory, and device-level structural complexity. Here, we experimentally investigate the temperature-dependent reservoir-computing performance of individual GV-MTJs with 600 nm and 800 nm diameters. Unlike previous simulation-based studies, this work presents an extensive measurement-driven evaluation of granular free-layer dynamics under thermal stress and assesses their computational capability using the Free Spoken Digit Dataset. Input waveforms are applied through a field line, while the measured reservoir responses are transformed using Mel-scaled filterbanks and classified with compact convolutional neural networks, enabling application-level benchmarking of the device response. Across ambient temperatures from 20 °C to 90 °C, the GV-MTJ reservoirs maintain stable spoken-digit classification performance, with accuracy degradation below 3 percentage points. At 160 °C, however, performance decreases sharply, consistent with thermally induced degradation of vortex dynamics and a reduction in effective grain-induced dynamical diversity, as supported by signal-level analysis and structural observations. These results show that free-layer granularity, traditionally regarded as a source of device variability in MTJs, can be exploited as a computational resource for reservoir computing, while also identifying the temperature range over which this resource remains effective. Overall, this work demonstrates the operational robustness and thermal limitations of GV-MTJ reservoirs and provides design guidelines for granular spintronic reservoirs in future neuromorphic edge-computing systems.

Introduction

Recent advances in spintronic devices have created new opportunities for developing compact, energy-efficient, and high-speed computing hardware [1-7]. Among these devices, magnetic tunnel junctions (MTJs) hosting magnetic vortex states have attracted particular interest because of their non-volatility, nonlinear magnetization dynamics, multilevel response, and compatibility with nanoscale integration [1, 8-11]. These properties make vortex-based MTJs promising candidates for neuromorphic and unconventional computing systems, where

computation can be performed by exploiting the intrinsic dynamics of physical devices rather than relying solely on conventional digital logic [12, 13].

In conventional spintronic device design, however, material granularity and microstructural disorder are typically regarded as undesirable sources of variability, since they introduce local pinning landscapes and non-uniform magnetic responses [14]. Polycrystalline ferromagnetic layers contain grains with local variations in magnetic anisotropy, exchange interaction, and pinning potential, which can perturb vortex motion and introduce stochasticity in the device response [15-17]. Such effects are often associated with reduced reproducibility, device-to-device variability, and degraded reliability. Consequently, considerable effort has been directed toward minimizing the impact of granularity in order to obtain stable and predictable spintronic device characteristics [18, 19]. In contrast to this conventional view, reservoir computing offers a fundamentally different perspective: the same disorder and nonlinear dynamics that are problematic for deterministic device operation can become useful computational resources.

Reservoir computing (RC) is a neuromorphic computing framework in which input signals are projected into a high-dimensional dynamical space by a nonlinear system with fading memory [20, 21]. Instead of training the full dynamical system, only a simple readout layer is typically optimized, which makes RC attractive for hardware implementation. Effective physical reservoirs require two key properties: nonlinearity, to transform input signals into separable representations, and short-term memory, to retain temporal information over relevant time scales [13, 22]. These requirements make vortex-based MTJs particularly appealing for reservoir computing. Compared with uniform precessional MTJs, vortex-based devices operate through gyrotropic vortex-core motion, typically at lower characteristic frequencies [23]. Within a damped gyrotropic-mode description, the relaxation timescale depends on both the oscillation frequency and the effective damping [24]; therefore, lower-frequency vortex dynamics can provide a longer fading-memory window when damping is comparable. Moreover, the spatial motion of the vortex core enables interactions with local pinning sites and grain-induced energy landscapes, producing nonlinear transient responses, relaxation processes, and history-dependent behavior. In granular vortex-based MTJs (GV-MTJs), the free-layer granularity further enriches the dynamical response by introducing local pinning landscapes and grain-dependent perturbations to vortex motion [7, 25-27]. Rather than treating these effects as imperfections, GV-MTJs allow granularity to be exploited as an intrinsic source of reservoir diversity.

The potential of GV-MTJs for reservoir computing has recently been explored in simulation-based and preliminary experimental studies [28, 29]. These works suggested that the grain-induced complexity of the free layer can support nonlinear transformation and short-term memory, enabling GV-MTJs to act as compact physical reservoirs. However, a key question remains unresolved: whether these reservoir properties remain robust under temperature variations. This question is important for both fundamental and practical reasons. Temperature can modify vortex dynamics, relaxation time, oscillation frequency, thermal noise, and the effective influence of grain-induced pinning. As a result, thermal stress may either enrich the reservoir response or degrade the dynamical features required for reliable computation. Understanding this balance is essential for evaluating GV-MTJs as practical neuromorphic hardware elements.

In this work, we experimentally investigate the temperature-dependent reservoir-computing performance of individual GV-MTJs with diameters of 600 nm and 800 nm. We combine extensive electrical measurements with micromagnetic simulations using MuMax3 to analyze how temperature affects vortex relaxation, characteristic frequency, signal stability, and the effective contribution of free-layer granularity. We then evaluate the computational relevance of these temperature-dependent dynamics using the Free Spoken Digit Dataset, where measured GV-MTJ responses are used as physical reservoir outputs for spoken-digit classification. This enables us to connect device-level magnetic dynamics with application-level reservoir-computing performance.

Our results show that GV-MTJ reservoirs maintain stable classification performance from 20 °C to 90 °C, with only minor degradation, indicating that grain-induced vortex dynamics remain computationally useful over a practical temperature range. At 160 °C, however, the classification performance decreases sharply, which we attribute to a combination of shortened vortex relaxation time, reduced effective grain-mediated pinning, smoother vortex-core trajectories, and weakened grain-induced dynamical diversity. These findings demonstrate that free-layer granularity, often considered a fabrication imperfection, can be harnessed as a physical computing resource, while also revealing the thermal limits of this approach. The results provide design guidelines for future spintronic reservoir-computing systems intended for operation in variable thermal environments.

Results

We investigated the role of free-layer granularity in GV-MTJs as a physical resource for reservoir computing and assessed how this resource evolves under thermal stress. The results are organized to first establish the device concept and reservoir-computing framework, then characterize the temperature-dependent vortex dynamics, and finally connect these physical responses to spoken-digit classification performance using measured device signals.

Granular vortex MTJs as physical reservoirs

The proposed reservoir-computing framework based on a granular vortex magnetic tunnel junction (GV-MTJ) is schematically illustrated in Fig. 1. The device consists of a multilayer MTJ stack fabricated on a Si substrate, with bottom and top electrodes used for electrical readout. The stack comprises a synthetic antiferromagnet (SAF), a reference layer (RL), an MgO tunnel barrier, and a granular free layer (FL) hosting a magnetic vortex configuration. A field line (FiL) integrated above the stack enables local magnetic excitation of the free layer. Input signals are applied as currents through the field line, producing magnetic fields that perturb the vortex dynamics. The resulting vortex motion within the granular magnetic landscape generates a nonlinear time-dependent response, which is measured electrically as the voltage across the MTJ.

In this framework, the intrinsic dynamics of the GV-MTJ serve as the physical reservoir. The input signal is transformed by the device into a time-dependent reservoir state, $x(t)$, determined by the vortex trajectory, relaxation dynamics, and interactions with the granular free-layer landscape. The resulting output response is then processed by a lightweight readout network, implemented here using compact convolutional and fully connected layers. This approach is consistent with the reservoir-computing paradigm, in which the physical reservoir

provides nonlinear temporal transformation of the input, while the trainable stage is restricted to the readout.

The computational capability of the GV-MTJ reservoir originates from the interplay between vortex dynamics and free-layer granularity. The granular structure introduces spatial inhomogeneity in the magnetic energy landscape, creating local variations in pinning strength and preferred vortex positions. Under external excitation, the vortex core can undergo both gradual relaxation and abrupt transitions between local pinning sites. These dynamics naturally provide two essential properties for reservoir computing: short-term memory and nonlinearity. Short-term memory arises from the finite relaxation time of the vortex state, allowing previous inputs to influence the present response. Nonlinearity emerges from the irregular and history-dependent vortex motion, particularly during transitions between grain-defined metastable states.

An important feature of this system is that the grain distribution can directly influence the richness of the reservoir dynamics. A larger number of effective pinning sites may increase the number of metastable states accessible to the vortex, thereby enhancing the diversity of internal responses. In this sense, the granular free layer can play a role analogous to an expanded set of dynamical nodes in a conventional reservoir. However, this computational benefit depends on the extent to which the granular landscape remains dynamically active under operating conditions. Temperature is therefore a key parameter, since it can modify pinning strength, thermal activation, vortex relaxation, and the effective visibility of grain-induced energy barriers.

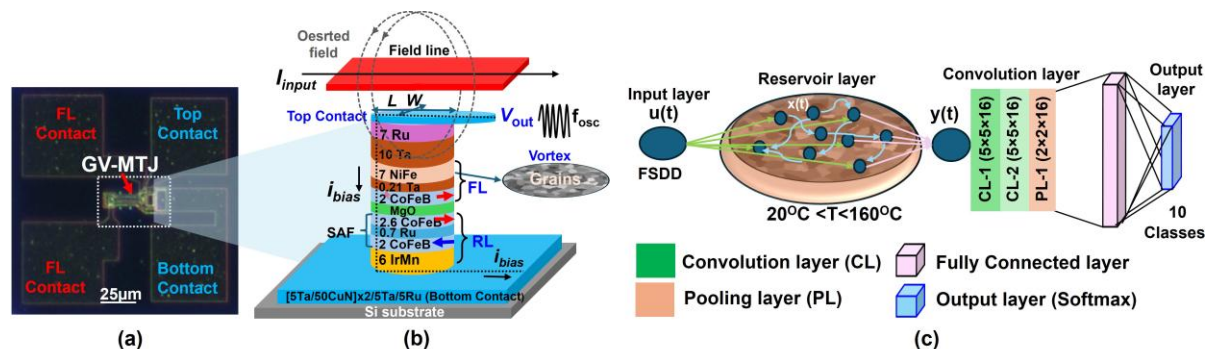


Figure 1. GV-MTJ device structure and reservoir-computing framework. **a)** Microscopic image of the fabricated granular vortex magnetic tunnel junction (GV-MTJ) device. **b)** Schematic cross-section of the fabricated GV-MTJ, showing the multilayer stack, layer sequence, and corresponding layer thicknesses. **c)** Conceptual representation of the GV-MTJ as a physical reservoir. External input signals excite the magnetization dynamics of the granular free layer, generating complex time-dependent internal states, $y(t)$, through recurrent magnetic interactions, vortex motion, and temporal memory. The measured reservoir response is processed using a compact neural-network readout consisting of one convolutional layer followed by one or two fully connected layers, depending on the network architecture. Only the readout stage is trained for tasks such as classification or regression.

Previous studies of vortex dynamics in magnetic thin films have shown that pinning centers can trap the vortex core, leading to intermittent stick-slip motion as the core moves between localized sites [30, 31]. Burgess reported that such vortex pinning and depinning can produce abrupt changes in the overall magnetization, characteristic of stick-slip motion [32]. In that study, smoother magnetization curves were observed at higher temperatures, whereas pinning effects became more pronounced at low temperature, around 77 K. In contrast, our measurements show that discrete grain-mediated transitions persist at room temperature and

above, resembling Barkhausen-type effects. This suggests that the granular landscape remains dynamically relevant over a broader temperature range than might be expected from purely thermally activated smoothing of pinning effects. By embedding these physical dynamics within a reservoir-computing framework, the present work investigates how free-layer granularity can be exploited as a computational resource and how its effectiveness evolves under thermal stress.

Simulated temperature-dependent vortex dynamics and material-parameter sensitivity

We begin with micromagnetic simulations because they allow temperature-dependent material parameters, device geometry, and grain-mediated pinning to be examined in a controlled manner before turning to fabricated devices. In fabricated devices, the material stack, device geometry, and grain structure are fixed after fabrication, which makes it difficult to isolate the individual contributions of material parameters to the measured dynamics. Simulations, in contrast, allow these parameters to be varied independently and therefore provide a controlled framework for studying their effects on the characteristic oscillation frequency and relaxation time of the vortex core. Although the simulated values are not expected to reproduce the experimental results quantitatively because of differences in exact geometry, material parameters, grain morphology, and measurement conditions, the simulations provide mechanistic insight into the experimentally observed temperature-dependent trends.

The simulations were performed using MuMax3 [33], which includes a built-in temperature model that introduces a stochastic thermal field across the simulated device, thereby accounting for thermal noise [34]. However, this model does not automatically include the temperature dependence of the material properties. To capture these effects, we manually adjusted the relevant magnetic parameters as a function of temperature using experimentally derived data reported by Kang et al. [35]. Specifically, we considered temperature-dependent variations in saturation magnetization, damping, and magnetic anisotropy for CoFeB/Ta/NiFe-based materials. Although the simulated stack is not identical to the experimentally measured devices, the comparable free-layer materials and device dimensions allow a trend-level comparison of relaxation time and oscillation frequency.

Previous studies have shown that increasing the saturation magnetization of CoFeB/Ta/NiFe free layers leads to an increase in the vortex relaxation frequency, while reducing the relaxation time [35]. In contrast, increasing the damping parameter mainly reduces the relaxation time, with comparatively little influence on the oscillation frequency. Our simulations reproduce these dependencies and further show that device diameter strongly affects both relaxation time and oscillation frequency, as shown in Fig. 2b. For the diameter-dependent simulations, the vortex core was initially positioned 50 nm from the device edge and then allowed to relax toward the center. The relaxation time was defined as the time required for the vortex core to reach a distance of 5 nm from the center. Under otherwise identical material parameters, larger devices allow the vortex core to be excited farther from the center; consequently, the core must travel a longer path before reaching equilibrium. This longer relaxation path explains the approximately linear increase in relaxation time with device diameter. In contrast, the oscillation frequency decreases nonlinearly with increasing diameter,

consistent with the expected size dependence of vortex gyrotropic dynamics. The temperature-dependent material parameters used in the simulations were derived from Kang et al. and are summarized in Fig. 2a.

To evaluate the temperature dependence of the relaxation dynamics independently of device-size effects, we selected a 500 nm diameter disc and used the same initial displacement for all simulated temperatures. Specifically, the vortex core was initially displaced by 100 nm from the disc center and then allowed to relax freely. The relaxation time was defined as the time required for the absolute distance of the vortex core from the disc center to decrease below 2 nm. This procedure was repeated 50 times for each temperature, and the average relaxation time is shown in Fig. 2c. The overall temperature-dependent trend remains similar with and without the built-in MuMax3 thermal field. However, including the stochastic temperature field results in a considerably shorter relaxation time, indicating that thermal fluctuations facilitate the return of the vortex core toward the equilibrium position.

Typical CoFeB/Ta/NiFe multilayers based FL are polycrystalline and contain internal defects that often lead to vortex core pinning [36, 37]. To model the microstructural disorder of realistic polycrystalline free layers, the circular disc was represented as a collection of randomly shaped grains generated using a Voronoi tessellation algorithm [38]. The average grain size was set to approximately 20 nm, resulting in approximately 20–25 grain regions for the simulated geometry using a fixed random seed. Each grain was assigned randomized cubic anisotropy axes derived from normally distributed vectors. In addition, the perpendicular magnetic anisotropy K_u of each grain was randomly varied around $K_0 = 2 \times 10^5$ J/m³ within the range $(K_0 - \Delta K, K_0 + \Delta K)$, corresponding to a roughness level of approximately 5–10%. To further account for grain-boundary disorder, the exchange coupling between neighboring grains was uniformly reduced by a factor between 0.9 and 0.7, representing weakened magnetic interactions across rough or irregular interfaces. This combination of randomized anisotropy orientation, anisotropy magnitude variation, and reduced inter-grain exchange provides an effective representation of the magnetic and microstructural disorder expected in polycrystalline thin films.

The simulations further show that, when a short external magnetic pulse (5 mT) is applied for 10 ns, the maximum vortex-core displacement increases with temperature, as shown in Fig. 2d. Thus, for the same external excitation, higher temperatures drive the vortex core farther from the center while also enabling faster relaxation. This behavior can be understood from the combined effects of reduced saturation magnetization and increased damping. A lower saturation magnetization reduces the energy required to perturb the magnetic configuration, leading to larger vortex displacement under the same excitation. At the same time, enhanced damping accelerates the relaxation process, reducing the time required for the vortex core to return toward equilibrium.

Temperature also affects the effective contribution of the granular landscape to the vortex dynamics. At lower temperatures, stronger pinning at grain boundaries causes the vortex core to interact with a larger number of individual pinning sites, resulting in discrete stick-slip motion and richer nonlinear dynamics. As temperature increases, thermal activation helps the vortex core overcome weaker pinning barriers more easily, leading to smoother trajectories and more collective motion across neighboring grains. Consequently, only the strongest pinning

sites remain dynamically active, reducing the number of grains that effectively contribute to the reservoir dynamics.

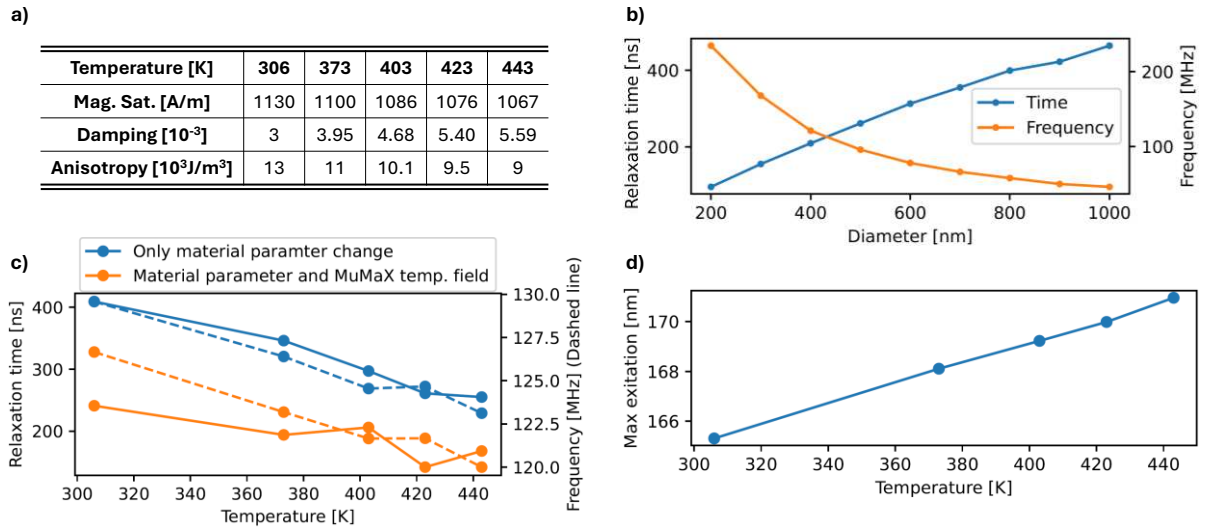


Figure 2. Micromagnetic simulation of temperature-dependent vortex dynamics. **a)** Temperature-dependent material parameters used in the MuMax3 simulations. **b)** Dependence of vortex relaxation time and oscillation frequency on disc diameter. **c)** Simulated variation of relaxation time (solid line) and oscillation frequency (dashed line) as a function of temperature. **d)** Maximum vortex-core displacement following the application of a 5 mT magnetic-field pulse for 10 ns, plotted as a function of temperature.

Taken together, the simulations establish the physical mechanisms through which temperature can reshape the reservoir properties of granular vortex MTJs. They indicate that relaxation time is primarily governed by damping and thermally assisted vortex motion, whereas changes in oscillation frequency are more strongly linked to the temperature dependence of saturation magnetization. At the same time, temperature modifies the effective grain-mediated pinning landscape by reducing the contribution of weaker pinning sites and promoting smoother vortex trajectories. Although the absolute simulated values differ from those measured experimentally, the simulations capture the key qualitative trends in relaxation time and oscillation frequency. By isolating the influence of material parameters and geometry before turning to fabricated devices, these results provide a mechanistic basis for the experimental analysis presented in the following section, where the temperature dependence of vortex dynamics is evaluated directly in GV-MTJs with different device diameters.

Experimental temperature-dependent dynamics of GV-MTJ devices

We next experimentally characterized the size- and temperature-dependent dynamics of fabricated GV-MTJs. The devices used in this study had the following multilayer stack: Ta(5)/CuN(50)/Ta(5)/CuN(50)/Ta(5)/Ru(5)/IrMn(6)/CoFe₃₀B(2.0)/Ru(0.7)/CoFe₄₀B₂₀(2.6)/MgO/CoFe₄₀B₂₀(2.0)/Ta(0.21)/NiFe(7)/Ta(10)/Ru(7), with thicknesses given in nm. Further details of the sample characteristics are provided in [18]. The selected temperature range is relevant for practical hardware integration, as it overlaps with the elevated operating-temperature regime of CMOS electronics, which can extend up to approximately 125 °C for high-reliability or military-grade applications [37]. In contrast to the simulations, where individual material parameters and grain configurations can be modified independently, the fabricated devices have fixed material stacks and microstructures. The measurements therefore

capture the combined influence of temperature, device size, and grain-mediated pinning on the experimentally observed vortex dynamics.

Relaxation time and frequency: We first examined the relaxation time and oscillation frequency of GV-MTJs as a function of temperature. These quantities are directly relevant to reservoir computing: the relaxation time determines the fading-memory timescale of the reservoir, whereas the oscillation frequency reflects the characteristic dynamical response of the vortex system. Measurements were performed on GV-MTJs with diameters of 1000 nm and 600 nm, with three devices tested for each size. To extract the relaxation time, the vortex core was first strongly excited by a field-line pulse designed to push it toward the edge of the device, while a constant MTJ bias current was maintained for electrical readout. After the field-line signal was switched off, the decay of the oscillatory voltage response across the MTJ was monitored as the vortex core relaxed back toward equilibrium near the device center. The relaxation time was defined as the time interval between the falling edge of the field-line pulse and the disappearance of the oscillatory component in the MTJ voltage trace. Further details of the extraction procedure are provided in the Methods section and illustrated in Fig. 9b. The corresponding relaxation times and frequencies are shown in Fig. 3.

For both device sizes, the relaxation time decreases with increasing temperature. Linear fits to the relaxation-time data show an overall reduction of approximately 15% for the 1000 nm devices and approximately 10% for the 600 nm devices across the measured temperature range. The larger 1000 nm devices exhibit longer relaxation times than the 600 nm devices, consistent with the simulation results showing that larger disc diameters lead to slower vortex relaxation. Although the absolute relaxation times measured experimentally are lower than those predicted by the simulations, the qualitative size and temperature trends are consistent. This difference in absolute values is expected, since the simulations do not fully reproduce the exact multilayer stack, grain morphology, material parameters, and measurement conditions of the fabricated MTJs.

The measured oscillation frequency also varies with temperature, although the behavior is more device-dependent than the relaxation time. For the 1000 nm devices, the relaxation frequency decreases with increasing temperature, with an average reduction of approximately 5.4%. This agrees well with the simulated trend, which predicted a reduction of approximately 4%. For the 600 nm devices, the average frequency reduction is approximately 4.3%, but the individual devices show stronger variability. In particular, one 600 nm device exhibits a non-monotonic frequency response, with an initial increase followed by a decrease at higher temperature. Such deviations suggest that local grain morphology, pinning configuration, and device-to-device variability can influence the temperature dependence of the vortex dynamics, especially in smaller devices where individual pinning sites may have a stronger relative effect.

Measurements were also extended to elevated temperatures up to 150 °C. However, under these conditions the integrated field line could not reliably sustain the high excitation currents required for repeated measurements, and field-line failure was observed in several samples. Despite this limitation, the 1000 nm MTJ 3 provided usable data over the extended temperature range without failure, showing a relaxation-time decrease from 130.6 ns at 100 °C to 120.7 ns at 150 °C, corresponding to an approximately 8% reduction. Considering that similar devices exhibited a relaxation-time reduction of approximately 15% over an 80 °C interval (from 10

°C to 90 °C as shown in Fig. 3a), this result supports the presence of an approximately linear decrease in relaxation time at elevated temperatures. Overall, both simulations and experimental measurements show consistent temperature-dependent trends. Since the reservoir capability of GV-MTJs depends not only on the relaxation timescale but also on the richness of grain-mediated vortex motion, we next examined how temperature affects the number of effective pinning events associated with the granular free layer.

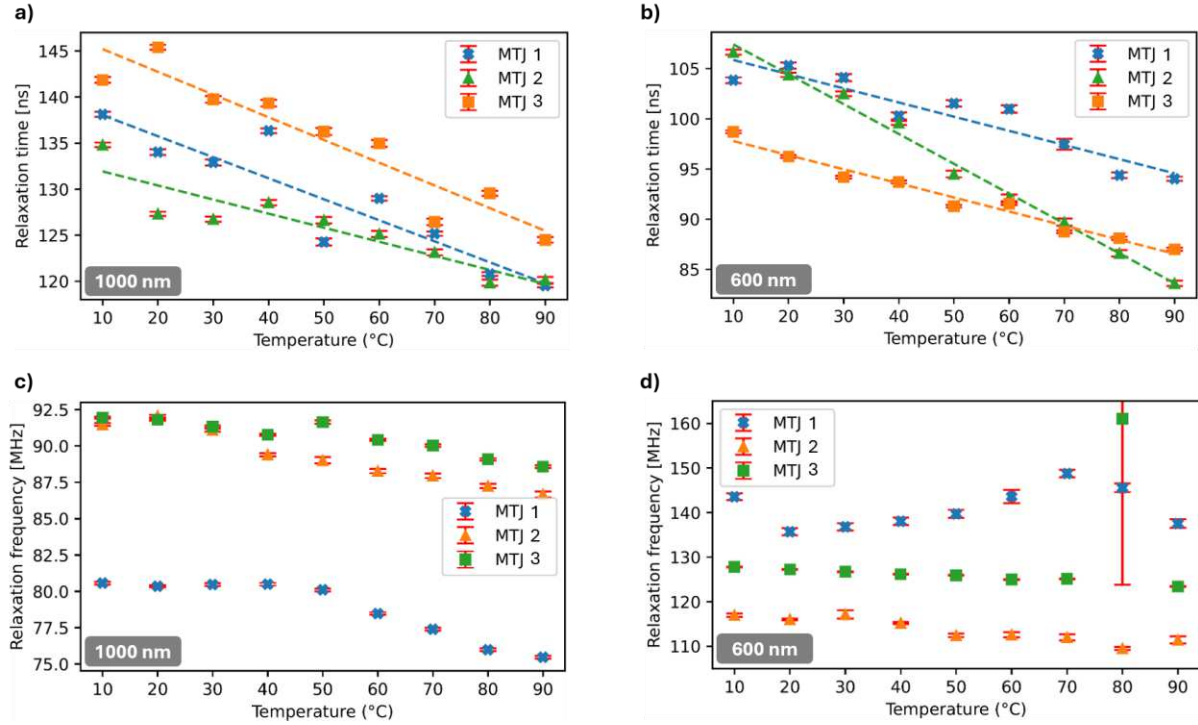


Figure 3. Temperature-dependent relaxation dynamics of GV-MTJ devices. Temperature dependence of the relaxation time and relaxation frequency for GV-MTJs with diameters of 1000 nm and 600 nm. **a,c)** Relaxation time and relaxation frequency, respectively, for 1000 nm devices (MTJ1, MTJ2, and MTJ3). **b,d)** Relaxation time and relaxation frequency, respectively, for 600 nm devices (MTJ1, MTJ2, and MTJ3). The relaxation time decreases with increasing temperature, with an overall reduction of approximately 15% for the 1000 nm devices and 10% for the 600 nm devices. Linear fits are applied to the relaxation-time data for both device sizes. The relaxation frequency also decreases with temperature, with average reductions of approximately 5.4% and 4.3% for the 1000 nm and 600 nm devices, respectively. Error bars represent the standard error of the mean (SEM).

Temperature-dependent effective granularity of GV-MTJ reservoirs

We next examined how temperature affects the effective contribution of the granular landscape to vortex motion. As discussed above, elevated temperature can reduce the number of dynamically active pinning sites by enabling the vortex core to overcome weaker local energy barriers more easily. Here, we refer to these dynamically active grain-related features as effective pinning sites, while noting that they are experimentally identified by counting abrupt resistance changes during magnetic-field sweeps. The detailed procedure used to identify and count these effective pinning sites is described in the Methods section and illustrated in Fig. 8. To investigate the temperature dependence of this effect, we applied this procedure to a 600 nm GV-MTJ and performed repeated magnetic-field sweeps at 20 °C, 40 °C, 60 °C, and 80 °C. The results are shown in Fig. 4.

The measured number of effective pinning sites decreases with increasing temperature, from approximately 21 at 20 °C to approximately 18 at 80 °C. This trend indicates that the granular landscape becomes progressively less visible to the vortex dynamics as thermal energy

increases. Higher thermal activation allows the vortex core to overcome weaker local energy minima more easily, leading to smoother motion and reduced interaction with grain-induced pinning sites. In addition, temperature-dependent changes in magnetic parameters, such as saturation magnetization, can further reshape the local energy landscape and modify the vortex trajectory.

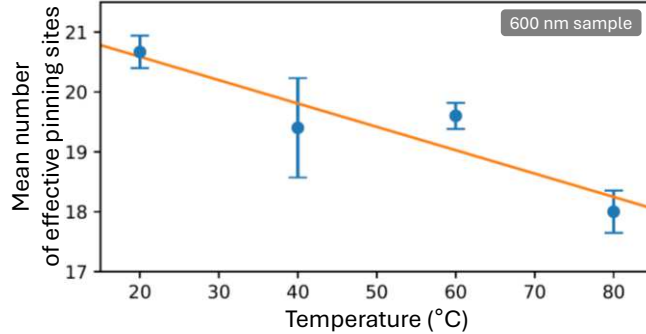


Figure 4. Temperature dependence of effective pinning sites in a 600 nm GV-MTJ. Average number of effective pinning sites encountered by the vortex core during magnetic-field sweeps at temperatures from 20 °C to 80 °C. The magnetic field was generated by sweeping the current through the field line integrated above the MTJ stack in both directions, using a current range of ± 100 mA. A small bias current of 50 μ A was applied through the MTJ to measure its resistance. The number of effective pinning sites was estimated by counting abrupt resistance changes during the field sweep, corresponding to grain-mediated pinning and depinning of the vortex core.

A linear fit to the data provides a phenomenological description of the observed decrease in effective pinning events. However, this trend should not be interpreted as a direct physical loss of grains in the free layer. Instead, it reflects a reduction in the number of grain-related energy barriers that remain dynamically active under the applied excitation conditions. As temperature increases, thermal activation enables the vortex core to overcome weaker local pinning potentials more easily, resulting in smoother trajectories and a reduced number of abrupt pinning/depinning signatures during the field sweep.

The observed reduction in effective grain-mediated pinning is important for reservoir computing. Grain-induced pinning sites contribute to irregular vortex trajectories, abrupt transitions, and nonlinear dynamical diversity. As temperature increases and weaker pinning sites become less dynamically relevant, the reservoir response is expected to become smoother and less diverse. Together with the reduction in relaxation time, this decrease in effective pinning sites suggests that elevated temperature can reduce both the fading-memory window and the intrinsic dynamical richness of the GV-MTJ reservoir, which may ultimately affect spoken-digit classification performance.

Reservoir-computing performance on the Free Spoken Digit Dataset

Reservoir computing (RC) is a brain-inspired computing paradigm that exploits the intrinsic nonlinearity and short-term memory of a dynamical system, referred to as the reservoir, to process temporal information with limited training [39]. In an RC framework, a fixed high-dimensional reservoir transforms input time series into a rich feature space, while only the readout stage is trained. This considerably simplifies the learning process compared with fully trainable recurrent neural networks. Since the reservoir itself remains unchanged during training, the classification performance depends strongly on its intrinsic dynamical properties,

particularly nonlinearity, which helps separate different input classes, and fading memory, which ensures that the present state retains information from recent inputs.

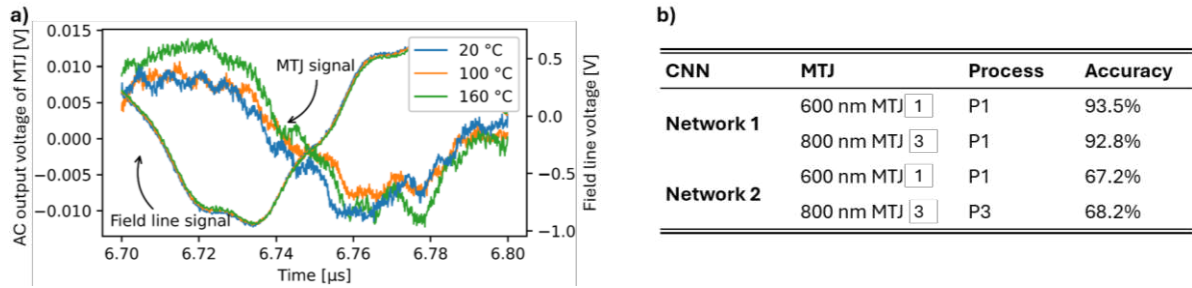


Figure 5. **GV-MTJ reservoir response and best-performing spoken-digit classifiers.** **a)** Representative 100 ns section of the measured AC component of the MTJ output voltage under a speech-derived input signal applied through the field line at different temperatures. The DC component was removed to highlight the dynamic voltage response associated with vortex motion. **b)** Best-performing classification accuracies obtained across different MTJ diameters, devices, preprocessing pipelines, and compact CNN readout architectures.

Here, we evaluate the use of GV-MTJs as physical reservoirs for spoken-digit classification and examine how their performance changes with temperature. Based on the temperature-dependent device characterization discussed above, we focus on ambient temperatures of 20 °C, 90 °C, 100 °C, and 160 °C. These measurements allow us to assess how thermally induced changes in relaxation time, oscillation frequency, and effective grain-mediated pinning influence application-level reservoir-computing performance. We note that the actual device temperature may be higher than the ambient temperature because of Joule heating induced by the bias and field-line currents.

The GV-MTJ-based reservoir computer was evaluated using the Free Spoken Digit Dataset [40]. The audio signals were time-compressed to 20 μs to match the memory timescale of the GV-MTJ reservoir. The input waveforms were applied to the device through the integrated field line, while a bias current of 3–4 mA was used to record the voltage response of the MTJ as a proxy for resistance changes. The measured reservoir responses were then processed using three different Mel-filterbank-based preprocessing pipelines, denoted as Process 1, Process 2, and Process 3, followed by down-sampling and classification using compact convolutional neural networks. Two lightweight network architectures were considered: Network 1, consisting of one convolutional layer followed by two fully connected layers, and Network 2, consisting of one convolutional layer followed by one fully connected layer. These compact architectures were chosen to limit the contribution of classifier complexity and to ensure that the observed performance primarily reflects the separability provided by the measured reservoir responses. Each model was trained 25 times using different random seeds, and the reported performance was evaluated across the full dataset, as described in the Methods section.

Fig. 5a shows a representative 100 ns section of the measured AC component of the MTJ output voltage when the device is driven by a speech-derived input signal applied through the field line. The DC component of the voltage response was removed in order to highlight the dynamic signal associated with the vortex motion. The AC response amplitude increases at 160 °C compared with the lower-temperature traces, which is consistent with the enhanced vortex-core displacement predicted by the simulations under equivalent excitation conditions, as shown in Fig. 2d. At the same time, the signal measured at 160 °C exhibits fewer abrupt transitions and oscillatory features. This behavior is consistent with the reduced number of

effective pinning sites discussed above, suggesting that thermal activation smooths the vortex trajectory by allowing the core to overcome weaker grain-induced energy barriers.

To evaluate classification performance, we compared the effects of MTJ diameter, temperature, preprocessing pipeline, and network architecture. Fig. 5b summarizes the best-performing configurations across the tested MTJ diameters and classifier structures. The highest accuracies were obtained with Network 1, reaching 93.5% for the 600 nm MTJ 1 and 92.8% for the 800 nm MTJ 3 using Process 1. Network 2 achieved lower peak accuracies, with 67.2% for the 600 nm MTJ 1 using Process 1 and 68.2% for the 800 nm MTJ 3 using Process 3. These results indicate that the measured AC responses of the GV-MTJs contain sufficient temporal and nonlinear information for spoken-digit classification, while also showing that the final accuracy depends on the readout architecture and preprocessing strategy.

Fig. 6 compares the classification accuracy obtained at 20 °C and 90 °C for 600 nm and 800 nm MTJs. The plotted values represent the change in accuracy relative to 90 °C, with positive values indicating improved performance at 20 °C and negative values indicating degraded performance at 20 °C. Accuracy differences are shown for both Network 1 and Network 2 across the three preprocessing pipelines. For the 800 nm MTJs, the accuracy change depends on the preprocessing method and device, with maximum improvements of approximately 2.5 percentage points for Network 1 and 2.9 percentage points for Network 2. A similar trend is observed for the 600 nm MTJs, although the device-to-device and process-dependent variability is larger. Overall, the relatively small accuracy differences between 20 °C and 90 °C suggest that GV-MTJ reservoirs maintain stable classification performance over this temperature range.

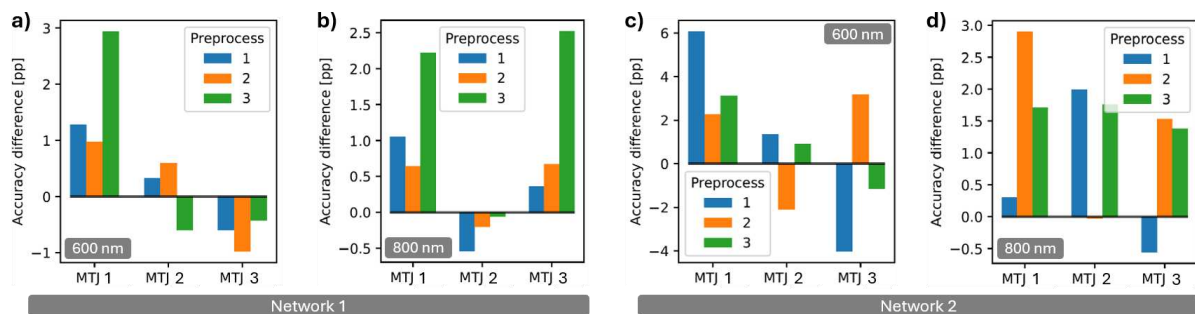


Figure 6. Classification-accuracy variation between 20 °C and 90 °C. Change in spoken-digit classification accuracy between 20 °C and 90 °C for different MTJ diameters and readout-network architectures. **a)** Network 1 using 600 nm MTJs. **b)** Network 1 using 800 nm MTJs. **c)** Network 2 using 600 nm MTJs. **d)** Network 2 using 800 nm MTJs. Positive values indicate higher accuracy at 20 °C than at 90 °C, whereas negative values indicate lower accuracy at 20 °C relative to 90 °C.

To assess the effect of elevated temperature on reservoir-computing performance, we further evaluated 800 nm GV-MTJ samples at 20 °C, 90 °C, 100 °C, and 160 °C. The resulting classification-accuracy changes are shown in Fig. 7 for both network architectures. The accuracy remains nearly unchanged at 90 °C and 100 °C compared with the 20 °C reference, indicating that moderate temperature increases do not substantially degrade the computational capability of the GV-MTJ reservoir. In contrast, a pronounced accuracy drop is observed at 160 °C for both networks, with the extent of degradation depending on the device and readout architecture. These results show that classification performance does not decrease linearly with temperature. Instead, the reservoir remains relatively robust up to approximately 100 °C before

undergoing a sharp performance degradation at higher temperature. This behavior is consistent with the signal traces in Fig. 5a, where the MTJ response at 160 °C differs noticeably from the responses at lower temperatures. Based on the simulation and measurement results discussed above, we attribute this degradation to the combined effects of reduced effective grain-mediated pinning, modified vortex dynamics, shortened relaxation time, and thermally degraded magnetic properties.

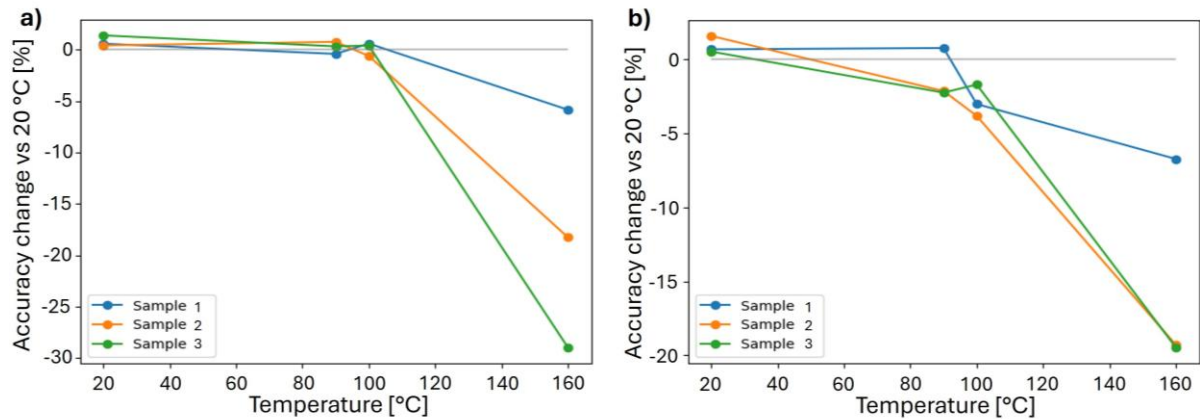


Figure 7. Temperature-dependent classification degradation in 800 nm GV-MTJ reservoirs. Change in classification performance at elevated temperatures relative to 20 °C for 800 nm GV-MTJ devices. Results are shown for **a)** Network 1 and **b)** Network 2 at 90 °C, 100 °C, and 160 °C. The plotted values compare the performance obtained from the MTJ reservoir response with the corresponding field-line signal, enabling separation of reservoir degradation from input-signal variations. Positive values indicate higher accuracy at the elevated temperature relative to 20 °C, whereas negative values indicate degraded accuracy compared with the 20 °C reference.

Discussion

This work demonstrates that GV-MTJs can operate as physical reservoirs for spoken-digit classification over a practical temperature range, while also revealing the thermal limits of grain-mediated vortex dynamics. The results show that classification performance remains relatively stable between 20 °C and 90 °C, but degrades substantially at 160 °C. This behavior indicates that the computational capability of the GV-MTJ reservoir is not simply a monotonic function of temperature, but is instead governed by the combined effects of vortex relaxation, effective grain-mediated pinning, thermal noise, field-line characteristics, and magnetic material stability.

The experimental temperature range was partly constrained by sample reliability. Measurements were performed at a limited number of temperatures because many devices failed during repeated high-temperature testing. Such failures are most likely associated with degradation or breakdown of the MgO tunnel barrier, which is a known consequence of excessive self-heating in MTJs [41, 42]. At lower ambient temperatures, the combined thermal load from Joule heating in the MTJ and field line, together with heating from the Peltier stage, remained within a tolerable range during the measurement period. At elevated ambient temperatures, however, the accumulated thermal stress frequently caused irreversible device degradation. This limitation highlights the importance of thermal management in future implementations of GV-MTJ-based reservoir-computing systems.

The field line used to excite the GV-MTJ also exhibits temperature-dependent behavior. The input signal is delivered by passing a current through the field line, thereby generating the

magnetic field that drives the vortex dynamics. As the temperature increases, the field-line resistance increases by approximately 50% between 20 °C and 160 °C. This increase leads to an approximately 5% reduction in the effective field-line signal amplitude, as reflected in the field-line voltage trace shown in Fig. 5a. Consequently, the magnetic excitation applied to the MTJ is slightly reduced at elevated temperature. Nevertheless, the measured MTJ voltage response increases at 160 °C, suggesting that the vortex core becomes more strongly excited under the same nominal input conditions. This enhanced vortex susceptibility at elevated temperature may partially compensate for the reduced magnetic-field amplitude caused by the increased field-line resistance. Such compensation could help explain the stable reservoir performance observed over the moderate temperature range, before intrinsic degradation of the GV-MTJ dynamics becomes dominant at higher temperature.

The classification results further clarify the role of temperature in GV-MTJ reservoir operation. Based on the simulated and measured device dynamics, some degradation in classification performance was expected at elevated temperature. This expectation is confirmed experimentally, particularly at 160 °C. Several mechanisms may contribute to this degradation. Increased thermal noise can reduce the signal-to-noise ratio of the measured reservoir response. At the same time, the reduction in relaxation time shortens the fading-memory window of the reservoir, while the decrease in the number of effective pinning sites reduces the diversity of grain-mediated nonlinear responses. These effects directly weaken the two key ingredients required for reservoir computing: short-term memory and nonlinearity.

Within the moderate temperature range from 20 °C to 90 °C, however, the degradation in classification performance is small. For the 800 nm GV-MTJ samples, the average accuracy drop remains below 1 percentage point, with a maximum degradation of 2.9 percentage points depending on the device, preprocessing method, and network architecture. This suggests that the combined effects of thermal noise, increased field-line resistance, shorter relaxation time, and reduced effective granularity are not strong enough in this temperature range to significantly compromise the reservoir response. The observed variability across preprocessing pipelines and CNN architectures indicates that readout design and signal conditioning also influence the final classification accuracy, but the overall trend remains consistent: GV-MTJ reservoirs retain robust computational performance up to approximately 90–100 °C.

At 160 °C, by contrast, the performance degradation becomes substantial. This sharp decline is attributed primarily to intrinsic changes in the GV-MTJ reservoir rather than to the reduced input amplitude caused by the increased field-line resistance. To isolate the influence of the field line, we applied input signals through the field line at both 20 °C and 160 °C and used the field-line voltage itself, rather than the MTJ voltage response, directly for classification. In this control experiment, the classification accuracy varied by no more than $\pm 0.4\%$. This confirms that the large accuracy degradation observed at 160 °C does not originate mainly from the reduced field-line signal amplitude. Instead, it arises from deterioration of the reservoir functionality, including reduced effective grain-mediated pinning, modified vortex dynamics, shorter relaxation time, and thermally degraded magnetic properties.

Overall, these findings show that free-layer granularity, traditionally regarded as a source of variability in MTJs, can be exploited as a computational resource for reservoir computing. This work provides a systematic experimental study of the temperature-dependent behavior of GV-MTJ reservoirs and demonstrates that they maintain stable spoken-digit classification

performance from 20 °C to 90–100 °C, with only minor variations across preprocessing methods, device samples, and compact readout architectures. At 160 °C, however, the classification performance degrades substantially. Control experiments using the field-line voltage confirm that this degradation is not primarily caused by reduced input-signal amplitude or field-line characteristics, but instead originates from the deterioration of the reservoir functionality itself. The combined effects of shortened relaxation time, reduced effective grain-mediated pinning, modified vortex dynamics, and thermally degraded magnetic properties weaken the reservoir’s ability to generate diverse nonlinear temporal responses. These results identify both the promise and the thermal limits of GV-MTJ reservoirs for neuromorphic edge-computing systems. They also highlight the importance of optimized device geometry, material stability, biasing conditions, field-line design, and thermal management for practical deployment of granular spintronic reservoirs in real-world operating environments.

Methods

Micromagnetic simulations

Micromagnetic simulations were performed using MuMax3 [33]. The baseline physical parameters are based on the model presented in [32]. Temperature was included in two complementary ways. First, the built-in MuMax3 temperature model was used to account for thermal fluctuations [34]. This model introduces a stochastic thermal field into the Landau–Lifshitz–Gilbert–Slonczewski equation, producing random variations in the effective magnetic field with zero mean. The thermal field correlation is given by

$$\langle \mathbf{H}_{th}(\mathbf{r}, t), \mathbf{H}_{th}(\mathbf{r}', t') \rangle = \frac{2k_B T \alpha}{M_{sat} \gamma} \delta(\mathbf{r} - \mathbf{r}') \delta(t - t') \quad (1)$$

where k_B is the Boltzmann constant, T is the temperature, α is the Gilbert damping constant, M_{sat} is the saturation magnetization, and γ is the gyromagnetic ratio.

Second, temperature-dependent material parameters were included manually. The built-in MuMax3 thermal model accounts for stochastic thermal noise, but it does not automatically update material parameters as a function of temperature. To capture these effects, the temperature-dependent changes reported by Kang et al. [35] were used for CoFeB-based layers. Specifically, saturation magnetization, Gilbert damping, and in-plane uniaxial magnetic anisotropy were modified according to temperature. Based on the available material-parameter measurements, the simulated temperature range was limited to 300–450 K.

Experimental estimation of effective pinning sites

The effective number of grain-mediated pinning sites encountered by the vortex core was estimated at different temperatures by sweeping the current through the field line integrated above the MTJ stack. The field-line current was swept bidirectionally over a range of ± 100 mA, while a small bias current of 50 μ A was applied through the MTJ to measure its resistance as shown in Fig. 8. This procedure verified both the expected sample resistance and the presence of grain-mediated vortex pinning.

Effective pinning sites were identified from abrupt resistance changes during the field sweep. These sharp changes are interpreted as sudden changes in the vortex-core position caused by pinning and depinning at grain-related local energy minima. Thus, the reported number of effective pinning sites represents the number of dynamically visible pinning features encountered by the vortex core during the sweep, rather than the physical number of grains in the free layer.

Not all samples exhibited usable granular behavior. Some devices showed no clear granular response, while others were short- or open-circuited. Before the high-temperature measurement campaign, all 18 available 600 nm samples showed granular characteristics. For the 800 nm samples, 17 out of 18 devices were functional; the non-functional device had the field line shorted to the MTJ contacts, suggesting that the MTJ itself may still have been intact. For the 1000 nm samples, 15 out of 18 devices were functional. Of the three non-functional 1000 nm samples, two failures were related to the field line and one sample did not show granular behavior. Considering only samples in which the field line was not responsible for failure, the MTJs exhibited a yield of approximately 98%.

These yield values refer to the device status before the start of long-duration high-temperature measurements. After repeated measurements at elevated temperatures, not all devices remained operational. As in the initial yield analysis, most high-temperature failures were caused by field-line shorting to the MTJ contacts, while only one MTJ became short-circuited and one became open-circuited. This indicates that the field-line structure, rather than the MTJ stack itself, was the dominant source of failure during extended high-temperature testing.

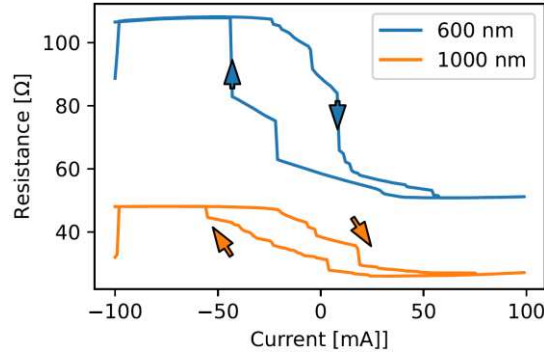


Figure 8. Experimental identification of effective pinning sites. Representative resistance–field-line-current traces measured from 600 nm and 1000 nm GV-MTJ devices during bidirectional field-line sweeps over ± 100 mA. A small bias current of $50 \mu\text{A}$ was applied through the MTJ to monitor the device resistance. Effective pinning sites were identified from abrupt resistance changes during the sweep, which are attributed to sudden vortex-core displacement caused by pinning and depinning at grain-related local energy minima.

Measurement of relaxation time and oscillation frequency

The experimental setup used to measure vortex relaxation dynamics is shown schematically in Fig. 9. The MTJ was connected to a source meter through the DC port of a bias tee to apply a bias current of 3 mA, while the AC port was connected to an oscilloscope for voltage readout. The integrated field line located above the MTJ was driven by a signal generator to apply an external magnetic-field excitation. The sample die was mounted on a Peltier module controlled by a thermoelectric controller to regulate the device temperature.

To excite the vortex dynamics, a voltage pulse from 0 to 5 V, scaled to 50Ω , was applied to the field line for $500 \mu\text{s}$ with an edge time of $20 \mu\text{s}$. The resulting current through the field line generated the magnetic field used to displace the vortex core. After the pulse returned to 0 V, the vortex core relaxed back toward its equilibrium position. Because the field-line resistance changes with temperature, the effective excitation amplitude can also vary between temperature points. Future studies could compensate for this effect using calibrated voltage adjustment or current-controlled excitation.

Experimentally extracting the relaxation time is more challenging than in simulations because of measurement noise and voltage offsets. To ensure consistent analysis across thousands of measured traces, the procedure summarized in Algorithm 1 and Fig. 9c was used. The different signal-processing steps are highlighted in Fig. 9b. Two independent methods were applied to estimate the relaxation time: an exponential fit and a mean-thresholding method. A measurement was accepted only when both approaches produced similar relaxation-time values.

Approximately 5% of the measured traces were rejected because they did not exhibit a clearly identifiable relaxation phase. For each MTJ and temperature condition, 1500 traces

were acquired and averaged. The start and stop points of the relaxation phase were then used to segment the signal for Fourier analysis, from which the relaxation frequency was extracted.

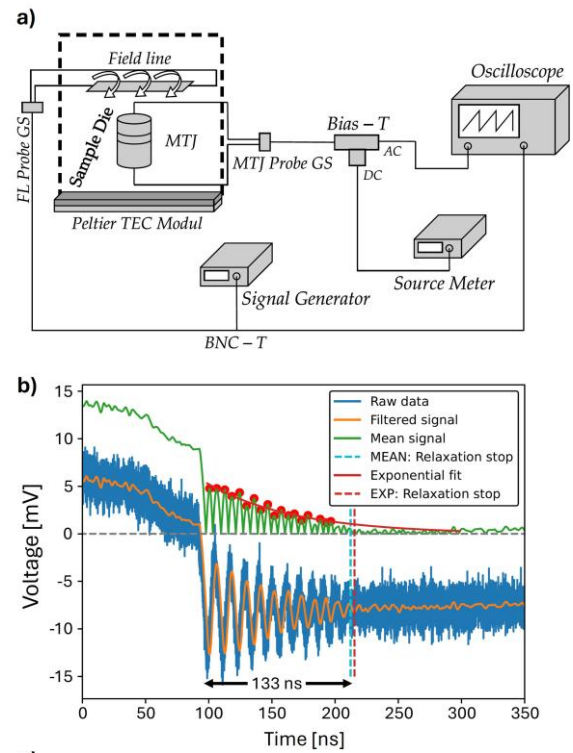
Hybrid experimental–computational reservoir-computing workflow

The GV-MTJ was used as a physical reservoir for spoken-digit classification. The overall implementation consisted of dataset preprocessing, field-line input excitation, MTJ voltage readout, post-processing using Mel filterbanks, and final classification using compact convolutional neural networks.

- **Dataset and input pre-processing:** The Free Spoken Digit Dataset was used to evaluate the classification performance of the GV-MTJ reservoir computer [40]. The dataset contains 3000 recordings of spoken digits from 0 to 9, recorded by six speakers. To match the temporal scale of the input signal to the fading-memory timescale of the GV-MTJ reservoir, the speech waveforms were compressed in time to 20 μ s, resulting in frequency components up to approximately 20 MHz.

- **Experimental interfacing with the GV-MTJ reservoir:** The measurement setup used for reservoir-computing experiments is shown in Fig. 9a. The time-compressed speech signal was applied to the GV-MTJ through the integrated field line. The current flowing through the field line generated a magnetic field that excited the vortex dynamics in the MTJ. To ensure vortex nucleation, a bias current of 3 mA was applied for 600 nm MTJs, while 4 mA was used for 800 nm and 1000 nm MTJs. The device temperature was controlled using the Peltier element and thermoelectric controller. The reservoir output was measured as the voltage change across the MTJ using an oscilloscope. This voltage response is directly related to resistance changes produced by the vortex dynamics.

For the reservoir-computing experiments, 600 nm and 800 nm GV-MTJ devices were selected because they provided the most stable responses during repeated high-throughput measurements. This stability was essential for generating the large number of reservoir-output traces required for training and evaluating the spoken-digit classification models.



Algorithm 1 Relaxation time processing steps	
INPUT:	Captured waveform
OUTPUT:	Relaxation time and frequency
Step 1:	Import the raw waveform data.
Step 2:	Apply a low-pass filter with 200 MHz cutoff.
Step 3:	Center the signal around 0 by subtracting the mean.
Step 4:	Detect peaks of the signal and estimate the parameters of an exponential decay function.
Step 5:	Determine the relaxation length, based on the fit or when the signal is below a threshold for several samples.

Figure 9. Experimental setup and signal-processing procedure for extracting vortex relaxation dynamics. a) Schematic of the laboratory setup used to measure the relaxation time and oscillation frequency of GV-MTJ devices. b) Representative voltage signal measured across the GV-MTJ, together with the processed signal components used to identify the relaxation window and extract the relaxation dynamics. c) Algorithm used to determine the oscillatory relaxation time and relaxation frequency from the measured voltage traces.

- 631 ▪ **Post-processing of measured reservoir responses:** The measured MTJ response was
632 passed through a post-processing stage before classification. This stage consisted of Mel-
633 filterbanks, which are commonly used in speech-processing tasks because their frequency
634 weighting approximates the response of the human auditory system [43, 44]. The signal
635 was also downsampled to reduce high-frequency noise in frequency ranges where no grain-
636 mediated features were observed. Three similar but distinct Mel-filterbank preprocessing
637 pipelines were used to test the robustness of the classification results and reduce
638 dependence on a single post-processing configuration.
- 639 ▪ **Classification networks:** The processed reservoir responses were classified using two
640 compact convolutional neural networks. CNN-based readouts were selected because they
641 are well suited for time-series data in which local temporal structure and translation
642 robustness are important [45]. Both networks used a single convolutional layer with four
643 output filters, a kernel size of 5, and a stride of 3. The convolutional output was normalized
644 and max-pooled before being passed to the fully connected layers. Network 1 used two
645 fully connected layers, whereas Network 2 used one fully connected layer.
646 Because the different preprocessing pipelines produced feature vectors of different sizes,
647 the number of trainable parameters varied between configurations. Network 1 contained
648 between 5750 and 9590 trainable parameters, while Network 2 contained between 2208
649 and 3408 trainable parameters. These models are intentionally small compared with
650 conventional audio-classification networks; for example, AudioNet contains approximately
651 17 million parameters [46], and even smaller audio networks often contain hundreds of
652 thousands of parameters [47]. The use of compact readout networks is consistent with the
653 reservoir-computing paradigm, where a significant part of the temporal and nonlinear
654 processing is performed by the physical reservoir itself, allowing the trainable readout to
655 remain lightweight. In addition, using small readout networks helps ensure that the
656 classification results reflect the separability provided by the GV-MTJ reservoir, rather than
657 being dominated by the capacity of a large neural network. This allows us to evaluate
658 whether the reservoir-induced separability is preserved across different temperatures.

659 To reduce run-to-run variation, each model was trained independently 25 times using different
660 random seeds. The performance of each model was evaluated on the full dataset.

661 **Data availability**

662 The data that support the plots within this paper and other findings of this study are available
663 from the corresponding author at a reasonable request.

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668 **Author Contributions**

669 H.F., A.S.J., F.M., and R.F. conceived the main idea of exploiting free-layer granularity in
670 vortex-based magnetic tunnel junctions for reservoir computing. H.F. designed the study.
671 A.S.J., T.B., L.B., and R.F. fabricated and prepared the GV-MTJ devices. O.F. and L.M.R.B.
672 performed the micromagnetic simulations and analyzed the temperature-dependent material-

parameter effects. O.F and L.M.R.B. carried out the experimental measurements of relaxation time, oscillation frequency, and effective pinning sites. O.F and L.M.R.B. developed the reservoir-computing workflow, performed the Free Spoken Digit Dataset experiments, and implemented the preprocessing and CNN-based classification. H.F., A.S.J., O.F and L.M.R.B. analyzed and interpreted the simulation, measurement, and classification results. H.F. wrote the first draft of the manuscript. All authors contributed to discussing the results, revising the manuscript, and approving the final version.

Competing interests

The authors declare no competing interests.

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