local fluid to rotate, a property known as its vorticity.

One way to understand the connection between flow gradients and fluid rotation is to imagine a boat positioned with its bow facing the direction of the water flow, with water flowing past the boat's right-hand side faster than on its left. If the boat were floating passively, when viewed from above, it would begin to rotate clockwise. The speed of this rotation would be proportional to the difference in the flow speeds on either side, which form a gradient across the boat. A similar information pathway — sensing the velocity around the fish's body through the lateral line, followed by deducing the corresponding direction of local vorticity and estimating the local flow-speed gradients, which are proportional to the vorticity — is at the heart of the proposed mechanism for flow-based navigation in zebrafish.

Successful navigation requires a way of using knowledge of local flow conditions to robustly guide a fish away from harm. The researchers made a striking observation in relation to this. Whenever a fish swam towards a region in which the difference between the flow speeds on either side of its body increased in comparison to the difference at the fish's previous location, the fish made a turn in the direction of the local flow vorticity (by veering either clockwise or anticlockwise). This action reliably steered the animal away from the region near the wall, and towards the centre of the oncoming flow. Conversely, when the fish swam towards a region in which the flow gradients decreased in comparison to those it encountered previously, it continued to swim in the same direction without a turning bias. Because flow gradients usually decrease the farther away a fish is from a solid object, this navigation strategy should translate into the avoidance of real-world obstacles and the bodies of predators.

The authors took important first steps towards extending their results beyond the realm of controlled laboratory experiments by developing computer simulations that demonstrated the robustness of their observations when modelling the situation in quasi-turbulent flows. However, real aquatic environments present other challenges, such as 3D flow that cannot be navigated solely with turns in a horizontal plane. In addition, the Kelvin–Stokes theorem that underlies the proposed navigation strategy can fail if there are local sources or sinks of water in the vicinity, such as the suction flow that some predators use to ingest prey[4]. Paradoxically, the proposed mechanism for rheotaxis could also lead fish towards regions of flow that, although they exhibit small flow gradients, could simultaneously have large, uniform flow speeds that overpower the fish's ability to escape such strong currents. Thus, the mechanism described by Oteiza and colleagues is probably paired with other sensing strategies — yet to be discovered, and perhaps also making use of the lateral line — that enable fish to navigate the full complexity of the underwater world. As the full repertoire of these sensing and control skills becomes apparent, we will not only learn more about fish ecology, but might also gain inspiration for new types of bio-robotic navigation in both water and air. ■

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APPLIED PHYSICS

A new spin on nanoscale computing

A nanoscale magnetic device that mimics the behaviour of neurons has been used to recognize audio signals. Such a device could be adapted to tackle tasks with greater efficiency than conventional computers. SEE LETTER P.428

FRANK HOPPENSTEADT

Neuromorphic (brain-like) computers offer many advantages over conventional systems, including energy efficiency, a high data-transfer speed and the ability to be trained. On page 428, Torrejon *et al.*[1] report one of the first nanoscale neuromorphic computers to perform a classification task — in this case, speech recognition. The core of the computer is a magnetic device called a spintronic oscillator that operates at gigahertz frequencies. Torrejon and colleagues' work is interesting not so much because of the application for speech recognition, the results of which are similar to those of other state-of-the-art technologies[2], but because of how the recognition is achieved.

How does a spintronic oscillator work? The device has a magnetization that can be thought of as an arrow that points in a particular direction. This direction can be regulated by applying an electrical current to the device — a state known as the equilibrium configuration. When the device is stimulated by a second electrical current (the input), the arrow begins to oscillate in a stable way, producing an oscillating voltage. Crucially, the device's response depends on the timing of the input. The arrow continues to oscillate until the input is removed, at which

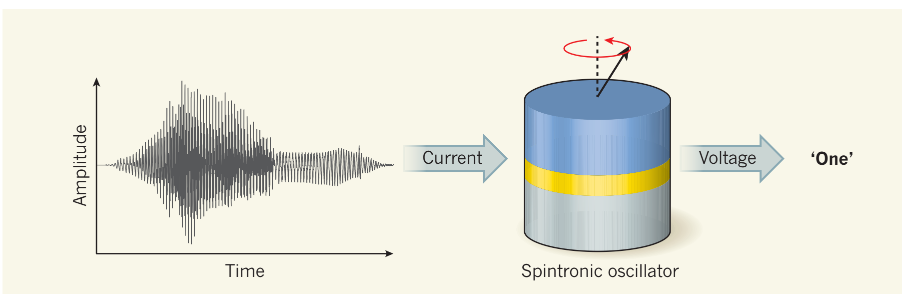

Figure 1 | Spoken-digit recognition using a spintronic oscillator. Torrejon *et al.*[1] show that a nanoscale magnetic device called a spintronic oscillator can be used for speech recognition. Their oscillator comprises a non-magnetic material (yellow), sandwiched between two magnetic materials (blue and grey). Shown here is a simplified version of their approach. The authors transform an audio signal for the word 'one' into an electrical current using signal-processing methods. The current causes the oscillator's magnetization (black arrow) to rotate (red arrow), producing an oscillating voltage. Torrejon and colleagues identify the spoken digit from this voltage using machine-learning methods, in which data are classified on the basis of the results of previous training. Unlike conventional electronics that would require a combination of several components and a larger microchip area, the authors' spintronic oscillator provides functionality in a single unit. Audio signal adapted from Fig. 2a in ref. 1.

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time the device returns to equilibrium.

Spintronic oscillators have a few key properties: they are tens to hundreds of nanometres in size; they are nonlinear (they can exhibit stable isolated oscillations); they can be analysed using signal-processing methods; and they produce analog, rather than digital, signals. Spintronic oscillators also have useful capabilities. For example, they can perform many distinct tasks simultaneously by combining (multiplexing) signals and they are capable of phase locking — a property that stabilizes the oscillations. The transistors used in conventional computing can be as small as spintronic oscillators, approaching the size of a single atom. However, a network of transistors that emulates the properties of a spintronic oscillator would be larger and more complex than the corresponding oscillator.

The approach of using oscillations for computations is based on biology. Recordings of electrical activity in the brain show that neurons transmit signals whose oscillations have a wide range of frequencies. Furthermore, biological rhythms operate on time scales ranging from milliseconds to months[3]. These oscillations are forms of analog information processing. One notable feature, which spintronic oscillators share, is that the oscillations are remarkably stable in the presence of noise and other perturbations.

In the 1940s and 1950s, the mathematician John von Neumann proposed using microwave-frequency oscillators for general-purpose computations[4]. By using one oscillation in voltage to represent '0' and the antiphase oscillation to represent '1', von Neumann showed that all arithmetic operations can be performed using simple electronic circuits called NAND gates. However, his proposal came immediately before the advent of transistors. Transistors took over the computing world because they are simple in design and, with ingenious engineering, can be interconnected to form complex switching circuits that perform the required arithmetic operations.

In the past decade, there has been an explosion in applications of artificial intelligence, machine learning and, in particular, 'deep' learning that require powerful computers to simulate massive artificial neural networks. At the same time, there have been concerns that transistors are reaching their limit in terms of size, functionality and cost effectiveness. New types of transistor and alternative technologies are being investigated throughout the computing industry, with the aim of producing ever-smaller computer circuits. Some researchers are revisiting von Neumann's ideas to use oscillators for arithmetic computation[5], whereas others are developing computers based on quantum mechanics[6]. Torrejon and colleagues' work is the first step in a different direction — it suggests that spintronic oscillators could pave the way to building specialized chips for large-scale neural networks. The present era feels similar to that of 60 years ago, when transistors were first used to replace vacuum tubes in computing machines.

Torrejon *et al.* used an approach called reservoir computing, which is derived from studies of neural networks in the prefrontal cortex of primate brains[7]. In this approach, an input signal is fed into a computing system called a reservoir. Another computer is trained to read the state of the reservoir and map this state to the desired output.

The authors' reservoir is a spintronic oscillator comprising a non-magnetic material sandwiched between two magnetic layers (Fig. 1). As the input signal, the authors used an audio file of an isolated digit (0 to 9) pronounced by one of five different speakers. They then transformed the audio signal into an electrical current using signal-processing methods (the pre-processing stage). The current drives the oscillator, producing a voltage that measures the deflection of the magnetization from equilibrium. Finally, the authors identified the spoken digit (the output) from this voltage using machine-learning methods (the post-processing stage).

Torrejon *et al.* achieve digit-recognition rates of up to 99.6%, independent of the speaker — a result that is competitive with other state-of-the-art technologies[2]. Currently, the pre-processing of inputs and the post-processing of outputs rely on digital computation, so the authors' system is a hybrid digital–analog machine. The reservoir cannot be tuned during the recognition process, but the pre- and post-processing systems can be (for example, during training).

Neuromorphic computers might not become general-purpose computational machines. It is more likely that they will make up arrays of specialized computers that communicate and synchronize their activities — much like the brain does — but at speeds of gigahertz rather than hertz, and on length scales of nanometres rather than micrometres. Such computers could also be hybrids of digital and analog devices, thereby taking advantage of the strengths of both technologies.

A natural next step for the authors is to investigate networking of spintronic oscillators to design and build more-complex arrays that have greater functionality. Connections between such oscillators could be achieved using electrical or optical pathways, or through excitations called spin waves that propagate in a common magnetic medium. In addition, input and output processing might eventually reach the scale and functionality of spintronic oscillators. Torrejon and colleagues' system is a breakthrough in terms of using oscillators for computing. The system works, and it holds promise for major gains in classification, computation, control and switching. ■

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NEUROBIOLOGY

Synapses get together for vision

A sophisticated analysis in mice of how inputs to neurons from other neurons are distributed across individual cells of the brain's visual cortex provides information about how mammalian vision is processed. **See Letter p.449**

TOBIAS ROSE & MARK HÜBENER

A typical pyramidal neuron in the brain's visual cortex receives thousands of excitatory signals from other neurons, transmitted across connections called synapses. These inputs from presynaptic neurons end on tiny protrusions called spines on the postsynaptic neuron's tree-like processes (dendrites). In principle, when a sufficient number of inputs are active at the same time, the postsynaptic neuron will fire. But not all inputs are equal: it matters where on the dendritic tree an input is located, and whether it is activated by similar stimuli to those that activate its neighbours, allowing simultaneously active inputs to team up for greater impact[1]. On page 449, Iacaruso *et al.*[2] describe how inputs activated by stimuli at different locations in visual space are mapped onto the dendrites of neurons in the visual cortex.

Neurons in the visual cortex respond to specific attributes of visual stimuli, including

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