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面向人工智能的物理神经网络专题 进 展
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磁斯格明子类脑器件

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摘要 类脑计算仿照人脑神经网络通过人工神经元和突触器件实现信息处理, 有望为加速人工智能发展、解决复杂认知问题提供更为高效节能的方案. 由于传统半导体器件与类脑计算要求(如非易失性等)不匹配, 其进一步发展需要从硬件层面着手, 研发新型器件. 自旋电子学器件天然具备非易失性, 是类脑计算硬件的潜在选择, 特别是磁斯格明子, 因其独特的拓扑性质、稳定性、低功耗及类孤子特性, 有望成为类脑器件的高效信息载体. 本文简要回顾了近年来磁斯格明子类脑器件的发展, 从斯格明子器件相关的基本物性展开, 进一步阐述了基于斯格明子的人工神经元和突触的基本工作原理及相关科研进展, 最后对磁斯格明子类脑器件未来发展中面临的机遇与挑战进行了讨论.

关键词 磁斯格明子, 类脑计算, 神经拟态计算, 拓扑磁结构, 自旋电子学

随着数据量呈现指数级增长, 基于传统冯·诺依曼架构的计算机在处理复杂任务和大规模数据时遇到了瓶颈[1]. 例如, 传统架构需在存储单元和计算单元之间进行频繁数据传输, 导致“存储墙”效应, 显著降低了系统效率. 与此同时, 半导体器件尺寸逐渐逼近物理极限, 进一步缩减尺寸以提升性能的空间越来越小, 随之而来的功耗问题也愈加突出. 这些瓶颈促使人们寻找新型的计算范式, 类脑计算(brain-inspired computing)或神经形态计算(neuromorphic computing)便是其中之一.

类脑计算的灵感来源于人脑中的神经网络(neural network), 与神经科学紧密相连, 其不仅可为解决复杂认知问题提供更为高效节能的方案, 也可为验证、理解人脑工作原理提供平台[2]. 人脑能够以极低的能耗(约20 W)处理大规模并行问题, 其计算主要由神经元(neuron)和突触(synapse)协同完成(图1). 与冯·诺依曼架构不同, 神经元及基于突触连接的神经网络结构本身作为计算单元的同时也兼备信息存储功能. 此外, 神经元和突触之间具备高度并行的异步信号传输, 以及通过突触可塑性实现的学习能力, 这些优点使得实现高度并行、低功耗的计算以及高效处理如图像识别和自然语言处理等认知类任务成为可能[3].

目前在硬件/软件层面均已有诸多类脑计算实现方案, 但这些方法通常基于传统半导体晶体管器件[3~5]. 基于晶体管的数字计算机更擅长处理高精度数值计算, 但在完成认知任务方面其性能与能耗则完全无法与人脑比拟. 例如, 在超级计算机上训练一套当下最先进的自然语言处理深度神经网络需耗电1000 kWh, 其能耗约可供人脑执行对等任务6年[1]. 此外, 传统场效应晶体管为易失性器件, 并不具有记忆存储功能, 与类脑计算中神经元和突触等具备存算一体能力的器件不匹配, 不利于上层神经网络的架构. 因此, 研发更高效的类脑计算架构需要从硬件层面着手, 开发出具备类神经元和类突触功能的新型器件, 这类器件需具备如多态性、可塑性、低功耗及可扩展性等特点, 以满足类脑计算对高效能、高度并行处理的需求[6].

自旋电子学(spintronics)器件为从硬件层面实现类

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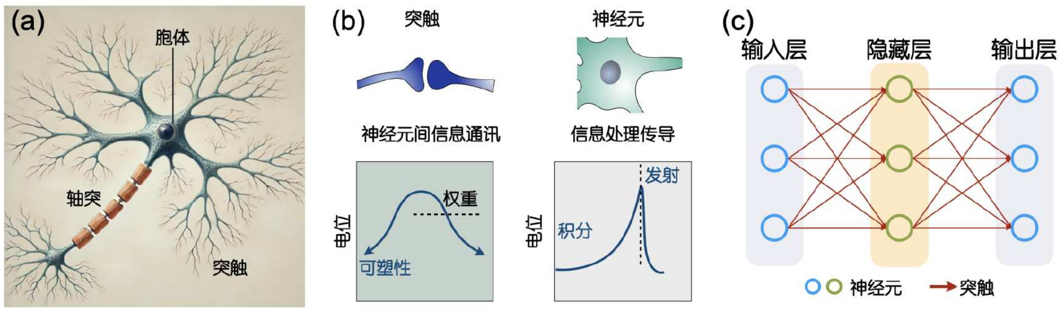

图 1 (网络版彩色)类脑计算原理. (a) 神经细胞结构示意图; (b) 突触(左)与神经元(右)的结构(上排)及功能(下排)示意图; (c) 神经网络示意图
Figure 1 (Color online) Brain-inspired computing. (a) Schematic of a neuron cell; (b) the structure (top) and function (bottom) of a synapse (left) and a neuron (right); (c) diagram of a neural network

脑计算提供了一条可靠途径，其利用电子的自旋自由度(而非传统的电荷)来存储和传输信息，相关器件本身便具有非易失性，契合类脑计算对硬件的基本要求[7~9]. 自旋电子学器件的研究为类脑计算提供了丰富的候选器件工作机制，例如基于磁隧道结的人工神经元器件及基于磁畴壁的人工突触器件等[10~16]. 近年来，在自旋电子学众多研究中，磁斯格明子(magnetic skyrmion)因其独特的拓扑性质、优异的稳定性和低电流驱动特性而受到广泛关注[17,18]. 磁斯格明子是一种纳米尺寸拓扑磁结构，基本磁结构型如图2(a)和(b)所示，其中心磁矩与背景磁矩方向相反，具有类涡旋结构. 斯格明子尺寸可小至几纳米，具有类准粒子特性，易于电流操控. 先前斯格明子的研究多关注其在磁存储及自旋逻辑器件中的应用，以磁斯格明子为信息存储单元可为制备高密度磁存储器和高效自旋逻辑单元提供理想备选方案[18~20]. 此外，斯格明子还具有类孤子特性，在一定外界激励下仍可保持其整体结构及特性，从而为单个斯格明子及其团簇和晶体相带来了相当丰富的动力学模式，可类比为神经通道中的离子携带电位信息，这为构建类脑器件提供了多种便利可选的工作机制. 因此，近些年来基于磁斯格明子的类脑器件也引起了人们的关注，众多基于磁斯格明子的类脑器件方案涌现而出，有望为研制新一代类脑计算器件提供技术支撑[8,13,21].

本文简要阐述磁斯格明子与实现类脑器件功能相关的基本特性，解释磁斯格明子类脑器件的基本工作原理，并进一步介绍近年来磁斯格明子类脑器件的科研进展以及其面临的机遇与挑战.

1 磁斯格明子基本物性

磁斯格明子类脑器件中的信息载体是磁斯格明子，器件需能通过电学方法操控，因此磁斯格明子的稳定性、电驱动和电读写是构建相关类脑器件的先决条件. 磁斯格明子的磁矩排列具有实空间非平庸拓扑性，其拓扑特性由拓扑荷$Q=\frac{1}{4\pi}\int \boldsymbol{m}\cdot\left(\partial_x\boldsymbol{m}\times\partial_y\boldsymbol{m}\right)\mathrm{d}x\mathrm{d}y$表征(其中$\boldsymbol{m}$为局域磁矩的单位矢量). 拓扑荷描述了斯格明子磁矩环绕其序参量单位球的次数，一般磁斯格明子拓扑荷为−1或+1，即其全部磁矩正好环绕单位球1次[22]. 磁斯格明子在磁性材料中通常需要通过Dzyaloshinskii-Moriya (DM)相互作用稳定. DM相互作用的诱因为材料中空间反演对称性破缺及自旋轨道耦合的协同作用，因此磁斯格明子通常在手性磁体或磁性薄膜/多层膜中存在，其中前者晶体结构自然缺失空间反演对称，而后者空间反演对称在薄膜界面处破缺[23]. 在这些材料中，尺寸小于100 nm的磁斯格明子均可在室温下稳定存在，为构建室温高密度类脑器件提供了便利[17,18,24,25].

磁斯格明子可以通过外部电流驱动，电流驱动下斯格明子的运动可通过Thiele方程来描述:

$$\boldsymbol{G}\times\boldsymbol{v}_d+\boldsymbol{\mathcal{D}}\cdot\boldsymbol{v}_d=\boldsymbol{F}, \quad (1)$$

其中，$\boldsymbol{v}_d$为斯格明子速度，$\boldsymbol{G}=(0,\ 0,\ 4\pi Q)$为陀螺矢量，$\boldsymbol{\mathcal{D}}$为耗散张量，主要由磁结构的形状和大小决定，$\boldsymbol{F}$则描述系统中斯格明子所受到的内禀和外部力(如外激励电流、与边界的相互作用等)[22]. 由于磁斯格明子具有实空间非平庸拓扑性，对应的自旋贝里相位使其具有天然易驱动特性，因此其电流驱动临界电流密度远小于磁畴壁等拓扑平庸磁结构. 斯格明子的非平庸拓扑性还使其具有陀螺矢量$\boldsymbol{G}$，导致斯格明子在运动中会产生与其运动方向垂直的位移(图2(c))，这种纵向运动也为斯格明子类脑器件的设计提供了一种新的自由度.

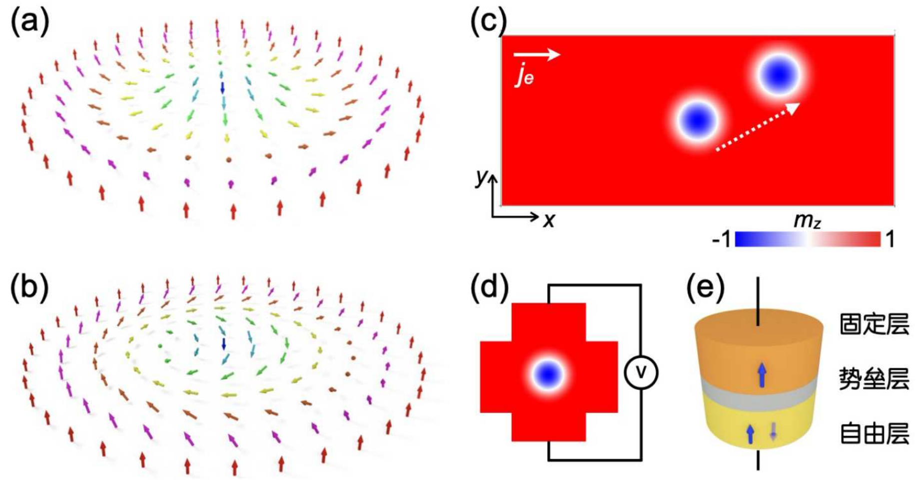

图 2 (网络版彩色)奈尔型(a)与布洛赫型(b)磁斯格明子构型; (c) 电流驱动斯格明子运动示意图; (d) 基于霍尔条反常霍尔效应读取斯格明子; (e) 磁隧道结示意图

Figure 2 (Color online) Spin arrangement of a Néel-type (a) and a Bloch-type (b) magnetic skyrmion; (c) current-driven skyrmion motion; (d) measuring a magnetic skyrmion via the anomalous Hall effect in a Hall bar device; (e) schematic of a magnetic tunnel junction

在手性磁体材料中，斯格明子可通过自旋转移力矩(spin transfer torque, STT)驱动，而在磁性薄膜/多层膜中，则可由自旋轨道力矩(spin orbit torque, SOT)驱动[26,27]．虽然这两种不同驱动模式下的动力学对称性不同, 但它们都可以实现对磁斯格明子的高效操控.

在电学读取方面，由于磁斯格明子中心磁矩与背景磁矩相反，因此可通过反常霍尔效应(各向异性磁电阻)或磁性隧道结读取．前者更易于在原理型器件中实现，但其开关比较小；后者具有较高的开关比，更具备实际应用价值[28~32]. 而在电学写入方面, 斯格明子可通过如磁性隧道结或几何缺口等方法写入，目前斯格明子的相关研究已为其类脑计算的开发提供了基本技术条件[33~36].

2 磁斯格明子类脑器件

大脑如何运作一直是脑、神经及认知科学的前沿课题, 人们对此尚无一个准确的答案. 但基于当前对大脑神经网络的理解, 其计算主要依赖神经元和突触, 并以脉冲(spike)为主要信号传输方式. 神经元处理信息并通过突触相连形成神经网络，突触则负责在传递信息的同时根据其自身的权重对传递信号进行处理[1,37]．因此，类脑计算的基本硬件主要包括人工神经元和人工突触两大类.

神经元结构主要包括胞体(soma)、树突(dendrite)和轴突(axon)，主要功能为信息的处理及传递．神经元会收集到其他神经元的输入信号，当信号积累超过一定临界值时便会转化产生一个神经脉冲传递给其他神经元, 如图1(b)(右)所示. 神经元具有的基本功能可由多种理论模型描述, 如Hodgkin-Huxley (HH)模型和leaky-integrate-and-fire (LIF)模型[38,39]. 其中HH模型虽然从生物仿生学角度更能精准地描述神经元功能，但其需要多参数和多微分方程来实现，复杂度较高．而LIF模型较为简化，可以低成本算力基本实现对输入脉冲信号的积分，及达到临界值后发射脉冲信号的神经元动态过程, 因此当前神经网络多采用LIF模型.

突触具有可塑性, 其具有调节自身权重的功能, 如图1(b)(左)所示, 这是生物学上学习和记忆的基础, 对实现神经网络的学习功能也至关重要．突触内权重的调节与诸多因素相关，其中最简单的便是直接施加增强或抑制信号调节权重，也有更为精确地通过引入时间维度来调节权重的模型，如脉冲时序依赖可塑性(spiking-time dependent plasticity, STDP)[40]．对于人工神经元及突触，至少应实现以上所描述的神经元及突触的基本功能, 才可进一步基于其构建类脑神经网络.

磁斯格明子类脑器件主要基于斯格明子的位置和数量来实现对应的神经元及突触功能．针对基于磁斯格明子的人工神经元器件，目前的研究主要通过操纵单个磁斯格明子位置来实现对应的基本功能，较为典型的器件结构如图3(a)和(b)所示．图3(a)中的器件模型由Li等人[41]在2017年提出，在该窄条带中，由于边界效

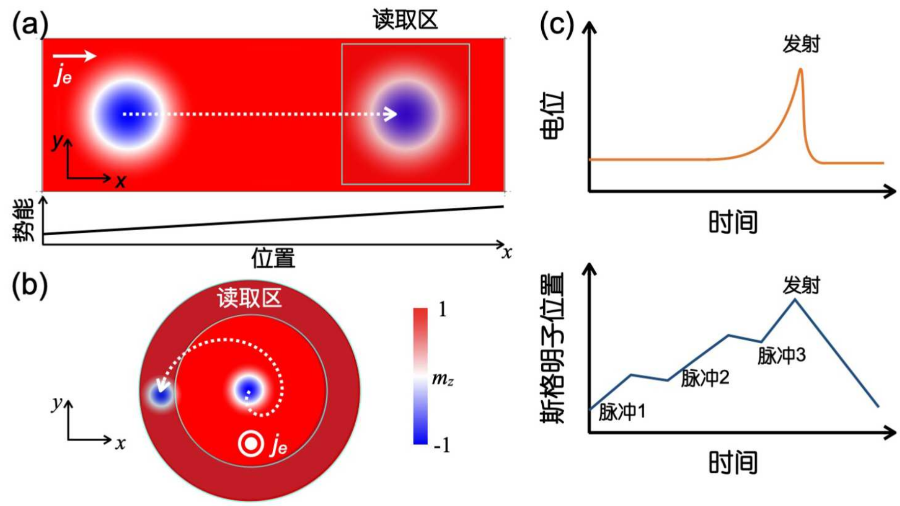

图 3 (网络版彩色)基于磁斯格明子人工神经元的工作原理. (a, b) 两种基于磁斯格明子人工神经元器件示意图, 深色区域为读取区; (c) 脉冲输入下器件中电位(上)和斯格明子位置(下)

Figure 3 (Color online) Working principle of skyrmion-based artificial neurons. (a, b) Schematics of skyrmion-based artificial neuron devices. The shaded part is the reading-regime. (c) The corresponding potential (top) and skyrmion position (bottom) of a skyrmion-based artificial neuron device

应, 斯格明子在外加电流下可沿直线运动[33,42,43]. 在窄条带一端设有读取区(通过如反常霍尔效应或磁隧道结读取), 斯格明子进入其中时, 便会产生信号变化从而实现发射功能. 而斯格明子从左到右的位置变化则可视为对信号进行积分的过程(图3(c)). 为了进一步完善器件功能, 通常还会针对窄条带进行非均匀材料调制, 如调节条带从左到右的垂直磁各向异性或DM相互作用[44]. 该调制会使得斯格明子在条带一端能量更低, 在未施加电流或电流小于临界值时, 斯格明子会自然向远离读取端移动, 进而实现LIF模型中的泄漏机制(即通过脉冲调整电位后, 在未施加下一脉冲时信号自然衰减的过程, 如图3(c)下排).

除条带结构外, 基于磁性纳米盘异质结构的自旋纳米振荡器也可用作实现斯格明子人工神经元. 如图3(b)所示, 该模型由Liang等人[45]提出, 纳米盘边缘一圈为读取区, 其中斯格明子信号可通过磁隧道结读取. 当施加一垂直电流时, 纳米盘上方自旋阀或磁隧道结可通过STT效应驱动斯格明子在圆盘中打转, 随着电流脉冲输入, 斯格明子位置会逐渐接近读取区, 从而实现积分-发射功能. 另一方面, 磁纳米盘的边界效应会产生一个从盘中心到边界的势, 当斯格明子接近边界时, 若无后续施加电流脉冲, 则会自然回到初始圆盘中心位置, 从而实现泄漏机制.

除以上两种器件外, 基于如斯格明子共振、斯格明子尺寸变化等机制也可构建神经元器件, 而外界激励也包含如电压调控磁各向异性(voltage-controlled magnetic anisotropy, VCMA)、表面声波(surface acoustic wave)等[46~52]. 与电流操控相比, 通过电压调控斯格明子的器件具有更好的能效. 近年来, 也有研究基于各类其他拓扑磁结构的神经元器件, 例如图4(a)和(b)中基于双斯格明子劈裂运动的神经元器件, 这些器件在能耗、速度及功能方面各有优劣[53,54]. 基于单个斯格明子位置的人工神经元器件中, 斯格明子的尺寸直接决定了器件的尺寸, 因此可通过优化斯格明子尺寸来进一步缩小器件尺寸.

磁斯格明子人工突触器件多利用斯格明子数量多少来调控其权重, 典型器件结构如图5(a)所示. 器件中具有一读取区(后突触区, 可通过如磁隧道结读取), 其中的斯格明子数量决定了器件电位高低, 即权重. 器件在初始态(图5(a))具有一定数量斯格明子(斯格明子池、前突触区), 当施加正向电流时, 通过STT或SOT效应, 可驱动池中斯格明子向读取区移动, 增加其中斯格明子数量, 从而实现权重的增强. 相反地, 当施加反向电流时, 斯格明子会从读取区返回斯格明子池, 相应的权重也会被抑制/减小(图5(b)). 一般在斯格明子池与读取区间还会通过材料调制(例如增加垂直磁各向异性)实现一个缓冲区(能量势垒), 从而防止斯格明子在两个区域间自发运动产生权重变化错误. 由于斯格明子数量与电信号的关系接近线性, 因此磁斯格明子人工突触具有良好的线性权重比及权重对称性(增强与抑制后

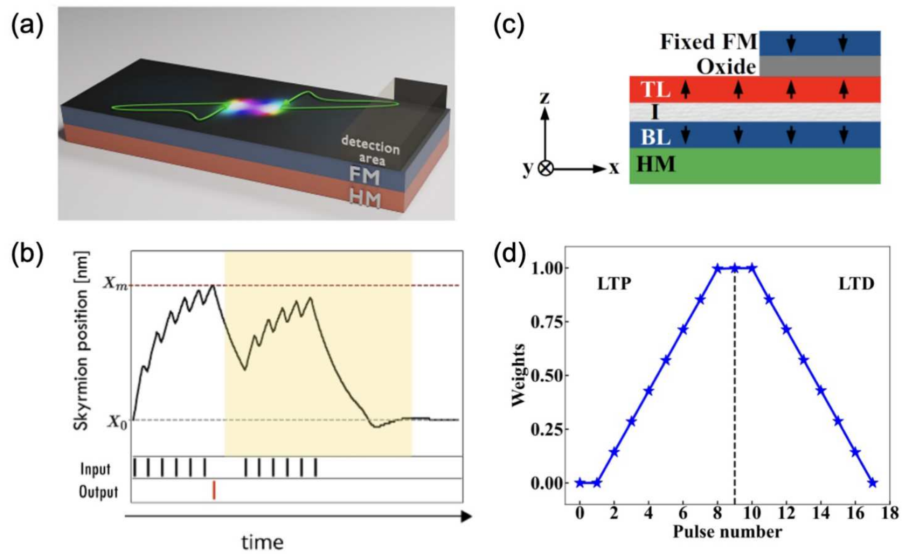

图 4 (网络版彩色)基于双斯格明子人工神经元和基于人工合成反铁磁斯格明子突触器件演示. (a) 基于双磁斯格明子的人工神经元器件示意图. HM为重金属层, FM为铁磁层, 最上方为读取区. (b) 斯格明子位置(上)及对应的输入(中)和输出信号(下)[54]. (c) 基于合成反铁磁斯格明子人工突触器件示意图. HM为重金属, TL和BL分别为上层和下层铁磁层, I为中间层. 上方Fixed FM和Oxide为读取区域. (d) 模拟计算得到对应人工突触权重调节曲线[55]

Figure 4 (Color online) Demonstration of the artificial neuron based on biskyrmions and the artificial synapse based on synthetic antiferromagnetic skyrmions. (a) Schematic of a biskyrmion-based artificial neuron. HM is the heavy metal layer, FM is the ferromagnetic layer, and the top part is the reading-regime. (b) Skyrmion position (top) and the corresponding input (middle) and output (bottom) signals[54]. (c) Schematic of a synthetic-antiferromagnetic skyrmion-based artificial synapse. HM represents the heavy metal layer, TL and BL represent the top and bottom ferromagnetic layers, respectively, and I represents the insertion layer. Fixed FM and Oxide constitute the reading regime. (d) Simulated modification of synaptic weights[55]

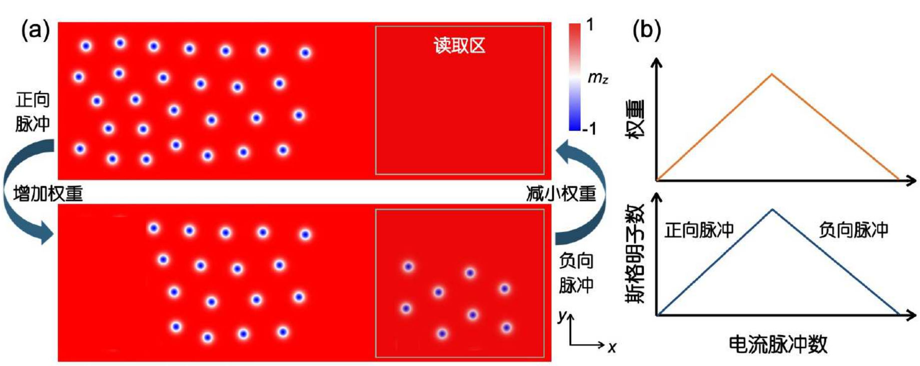

图 5 (网络版彩色)斯格明子人工突触工作原理. (a) 基于磁斯格明子的人工突触器件示意图, 深色区域为读取区. (b) 读取区内的斯格明子数量(下)及对应的权重(上)

Figure 5 (Color online) Working principle of a skyrmion-based artificial synapse. (a) Schematic of a skyrmion-based artificial synapse. The shaded part is the reading-regime. (b) Number of skyrmions (bottom) in the reading regime and the corresponding weight (top)

相对权重变化的对称性). 器件权重的可调范围由其中斯格明子的数量和读取方法的开关比决定, 通过增加斯格明子的数量及提升读取开关比, 斯格明子人工突触可实现类模拟权重, 从而更接近真实突触的功能.

Huang等人[41]于2017年提出了基于上述机制的磁斯格明子人工突触器件, 该团队提出利用能量势垒(高垂直磁各向异性)分隔前突触与后突触区域, 并基于微磁学模拟验证了器件的基本突触功能. 2020年, Song等人[56]在实验上展示了类似的斯格明子人工突触器件, 他们的实验基于亚铁磁多层膜, 其中可通过强电流脉冲方向控制斯格明子数量, 同时通过反常霍尔效应实现斯格明子读取. 配合原位X射线扫描穿透成像技术,

他们成功确认了器件中斯格明子数量与反常霍尔电阻率变化的关系，并展示了该器件良好的线性权重比及权重对称性. 近年来, 也有基于人工合成反铁磁斯格明子的器件(图4(c)和(d)), 这类器件在单元尺寸和速度上具有一定优势[55]. 除上述器件外, 也有利用斯格明子尺寸变化实现权重调节的器件方案，以及利用应力等手段代替电学方法调控权重的斯格明子人工突触器件[50,55,57~59].

3 挑战与展望

目前虽已有诸多基于磁斯格明子的类脑器件方案, 但大部分集中于理论模拟，相关实验由于面临较大挑战(如磁成像配合原位电输运测量), 因此仍处于起步阶段, 仅斯格明子人工突触原型器件得到演示, 从实验上验证如斯格明子神经元器件及具有不同工作机制的器件, 并进一步对理论模型给出反馈, 对后续器件的研究具有重要意义. 斯格明子类脑器件的性能和尺寸还具有很大的提升空间，其中性能方面提升主要依赖于针对斯格明子操控方式的改进，例如通过电压调控等低能耗方式，也可利用人工合成反铁磁、亚铁磁等新材料从而提升斯格明子的速度[60,61]. 另一方面, 由于斯格明子为器件信息基元，相关器件尺寸的缩减便依赖于对斯格明子尺寸的优化，如能稳定小于10 nm的室温磁斯格明子, 则可以大大减小器件的尺寸. 斯格明子类脑器件所需材料通常与CMOS具有兼容性, 因此更容易与之集成从而实现对应电路及类脑神经网络系统，但由于材料和器件的电阻值及开关比等问题，其信号通常需要放大. 虽然目前已有研究给出了初步电路设计, 但如何具体在电路中使用斯格明子类脑器件并构建神经网络及可能的芯片设计也需要进一步研究[62,63]. 此外, 如何在电路及系统层面整体评估斯格明子类脑神经网络的能耗及计算能力也是需要值得思考的问题.

目前已有研究表明三维拓扑磁结构如磁霍普夫子(magnetic hopfion)可用于元学习, 因此除斯格明子等二维拓扑磁结构外，能否利用三维拓扑磁结构进行类脑计算尚有待挖掘[64~66]. 由于三维体系具有额外空间维度, 有可能更好地提高器件的连接度, 从而为类脑计算中扇进(fan-in)扇出(fan-out)问题提供新的思路.

当前人们对大脑运作方式的理解仍处于初级阶段, 对诸多细胞和组织的完整功能尚不明了，比如星形胶质细胞在神经网络中的功能、突触中轴突和树突的功能差异化等. 最近有研究揭示树突也会参与神经网络中信息处理，因而需在神经网络中考虑它的具体功效[67~69]. 随着人们对神经网络及其基本工作单元的认知加深，新型神经拟态器件及对应的神经网络也需要随同发展，而如何基于磁斯格明子等拓扑磁结构实现新的器件功能(如轴突), 从而能更好地模拟、完成人脑的功能, 也有待进一步研究.

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Summary for “磁斯格明子类脑器件”

Magnetic skyrmion-based brain-inspired devices

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Neuromorphic computing mimics the brain’s neural networks, using artificial neurons and synapses to process information. This approach holds promise for more efficient and energy-saving solutions in artificial intelligence (AI) applications. However, traditional semiconductor devices struggle to meet the demands of neuromorphic computing, particularly in terms of non-volatility and integrated memory-processing functions. To advance this field, new hardware solutions are required. Spintronic devices, which utilize the spin of electrons in addition to their charge, offer a promising alternative for neuromorphic computing due to their inherent non-volatility. Among these, magnetic skyrmions—nanoscale, vortex-like magnetic structures—are especially attractive. Their unique topological properties, stability, and low-power manipulation make them ideal for use as information carriers in neuromorphic systems. Skyrmions are stabilized in materials through the Dzyaloshinskii-Moriya interaction (DMI), which breaks spatial inversion symmetry. This stability, combined with the ability to move skyrmions using low-energy electrical currents, makes them highly efficient for information storage and processing. Unlike conventional magnetic domain walls, skyrmions are more stable against external perturbations, providing an advantage in neuromorphic applications, where robustness and energy efficiency are critical.

This review examines recent developments in skyrmion-based neuromorphic devices. It begins by outlining the fundamental physical properties of skyrmions, including their stabilization mechanism and electrical current-driven motion. The review then discusses how these properties can be exploited to replicate the functions of artificial neurons and synapses—the core components of neuromorphic systems. In skyrmion-based artificial neurons, the motion of a skyrmion through a nanowire can simulate the integration of input signals. When the skyrmion reaches a specific point, it triggers the neuron to “fire”, mimicking the behavior of biological neurons. Similarly, skyrmion-based synapses regulate the strength of connections between neurons by adjusting the number of skyrmions in a region, thereby modifying the synaptic weight—a key feature for learning and memory. We then explore different device architectures proposed for implementing these skyrmion-based neurons and synapses. These include structures based on magnetic tunnel junctions and nanostructured spintronic materials, offering benefits in scalability, energy efficiency, and non-volatility. Furthermore, some research shows the potential for these devices to integrate with conventional CMOS technology. Despite significant progress, challenges remain before skyrmion-based neuromorphic devices can be implemented into neuromorphic systems. These include improving skyrmion stability at room temperatures, optimizing material systems for better performance, and achieving integration with existing electronics. Additionally, most current research is either theoretical or in early experimental stages, with large-scale demonstrations yet to be realized. Magnetic skyrmions offer a novel path for neuromorphic computing, providing a potential solution to the limitations of traditional semiconductor devices. With further research, skyrmion-based systems could lead to highly efficient, low-power computing architectures capable of emulating the brain’s complex functions.

magnetic skyrmion, brain-inspired computing, neuromorphic computing, topological magnetic texture, spintronics

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