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机器学习策略下的超快光子学设计：回顾与展望（特邀）

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摘　要：从行为组织学开创了光子计算的先河以来，基于人工智能的光学计算已经发展了七十多年，这一历程对超快光子学的智能化研究产生了重要影响。近年来，因超短脉冲非线性多维相互作用的复杂化，让超快光子学方向的研究产生了巨大的发展潜力。智能超快光子学的研究，为超短脉冲数据的完整、准确和有代表性提供了新的推动力量。在这里，我们回顾了机器学习策略下超短脉冲光纤激光系统的最新进展。通过算法和控制元件两方面的设计，进一步概述了满足这些进展所需的技术条件。并对机器学习与超快光子学这一新兴交叉技术所存在的挑战与未来研究前景做出展望。

关键词：机器学习；超快光子设计；模式锁定技术；智能算法；光纤激光器
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0　引言

如今在云计算、大数据的人工智能时代，人们对更快、更高效的信息处理和存储超快光子器件的需求将越来越大[1-5]。但同样伴随着的是，半导体芯片、算法编程开发、物联网集成与光子学的开拓融合与发展面临着重大挑战。超快光子作为激光能量的输出与传输通信的媒介，还没有在信息处理和数据计算中得到广泛应用[6-11]。随着人工智能技术的发展，机器学习策略由于强大的计算性能、硬件的可移植性，以及生成和访问大型数据集的快速便捷化，使其在解决和控制光子数据时显得非常有效和强大[12-13]。通过基于机器学习策略的数据驱动解决方案，不仅使得光子器件的目的性更加明确，获取、处理和存储所需的数据方面更加高效，而且在传输速率、能耗、性能、整体尺寸、成本等方面具有显著优势，创建可以在新的操作机制中运行的光学设备[14-15]。如今，机器学习已经成为包括高速光通信和计算[16-20]、超灵敏生化检测[21]、特定目标特性的纳米材料和结构[22-24]、无标签细胞分类[25]、量子光学[26]、高效太阳能收集[27]和超分辨率成像[28-29]，以及量子信息处理[30-31]的变革驱动性技术。

然而，机器学习策略虽然提供了重要的指导方针，但当时间和空间的几何维度变得复杂甚至无法度量时，要找到合适的算法和器件结构来实现所需的光子特性并非易事。在寻找最优模型时，我们需要利用数据驱动执行参数设计和迭代模拟，以趋近于理论优化的极限，而这一过程很大程度上依赖于以往的设计经验[32-33]，因此更具未知与挑战性。在现阶段超快光子学中，由于自调谐和优化控制的需求不断增加，导致目前新兴产业对超快光子具有更加精确的调控方式和特定的光谱特性提出了更高要求，而现有超快光子设计和模式已被证明是不够精准、不可调控和不确定性的[34-36]。这种不足是由于脉冲发生机制通常涉及复杂的损耗、非线性和色散传播效应，并且涉及到噪声动力学的抑制过程。因此在高维空间传输中需精确平衡多

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个参数才能达到较为稳定的工作状态[37-39]。随着用户需求的不断提高，通过试错的方法对激光系统校准已不再适合优化。对于这种复杂性较高的系统，机器学习方法在驱动下一代超快光子技术上具有巨大的潜力。通过建立足够的机器学习策略，我们可以准确地控制并计算出光子特性，甚至可以应用于复杂时间序列来确定和分析潜在的物理模型[40]。

在超快激光器领域，由于许多超快现象是非线性和多维的[41-43]，导致在外部扰动存在时自动控制的需求日益增加。同时，脉冲特性在与传播介质或材料相互作用下要求具有较强的适应能力。因此，将腔内各项参数（例如偏振控制、泵浦功率、光谱滤波和损耗）结合进行精准调控，在多维空间中寻求最优值来控制入射场的性质，最终创造出更多可能的工作机制是我们的不懈追求[44-45]。

本文介绍了机器学习策略下超快光纤激光器的背景与模型，从理论与实验架构两方面回顾了机器学习策略应用于超快光子学的设计与实现，对最新研究进展进行了对比总结。这些结果展示了机器学习在光子学设计中的力量。最后，我们评论了这一新兴跨学科研究领域的挑战和未来的研究方向，以及在未来几年有望产生重大影响的应用。

1 机器学习超快光纤激光器架构

机器学习-自动锁模（Machine Learning-Automatic Mode-Locking, ML-AML）技术作为超快激光一项新的研究课题是下一代锁模激光器研究的重点。机器学习-自动锁模技术通过各种智能化算法和控制腔内参数来设计反馈电路（如偏振控制）。最终产生的激光器无需人工辅助控制，达到自动启动锁定且锁定到不同的模式状态，并且具有优秀的抗环境干扰性能[46-49]。研究初期，实验结合了算法反馈回路和腔内参数两方面的控制，实际上是对非线性演化光纤激光器的概念验证与数值模拟。基于此，光子结构方面首先研制了基于压电器的自动偏振控制器和自制的高速全光纤振幅分度偏振计的组合，成为自动锁模的开创性工作[50]，但这个模型很快被电控偏振控制器所取代[51]。进一步地，识别非线性偏振演化（Nonlinear Polarization Evolution, NPE）激光器中的自启动机制的研究受到关注，经历了遍历算法搜索偏振状态与脉冲计数来判别锁模区域[52]、高速光电探测器自动锁模电路开发[53]、进化算法与两个电控偏振控制器的组合[54]，直到六个计数器同步计数与现场可编程门阵列（Field-Programmable Gate Array, FPGA）开启了实时可编程控制的先河[55]。算法方面完成了由复合适应度函数、遗传算法再到神经网络的转变，朝着耗时性能优、简化精确与适应多变量的趋势发展。现已实现NPE、环形腔、“8”字形等各种激光腔型在不同机制下的自调整与控制。根据参数的精确选择，可以锁定包括基频、高阶谐波、调Q、连续波激光、类噪声脉冲、Q开关、多重脉冲和束缚态等各种体制，促进了特定模式锁定状态的精确再生，现已形成分析复杂非线性动力学的标准方法[56-59]。图1

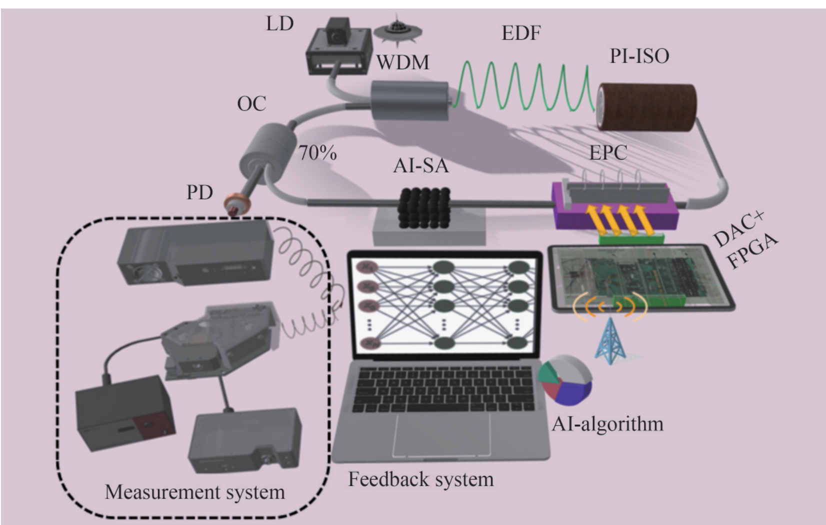


图1 机器学习策略下反馈环路控制腔内元素和算法控制的自动锁模超快光纤激光器的基础架构

Fig. 1 Infrastructure of machine-learning strategies for automatic mode-locking ultrafast fibre lasers using control of intracavity elements via a feedback loop and control algorithm

是机器学习策略下超快光纤激光器的基础架构，其中光子系统包括泵浦源（LD）、波分复用器（Wavelength Division Multiplexer，WDM）、掺铒光纤（Er-Doped Fiber，EDF）、偏振无关隔离器（Polarization Independent-Isolator，PI-ISO）、人工智能饱和吸收器（Artificial Intelligence-Saturable Absorber，AI-SA）、光耦合器（Optical Coupler，OC）和光电探测器（Photodetector，PD）。反馈系统包括电控偏振控制器（Electric polarization controller，EPC）、现场可编程门阵列（FPGA）、数模转换器（Digital to Analog Converter，DAC）和智能算法（AI-Algorithm）。输出特性由测量系统进行分析，包括光学频谱分析仪、示波器、自相关仪、射频频谱分析仪。通过将机器学习算法驱动到反馈电路系统控制的光电子器件中，通过训练算法即可达到快速参数选择的最佳操作，最终将系统锁定到所需区域。

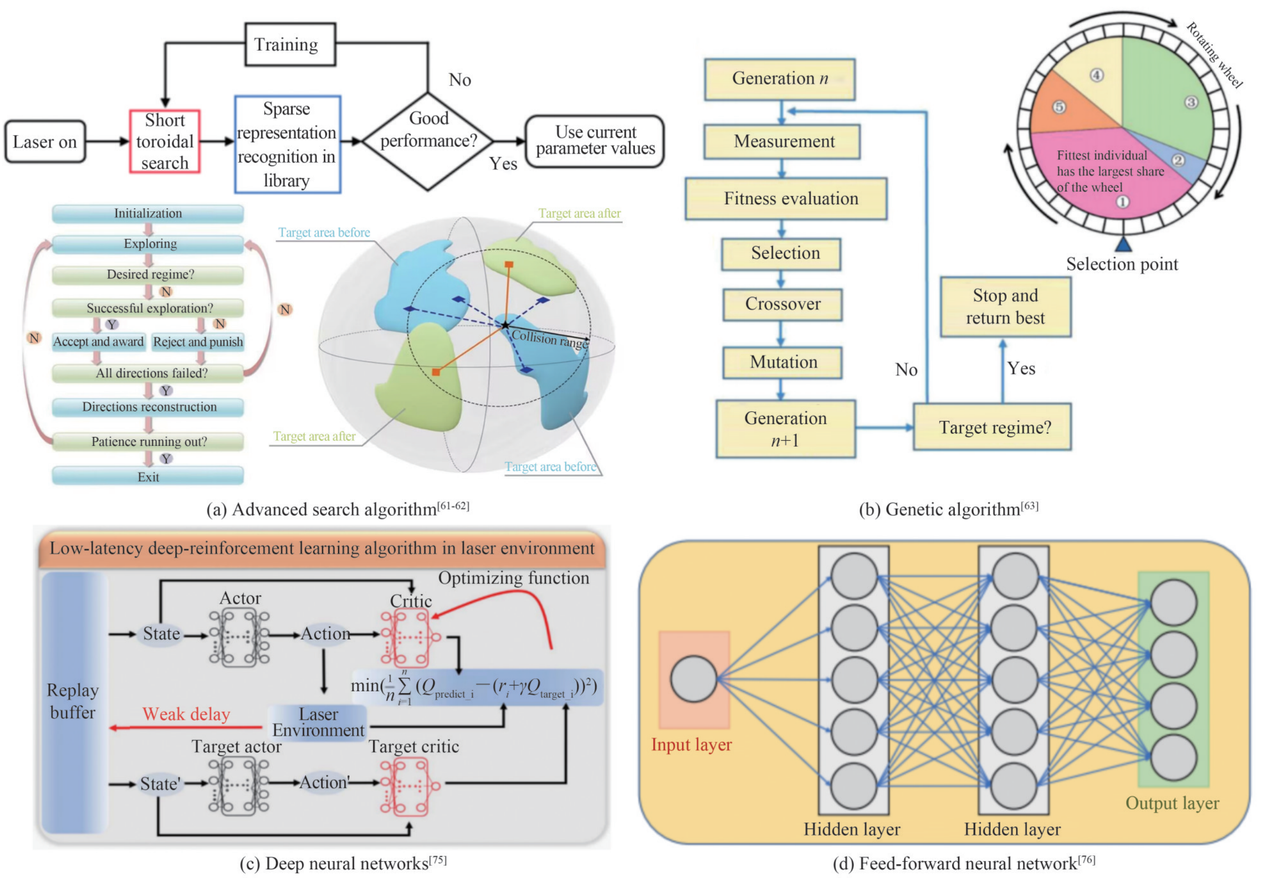
2 机器学习策略下算法的实现

算法改变了基于经验设计的方式。它通过多维度触发式的策略，利用较短的耗时来执行非正态式分布式信息处理，最大程度的适应光子结构本身不可预测的性质。时间复杂度和全局优化能力是算法重要的衡量指标。为了高效且准确地搜索庞大且复杂的偏振空间，需要不断优化算法的目标函数，从而减少运行时间。在超快光子系统中，机器学习算法应用于特定光子的预训练，用于实时优化和调优。本节将回顾算法策略及在超快光子学中控制和表征的应用。

2.1 超快光子学的机器学习算法

在未来数据规模爆炸式发展的推动下，探索超短脉冲所产生巨大的参数空间显得尤为重要。算法提供了在不同目标、功能、体系情况下数据驱动策略，从而构建具有更好鲁棒性的光子系统。以下将列举目前具有代表性的三种算法策略，见图 2。

1）高级搜索（Advanced Rosenbrock searching，ARS）。该算法是一种无约束直接搜索方法。通过预先



(a) Advanced search algorithm[61-62]
(b) Genetic algorithm[63]
(c) Deep neural networks[75]
(d) Feed-forward neural network[76]

图 2 算法策略

Fig. 2 Algorithm policies

设定连续搜索失败最大值参数。当超过阈值优化将立即终止。随后，一个新的搜索从新的随机点开始。具有独特的退出机制，避免适度选择。算法目标根据激光的工作范围选择时域波形或快速傅里叶变换（Fast Fourier transform，FFT）结果的某些特殊特征。

2）遗传算法（Genetic Algorithm，GA）。它的灵感来源生物进化中的自然选择概念，从而产生进化的算法。首先用灵巧度函数评估基因（系统参数）的初始（随机）染色体，根据适应度评分利用亲本选择传至下代。繁殖包括父母的基因交叉以及引发下一代突变导致个体基因随机改变。包括最好的个体克隆给下一代的精英主义。遗传算法通过选择、交叉和变异，避免坚持局部最优，使其具有天然的优势。

3）深度神经网络（Deep Neural Networks，DNNs）。该算法模仿生物神经网络，采用数据驱动的方法允许模型从大量数据中自动发现有用的信息，进行分布式并行信息处理。依靠系统的复杂程度，通过调整内部大量节点之间相互连接的关系，推断潜在变量和自适应学习。这与基于物理或规则的方法形成鲜明对比。前馈神经网络（Feed-forward neural networks，FNN）使用一种称为“贪婪分层预训练”的策略进行有效训练。信息从输入层通过隐含层向前传递到输出层。使用各种权重和非线性激活函数对数据进行操作，以及一个计算网络输出层，用于回归或分类。卷积神经网络（Convolutional neural network，CNN）是一种特殊类型的前馈神经网络，其中输入被一组过滤器或内核卷积，进行非线性处理。然后，产生的特征图被池化函数采样，通过将附近的点合并为一个单一的值来降低数据的维度。卷积和池化操作之后，还可以增加卷积层，从以前的特征图中提取进一步的相关信息。最后，输出可以被强化为向量形式，用于分类或回归任务。

2.2 算法策略在超快光子结构中的实现

对应上节的算法策略，我们将介绍其在超快光子学中实现的技术手段。

1）高级搜索策略。光纤双折射固有的随机性一直是光纤激光器精确建模和优化性能的主要技术突破点。超快光子系统中的其他物理参数（如克尔非线性，色散特性）都可在理论模型中表征，但双折射对环境因素（如弯曲，扭曲，各向异性应力，温湿度等）非常敏感，导致其随机变化[60]。这样的系统需要数据驱动建模方法对双折射进行分类[61]。建立腔体双折射值映射库与偏振器电压值的训练模型。通过改变不同角频率下波片及偏振器角度，从而产生目标函数的时间序列。然后用奇异值分解进行降维，并连接到模态库，对激光器的双折射进行分类，最终获得环面搜索的最佳位置。采用可识别的判别模式和直接测量的方式，具有较高的直观性和便捷性。同时具有代表性的是采取Rosenbrock搜索算法、随机碰撞恢复算法和各个区域识别相结合的方式，与手动锁模过程中行为特点相似的类人算法[62]。针对不同的操作制度设定一系列的目标函数，在提升时间性能、可移植性、多体系输出、灵活性方面具有潜力。

2）改进遗传算法。在传统的判别准则和搜索算法之上提出改进遗传算法[63]，以进一步提高算法耗时性能。核心思想是在适应度计算过程中同时判断当前是否达到目标状态的操作。当检测到期望状态时算法立即停止搜索，从而减少算法的运行时间。之后根据识别顺序进入监测阶段。当检测到脱离时，再次发射遗传算法自动恢复到所需状态。在搜索罕见状态时，其具有的全局优化能力显示出耗时性能上巨大的优势。另一种通过搜索遍历非线性偏振演化的偏压值实现锁模光纤激光器系统的自优化[64]。根据激光输出的射频频谱特征定义目标函数，同时控制非线性偏振演化传递函数来访问目标函数，可实现多模式下的操作机制。它为超快光子在高动态、非平稳工作机制下（如孤子爆炸、罕见体系、间歇性非线性机制等）复杂动力学的探索和优化开辟了一条新的途径。

3）深度神经网络。为了平衡机器学习的训练和运行时间，需要对数据实时演进，这样可以达到高效利用数据的效果。在某种程度上，深度学习与遗传算法有相似之处，前者的优势在于使用大量预先收集的训练数据，将设计范围扩大到远远超出优化方法所能达到的范围。通过潜在的变量和生成模型避免探索不必要的解决方案[70-72]。而后者主要在进化过程中探索数据空间[68-69]。另外，光子结构具有特定应用的模型架构，或从其他领域移植成型的特点。这就需要具有局部语义相关性的卷积神经网络（CNNs），以及处理结构化输出条件的深度生成模型来匹配[73-74]。更重要的是，超快光子系统实现长期稳定的运行是另一个关键目标。环境条件的变化导致性能下降主要取决于训练和测试过程中所探索的参数空间和机制。因此，包含各种环境变化的训练数据是重要的。

在此背景下，一种低延迟深度强化学习算法[75]超快光纤激光器被提出。该算法包含两个修改腔内偏振

策略的训练网络和两个评估网络组成。在有效性方面，通过验证训练后的网络模型性能，可以达到自动锁定且快速失锁状态的情况下也能瞬间恢复。在鲁棒性方面，建立不同温度环境数据库。通过训练模型对其性能进行测试。平均锁模恢复时间为1.948 s，系统中最短的锁模状态恢复时间为0.476 s。数据之间的反馈延迟算法和激光腔通过无线网络系统完成，为远程维护和集中控制提出了解决方案。

另一种具有代表性的自调谐激光器将深度学习与基于数值模拟的模型预测控制（Model Predictive Control，MPC）相结合[76]。由于双折射随时间变化且无法直接测量，如果不进行控制会逐渐偏离目标函数，最终导致无法锁模。MPC通过递归神经网络（RNN）自行训练目标函数下的输入数据以获得足够的训练数据，在双折射随机漂移的情况下保持脉冲状态。同样，采用变分自编码器（Variational Auto-Encoder，VAE）以自优化的方式训练数据[77-78]也可以推断真实双折射状态。它们都具有良好的鲁棒性能，现已成为在强非线性系统中先进的控制体系结构[77-81]。

在这些研究中，算法经历了从局部到全局优化趋势的演变。高级搜索算法基于特定适应度或目标函数，监控单一参数且只收敛到局部最优，限制了操作机制的同步优化功能。在此基础上设计遗传算法解决这一瓶颈，但暴露了相对较慢收敛速度的缺点。随着机器学习的发展，深度神经网络得到了广泛普及，研究人员从理论上认识到模型结构深度的重要性，在可用数据规模不断扩大的趋势下极大缩短了时间成本。目前，深度神经网络已被应用于脉冲整形的控制[65]、不同非线性传播模式的分类[66-67]以及控制复杂的非线性动力学中。然而，由于其需大量的实验数据作为训练基础，并且精确的建模需要广泛的参数。这对于初期研究来说仍具有挑战性。但可以预见，深度神经网络互连的高性能优势将会成为超快光子集成产业化的未来趋势。

3 机器学习策略下反馈模型的实现

在本节，我们将讨论相关的反馈模型及在解决光子学问题中的应用。机器学习策略下的超快光子工程试图将智能算法的元素移植到能够反映其大规模分布式特性的硬件上，将硬件与算法相匹配，可能会带来更快、更节能的信息处理，以致力于光电结构的集成创新[82-86]。

3.1 反馈模型下控制元件的设计

通用的电子电路或微控制器驱动的光子器件成为目前光子平台在电子领域常见的构建模块，如逻辑门[87-88]、高级编译器[89]、存储器[90-91]和模拟数字互转[17,92-93]等。但模拟电光接口的电子存储器因只适合存储特定类型的数据，精度和噪声有限[94-95]。在集成光子学中，高速光电转换器件对电路进行预编程使其主动微调，有助于抵消如温度和振动环境的变化，从而对变量和环境敏感性进行校正[96-97]。下文将对现阶段主要用于光子模型的可驱动控制元件进行讨论。

1）铌酸锂（$LiNbO_3$）偏振控制器。由于铌酸锂（$LiNbO_3$）晶体独特的非线性光学特性、覆盖中红外波长的宽透明窗口和强大的电光系数[98-103]，目前已成为具有巨大潜力的光子平台。铌酸锂（$LiNbO_3$）与纳米光子波导相结合，加速了集成非线性光子学的发展。目前，相干技术的一个复杂之处在于需要传输的光信号与来自本振信号之间的偏振匹配。由于传输信号的偏振状态会随着光纤的温度、应力和湿度的变化而波动，导致输出电信号出现衰落，而集成在铌酸锂衬底上的宽带光偏振控制器能在极短的时间内通过偏压信号进行偏振模式匹配，实现偏振自动检测、控制、识别、调控的技术要求。并且，它在接收灵敏度、调制频率、能源消耗、体积、可靠性，（多级）极化移位键控等方面具有诸多优势，可以在皮秒时间尺度上进行大规模超低损耗光子电路的设计，是符合未来智能化发展趋势的光电子技术。

2）微控制单元（Microcontroller Unit，MCU）。MCU采用检测偏振态的不连续跳跃来实现自动模式锁定[47]。模式锁定取决于映射机制，但是无法达到实时的优化调谐。在此基础上开发的基于光纤的快速振幅偏振计（Division-Of-Amplitude Photopolarimeter，DOAP）和基于压电挤压机进行自动偏振控制（Advanced Process Control，APC）的非线性偏振旋转锁模（Nonlinear Polarization Rotation，NPR）掺铒光纤激光器[50]。通过APC扫描Poincaré球体，获得所有可能偏振状态的映射，建立偏振态与脉冲持续时间、中心波长和平均输出功率参数之间的关系。之后，利用入射光投射到不同偏振方向的功率分布得到其偏振状态，施加数值滤波器即可得到偏振状态对应的锁模区域。这种方案极大地降低了模式锁定的相关参数之间的映射时间。

3）“8”字型非线性放大环路的电子控制[57]。采用非线性放大环路镜（Nonlinear Amplifying Loop Mirror， NALM)(包括电控偏振控制器(EPC)与四个四分之一波片(Quarter-Wave Plates,QWPs))作为人工饱和吸收器构成全光纤超快光纤激光器。控制部分由单向和双向环组成,双向环诱导差分相位从而产生功率,促进主激光腔中的脉冲产生。NALM从时间波形、光谱和频谱中提取三个分量的等加权和,提出非线性传递函数调节可饱和吸收器以实现稳定的超短脉冲。但此种策略电子集成度低和可移植性差导致了延迟较高和无法重复。在此基础上研究人员进行了技术改进,利用纳秒光电探测器确定皮秒级激光的脉冲持续时间[104]。激光腔由两个单向的光纤回路和双向的非线性放大环路镜组成,使用离散傅里叶变换(Discrete Fourier Transform,DFT)跟踪技术、滤波噪声和不稳定信号产生机制,可以单从示波器提取的数据准确预测时间宽度、光谱和射频频谱的脉冲特性。该技术为复杂激光系统的紧凑型、低成本的反馈控制系统奠定了基础。

4)现场可编程门阵列(FPGA)。以FPGA为计算中心,ADC和DAC分别进行数据采集和反馈数据的控制架构,已经展现出了良好的耗时性能[64,105]。快速傅里叶变换分析作为光谱鉴别判据,结合智能偏振搜索算法,建立光谱和时域脉冲之间的映射,以达到实时光谱采集和分析控制。这为传统锁模激光器无法观察到的超短脉冲的形成过程提供了一种视角。

3.2 机器学习策略下模型架构的分析

通过反馈模型下控制元件的设计,我们总结了建立模型的指导原则,阐释了如何应用这些模型的通用方式与关键因素。1)光子芯片。制作工艺着眼于平衡光子性能与模拟或数字控制的电子电路[110-112]。通过EPC施加直流模拟信号(偏置电压/电流)、FPGA实时可编程控制系统(例如反馈、算法等)、电子接口(数模转换器(DAC)和模数转换器(ADC))及光电子电路,实现电子模块独立优化,与对应的光学元件共存的效果。2)建立材料数据库。利用半导体介质、石墨烯等二维材料作为可饱和吸收器,将线性和非线性光学特性对材料参数的依赖关系集成到训练过程中,获取最佳制备与沉积参数。最终达到优化材料特性的目的,从而驱动高质量脉冲输出[107-109]。3)光电子互联计算。作为计算处理中枢系统,光电器件对光子信息处理实现了光电转换及传输速率的提升[113]。但是,其系统的局限性越来越多地体现在数字到模拟和电子到光子的域交叉上。相比之下,光子DAC[114]在能源效率和延迟方面实现了无缝转换。未来,光子DAC将会构建高采样率与精度、低失真与功耗,比电子更少受到抖动或电磁噪声影响的光电子互联系统。4)泵浦光源。作为光子转换效率和可扩展性的关键,光源在热效率、集成兼容性、可伸缩性和温度稳定性方面发挥了决定性作用[115]。通过智能泵浦参数反馈,可降低多脉冲不稳定性以提高所需区域稳定性。另外,通过自动控制泵浦功率来降低连续波辐射,以最小的泵浦功率获得最大的脉冲峰值功率,从而提高能效。5)混沌和不稳定性脉冲分析。非相干噪声如何自组织产生相干呼吸结构已引起广泛的研究兴趣[116-119]。然而,在超快时间尺度上捕捉这种混沌状态仍具有很大的复杂性。机器学习利用时间拉伸色散傅里叶变换(Time Stretch Dispersive Fourier Transformation,TS-DFT)的快速光谱分析,同时采用延时辅助实时脉冲控制器(Time-Stretch-Assisted Real-Time Pulse Controller,TSRPC)和算法相结合,为脉冲动力学的研究搭建了平台。

表1总结了目前为止该领域取得的一些代表性结果。从控制元件、目标函数、算法设计三个角度进行对比分析,总结了各光子系统的优缺点。在大多数研究中,反馈设计通常使用高级搜索、遗传进化算法再到神经网络。进一步提高自动锁模的性能需要从包括脉冲生成机制模型在内的算法来提供更有针对性的控制。我们可以预见,利用机器学习进行模式识别,能够更好的了解超快激光的动态,从而打造稳定性更好的激光系统。

表1 机器学习策略下超快光纤激光器设计方法与性能的比较

Table 1 Comparison of design methods and performance of ultrafast fiber lasers based on machine learning strategy

Laser system	Control elements	Objective function	Algorithms	Targeted parameters	Advantages	Disadvantages	Performance	References
Mode-locked fibre laser	Waveplates, polarizer, birefringence	Pulse energy divided by spectral kurtosis of the waveform	Search algorithm, singular value decomposition, local optimization algorithm	Stable mode locking	Fast identification of birefringence state and optimization of controller parameters	Requires a large number of measured parameters	10 min~1 h	[16, 61, 120, 121]

续表

Laser system	Control elements	Objective function	Algorithms	Targeted parameters	Advantages	Disadvantages	Performance	References
NPE fibre laser	Electronic polarization controller, liquid crystal variable retarder	FFT, corresponding function of different systems, RF peak	Advanced search algorithm, random collision recovery, genetic algorithm, human-like algorithm	Fundamental and harmonic mode locking, Q-switching and mode locking	Multi-function, real-time, multi-regimes of operation	Instability cannot be detected in real time	Mode-locking time of a few seconds, subsecond recovery time	[62, 63, 105, 128]
NPE fibre laser	Electronic polarization controller	Anomalous Harmonic power for anomalous dispersion, intensity of FSR radio-frequency component for normal dispersion	Evolutionary algorithm	Q-switching and stable mode locking	Two regimes of operation	Slow convergence	Mode-locking time of 30 min	[54]
NPE fibre laser	Polarization control	Repetition frequency	Evolutionary algorithm	Harmonic mode-locking with anomalous dispersion	Optimized high harmonic mode locking	Slow convergence	Harmonic mode-locking time of 2 h	[122]
Ring fibre laser	Electronic polarization controller, pump power	Peak power, maximized RF signal	Genetic algorithm	Anomalous dispersion with stable single-pulse mode locking	High contrast between stable and unstable pulses	Complex fitness function, slow convergence speed	Mode-locking time of 30 min	[57]
Ring fibre laser	Electronic polarization controller, electric dial, Normal dispersion	Centre wavelength, coefficient between pulse amplitude jitter spectrum and target	Genetic algorithm	Stable tunable, birefringent filtering	Adjust center wavelength and repetition frequency	Limited tuning	Unable to integrate	[58, 123, 126]
NPE fibre laser	Electronic polarization controller	Radio-frequency power at expected repetition rate, spectral similarity and output power	Genetic algorithm	Stable mode locking	Spectra can be tuned	Only fundamental mode locking	Mode-locking time of 90 seconds, 30 s recovery time	[124]

续表

Laser system	Control elements	Objective function	Algorithms	Targeted parameters	Advantages	Disadvantages	Performance	References
NPE fibre laser	Polarizer, amplifier, counter	Pulse energy of single pulse solution	Genetic algorithm	Multipulse mode	Simple fitness function	Complex polarization control	Numerical simulation results	[55, 125]
Figure-of-eight laser	Pump diode powers	Autocorrelation duration	XGBoost, Feed-forward neural network	Replace time domain comb	Real-time multiparameter monitoring with a single oscilloscope	Requires a large number of measured parameters	Unable to integrate practicality	[104]
Mode-locked fibre laser	Waveplates, polarizer	Pulse energy divided by spectral kurtosis of the waveform	Feed-forward neural network, recurrent neural network	Stable mode locking	Fiber birefringence changes quickly	Slow training process	Numerical simulation results	[76]

4 挑战与未来研究前景

图3是机器学习策略下超快光子学设计的核心概念和相应的实现方法。这些方法已经应用到了超快光子设计的特定领域，证明了机器学习方法在推动下一代超快光子技术方面具有的特殊潜力。可以看出，机器学习策略下超快光子学的发展具有极大的潜力。一方面，从硬件来说，将激光系统各模块智能化是一个

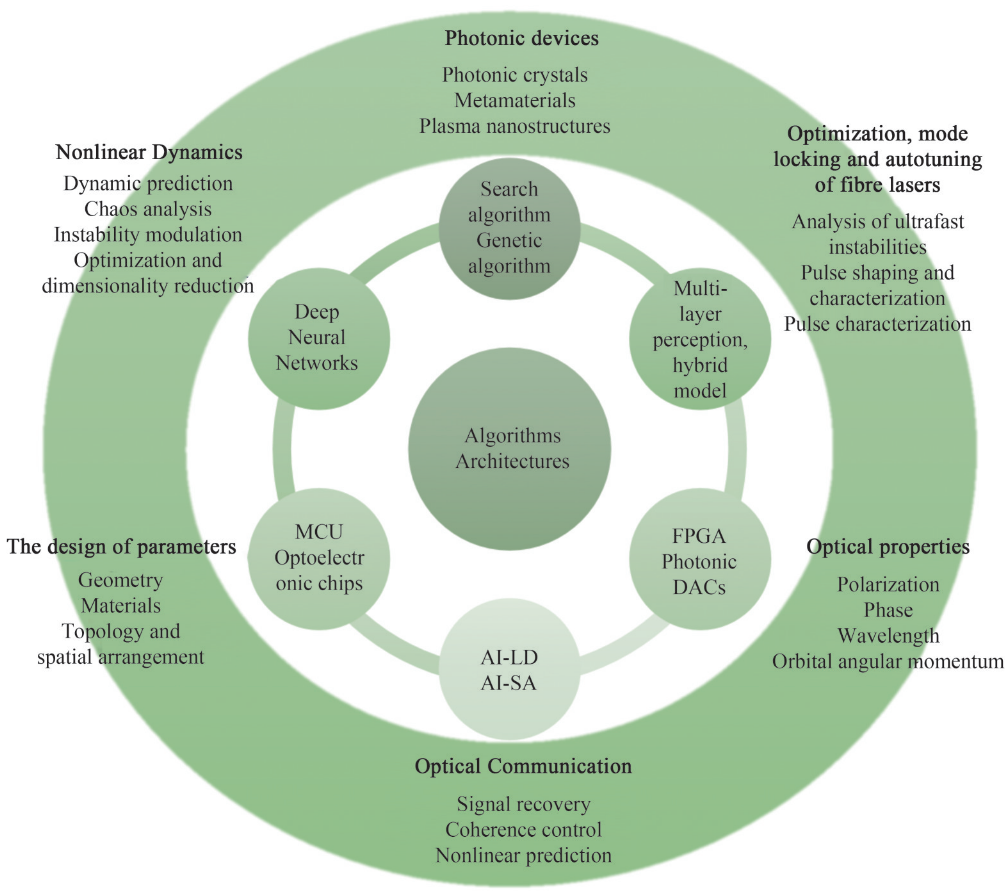


图3 机器学习策略下超快光子学的主要原理和设计

Fig 3 The main principles and design of ultrafast photonics under machine learning strategies

重要的发展方向。到目前为止，光学技术主要是在有限的设计空间中进行优化，这在很大程度上限制了光子结构，进一步发展先进的混合方案将是解决此挑战的关键一步，而智能光电子器件的组合将极大的促进激光器的先进水平，扩大光子的设计空间，以实现目标系统的最佳性能。另一方面，从算法的角度出发。为了在反馈中控制更多维变量，算法的效率就显得至关重要。到目前为止，大多数设计是基于遗传算法或神经网络架构。虽然这些算法的实现无疑带来了显著和开拓性的结果，但事实上，要挖掘机器学习的全部潜力，需要将多种策略结合起来。从实验数据中揭示模型，经无数数据挖掘后形成神经网络，建立目标与参数之间无限训练关系，这将极大优化超快激光快速定位所需运行状态的耗时性能[129-130]。此外，包括聚类、期望最大化等无监督学习算法具有从没有标记响应的数据中推断和揭示隐藏内部结构的能力，可对非线性复杂系统降维等关键问题产生重大作用。同样，通过监测收集环境各项信息来实时调整参数作为深度学习模型的正则化器，以确保光学研究依赖于稳定和长久性。在未来，如何提升智能光子系统的可移植性以及作为特定产品如何设计推理模型是探索下一代超快光子技术的重要课题。

5 结论

本文综述了机器学习策略下超快光子的模型架构，介绍了从算法及目标函数体系的演变到智能化模型架构的设计，概括了未来的设计思想与趋势，对比分析了现阶段的研究现状。人工智能背景下机器学习与超快光子学前沿交叉技术的融合，采用了非常规的方式为我们提供了无与伦比的光子视角。这种融合了计算机科学、光子学和材料平台的交叉技术将实现独特功能的大规模光子设计以及光学表征的新方法，为高效的能量转换系统奠定了基石。我们设想，基于多步机器学习策略的全局优化框架可以构建一个更加通用的智能超快光子系统，第一步，定义器件的主要目标功能并确定适当的光子概念以提供最佳性能；第二步，选择合适的材料平台建立广泛的光学材料数据库，通过使用所选材料属性，提供材料器件的优化设计方案；第三步，确定合适的制造条件（生长条件、掺杂水平、化学计量等）和集成方案。新的光子结构和机器学习之间的相互作用可能会克服当前计算方法和系统的局限性，在光物质相互作用和解锁新的器件概念方面具有无与伦比的能力，并可能将超快光子学研究引向新的领域，从而迎来一个更加光明的人工智能时代。

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Intelligent Ultrafast Photonics Based on Machine Learning: Review and Prospect (Invited)

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Abstract: Artificial intelligence-based optical computing has evolved for over seventy years since behavioral histology pioneered photonic computing, a journey that has had a significant impact on the study of intelligence in ultrafast photonics. The use of machine learning techniques in ultrafast photonics is an exciting new field, positioning innovative research in fundamental science and cutting-edge technologies. On the one hand, the systems of ultrafast photonics and the techniques that generate information reproduction, transformation and transmission can be used for photonics implementation of machine learning techniques; on the other hand, the powerful and precise, efficient and flexible data analysis and processing capabilities of machine learning can solve the challenges of ultrafast photonics in design and control. In recent years, the development of research in ultrafast photonics has been greatly hampered by the complexity of nonlinear multidimensional interactions of ultrashort pulses. The research of smart ultrafast photonics provides a new driving force for complete, accurate and representative data of ultrashort pulses. The prospect of machine learning in generating ultrashort pulse lasers has been realized by the intelligent design and operation of ultrafast fiber lasers composed of nonlinear photonic devices based on saturable absorbers to control photonic elements to produce nonlinear effects. At the same time, machine learning strategies are used to optimize control algorithms and feedback loops to achieve technological breakthroughs in nanophotonics and pulse dynamics. This results in the characterization and control of ultrafast photonics. Here, we review recent advances in intelligent machine learning-based ultrashort pulsed fiber laser systems, further outlining the scientific and technical conditions required to meet these advances through algorithmic foundations and key architectures. We also provide an outlook on the challenges and future research prospects for the emerging cross-technology direction of machine learning and ultrafast photonics.

The development of ultrafast photonics with machine learning strategies has great potential. On the one hand, in terms of hardware, the intelligence of the modules of the laser system is an important development direction. So far, optical technology has been mainly optimized in a limited design space,

limiting the photonic structure. Further development of advanced hybrid schemes will be a key step to solving this challenge, and the combination of smart optoelectronic devices will greatly contribute to the advanced level of lasers and expand the design space of photons to achieve the best performance of the target system. On the other hand, from an algorithmic point of view. To control more dimensional variables in the feedback, the algorithm's efficiency becomes crucial. So far, most designs are based on genetic algorithms or neural network architectures. While these implementations have undoubtedly led to remarkable and pioneering results, the fact remains that a combination of strategies may be required to exploit the full potential of machine learning. Revealing models from experimental data, forming neural networks after countless data mining sessions, and establishing infinite training relationships between targets and parameters will greatly optimize the time-consuming performance of ultrafast lasers to quickly locate the desired operating states. In addition, unsupervised learning algorithms, including clustering and expectation-maximization, have the ability to infer and reveal hidden internal structures from data without labeled responses, which may have a significant role in key problems such as dimensionality reduction of complex nonlinear systems. Similarly, real-time adjustment of parameters by monitoring the collection of various information about the environment serves as a regularizer for deep learning models to ensure that optical research relies on stability and longevity. In the future, improving the portability of intelligent photonic systems and designing inference models as specific products are important topics for exploring the next generation of ultrafast photonic technologies.

The convergence of machine learning and ultrafast photonics cutting-edge crossover technologies in the context of artificial intelligence takes an unconventional approach to provide an unparalleled photonic perspective. This intersection of computer science, photonics, and materials platforms will enable new approaches to the large-scale photonic design of unique functions as well as optical characterization, laying the cornerstone for efficient energy conversion systems. We envision that a global optimization framework based on a multi-step machine learning strategy can build a more general intelligent ultrafast photonic system, where the first step can be to define the main target function of the device and determine the appropriate photonic concept to provide the best performance. The second step is to select a suitable material platform and build an extensive database of optical materials. By using the selected material properties, an optimized design solution for the material device can be provided. The third step is to determine the appropriate fabrication conditions (growth conditions, doping levels, stoichiometry, etc.) and integration schemes. The interplay between new photonic structures and machine learning may overcome the limitations of current computational methods and systems, provide unparalleled capabilities in light-matter interactions and unlock new device concepts, and may lead ultrafast photonics research to new frontiers that could usher in a brighter era of artificial intelligence.

Key words: Machine learning; Ultrafast photonics design; Mode-locking technology; Intelligent algorithms; Fiber lasers

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