



桂林电子科技大学
GUILIN UNIVERSITY OF ELECTRONIC TECHNOLOGY

“四个一”工程
国内外访学研修工程业绩支撑材料
(2026 年度)

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一、符合人才类型申报条件支撑材料

(一) 博士学位学历证



(二) 身份证



二、科研项目

(一) 目标检测任务中基于联邦学习的关键技术研究, 广西博士研究生创新项目, 2022-2024, 已结题, 主持.

附件 3

博士硕士研究生创新项目申报书

申请 者 姓 名: 陈晓

学科代码及名称: 081000 信息与通信工程

申请项目层次: ☒ 博士 ☐ 硕士

申请项目名称: 目标检测任务中基于联邦学习的关键技术研究

所 在 学 校: 桂林电子科技大学

广西壮族自治区学位委员会

广西壮族自治区教育厅

2021 年 11 月 5 日

申请者承诺

本人保证项目申报材料真实、可信，并对填报各项内容的真实性负责；如获准立项，本人承诺以本表为有约束力的协议，将严格按照主管部门制定的项目实施管理办法，承担相关责任和义务，保证项目的顺利实施，取得预期研究成果。

承诺人：陈晓

2021年11月15日

项目概况	项目名称		目标检测任务中基于联邦学习的关键技术研究						
	项目类别		社会科学项目 ☐ 自然科学项目 ☒		学科专业代码		081000	学科专业名称	信息与通信工程
	研究方向		联邦学习						
	研究类型		基础研究 ☒ 应用研究 ☐ 综合研究 ☐ 其它研究 ☐						
	拟申请经费额度		4 万元		其中学校资助		2 万元	其他来源经费	2 万元
	项目起止年限		2022 年 3 月 至 2024 年 3 月						
项目组成员简介	项目负责人简介								
	姓 名	性 别	年 龄	年 级	代表性成果	在项目中承担的任务	联系电话	电子邮箱	
	陈晓	女	33	2021 级	[1]Yanlong Li,Hongbing Qiu,Xiao Chen*,Jielin Fu. A novel PAPR reduction algorithm for DCO-OFDM/OQAM system in underwater VLC[J]. Optics Communications,2020,463: (SCI 通信作者) [2]李燕龙,陈晓,詹德满,王俊义. 非正交多址接入中稀疏多用户检测方法[J]. 西安电子科技大学学报, 2017,44(03):151-156. [3]温佩芝,陈晓,吴晓军,王浩. 基于三次样条插值的 GrabCut 自动目标分割算法 [J]. 计 算 机 应 用 研 究,2014,31(07):2187-2190. [4]实用新型专利:陈晓等,一种基于数据安全的设备巡检系统、一种应用于图书馆信息交互中的 NFC 系统。	总体负责,理论研究	15295872103	782169620@qq.com	

项目参与者简介								
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彭 国 晋	男	33	2020 级	彭国晋, 玉振明, 于健海. 光学显微镜 自动聚焦取窗方法研究[J]. 应用光 学, 2015, 36(04): 550-558	理 论 研 究	1880 7744 469	pgj5 55@q q. co m	
唐 亚 欣	女	28	2021 级	唐亚欣, 李燕龙, 杨超, 王波. 地空信道 下基于 OFDM/OQAM 系统的时频同步算 法[J]. 计算机应用, 2018, 38(03): 741-745	算 法 实 现	1829 0100 075	9650 8187 9@qq . com	
项目指导教师								
姓 名	性 别	年 龄	学 历 / 学 位	所 在 院 系	职 务 / 职 称	联 系 电 话	电 子 邮 箱	
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一、项目研究目的和意义

(请从项目研究目的和意义、国内外研究现状、研究可行性和必要性等方面分析)

研究意义:

目标检测是一种使计算机不仅可以识别图像中存在的物体，还能够给出这些物体在图像中位置的技术。即目标检测不仅要为各个对象输出边界框（BBBox），而且需要对很多对象进行分类和定位。

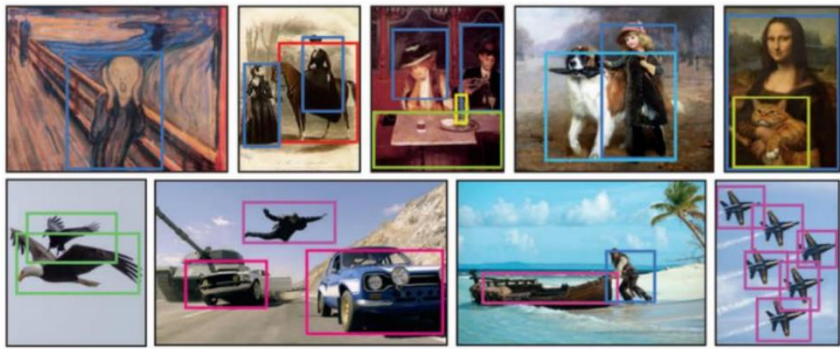


图 1 目标检测示例

目标检测是计算机视觉领域一个基础性又具有挑战性的任务。电子图像设备在人们日常生活和生产的普及使得图像逐渐成为必不可少的传播媒介。伴随着大量图像数据的涌现，实现图像中物体的准确识别越来越受到关注。人们不仅简单关心图像中的目标是什么，还希望准确获取图像中感兴趣目标及其位置。目标检测是图像理解和分析的重要环节，是解决更为复杂的视觉任务的基础。目标检测的研究能够推动很多领域的发展：

- (1) 自动驾驶：感知是无人驾驶决策系统的基础。为了实现准确的视觉感知，在自动驾驶系统采用摄像头代替人眼视觉系统进行观察。对交通信号灯、车道线、行人、车辆及周围的其他物体进行检测实现在行驶过程中准确规避危险^[1]。
- (2) 智能监测：对特定区域进行实时监测。比如在红绿灯路口拍照监测驾驶者是否行车规范；在机场、车站等交通管制场所，监测人群密度，为管理者提供流量数据。
- (3) 辅助医疗诊断：随着医学图像的成像技术的发展，医学图像的质量越来越高。目前医学影像的解读主要依赖医生的专业知识，但肉眼观察不可避免受到个人经验等主观因素的影响，且繁重的医学影像学分析工作也加重了

项目 研究 方案	医生的负担，采用目标检测技术实现医学影像的精准识别和定位^[2]，有效提升诊断效率。 (4) 农业生产：随着现代化的计算机技术在农业生产领域的应用，智能农业的发展展现了前所未有的活力。目标检测技术为智慧农业发展提供技术支持和数据支持^[3]。比如采用目标检测技术实现农作物病虫害的自动识别、检测和计数以指导农业生产。 上述这些具体的应用实例仅仅是计算机视觉领域应用的其中一部分。在安全领域，目标检测通常用于检测废弃和可疑的对象。增强现实、机器人视觉等应用场景也逐步发展，这些应用都是以目标检测技术为核心。综上所述，研究高效的目标检测技术具有较高的学术价值和经济效益。 研究现状： 在传统的目标检测方法中，一般性的方案框架有三个阶段： (1) 候选区域生成：给出物体可能出现的建议区域。通常使用不同尺寸的滑动窗口框^[4,5]，在给定的图像的不同位置处选取候选区域。 (2) 特征提取：对候选区域进行特征提取，包括图像的颜色、纹理和空间特征等，如最具代表性的是 SIFT 特征^[6,7]。 (3) 分类器分类：根据提取的特征使用一种分类方法对候选区域中的内容进行分类。 传统的目标检测算法中，特征提取的好坏对最后的结果影响极大，直接关系到后续分类结果的准确性。经典的人脸检测算法通常选用 Harr 特征和 Adaboost 分类器，在滑动窗口搜索区域中进行人脸检测。多尺度形变部件模型^[8]（DPM）则利用梯度直方图特征（HOG）^[9]，并使用支持向量机作为分类器，并连续两年取得 PASCAL VOC 比赛的冠军，是传统目标检测方法的巅峰。DPM 认为物体由多个部件组成，并用部件间的关系来描述物体，检测器的训练被视为学习一种合适的物体分解方法，而推理被视为对不同的物体部分的检测集合，在人脸检测、行人检测等任务上取得了不错的效果。后期改进算法^[10-13]能够解决现实中变化更大的目标检测问题。 但传统目标检测算法存在两个方面的问题。 (1) 特征工程：需要人工从图像中获取有关的目标特征信息。针对某种特定的检测任务、人工设计不同的方法。对不同的目标或者同一目标的不同形态，需要不同的特征，鲁棒性和可移植性差。
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(2) 传统方法多采用滑动窗口进行遍历搜索，把图片分成各种尺度和大小的区域，然后识别筛选。这种方法没有针对性，时间和空间复杂度都很高，在实践中难以真正使用。

随着手工设计特征的性能趋于饱和，目标检测方法的研究也随之陷入瓶颈。而近些年兴起的卷积神经网络在特征表达方面能力强大，其结构特别适用于解决目标检测任务。2014 年，基于卷积神经网络的物体检测方法 R-CNN 将 Pascal VOC2007 目标检测的 mAP 从 24% 提升到 48%，并在后续衍进的方法中不断取得更高的准确度，开启了目标检测的新篇章^[14]。这一类方法继承了传统物体检测的思想，生成目标的候选区域，然后对候选区域进行分类，属于两阶段的检测方法，如图 2 所示。

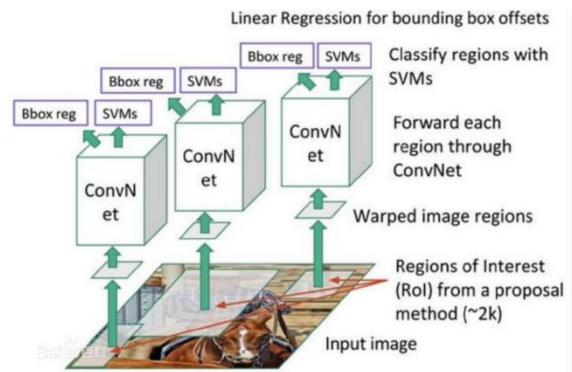


图 2 R-CNN

其主要步骤如下：

- (1) 生成候选区域：输入原始图像，使用选择性搜索算法^[15]产生 2000 个左右的候选区域，以尽量包含目标可能会出现的区域；
- (2) 候选区域缩放：将裁减下的所有候选区域缩放到固定大小（如卷积神经网络常用的输入大小 224*224）；
- (3) 特征提取：使用卷积神经网络提取候选区域的特征，得到 4096 维的特征向量；
- (4) 候选区域分类：使用已经预训练好的支持向量机对 2000 多个 4096 维的特征向量进行分类，需要对每一个类别训练一个支持向量机；
- (5) 非极大值抑制：对每一类候选区域进行非极大值抑制去除冗余，保留分类得分高且重合较少的区域；

(6) 边界精调：使用一个线性回归器来精调边框的位置，使预测边框的位置与真实的位置更加接近，需要对每一个类别训练一个线性回归器。

R-CNN 虽然在目标检测上有很好的效果，但依然存在很多问题。如选择性搜索算法产生的每个候选区域进行卷积的前向传播总次数达到 2000 次，使用 GPU 加速仍然比较费时；候选区域统一缩放到相同的尺度，导致部分图像失真；需要分别训练卷积神经网络、支持向量机和线性分类器，过程复杂且缓慢等。随后出现了基于 R-CNN 的改进算法，如何恺明等人提出的空间金字塔池化 SPP-Net^[16]、Fast-RCNN^[17]、Faster-RCNN^[18]、区域提名网络 RPN。从 R-CNN、Fast-RCNN 发展到 Faster-RCNN，基于区域的检测方法开始成熟，其精度与速度都有了很大的提高。

在 FasterRCNN 的基础上，研究人员设计了各种算法^[19-25]提升目标检测的精度和速度，包括 Mask RCNN^[19]、Feature Pyramid Network(FPN)^[20]、Scale Normalization for Image Pyramid(SNIP)^[23]和 Libra RCNN^[24]等。虽然这些算法在 PASCAL VOC，MS COCO，Kitti 等数据集上取得较高的检测精度，但是其“多阶段”目标检测策略使得计算开销很大，速度还是达不到实时检测的要求，极大地限制了实际场景下的应用。因此研究人员将注意力转向设计一种“单阶段”的目标检测框架，即不采用感兴趣区域生成，仅使用单一的 CNN 网络直接预测类别概率和边界框位置，得到最后的检测结果。OverFeat 检测器^[26]是第一个基于全卷积深度网络的“一阶段”目标检测器，获得了 ILSVRC2013 年定位竞赛冠军。此后 Redmon 等人构建了一个高效的目标检测框架 YOLO 即 You Only Look Once^[27]，将检测问题视为回归问题，将目标检测任务推向了一个新的高度。YOLO 算法实现了卷积神经网络端到端的目标检测，其过程非常简洁，如图 3 所示。

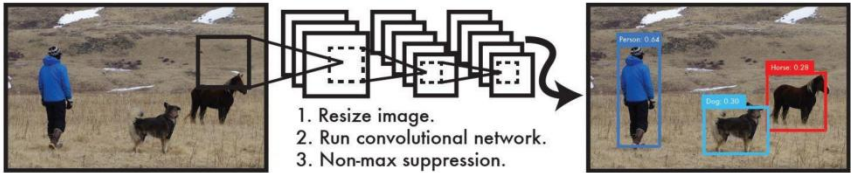


图 3 YOLO 流程图

YOLO 进行目标检测时的主要步骤如下：

- (1) 缩放图像：将输入图片缩放至 448*448，然后送入 CNN 网络；
- (2) 预测边界框：将图像分割为 S*S 的网络，每个网络对应 B 个边界框（假设物体的中心在这个网格中），运行网络，预测所有网格对应的边界框位置，并对网络中的内容进行分类；

(3) 非极大值抑制：执行 NMS 算法去除重复边界框。

为了获得更快的速度，YOLO 中使用了一个精简高效的网络，其结构如图 4 所示。与 FasterRCNN 这种基于局部特征进行目标检测不同的是，YOLO 检测算法使用的是整个图像的全局特征信息。YOLO 算法中，输入的图像被分割为 $S \times S$ 的网格，每个网格对应 B 个边界框，每个边界框包含 5 个参数，包括边界框的位置 (x, y, w, h) 和一个置信度。置信度表示边界框中包含目标且边界位置准确的概率。

$$C_i = \Pr(\text{Object}) * IOU_{pred}^{truth}$$

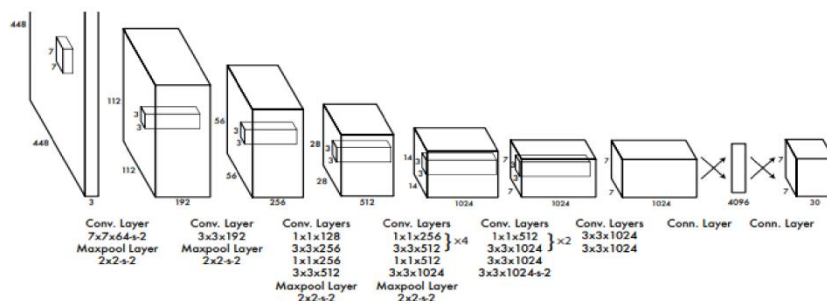


图 4 YOLO 网络结构图

此外，还要对网格中的物体进行分类，总共有 C 个类别，则 $S \times S$ 的网格总共对应 $S \times S \times (B \times 5 + C)$ 的特征，每个网络虽然对应不同的边界框，但是这些边界框的类别是一样的。在 YOLO 中边界框的质量就是用其分类的分数与边界框置信度相乘所得的分数来评价。

$$p_b = \Pr(\text{Class}_i | \text{Object}) * \Pr(\text{Object}) * IOU_{pred}^{truth} = \Pr(\text{Class}_i) * IOU_{pred}^{truth}$$

YOLO 模型如图 5 所示，YOLO 预测每个网格单元对应 B 个边界框，但在训练时，只希望一个网格中的边界框预测器负责一个边界框对象，此时取当前 IOU 最高为检测对象，然后根据预测边界框与真实边界框间的损失函数来训练网络。

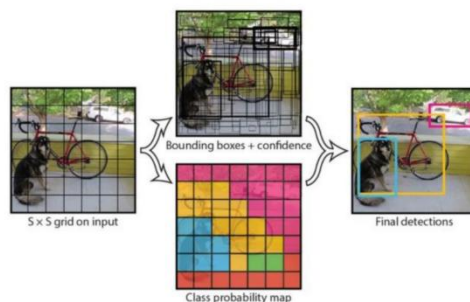


图 5 YOLO 模型

YOLO 的总损失函数为：

$$L = \lambda_{coord} L_{coord} + L_{conf} + L_{cls}$$

可以看到损失函数包含三个部分：边界框坐标与大小的损失函数 L_{coord} 、边界框置信度的损失函数 L_{conf} 和分类的损失函数 L_{cls} ，下面分别给出这三部分公式。

$$L_{coord} = \sum_{i=1}^{s^2} \sum_{j=0}^B l_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] +$$

$$\sum_{i=1}^{s^2} \sum_{j=0}^B l_{ij}^{obj} [(\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2]$$

$$L_{conf} = \sum_{i=0}^{s^2} \sum_{j=0}^B l_{ij}^{obj} (c_i - \hat{c}_i)^2 + \lambda_{noobj} \sum_{i=0}^{s^2} \sum_{j=0}^B l_{ij}^{noobj} (c_i - \hat{c}_i)^2$$

$$L_{cls} = \sum_{i=0}^{s^2} l_i^{obj} \sum_{c \in classes} (p_i(c) - \hat{p}_i(c))^2$$

其中， l_i^{obj} 表示目标在第 i 个网络中， l_{ij}^{obj} 表示第 i 个网格中分配了第 j 个边界预测器， λ_{coord} 和 λ_{noobj} 为权重，默认为 5。

YOLO 将目标检测任务作为一个回归问题，无须生成建议区域，极大地提升了检测的速度，达到了 45fps，适合在资源紧张、实时性要求高的场景中使用。

虽然目标检测近年来取得了空前的进步，但其强大的检测能力大部分是建立在巨大数量的图像数据的可获得性基础上的。市面上最为成功的目标检测应用，例如适合安装于密集人流区的可疑目标检测系统，通常都是由具有大量资源或庞大用户基础的组织研发的，因为他们可以收集到大量且高质量的数据。我们普遍认为训练数据量越大，训练得到的模型的鲁棒性和准确性越高。而为了获取大量的训练数据，人们一般需要汇聚各个机构或者多源的用户数据。

而图像数据除了紧密围绕其本身的版权、肖像权之外，在人工智能和大数据分析盛行的当代，其中隐含了巨大的用户隐私和商业价值。互联网公司可以通过用户发表的图片信息来分析用户的年龄阶段、消费水平等，并给出合适的推荐应用。近些年出现了部分运营商窃取用户隐私、互联网企业利用获取的用户数据“杀熟”等现象，人们越来越多的意识到每天产生的所有的图像都是可以被收集、分析、利用并可能产生一系列隐私泄露和威胁的数据。

项目研究方案	换言之，对普通的用户而言，如何保护自己的隐私不被泄露？拒绝和防止所有图像数据流出本地即可大幅度提高用户隐私的安全性。除个人隐私保护意识的增长之外，国家社会的法律法规也逐渐完善。2018 年欧盟开始执行《通用数据保护条例》。2020 年 1 月《加利福尼亚州消费者隐私法》在美国加利福尼亚州正式生效。中国的《中华人民共和国民法通则》以及 2017 年开始实施的《中华人民共和国网络安全法》同样对数据的收集和处理提出了严格的约束和控制要求。2021 年 11 月初《中华人民共和国个人信息保护法》（含草案说明）施行，其中规定未经个人信息处理者同意，受托人不得转委托他人处理个人信息。如第二十四条规定：个人信息处理者不得对个人在交易价格等交易条件上实行不合理的差别待遇，这条直接打击大数据杀熟。第十条规定：任何组织、个人不得非法收集，使用、加工、传输他人个人信息，不得非法买卖，提供或者公开他人个人信息。这条瞄准的是偷偷出售或者泄露个人信息的公司或者员工。 在这样的法律环境下，随着时间推移，在不同组织间收集和分享图像数据将会变得越来越困难。图像数据通常由不同公司出于不同业务目标来收集和标注，由于数据隐私和监管的顾虑，这些公司并不愿意分享他们的数据。另一方面，这些公司有强烈的动机去建立强大的目标检测系统，以提高他们的业务利润率。某些高敏感的图像数据拥有者也会拒绝和极力反对无限制的计算和使用这些数据。在这种情况下，图像数据拥有者只允许这些图像保存在本地，进而会形成各自孤立的图像数据孤岛。 此时前面所述具有强大目标检测能力、基于数据聚合的集中式深度学习模型，对分散的、不均衡的目标检测样本则无能为力。因此如何在遵守隐私保护条例、保护用户图像数据隐私的前提下，完成目标检测模型的训练和学习任务，是当下亟待解决的技术难题。 2016 年 google 提出了联邦学习的数据训练模式。联邦学习通过将深度学习与协作性模型相结合，使各个机构或者用户在不交换数据的情况下进行协作训练并获得更加精准的深度学习模型，以便在满足隐私保护和数据安全的前提下实现数据的有效利用。该策略将模型训练过程从聚合服务器转移至用户端，允许各方参与者在暴露数据的情况下完成本地训练，只将模型参数上传至聚合服务器，之后聚合服务器将从参与方处接收到的模型更新聚合起来(例如使用联邦平均算法^[28])，并将聚合后的模型更新发回给参与方。这一过程将会重复进行，直至模型收敛、达到最大迭代次数或者达到最长训练时间。图 6 展示了集中式深度学习和分布式联邦学习训练模式的区别。集中式深度学习收集各用户数据到数据中心中完成模型训练和学习，而联邦学习的各用户端在本地训练模型，与数据中心只进行模型参数的上传和下载。
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项目研究方案	图 6 集中式深度学习和分布式联邦学习训练模式 联邦学习策略保证了用户端的目标检测图像永远不会分享和上传到其他节点，极大的降低了用户隐私泄露的风险，并且减少了分布式计算的原始数据传送带来的通信开销。此外，聚合服务器和参与方还能使用加密的方法来防止模型信息泄露^[29]。该方法一经提出就成为国际学术界和产业界关注的焦点。 然而联邦学习并不是简单的分布式计算那么简单，除了用户数据不外传只更新核心参数的区别外。联邦学习也有着数据在参与方和聚合服务器之间传输更新时类似于分布式计算中的隐私加密解密问题。同时联邦学习的分布式终端训练学习的模式也由于各终端数据异构、设备独立等原因带来了新的研究问题，也包括分布在各地的终端训练过程中遭受安全攻击的机会增多。因此由于分布式学习的特征而带来的隐私保护和安全攻击和防御问题也是伴随联邦学习场景而产生的待解决问题。具体到本课题即在分散数据分布的前提下完成精准、实时、安全的目标检测任务。新的研究场景下问题分析如下。 (1) 数据集的非独立同分布问题 对于一个在数据中心内的分布式学习，确保每一台机器都有着独立同分布的数据集是容易办到的，因此所有参与方的模型参数更新操作非常相似。而在联邦学习中，这一条难以实现，因为由不同参与方拥有的数据可能有着完全不同的分布，即我们不能对分布式数据集进行独立同分布的假设^[30-32]。例如，相似的参与方可能拥有相似的本地训练数据，而两个随机选取的参与方可能拥有不同的训练数据，因而他们会产生非常不同的模型参数更新。 (2) 不平衡的数据量 对于一个数据中心内的分布式学习，可以将数据均匀地分配到各工作机器中。然而在现实环境中，联邦学习的不同参与方通常拥有不同规模的训练数据集^[33-35]。例如，
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项目研究方案	相似的参与方可能拥有相似体量的本地训练数据集，而两个随机选取的参与方可能会拥有不同大小的训练数据集。 (3) 数据量很大的参与方 对于一个数据中心内的分布式学习，并行工作机器的数量是可以轻易控制的。然而，由于机器学习一般需要大量数据，使用联邦学习的应用可能需要涉及许多参与方，尤其是使用移动设备的参与方^[36]。每一个用户都可以在理论上参与到联邦学习中来，这使得会出现参与方的数量和分散程度远远超过数据中心的情况。大量异构的参与方，通信性能参差不齐，一些客户还可能某些时候暂时失去网络连接，这些都极易影响模型收敛的速度。 (4) 加密和解密计算复杂 常用的用于保护数据隐私的方法大概分为：模糊处理和密码学方法。模糊处理是通过随机化、添加噪声或修改数据使其拥有一级别的隐私，如差分隐私方法。该方法计算复杂度低，但牺牲了一定的梯度精度。密码学的方法是通过不将输入值传给其他参与方的方式或者不以明文方式传输，使分布式计算过程安全化，如安全多方计算，包括不经意传输、秘钥共享、混淆电路和同态加密。 文献[37]提出了一种基于差分隐私的隐私保护逻辑回归算法。他们在随机数据上进行优化，使得在模型性能和隐私保护之间取得平衡成为可能，并使得隐私的界限更为严格。文献[38]第一次提出了基于横向划分数据集的隐私保护分布式决策树算法。其中文献作者提出了一种不经意安全协议，以不需要展示每个值给其他参与方的方式进行安全计算，使得分布式决策树能够不泄露隐私的前提下计算样本集在不同参与方上的节点切分。文献[39]和文献[40]分别研究了面向隐私保护的支持向量机模型在横向和纵向划分数据集上的实验。他们使用随机生成的核函数来隐藏原始的学习核函数，达到了与不具有隐私保护的 SVM 模型相近的性能。在分布式学习领域，最有代表性的工作是由文献[41]提出的安全聚合算法。该研究基于由谷歌发布的联邦平均算法 FedAvg，使用了 FedAvg 中的秘密共享、不经意传输，并考虑了在一个沟通成本高昂、客户加入退出频繁的复杂移动环境下的使用。 基于密码学的加密操作和解密操作较好地提升了数据隐私的安全性，但其同时也提高了计算的复杂度，并且秘文的传输也会增加额外的通信开销^[42]。因此改进基于同态加密、安全多方计算的轻量级隐私加密算法仍需要进一步研究。 (5) 隐蔽的恶意攻击 各参与方数据的分散分布，使得来自终端的恶意攻击很难被察觉。一些攻击者可
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以通过一些恶意样本，对联邦学习模型的结果产生负面影响，从而对整个系统造成严重的安全隐患；或者在协同学习过程中，若有一个恶意的参与方训练生成对抗网络GAN,将可能导致系统容易遭受攻击^[43]。

数据投毒攻击通常通过修改、删除或者注入精心挑选的数据内容，来影响模型的训练结果。如图 7 所示，攻击者通过有害数据样本，使分类器的决策边界发生变化，导致数据样本被错误分类。文献[44]通过植入反转标签来攻击向量机模型，将训练数据中 (x,y) 标签替换为 (x, y') ，使模型在训练过程中学习错误的特征。作者通过设计最大化支持向量机损失函数的优化框架，进行随机标签翻转，使分类误差最大化，从而降低了模型准确性。

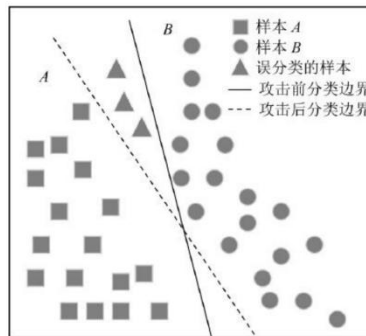


图 7 投毒攻击过程

对抗样本攻击^[45]是一种能够让模型产生错误分类的攻击方式，攻击者利用模型对输入样本的中间参数构造相应的对抗扰动，并将其注入输入样本即得到对抗样本。数据投毒攻击、对抗样本攻击和后门攻击等都会造成系统的安全损害。因此，联邦学习中的安全攻击与防御也是近年来研究者关注的热点。

综合以上五点，本课题研究分布式联邦学习框架下，针对目标检测任务中由于图像数据的分布不同、体量不均引发的联邦模型优化问题，轻量级的加密解密策略和针对参与方的恶意攻击和防御策略。

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二、项目研究内容和方法（限 500 字）

（主要研究内容、拟解决的关键问题及采取的研究方法、手段或技术路线等）

研究内容和拟解决的关键问题：

本课题研究目标检测任务下基于联邦学习框架的关键技术，拟解决非集中式数据分布下，目标的精准、实时检测以及研究目标检测系统遭受安全攻击的方法。拟解决的关键问题和对应研究内容总结如下：

（1）针对目标检测各参与方数据量不均匀、数据非独立同分布导致的联邦模型训练偏差问题，研究模型异常更新和联邦优化算法以完成目标的快速、实时检测，并提升联邦目标检测模型的鲁棒性。

（2）针对各参与方参数上传、下载更新过程中加密计算复杂问题，研究基于模糊和加密策略的联邦学习隐私保护技术。

（3）针对因设备间的独立性、数据间的异构性、数据分布的不平衡和隐私设计等特点，而导致的联邦模型易受安全攻击问题，研究对抗网络攻击、对抗样本攻击策略，以制定基于数据集、输入样本与模型的防御策略。

方法和技术路线：

联邦目标检测模型的训练流程如图 8 所示，详细步骤如下：

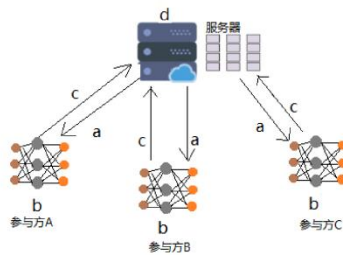


图 8 联邦目标检测模型的训练流程

a.各参与方（即数据的原始拥有者）从服务器下载现有的共享目标检测模型，例如YOLO。

b.各参与方使用本地标记数据对模型进行训练。

c.各参与方通过安全协议，将训练后的模型参数上传至服务器。

d.服务器聚合所有参与方的模型参数，并更新共享目标检测模型。

联邦目标检测算法循环执行这些步骤直至算法收敛。之后，本地目标检测模型被部署并开始工作。整个模型训练和部署过程都能以持续的方式执行，因为新的标注数

项目 研究 方案	据可以源源不断地加进来。针对研究内容拟采用如下解决方案。 (1) 改进基于回归的 YOLO 目标检测模型，基于随机梯度下降来搭建联邦优化算法以完成目标的快速、实时、强鲁棒性检测。 (2) 拟采用综合利用同态加密、安全多方计算、差分隐私混合分层加密策略完成参与方和聚合器参数轻量级加密问题。 (3) 首先，研究利用生成对抗式网络 (GAN) 获取用户隐私的攻击策略。拟在本地训练生成对抗式网络伪造目标类样本作为模型训练数据，提高本地生成器的伪造能力，从而获取目标类的隐私训练数据信息。然后，研究对抗样本攻击策略。拟通过对输入样本的中间参数构造设计相应的对抗扰动，绑架模型来输出受到攻击之后的结果。	
	主题词	(不超过 3 个) 目标检测、联邦学习、攻防策略
	三、项目创新之处 (限 500 字) (请在项目研究意义及研究内容的基础上，提炼本项目的创新点或应用价值、推广价值等) 本课题研究目标检测任务下基于联邦学习的关键技术，以摆脱集中式深度学习数据中心化的限制，实现目标检测模型在本地训练，使多方参与者在交换数据的情况下协作完成精准、实时目标检测的任务，降低数据隐私泄露和遭受安全攻击的风险。主要创新点如下： 1. 提出了强鲁棒、实时、精准目标检测算法 针对去中心化数据集在各参与方分布不均衡，且来自不同参与方的数据可能会存在非独立同分布的情况进而导致联邦模型产生偏差或训练失败的情况，从模型更新环节出发，采用剔除异常更新和联邦平均算法，提升 YOLO 目标检测模型的稳定性、实时性能和精准度。 2. 提出轻量级的隐私保护方法 针对现有同态加密、安全多方计算和差分隐私等经典密码学方法在用户数据和模型参数保护方面开销巨大的问题，采用分层混合加密策略，设计轻量级加密算法，优化非关键环节的隐私保护处理，减少计算开销，提升模型整体性能。 3. 提出有效的联邦学习攻击方法 首先，针对联邦学习数据分散在各参与方本地，聚合服务器难辨各参与方的身份，致使联邦学习模型极易受到难以察觉的恶意攻击的情况，采用生成对抗式网络 (GAN) 进行隐私攻击。其次，在训练样本中设计加入合理的对抗扰动，以绑架模型完成错误的训练，进而达到对抗样本攻击的目的。	

项目 研究 方案	四、项目研究进度安排 (包含项目的主要研究阶段、时间安排、进展目标等) 2022.3.1-2022.8.31 (1) 阅读课题相关的国内外文献, 并与相关领域研究专家交流。 (2) 学习深度学习和目标检测相关理论知识, 理论分析并实现改进以 YOLO 为代表的多目标实时检测方法。发表论文一篇。 2022.9.1-2023.7.1 (1) 选择并学习安全的计算框架和联邦学习平台, 比如第一个工业级联邦学习开源框架 FATE、联邦学习开源框架 TFF 等。 (2) 研究解决联邦学习模型在参与方数据不均匀、数据非独立同分布情况下的模型偏差问题, 保证联邦学习策略的稳定性和提升目标检测的精准度。 (3) 针对本地模型训练参数与聚合服务器参数更新交流过程中数据易泄露的问题, 研究基于同态加密、安全多方计算策略的数据加密技术。发表论文一篇。 2023.7.1-2023.12.31 针对联邦学习系统中存在的数据投毒攻击、对抗样本攻击和后门攻击等, 研究该领域中的安全攻击与防御方法。发表论文一篇。 2024.1.1-2024.3 整理研究结果, 完成项目研究的总结报告。
	五、项目预期成果及提交形式 (包括论文、专著、专利或其他形式; 同时还需明确成果的相应级别、水平或影响、社会效益等) 预期研究成果: 本课题研究目标检测任务下基于联邦学习的关键技术, 以摆脱集中式深度学习数据中心化的限制, 实现模型在本地训练, 使多方参与者在交换数据的情况下协作完成精准、实时目标检测的任务, 降低数据隐私泄露和遭受安全攻击的风险。预期完成提升鲁棒性的目标检测技术、面向隐私保护的加密参数更新传输方法和联邦模型安全攻击和防御方法研究。本课题涉及的第一个关键技术研究可为终端实时、精准目标检测任务, 如智能驾驶、辅助医疗诊断、智能检测、农业生产提供有效参考。第二和第三个关键技术可为大数据和人工智能联合背景下的数据隐私保护提供突破性的解决办法。 成果提交形式: 发表论文 2 篇, 其中 SCI 期刊论文 2 篇, 申请发明专利 1 件。

	六、经费概算（单位：万元）		
	支出科目	金额	计算根据及理由
	材料费	1	购买元器件、耗材、GPU 服务器等。
	差旅费	1	调研、参加国内外学术会议及交流活动。
	出版/文献/信息传播/知识产权事务	1	论文发表，专利申请等。
	会议费	0.5	用于会议注册费用。
	劳务费	0.5	用于直接参加项目的研究生劳务费。
	合 计	4	
审核意见	一、指导教师推荐意见 （是否同意推荐及简要文字推荐意见，包括课题的意义，申请人的学术水平、创新能力评价，对项目结果的预测，以及可能提供的指导、支持等） 所申请题目为学科前沿问题，研究意义重大，申请人具备较好的前期研究基础和研究能力。将结合博士课题按照计划完成研究，发表相关创新论文和发明专利，本团队将予以提供相应的指导和实验支持。 签名: 叶苗 2021 年 11 月 15 日		

二、所在院系审核意见：

(是否同意推荐，并为项目实施提供必要协助。)

同意推荐,并为项目实施提供必要协助

院系负责人(签章)

李海印



2021年11月29日

三、学校审核意见：

(是否同意推荐，并保证在项目研究期间按照本申报书安排相应资助经费，承担项目管理任务。)

同意推荐并提供经费资助
承担课题管理任务



2021年12月27日

桂林电子科技大学文件

桂电研〔2024〕16号

关于公布2024年桂林电子科技大学研究生 教育创新计划项目结题情况的通知

各单位、各部门：

根据《关于印发〈广西壮族自治区研究生教育创新项目管理办法〉的通知》（桂学位〔2014〕18号）文件精神，经个人申请、学院评审、学校审核，同意《目标检测任务中基于联邦学习的关键技术研究》（负责人：陈晓）等280项区级、校级研究生创新项目结题，同意《以需求为导向硕士研究生教育模式中的导师科研引路人角色研究》（负责人：秦红波）等16项校级学位与研究生教育改革项目结题，同意《基于5G移动通信系统的外辐射源雷达波形预处理研究》（负责人：乔睿萌）等9项校级研究生创新项目终止。

— 1 —

- 附件：1. 2024年桂林电子科技大学研究生创新项目结题汇总表
2. 2024年桂林电子科技大学学位与研究生教育改革项目
结题汇总表
3. 2024年桂林电子科技大学研究生创新项目终止汇总表



（此件公开发布）

附件1

2024年桂林电子科技大学研究生创新项目结题汇总表

序号	课题编号	负责人	课题组成员	课题名称	导师	专业
1	YCBZ2022106	陈晓	彭国晋、唐亚欣	目标检测任务中基于联邦学习的关键技术研究	仇洪冰	信息与通信工程
2	YCBZ2022107	梁杨帆	程洪圆、蒋晟	车联网安全认证与隐私保护	刘忆宁	网络空间安全
3	YCBZ2022108	林上君	侯雪贺、贾明鑫、邓淳元、张宇凡	太赫兹超表面传感器结合分子印迹技术在肿瘤标志物检测中的应用	彭振贤	仪器科学与技术
4	YCBZ2022112	路皓翔	王文颖、龚俊名、黄颖忻	低质量图像恢复的关键技术研究	刘振丙	网络空间安全
5	YCBZ2022114	焦辉	周辽、黄平、简泽	气液射流辅助激光加工碳纤维复合材料的特性研究	龙芋宏	机械工程
6	YCBZ2022115	白玉潭	周漫、刘家驹	可视化高温热管的制备及其固-液-气三相流传热机理研究	张平	机械工程
7	YCSW2021171	何滨冰	郭彬、陈文杰、马杰灵、罗杰	应用于装配式建筑的掺钢渣超高性能混凝土配制与性能研究	唐成远	交通运输工程
8	YCSW2022259	刘秋霞	赵文哲、闫奕、郭星、黄红婷、刘晶晶	建国初期中国共产党提升广西民众政治认同研究	张季	马克思主义理论
9	YCSW2022260	刘冲	夏凯祥、陈思敏、彭秀慧、黄娜	菲律宾英语儿童文学翻译研究——以卡班班作品为例	韦汉	翻译

— 3 —

(二) 水下光空分多址及三维分布式动态接入优化研究, 国家自然科学基金, 2023. 1 至 2026. 12, 在研, 参与.



申请代码	F0107
接收部门	
收件日期	
接收编号	6226010005



国家自然科学基金 申 请 书

(2022 版)

资助类别: 地区科学基金项目

亚类说明:

附注说明:

项目名称: 水下光空分多址及三维分布式动态接入优化研究

申 请 人: 李燕龙 电 话: 0773-2291274

依托单位: 桂林电子科技大学

通讯地址: 广西区桂林市金鸡路1号桂林电子科技大学

邮政编码: 541004 单位电话: 0773-2290811

电子邮箱: lyulong@guet.edu.cn

填写日期: 2022年02月05日

国家自然科学基金委员会



基本信息

申请人信息	姓名	李燕龙	性别	男	出生年月	1989年06月	民族	汉族
	学位	博士	职称	高级实验师				
	是否在站博士后	是	电子邮箱	lylong@guet.edu.cn				
	电话	0773-2291274	国别或地区	中国				
	申请人类别	依托单位全职						
	工作单位	桂林电子科技大学/信息与通信学院						
	主要研究领域	水下光通信、无人机感知与组网、空间信息网络资源优化						
依托单位信息	名称	桂林电子科技大学						
	联系人	赵松克	电子邮箱	dsroffice@guet.edu.cn				
	电话	0773-2290811	网站地址	www.guet.edu.cn				
合作研究单位信息	单位名称							
项目基本信息	项目名称	水下光空分多址及三维分布式动态接入优化研究						
	英文名称	Research on underwater optical space division multiple address and 3D distributed dynamic access optimization						
	资助类别	地区科学基金项目				亚类说明		
	附注说明							
	申请代码	F0107. 海上和水下通信				F0109. 光通信		
	研究期限	2023年01月01日 -- 2026年12月31日				研究方向：水下光通信		
	申请直接费用	39.6000万元						
中文关键词	水下光通信；方向性光束；空分多址；协同分配；三维分布式接入							
英文关键词	Underwater optical communication; Directional beam; Space Division Multiple Address; Collaborative allocation; Three-dimensional distributed access							



中文摘要	水下AUV等移动节点集群组建、执行海洋探测和数据回传等对构建水下物联网体系具有重大意义。水声通信带宽窄，难以应用于短距高速数据传输。本项目围绕基于水下LED光链路的大容量快速组网问题，突破光束方向性辐射限制，解决三维LED阵列下的空分等多维资源复用和接入问题。拟研究：1) 针对方向性光束形成问题，探索水下AUV节点体积受限条件下的LED阵列通信中光学收发透镜、阵元间距、密度、特性与空分光束形成相互影响机理，奠定空分多址基础；2) 针对水下LED阵列通信中多维资源复用问题，研究LED方向性通信中空、时、码、功率域资源联合分配优化，并基于多维资源联合复用提出非正交多址策略，提升系统容量；3) 针对水下光通信节点拓扑动态变化问题，建立三维分布式节点轮询感知与动态接入时延模型，并优化求解，进而提出三维分布式动态接入机制，降低发现时间和组网时延。为水下AUV等节点构建移动自组网奠定理论基础和提供实践依据。
英文摘要	The formation of mobile node clusters such as underwater AUVs, the implementation of marine reconnaissance and data transmission, are of great significance to the construction of an underwater Internet of things system. The bandwidth of underwater acoustic communication is narrow. It is difficult to apply to short-distance high-speed data transmission. This project focuses on the problem of large-capacity and rapid networking based on underwater LED optical links, breaking through the limitation of optical directional radiation, and intends to study the following content. Firstly, for the problem of directional beam formation, explore the interaction mechanism of optical transceiver lens, array element spacing, density, characteristics and spatial division beam formation in LED array communication under the condition of limited volume of underwater AUV nodes, and propose a space division multiple access strategy. Secondly, for the problems of multiple access interference and multi-dimensional resource multiplexing in underwater LED array communication, study the joint allocation optimization of LED directional communication resources in the space, time, code and power domains, and proposes a non-orthogonal multiple access strategy based on the joint multiplexing of multi-dimensional resources, improve network capacity and throughput. Thirdly, for the perception and access problems of communication beam directional radiation and node topology dynamic change, a three-dimensional distributed neighbor node polling perception and dynamic access delay model will be established and optimized, and then a three-dimensional distributed dynamic access mechanism will be proposed to reduce the discovery time and network delay. It lays a theoretical foundation and provides a scientific guidance for the construction of mobile ad hoc networks for nodes such as underwater AUVs.



主要参与者 (注: 主要参与者不包括项目申请人)

编号	姓名	出生年月	性别	职 称	学 位	工作单位	项目分工	电话	证件号码
1	符杰林	1975-06-28	男	副教授	硕士	桂林电子科技大学	理论研究	0773-2291274	4*****6
2	陈哲	1993-01-01	男	讲师	博士	桂林电子科技大学	理论研究	18978669094	4*****4
3	陈晓	1988-11-12	女	讲师	硕士	桂林电子科技大学	算法研究	0773-2291274	3*****9
4	陈冬梅	1976-10-19	女	副教授	硕士	桂林电子科技大学	算法研究与实验		4*****5
总人数		高级		中级	初级	博士后	博士生	硕士生	
11		3		2	0	0	2	4	

国家自然科学基金资助项目批准通知

(预算制项目)

李燕龙 先生/女士:

根据《国家自然科学基金条例》、相关项目管理办法规定和专家评审意见,国家自然科学基金委员会(以下简称自然科学基金委)决定资助您申请的项目。项目批准号: 62261009, 项目名称: 水下光空分多址及三维分布式动态接入优化研究, 直接费用: 33.00万元, 项目起止年月: 2023年01月至 2026年12月, 有关项目的评审意见及修改意见附后。

请您尽快登录科学基金网络信息系统(<https://isisn.nsfc.gov.cn>), **认真阅读《国家自然科学基金资助项目计划书填报说明》并按要求填写《国家自然科学基金资助项目计划书》(以下简称计划书)**。对于有修改意见的项目,请您按修改意见及时调整计划书相关内容;如您对修改意见有异议,须在电子版计划书报送截止日期前向相关科学处提出。

请您将电子版计划书通过科学基金网络信息系统(<https://isisn.nsfc.gov.cn>)提交,由依托单位审核后提交至自然科学基金委。自然科学基金委审核未通过者,将退回的电子版计划书修改后再行提交;审核通过者,打印纸质版计划书(一式两份,双面打印)并在项目负责人承诺栏签字,由依托单位科研、财务管理等部门审核、签章并在承诺栏加盖依托单位公章,且将申请书纸质签字盖章页订在其中一份计划书之后,一并报送至自然科学基金委项目材料接收工作组。纸质版计划书应当保证与审核通过的电子版计划书内容一致。**自然科学基金委将对申请书纸质签字盖章页进行审核,对存在问题的,允许依托单位进行一次修改或补齐。**

向自然科学基金委提交电子版计划书、报送纸质版计划书并补交申请书纸质签字盖章页截止时间节点如下:

1. **2022年10月8日16点:** 提交电子版计划书的截止时间;
2. **2022年10月14日16点:** 提交修改后电子版计划书的截止时间;
3. **2022年10月19日:** 报送纸质版计划书(一式两份,其中一份包含申请书纸质签字盖章页)的截止时间。
4. **2022年10月28日:** 报送修改后的申请书纸质签字盖章页的截止时间。

请按照以上规定及时提交电子版计划书，并报送纸质版计划书和申请书纸质签字盖章页，逾期不报计划书或申请书纸质签字盖章页且未说明理由的，视为自动放弃接受资助；未按要求修改或逾期提交申请书纸质签字盖章页者，将视情况给予暂缓拨付经费等处理。

附件：项目评审意见及修改意见表

国家自然科学基金委员会
2022年9月7日

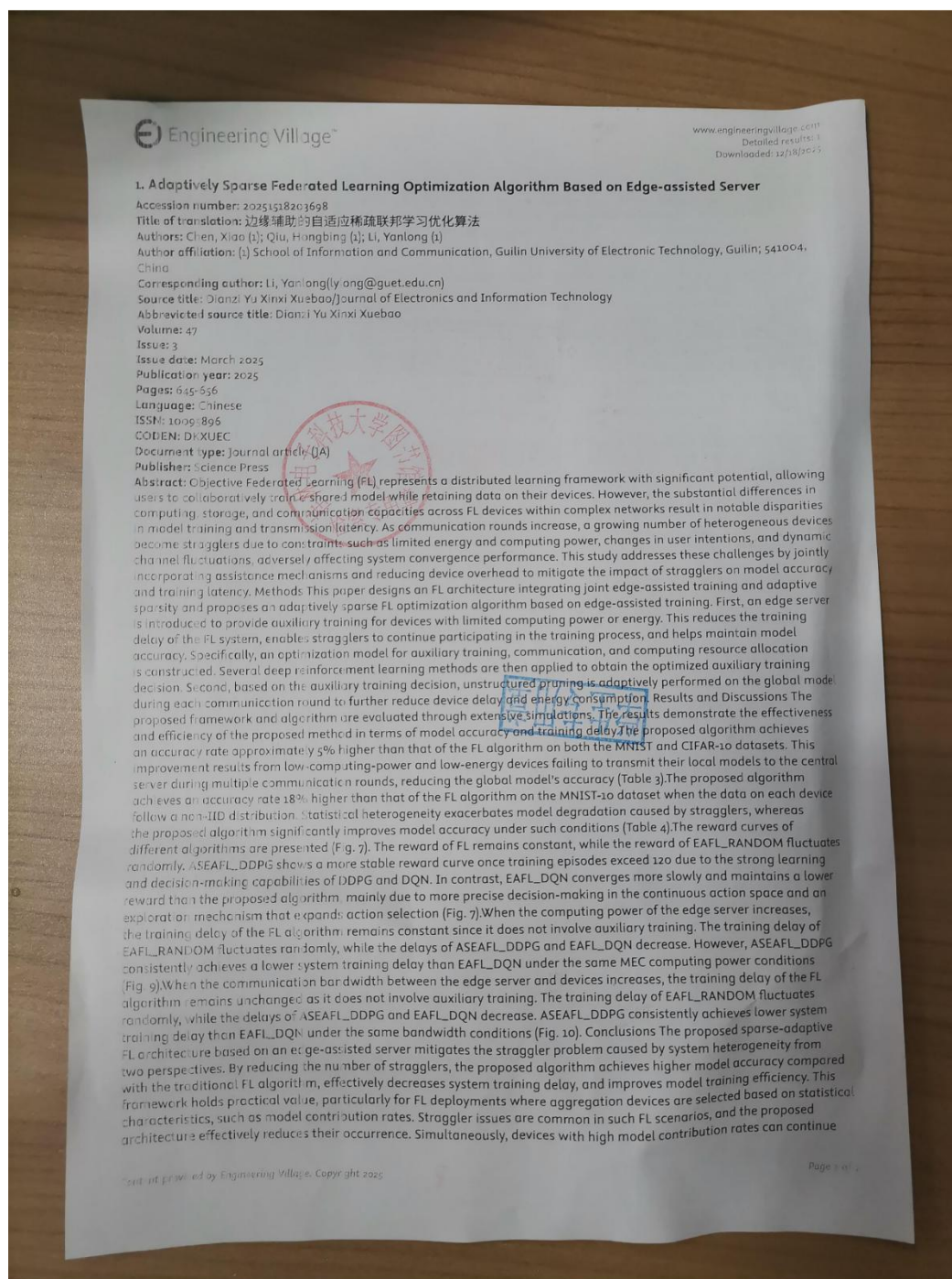
附件：项目评审意见及修改意见表

项目批准号	62261009	项目负责人	李燕龙	申请代码1	F0107
项目名称	水下光空分多址及三维分布式动态接入优化研究				
资助类别	地区科学基金项目	亚类说明			
附注说明					
依托单位	桂林电子科技大学				
直接费用	33.00 万元	起止年月	2023年01月 至 2026年12月		
通讯评审意见： <1>具体评价意见： 一、请针对创新点详细评述申请项目的创新性、科学价值以及对相关领域的潜在影响。 水下光通信是实现水下近程高速通信的一种可行途径。突破光束方向性辐射限制，解决三维LED阵列下的多维资源复用和接入问题，具有重要的意义。 水下光通信的定向性确实给通信组网带来技术挑战，但这一问题并不是水下光通信独有。无论是无线电组网通信还是水声组网通信，均有大量的文章研究定向协议设计。申请人应在广泛调研的基础上，结合UWOC的特点，针对性地开展水下光通信的定向协议研究。 二、请结合申请项目的研究方案与申请人的研究基础评述项目的可行性。 本项目申请人及团队，在水下光通信的物理层方面具有一定的研究基础；但是在组网协议方面的基础较弱，还需要加强此方面的研究。 三、其他建议 无 <2>具体评价意见： 一、请针对创新点详细评述申请项目的创新性、科学价值以及对相关领域的潜在影响。 本项目的创新性在于提出水下光三维空分多址策略，提出功率受限下的非正交多址技术，建立三维分布式动态接入模型并采用深度强化学习方法求解。项目的创新性较强，具有较强的科学价值，对于水下光通信领域具有较强的潜在影响力。 二、请结合申请项目的研究方案与申请人的研究基础评述项目的可行性。 项目的研究方案合理，技术路线清晰，总体具有很强的可行性。申请人前期发表了与项目相关的论文，研究基础较好，保证了项目可以顺利开展。 三、其他建议 建议优先资助 <3>具体评价意见： 一、请针对创新点详细评述申请项目的创新性、科学价值以及对相关领域的潜在影响。 该项目围绕水下LED光链路的大容量快速组网问题，突破光束方向性辐射限制，旨在解决三维LED阵列下的多维资源复用和接入问题，对动态水下组网理论和实践有重要意义。 二、请结合申请项目的研究方案与申请人的研究基础评述项目的可行性。 申请人发表多篇SCI期刊论文，有一定的研究基础，该申请研究方案设计较为合理，与申请人先前研究较为吻合。因此，该项目具有一定的可行性。 三、其他建议 <4>具体评价意见：					

一、请针对创新点详细评述申请项目的创新性、科学价值以及对相关领域的潜在影响。 该项目的创新性在于：（1）提出水下光三位空分多址策略；（2）提出功率受限下的非正交多址技术。其科学价值在于在分析水下AUV载体的LED光学收发透镜、阵元特性的基础上，揭示阵列结构、特性、光学收发透镜与空分光束形成的影响规律。研究成果可提高水下光通信的容量和网络的吞吐量。 二、请结合申请项目的研究方案与申请人的研究基础评述项目的可行性。 技术方案采取理论探索、算法设计和分析、计算机仿真与测试平台演示验证相结合的方法。在模型、空时码分多维资源联合分配、水下三维分布式近邻节点发现与动态接入协议及实验方面均给出了可行的方案，且有较好的研究基础。 三、其他建议 水下UUV是3维网络，UUV对光束的遮挡怎么考虑？建议给出方案。 <5>具体评价意见： 一、请针对创新点详细评述申请项目的创新性、科学价值以及对相关领域的潜在影响。 随着海洋战略的推进，研究水下光链路的组网技术具有重要的战略意义与应用价值。该申请项目拟研究水下AUV节点体积受限情况下的LED阵列各组件的耦合机理；针对水下LED阵列资源分配问题，研究非正交多址接入策略；针对水下节点动态拓扑问题，构建节点轮询感知和动态接入模型。尽管研究课题对于当前水下无线传感网面临的困难与挑战具有一定价值，但是国内外研究现状调研不充分，缺少与主流的水声通信和水下光通信方案的对比，难以判断本研究对目前水下传感网组网的实质贡献。申请书所提中的第二个和第三个关键科学问题是工程技术问题，缺乏科学性描述。相比于已发表的关于水下无线传感网的资源分配问题和多址接入机制的研究成果，所提出的研究方案并没有突出的创新性。 二、请结合申请项目的研究方案与申请人的研究基础评述项目的可行性。 申请书研究了空分光束与光学收发透镜阵元结构、特性间相互影响机理；研究了空、时、码、功率等多维资源协同分配和非正交复用策略以解决多维资源复用问题；探索三维分布式邻居节点感知策略与动态接入机制。其中主要问题如下： 1. 针对AUV节点的移动性，及其导致的拓扑动态性，需要重点分析这种场景下水下LED蓝绿光通信设备的可行性，光源对准的解决方案。 2. 作者在3.2.2节给出的信道模型并未考虑水下信道特征。水下光通信是否还能建模为高斯信道？ 3. 水下蓝绿光通信的距离远小于水声通信方案，并且AUV上光束扫描的时间对网络性能的影响也需要讨论。 4. 3.2.3节中的深度强化学习方案时间复杂度较大，且并不能保证结果收敛到最优。 5. 图26标题是“水下...测试图”，但是图中展示的实验环境却不是在水下。PCB板部分未做密封防水处理。 综上，本项目缺乏和国内外先进项目的优势对比，部分研究内容缺乏依据。信道建模未能体现水下传感网信息传输的特殊性，与陆上传感网建模极为相似，在实际水下环境中可行性有限。 三、其他建议 申请书所提研究方案未能实际着眼于水下光链路组网中的痛点问题，在建模层面未能体现水下链路信道的特殊性，建议申请人加深对相关问题的论述深度，并重新探讨研究方案的合理性与可行性。 修改意见：	信息科学部 2022年9月7日
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三、论文与著作

(一) 陈晓, 仇洪冰, 李燕龙. 边缘辅助的自适应稀疏联邦学习优化算法[J]. 电子与信息学报, 2025, 47 (3) : 645–656.



participating in multiple rounds of federated training, lowering the central server's frequent device selection overhead. Additionally, in resource-constrained FL environments, edge servers can perform more diverse and flexible tasks, such as partial auxiliary training and partitioned model training. © 2025 Science Press. All rights reserved.

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Main heading: Energy utilization

Controlled terms: Access control - Benchmarking - Computing power - Deep learning - Deep reinforcement learning - Digital storage - Edge computing - Energy dissipation - High level languages - Linear programming - Multitasking - Network security - Nonlinear programming - Reinforcement learning - Resource allocation - Steganography

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边缘辅助的自适应稀疏联邦学习优化算法

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摘要: 联邦学习中, 高模型贡献率的无线网络设备通常由于算力不足、能量有限成为掉队者, 进而增加模型聚合时延并影响全局模型精度。针对此问题, 该文设计了联合边缘服务器辅助训练和模型自适应稀疏联邦学习架构, 并提出了基于边缘辅助训练的自适应稀疏联邦学习优化算法。首先, 引入边缘服务器为算力不足或能量受限的设备提供辅助训练。构建了辅助训练和通信、计算资源分配的优化模型, 并采用多种深度强化学习方法求解优化的辅助训练决策。其次, 基于辅助训练决策, 在每个通信轮次自适应地对全局模型进行非结构化剪枝, 进一步降低设备的时延和能耗开销。实验结果表明, 所提算法极大地减少了掉队设备, 其模型测试精度优于经典联邦学习的测试精度; 利用深度确定性策略梯度(DDPG)优化辅助资源分配的算法有效地减少了系统训练时延, 提升了模型训练效率。

关键词: 联邦学习; 边缘服务器; 自适应稀疏; 深度强化学习; 非结构化剪枝

中图分类号: TN92; TP393

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1 引言

近年来, 人工智能技术越来越多地应用到物联网领域^[1]。大量的物联网设备采集数据进行数据分析和机器学习, 以满足用户多样化、实时、安全的计算需求^[2-4]。随着物联网数据的剧增, 设备收集数据到中心服务器进行集中智能处理的模式遇到了显著的时延和通信带宽瓶颈。为解决这一问题, 文献[5]提出了一种分布式智能框架——联邦学习(Federated Learning, FL)。联邦学习允许数据在本地设备上训练, 而无需将大量的本地数据上传到中心服务器。参与联邦学习的设备从服务器下载模型、完成本地训练后再上传本地模型, 由中心服务器对多个上传模型进行聚合。多个轮次的通信与训练迭代后, 可获得精度近似于集中式深度学习的模型。联邦学习使得本地数据不外传, 而只传输模型参数, 极大地减小了传输数据量, 满足了用户低时延响应需求, 同时在一定程度上保障了用户隐私和原始数据安全。

作为一种分布式协同训练范式, FL存在掉队者^[6-8]问题。这是因为分布于复杂网络中的FL设备在计算、存储和通信能力方面存在显著差异, 导致

模型训练和回传时延存在较大差距。随着通信轮次的增加, 更多异构终端由于能量和算力限制、用户意愿变化以及动态信道波动等原因, 无法及时完成模型回传而掉队, 进而影响模型的整体收敛性能。

由此可见, 掉队者问题多源于系统的高度异构性, 目前有较多的研究通过降低设备能量开销、缩减异构终端的训练和通信时延到FL预设范围内、用户参与激励机制等, 缓解FL中的掉队效应。例如, 分层联邦学习^[9-11]通过在设备和中央服务器中间搭建边缘聚合服务器, 避免频繁的云聚合, 以减少设备通信开销; 参数量化、知识蒸馏、稀疏化等模型压缩^[12-14]策略在保证模型精度的前提下, 致力于减少系统冗余通信量。上述研究主要缓解因通信压力导致的设备掉队问题。众所周知, 编码计算^[15-17]可以缓解分布式计算中的掉队者问题。文献[15]首次给出了线性模型的联邦学习编码计算方案。不同于其它减少掉队设备的方法, 中央服务器通过进行冗余梯度计算来弥补设备掉队后缺失的模型参数, 但由于设备在训练初始阶段需与中央服务器共享编码数据, 增加了系统通信量。

鉴于FL的随机设备选择策略使系统较易受到掉队设备影响, 文献[18]提出一种综合考虑带宽容量、处理和存储能力的自适应设备选择方法, 以减少FL过程中掉队者的影响。然而不考虑客户端数据统计特征的设备选择方案在非独立同分布(Non-Independent Identically Distribution, Non-IID)数据上的收敛性能不佳。FL的异步聚合策略^[19-21]使全局模型更新不再受制于最落后设备的影响, 极大地减少了掉队设备的发生, 但其在Non-IID数据上

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的收敛性难以保证。HeteroFL^[22]通过降低隐藏层宽度的方法构建了适配于不同设备的不同复杂度的局部模型,但仍然产生一个全局推理模型,该方法首次挑战了现有工作的基本假设。文献[23–25]通过辅助训练减少异构终端的掉队者效应。

综上,现有研究大都从单方面缓解系统异构性带来的设备掉队问题,本文从联合引进辅助和降低设备开销的角度出发,提出边缘辅助训练的自适应稀疏联邦学习架构。本架构易与基于数据统计特征选择设备,如高模型贡献率设备选择方案的联邦学习结合,提升数据异构下的联邦学习收敛性能。本文考虑了在自适应稀疏联邦学习中参与多轮训练的设备累积能耗、系统训练时延和模型稀疏比例,减少了掉队设备对FL性能的影响。一方面,自适应地调整全局模型的稀疏度降低设备的开销,另一方面,优化边缘辅助服务器的资源分配,最大限度地辅助算力不足或能量受限设备完成训练任务。具体如下:

(1)构建有边缘服务器辅助训练并进行模型自适应稀疏联邦学习的架构,旨在缓解落后设备的能耗压力,并减少系统的模型更新延迟,提升联邦学习系统的效率。

(2)考虑到资源受限设备的计算频率和累积能耗约束,以最小化系统训练时延为目标,构建边缘服务器在计算频率和通信带宽分配上的优化模型,并转化为马尔可夫过程,使用深度强化学习理论求解。

(3)对FL的全局模型进行非结构化剪枝,在模型训练过程中自适应地调整稀疏比例,降低设备的能耗开销。

(4)通过仿真实验探索了深度强化学习算法的超参数选取,与多种基线算法、采用深度Q网络(Deep Q-Network, DQN)的辅助优化算法进行时延对比,证明所提算法可以有效减少系统训练时延,从而降低设备掉队效应;基于优化的辅助训练决策与无辅助无稀疏的联邦学习进行了模型测试精度的对比实验,验证了所提算法通过减少掉队设备提升模型测试精度的有效性。

2 系统模型和问题形成

2.1 系统模型

如图1所示,该系统由1个中心服务器、Z个相同配置的可信边缘服务器和多个异构设备组成,其中每个边缘服务器范围内有N个设备参与模型聚合。中心服务器是由云服务提供商提供的服务器集群,执行模型聚合、模型稀疏和模型分发任务,其与边缘服务器和设备之间的通信条件良好。图中设备具有较高的模型贡献率,其中部分设备的算力或能量较低,参与 $M(M \geq 1)$ 轮本地训练时存在掉队情况,此时可借助边缘服务器完成模型的本地训练。边缘服务器位于更加靠近设备的网络边缘环境中,具有比设备更强的计算和存储性能以及稳定的电源供应,与设备采用正交频分多址接入技术进行通信。边缘服务器与设备之间数据链路短、带宽资源较充足,因此,样本数据能较快地从设备传输到边缘服务器。出于隐私保护考虑,该系统假设边缘服务器与设备处于可信执行环境中,即传输的样本数据和在边缘服务器训练的模型不存在泄露和被攻击的风险。

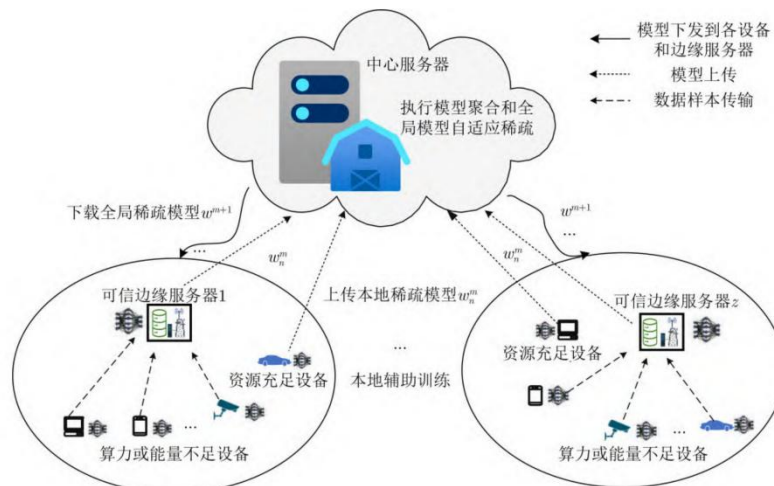


图1 系统模型

2.2 问题形成

在联邦学习中，算力和能量较低的设备严重影响系统的聚合时延，因此，本文引入边缘服务器辅助落后设备完成本地训练。辅助训练时延包括样本数据传输时延和样本数据训练时延。本文构建了样本数据传输模型和样本数据训练模型，主要符号描述如表1所示。

联邦学习的第 m 个通信轮次中，设备 n 与其覆盖范围边缘服务器 z 之间的数据传输速率如式(1)所示

$$r_{m,z,n}^{\text{up}} = B_{m,z,n} \frac{B_z}{b_z} \log_2 \left(1 + \frac{p_{z,n} h_{z,n}}{\delta^2} \right) \quad (1)$$

其中， $B_{m,z,n}$ 为第 m 个通信轮次中设备 n 与边缘服务器 z 之间通信的单位带宽数目， B_z 为辅助训练系统的带宽， b_z 为单位带宽总数。1个设备可分配到多个单位带宽，每个单位带宽只能分配给1个设备使用。 $p_{z,n}$ 为边缘服务器 z 覆盖范围下设备 n 的传输功率， $h_{z,n}$ 为设备 n 与边缘服务器 z 之间传输信道的增益， δ^2 为噪声功率。局部模型在各设备上进行多个批次的本地更新，算力或能量不足的设备可将数据量为 D_n 的样本数据传输到边缘服务器上训练，其数据传输时延如式(2)所示

$$t_{m,z,n}^{\text{up}} = \frac{D_n}{r_{m,z,n}^{\text{up}}} \quad (2)$$

D_n 代表设备 n 在每个通信轮次内训练的总数据量，

单位为bit。将样本数据传输到边缘服务器的过程中，设备 n 用于数据传输的能耗如式(3)所示

$$e_{m,z,n}^{\text{up}} = t_{m,z,n}^{\text{up}} \cdot p_{z,n} \quad (3)$$

边缘服务器 z 可以同时辅助多个设备完成模型训练，在第 m 个通信轮次中来自设备 n 的样本数据在边缘服务器 z 上的训练时延如式(4)所示

$$t_{m,z,n}^{\text{MEC}} = \frac{\varphi_n}{F_{m,z,n}} \quad (4)$$

其中， $F_{m,z,n}$ 为第 m 个通信轮次中设备 n 的训练样本从边缘服务器 z 分配到的计算频率，单位为cycle/s。 $\varphi_n = D_n \cdot r$ ， r 为处理每比特数据所需的CPU周期数。

若设备 n 在本地完成模型训练，则其训练时延如式(5)所示

$$t_{z,n}^{\text{IOT}} = \frac{\varphi_n}{f_{z,n}^{\text{IOT}}} \quad (5)$$

其中， $f_{z,n}^{\text{IOT}}$ 为边缘服务器 z 覆盖范围下设备 n 的计算频率，单位为cycle/s。此时，设备 n 训练模型耗费的能量如式(6)所示

$$e_{z,n}^{\text{IOT}} = k \cdot \varphi_n^3 \cdot (f_{z,n}^{\text{IOT}}) \quad (6)$$

其中， k 表示由芯片结构决定的有效开关电容。综合起来，第 m 个通信轮次中，边缘服务器 z 覆盖范围内设备 n 上的样本数据训练时延如式(7)所示

表1 主要符号描述表

符号	含义	符号	含义
Z, N	边缘服务器个数，每个边缘服务器范围内被选中参与聚合的设备数	$p_{z,n}$	边缘服务器 z 覆盖范围下设备 n 的传输功率
M	联邦学习的总通信轮次	k	由芯片结构决定的有效开关电容
D_n	每个轮次的本地训练样本数据量	$t_{m,z,n}^{\text{up}}$	第 m 个通信轮次内设备 n 上传样本数据到边缘服务器 z 的时延
D_ω	联邦学习模型参数数据量	$t_{z,n}^{\text{IOT}}$	边缘服务器 z 覆盖范围下设备 n 的本地训练时延
r	处理单位比特数据所需的CPU周期数	$t_{m,z,n}^{\text{MEC}}$	第 m 个通信轮次内边缘服务器 z 训练设备 n 上传的样本数据的时延
s_m	第 m 个通信轮次的模型稀疏率	$t_{m,z,n}^{\text{up,c}}$	第 m 个通信轮次内边缘服务器 z 覆盖范围下设备 n 上传模型到聚合服务器的时延
$\alpha_{m,z,n}$	第 m 个通信轮次内边缘服务器 z 覆盖范围下设备 n 是否接受辅助训练	$e_{m,z,n}^{\text{up}}$	第 m 个通信轮次内设备 n 上传样本数据到边缘服务器 z 的能耗
$r_{m,z,n}^{\text{up}}$	第 m 个通信轮次内设备 n 到边缘服务器 z 的数据传输速率	$e_{z,n}^{\text{IOT}}$	边缘服务器 z 覆盖范围下设备 n 的本地训练能耗
$r_{m,z,n}^{\text{up,c}}$	第 m 个通信轮次内边缘服务器 z 覆盖范围下设备 n 到聚合服务器的数据传输速率	$e_{m,z,n}^{\text{up,c}}$	第 m 个通信轮次内边缘服务器 z 覆盖范围下设备 n 上传模型到聚合服务器的能耗
$B_{m,z,n}$	第 m 个通信轮次内边缘服务器 z 覆盖范围下设备 n 分配到的单位带宽数目	$E_{z,n}^{\text{start}}$	边缘服务器 z 覆盖范围下设备 n 的初始能量
B_z	辅助训练系统带宽	$E_{m,z,n}$	边缘服务器 z 覆盖范围下设备 n 在第 m 个通信轮次的总能耗
b_z	辅助训练系统的单位带宽数目	$F_{m,z,n}$	第 m 个通信轮次内边缘服务器 z 用于设备 n 上样本训练的计算频率
$h_{z,n}$	设备 n 与边缘服务器 z 之间的传输信道增益	$f_{z,n}^{\text{IOT}}$	边缘服务器 z 覆盖范围下设备 n 的计算频率
δ^2	噪声功率	F_z^{MEC}	边缘服务器 z 的计算频率

$$T_{m,z,n} = \alpha_{m,z,n} \cdot (t_{m,z,n}^{\text{up},z} + t_{m,z,n}^{\text{MEC}}) + (1 - \alpha_{m,z,n}) \cdot t_{z,n}^{\text{IOT}} \quad (7)$$

$\alpha_{m,z,n} = 0$ 代表在设备 n 上对样本数据进行本地训练, $\alpha_{m,z,n} = 1$ 代表边缘服务器辅助设备 n 完成模型训练。鉴于稀疏模型的参数量远小于样本数据量, 模型上传时延 $t_{m,z,n}^{\text{up},c}$ 如式(8)所示, 可忽略不计。设备 n 完成本地训练后, 用于上传模型所耗费的能量如式(9)所示

$$t_{m,z,n}^{\text{up},c} = \frac{\prod_{m=0}^m (1 - s_m) D_\omega}{r_{m,z,n}^{\text{up},c}} \quad (8)$$

$$e_{m,z,n}^{\text{up},c} = t_{m,z,n}^{\text{up},c} \cdot P_{z,n} \quad (9)$$

设备 n 的能耗如式(10)所示

$$E_{m,z,n} = \alpha_{m,z,n} \cdot e_{m,z,n}^{\text{up},z} + (1 - \alpha_{m,z,n}) \cdot (e_{z,n}^{\text{IOT}} + e_{m,z,n}^{\text{up},c}) \quad (10)$$

在通信条件良好的联邦学习系统中, 算力不足或能量受限设备的模型训练时延过大, 常导致设备掉队情况, 因此, 本系统对模型训练时延进行优化。基于上述样本数据传输和训练模型, 本文优化问题可表示为式(11)

$$B_{m,z,n}, F_{m,z,n}, \alpha_{m,z,n} \quad \text{Min} \quad \sum_{m=1}^M \sum_{z=1}^Z \text{Max}\{T_{m,z,n}\} \quad (11)$$

$$\sum_{n=1}^N F_{m,z,n} \leq F_z^{\text{MEC}}, \forall m, \forall z \quad (11a)$$

$$\sum_{n=1}^N B_{m,z,n} \leq b_z, \forall m, \forall z \quad (11b)$$

$$\sum_{m=1}^M E_{m,z,n} \leq E_{z,n}^{\text{start}}, \forall n, \forall z \quad (11c)$$

$$\alpha_{m,z,n} = \{0, 1\}, \forall m, \forall z, \forall n \quad (11d)$$

$$F_{m,z,n} \geq 0, \forall m, \forall z, \forall n \quad (11e)$$

$$B_{m,z,n} \geq 0, \forall m, \forall z, \forall n \quad (11f)$$

容易看出, 上述优化模型是一个混合整数规划问题, 且第 m 个通信轮次的辅助训练和资源分配决策受前 $m-1$ 个通信轮次的决策影响, 因此本文采用深度强化学习智能体不断探索环境进行学习, 以给出优化的辅助训练和资源分配决策。约束条件式(11a)保证了分配到所有设备的计算频率之和不超过边缘服务器 z 的计算能力。约束条件式(11b)保证了分配到边缘服务器 z 范围内所有设备的带宽之和不超过系统带宽。式(11c)约束了设备的累积能耗不超过设备的初始能量。式(11d)约束了样本数据在设备或边缘服务器上完成训练。式(11e)和式(11f)表示系统分配给落后设备的辅助算力和通信带宽非负。

3 基于边缘辅助训练的自适应稀疏联邦学习优化算法

本文提出联合辅助训练和模型自适应稀疏的联邦学习架构, 确保重要设备能连续参与多轮联邦训练, 算法1给出了基本流程。本算法综合考虑各设备算力、能量以及联邦模型训练进程, 对每个通信轮次内的模型稀疏度进行自适应调整, 动态决策辅助训练设备以及辅助资源的分配情况。首先, 在边缘服务器 z 上部署深度强化学习智能体, 智能体收集当前设备选择下的总通信轮次 M (若 $M=1$ 则每个通信轮次都更新聚合设备集合, 若 $M>1$ 则选定的设备参与多轮联邦训练)、其覆盖范围内所有参与模型聚合的设备的状态信息并初始化策略网络和价值网络。为最小化系统训练时延, 智能体的奖励函

算法 1 基于边缘辅助训练的自适应稀疏联邦学习

输入: 初始稀疏比例 s_0 , 最终的稀疏比例 s_M , 稀疏频率 U , 稀疏速率控制指数 c , 开始稀疏的轮次 m_0 , 初始掩码矩阵 $\mathbf{X}^{m_0}$, 边缘服务器 z 下参与聚合的设备集合 Ψ_z , 当前设备选择下总的通信轮次 M , 初始模型 ω , 各设备的初始能量 $E_{z,n}^{\text{start}}$ 、计算频率 $f_{z,n}^{\text{IOT}}$, 传输功率 $p_{z,n}$, 边缘服务器的计算频率 F_z^{MEC} 、边缘服务器和设备间的通信带宽 B_z , 每轮训练数据量 D_n , 由芯片结构决定的有效开关电容 k

输出: 联邦学习模型 ω^M

(1) 在边缘服务器 z 上部署深度强化学习智能体, 智能体收集联邦学习在当前设备选择下的总通信轮次 M 、其覆盖范围内所有参与模型聚合的设备的状态信息并初始化策略网络和价值网络, 智能体的奖励函数为式(14), 通过不断地与环境交互, 智能体将学习到最佳的辅助训练决策

(2) 智能体下发 M 个通信轮次的辅助训练决策, 包括辅助训练标识 $\alpha_{m,z,n}$ 、传输带宽 $B_{m,z,n}$ 和 CPU 频率 $F_{m,z,n}$

(3) For $m=1$ to M do

For $n=1$ to N do (并行)

IF $\alpha_{m,z,n} == 1$

设备 n 依据传输带宽 $B_{m,z,n}$ 上传样本数据到边缘服务器, 边缘服务器依据分配到的算力 $F_{m,z,n}$ 完成辅助训练, 模型训练更新依据式(21)

边缘服务器上传辅助训练模型 ω_n 到聚合服务器

ELSE

设备 n 完成本地训练, 模型更新依据式(21)

设备 n 上传本地训练模型 ω_n 到聚合服务器

End For

(4) 执行全局模型聚合 $\omega^{m+1} = \sum_{n=1}^N \frac{D_n}{D} \omega_n^m$

(5) 依据式(20)计算全局模型稀疏度 s_m , 然后根据稀疏度 s_m 计算全局模型的掩码矩阵 $\mathbf{X}^m$

(6) 全局模型和掩码矩阵进行哈达玛积运算 $\omega^{m+1} = \omega^{m+1} \odot \mathbf{X}^m$, 获得非结构化剪枝模型 ω^{m+1} 作为新的全局模型

(7) 将全局稀疏模型 ω^{m+1} 和掩码矩阵 $\mathbf{X}^m$ 下发给参与训练的设备

End For

数定义如式(14)所示。通过对各设备剩余能量、前期辅助训练情况等进行探索和分析,智能体将学习到最佳的辅助训练决策并下发给边缘服务器和参与聚合的设备。本算法执行 M 个通信轮次,依据智能体的决策,每个通信轮次内无需辅助的设备通过小批次随机梯度下降进行局部模型更新,算力或能量较低的设备将样本数据传输到边缘服务器上完成训练,再将各本地模型回传到中央服务器。中央服务器在接收到本地模型后进行同步聚合,得到新一轮的全局模型。依据式(20),可计算出当前轮次的模型稀疏度,进而得到非结构化剪枝的掩码矩阵。中央服务器使用掩码矩阵对全局模型进行哈达玛积运算,获得的稀疏模型作为新的全局模型。然后,将稀疏后的全局模型和掩码矩阵同时下发给各设备和边缘服务器,以执行下个轮次的本地模型训练。值得注意的是,本地训练只需完成未剪枝模型参数的更新即可。

本文所提架构和算法稳定高效且易于部署实现。边缘服务器上的强化学习智能体利用设备电量、计算频率等简单易懂的基本信息,以最小化系统训练时延为目标探索并学习设备参与 M 轮联邦训练的最优辅助训练决策,然后使用该决策进行 M 轮稀疏联邦学习。由于强化学习决策先于联邦学习得出,实际执行联邦学习的时间复杂度不受强化学习影响,并且当 $M>1$ 时,设备连续参与多轮联邦训练,减小了系统用于设备选择的额外开销。边缘服务器或设备与中央服务器之间传输的稀疏模型自适应变化,这在一定程度上提升了模型参数的安全性。

3.1 边缘辅助训练

本文在边缘服务器上部署深度强化学习智能体,对于需要边缘服务器辅助训练的设备,智能体经过对环境的不断探索给出每台设备所分配到的计算频率和样本传输带宽。为解决辅助训练和资源分配问题,本文将上述模型优化问题转换成马尔可夫决策过程,并采用基于深度确定性策略梯度(Deep Deterministic Policy Gradient, DDPG)的强化学习算法求解。

3.1.1 问题转换

在每个边缘服务器下部署强化学习智能体,其状态空间、动作空间和奖励函数定义如下。

(1)状态空间:在第 m 个通信轮次,智能体的状态包含所有设备的基本信息、辅助训练标志和当前资源分配情况等。智能体的状态可表示为式(12)

$$S^m = \{e_n^m, B_n^m, F_n^m, \text{flag}_n^m\} \quad (12)$$

其中, $n \in \{1, 2, \dots, N\}$, e_n^m 表示在第 m 个通信轮次设备 n 的剩余电量, B_n^m 表示在第 m 个通信轮次设备

n 分配到的样本数据传输带宽, F_n^m 表示在第 m 个通信轮次设备 n 从服务器分配到的计算频率, flag_n^m 表示在第 m 个通信轮次设备 n 是否接受辅助训练。

(2)动作空间:在第 m 个通信轮次,智能体的动作包含资源分配决策和辅助训练决策。智能体的动作可表示为式(13)

$$A^m = \{\Delta B_n^m, \Delta F_n^m, \Delta \text{flag}_n^m\} \quad (13)$$

其中, $n \in \{1, 2, \dots, N\}$, ΔB_n^m 表示在第 m 个通信轮次设备 n 分配到的传输带宽变化量, ΔF_n^m 表示在第 m 个通信轮次设备 n 从服务器分配到的计算频率变化量, Δflag_n^m 表示在第 m 个通信轮次设备 n 的辅助训练标志变化量。

(3)奖励函数:奖励函数的设置无固定标准,好的奖励函数能引导模型更快的收敛。一般而言,奖励函数与优化目标相关。为提升联邦学习的性能,本系统以最小化联邦训练时延为目标,而强化学习以最大化长期累积奖励为目标。因此,智能体的奖励函数定义如式(14)所示

$$R^m = -\text{Max}\{T_{m,z,n}\} \quad (14)$$

3.1.2 基于DDPG的辅助训练和资源分配

DDPG使用深度神经网络表示确定性策略 $\mu(s^m, \theta)$,采用确定性策略梯度来更新网络参数,有效应用于连续动作空间的强化学习决策中。如图2所示,DDPG基于价值网络和策略网络架构,为价值网络和策略网络分别引入了目标网络。DDPG的目标是最大化策略目标函数 $J(\theta)$,同时最小化价值网络的损失函数 $L(w)$ 。

如式(15)所示,在DDPG的策略网络中,优化目标 $J(\theta)$ 被定义为累积折扣奖励。 $J(\theta)$ 关于 θ 的梯度等价于Q值函数关于 θ 梯度的期望。如式(16)所示,利用小批量梯度上升(Mini-Batch Gradient Ascent, MBGA)算法,从经验池中随机采样获得 I 个小批量数据作为对期望值的采样估计

$$J(\theta) = E_{\theta}(r_0 + \gamma r_1 + \gamma^2 r_2 + \dots) \quad (15)$$

$$\nabla_{\theta} \hat{J}(\theta) \approx \frac{1}{I} \sum_{i=1}^I [\nabla_a Q(S_i^m, a_i, w) \nabla_{\theta} \mu(s_i^m, \theta)] \quad (16)$$

DDPG利用基于时序差分(Temporal-Difference, TD)的均方误差(Mean Squared Error, MSE)作为价值网络的损失函数,如式(17)所示。为最小化价值网络的损失函数,采用小批量梯度下降(Mini-Batch Gradient Descent, MBGD)算法,从经验池中随机采样获得 I 个小批量数据作为对期望值的采样估计。式(18)给出了价值网络的梯度公式

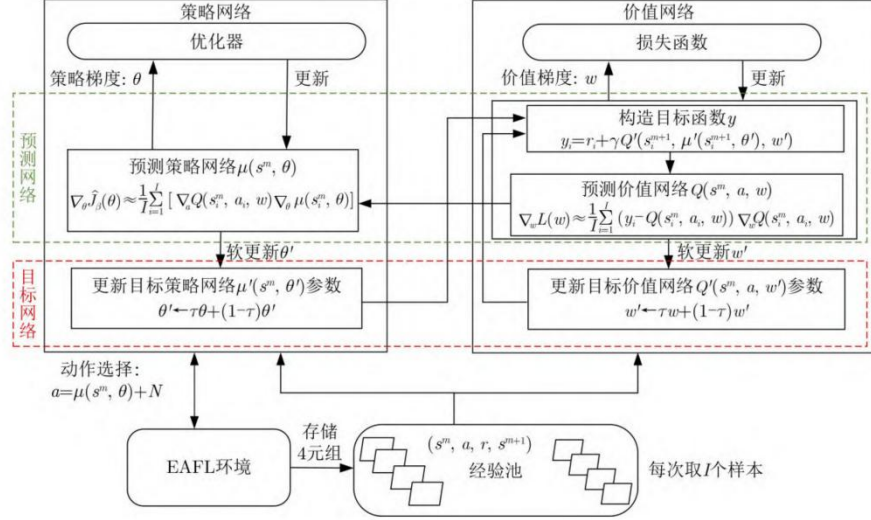


图2 DDPG算法结构图

$$L(w) = E[(r + \gamma Q'(s^{m+1}, \mu'(s^{m+1}, \theta'), w') - Q(s^m, a, w))^2] \quad (17)$$

$$\nabla_w L(w) \approx \frac{1}{I} \sum_{i=1}^I (r_i + \gamma Q'(s_i^{m+1}, \mu'(s_i^{m+1}, \theta'), w') - Q(s_i^m, a_i, w)) \nabla_w Q(s_i^m, a_i, w) \quad (18)$$

其中, s^{m+1} 表示 s^m 的下一状态, Q' 和 w' 分别表示目标策略网络 μ' 和目标价值网络 Q' 的权重。不同于DQN中每隔 n 步更新目标网络参数, DDPG的目标网络缓慢更新参数, 如式(19)所示

$$\left. \begin{aligned} w' &\leftarrow \tau w + (1 - \tau) w' \\ \theta' &\leftarrow \tau \theta + (1 - \tau) \theta' \end{aligned} \right\} \quad (19)$$

DDPG算法中目标值 $y_i = r_i + \gamma Q'(s_i^{m+1}, \mu'(s_i^{m+1}, \theta'), w')$ 的计算过程涉及目标策略网络 μ' 和目标价值网络 Q' , 这使价值网络在学习时更加稳定, 也更易收敛。另外, 通过为动作空间添加随机噪声, 增加与环境的交互, 使得策略的探索更加充分。同时经验回放机制通过将训练得到的数据储存并随机采样以更新模型, 降低了样本数据的相关性。

3.2 模型自适应稀疏

通常深度神经网络有相当一部分参数的训练和更新对降低模型误差贡献不大^[26], 本文算法在辅助训练框架下通过删除神经网络中的冗余连接或神经元对全局模型进行自适应剪枝, 以进一步减少设备的开销。

一般对模型进行结构化剪枝简单易行, 但会剪

掉对模型性能影响较大的权重。因此, 本系统在具有良好硬件加速性能的中心服务器上部署非结构化剪枝算法。一方面全局稀疏能够获得比本地稀疏更好的FL性能; 另一方面, 聚合服务器完成模型稀疏, 减少了本地稀疏带给设备的额外计算压力^[27]。本文对联学习模型进行非结构化剪枝过程如图3所示。

在联邦学习的多个通信轮次内, 固定模型稀疏比例不利于精准联邦模型的训练。联邦学习初期模型参数距离最优取值有较大的差距, 此时减少模型的稀疏比例有助于模型朝着正确方向收敛; 随着多个通信轮次的聚合, 模型参数趋于稳定, 此时提高模型稀疏比例有助于减少冗余通信和计算。为此, 每个通信轮次内, 中心服务器将设备和边缘服务器回传的局部模型进行聚合后, 自适应地计算当前全局模型的稀疏比例。本文改进了联邦稀疏算法^[27]关于自适应稀疏系数的计算过程, 如式(20)所示。其中, η 为精度控制因子, 当模型测试精度满足预设范围时, η 取值为1, 否则为0。 m 为当前通信轮次, S_M 为最终稀疏比例, S_0 为初始稀疏比例, M 为当前设备选择下的总通信轮次, m_0 为初次对模型进行稀疏化的通信轮次, U 为稀疏频率, 指数 c 控制了稀疏化的速率。精度控制因子 η 的引入, 参考了模型的实时测试精度, 使得剪枝操作更贴合去除冗余参数的初衷, 有利于模型的正确收敛

$$s_m = \eta \cdot \left[S_M + (S_0 - S_M) \left(1 - \frac{U \lfloor m/U \rfloor - m_0}{M - m_0} \right)^c \right] \quad (20)$$

$$\omega_n = \omega_n - \lambda \cdot \nabla f_n \odot \mathbf{X}^m \quad (21)$$

将模型权重绝对值从小到大排序, 获取 s_m 比例位置的权重值。模型权重绝对值小于该值的对应掩码矩阵元素设为0, 否则为1, 便得到当前全局模型的掩码矩阵 $\mathbf{X}^m$ 。使用掩码矩阵与全局模型进行哈达玛积运算可获得全局稀疏模型。然后中央服务器将全局稀疏模型和对应掩码矩阵下发给参与训练的设备和边缘服务器, 进行下一轮的训练。如式(21)所示, 局部模型的梯度与该轮的掩码矩阵计算哈达玛乘积, 即下一轮训练只需对剩余权重参数进行梯度更新即可。

4 实验结果分析

4.1 实验设置

本文首先对不同的辅助训练优化算法进行了仿真实验, 然后基于优化的辅助训练决策进行自适应稀疏联邦学习, 与无辅助无稀疏的联邦学习进行了模型精度的对比实验。代码通过Python 3.8.8实现, 并在配有一块NVIDIA GeForce GTX 1650 Ti with Max-Q Design的GPU的电脑上运行。为验证所提算法的性能, 本文分别在联邦学习广泛使用的MNIST数据集和CIFAR10数据集上训练具有两层卷积层、两层池化层、两层全连接的CNN网络和ResNet18网络。有关辅助训练、稀疏化和不同数据集上训练任务的相关实验参数参考文献[23-25,27], 具体如表2所示。

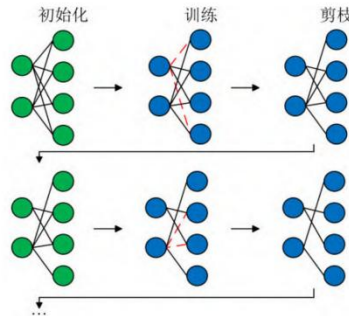


图3 模型剪枝示意图

4.2 实验结果和分析

4.2.1 精度分析

本文对比了基于DDPG边缘辅助的自适应稀疏联邦学习(Adaptively Sparse and Edge-Assisted Federated Learning based on DDPG, ASEAFLL_DDPG)和经典的无辅助无稀疏联邦学习(FL)所得模型的测试精度。实验设计参与聚合的设备集中存在40%算力较低或能量受限的设备。表3给出了各终端数据服从IID情况下, 不同算法的模型测试精度。由表3可知, 本文算法在MNIST数据集和CIFAR10数据集上均获得了比FL算法高5%左右的准确率。这是由于在FL的多轮通信中, 算力低的设备由于训练时延超出联邦学习最大等待时延而被抛弃, 能量低的设备因能量不足以完成本地训练而掉线, 导致中央服务器上缺失部分模型参数, 影响模型精度。本文算法通过合理地分配辅助训练资源, 并自适应地

表2 各参数取值表

参数	取值
边缘服务器下参与聚合的设备数 N	5
系统单位带宽数目 b_z	8
处理单位比特数据所需CPU圈数 r	1 000
距离1 m时的参考信道增益 h	-30 dB
上行链路传输功率 $p_{z,n}$	0.1 W
噪声功率 δ^2	-100 dBm
由芯片结构决定的有效开关电容 k	10^{-25}
边缘服务器 z 计算频率 F_z^{MEC}	4 GHz
模型初始稀疏系数 S_0	0
模型最终稀疏系数 S_M	0.6
稀疏频率 U	1
初始稀疏轮次 m_0	1
当前设备选择下总的通信轮次 M	10
稀疏速率控制指数 c	2
MNIST数据集上的学习率 Lr_mnist	0.001
CIFAR10数据集上的学习率 Lr_cifar	0.01
MNIST数据集的批量大小 Bs_mnist	32
CIFAR10数据集的批量大小 Bs_cifar	64
本地更新批数 Local_eps	4

表3 不同算法模型测试精度对比(%)

算法	数据集	通信轮次									
		1	2	3	4	5	6	7	8	9	10
FL	MNIST	62.65	73.41	75.24	76.18	77.00	77.45	78.52	79.18	79.78	80.38
	CIFAR10	15.03	47.06	55.79	58.75	59.65	61.1	61.21	62.05	61.83	62.39
ASEAFLL_DDPG	MNIST	62.65	73.13	77.51	80.04	82.2	82.73	84.17	84.71	85.27	85.65
	CIFAR10	15.03	41.01	55.90	60.75	63.23	64.60	65.80	66.33	67.10	67.26

压缩模型冗余信息,减少了设备的训练时延和能耗开销,极大地避免了设备掉队情况,进而保证了模型的收敛性能。

表4给出了Non-IID设置下MNIST数据集上的模型测试精度。首先,将MNIST数据集按照标签排序,每300个样本一组,分为200组数据。通过调整设备的随机采样组数,可实现不同程度的非独立同分布设置。由表4可知,本文算法相比FL算法提升了约18%的模型测试准确率。这是因为当各终端数据服从非独立同分布时,FL算法中掉队设备未回传的模型参数会严重影响全局模型的精度。结合式(20)和表2取值,图4给出了随通信轮次自适应调整的稀疏比例变化曲线。

4.2.2 时延与奖励值

为最小化系统训练时延,本文基于深度确定性策略梯度算法优化多轮辅助资源分配,并与几种辅助训练基线算法进行了对比。其中,基线算法包括无辅助的联邦学习(FL):所有样本数据均在设备上完成训练;随机边缘辅助的联邦学习(Edge-Assisted Federated Learning based on RANDOM strategy, EAFL_RANDOM):边缘服务器随机选择待辅助设备并随机分配系统带宽和服务器算力;基于DQN的边缘辅助联邦学习(Edge-Assisted Federated Learning based on DQN, EAFL_DQN):采用离散动作空间的DQN算法选择待辅助设备、分配系统带宽和服务器算力,按照马尔可夫转换过程其动作空间取值为5 832。本文首先通过大量实验优化了基于DDPG的辅助训练和资源分配方案中的最优超参数,如折扣系数、策略网络的学习率和价值网络的学习率。

本文算法在不同折扣系数 γ 下的收敛曲线如图5所示。折扣系数 γ 在计算目标值 $y_i = r_i + \gamma Q'(s_i^{m+1}, \mu'(s_i^{m+1}, \theta'), w')$ 时引入。一般而言,折扣系数 γ 越趋近于1,优化目标越注重长期累积收益。如图5所示,对比了 γ 为0.7,0.8和0.9时的奖励值曲线,当训练回合 >350 时, γ 为0.9的奖励函数收敛值更加稳定。图6给出了策略网络学习率 lr_a 和价值网络学习率 lr_c 不同取值时的损失值曲线。如图6所示,当 lr_a 为0.001, lr_c 为0.02时,损失函数随训练回合的增加下降明显,并于训练回合达到100时趋于平稳;当训练回合大于150时,4条曲线均收敛,但 lr_a 为0.001, lr_c 为0.02时的损失值曲线更加稳定。

图7给出了不同算法的奖励值曲线。由图7可知,FL的奖励值恒定,EAFL_RANDOM的奖励值随机变化,DDPG和DQN具有较强的学习和决策能力,当训练回合 >120 时,ASEAFL_DDPG的奖励值曲线率先趋于平稳,而在同样的奖励函数设置下EAFL_DQN的奖励值曲线收敛较慢,并且低于所提算法曲线。这主要是因为连续动作空间上的决策更加精准,探索机制拓宽了智能体对动作的选取。

部署于设备终端的各类推理、分类、识别任务在不同数据集上训练的样本数据量存在较大差异。图8给出了所提算法在不同训练数据量下的奖励值变化曲线。如图8所示,奖励值随训练数据量的增大而减小,这是因为系统训练时延随训练数据量的增大而增大,而奖励函数与系统训练时延负相关。当训练回合 >200 后,奖励值曲线趋于收敛状态,但极少数出现的波动值随训练数据量增长而变大。这是因为一方面,探索机制增强了系统在动作空间的可选择性;另一方面,当动作策略对应的资源分

表 4 Non-IID设置下MNIST数据集上的模型测试精度(%)

算法	通信轮次									
	1	2	3	4	5	6	7	8	9	10
FL	16.25	15.97	19.53	21.76	26.33	32.98	37.62	40.18	42.69	45.84
ASEAFL_DDPG	16.25	25.72	35.02	42.51	48.81	54.31	57.32	60.17	62.75	63.97

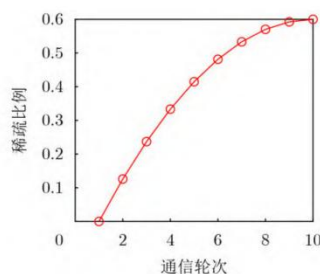


图 4 模型稀疏比例随通信轮次变化曲线

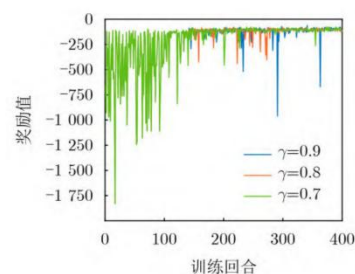


图 5 不同折扣系数 γ 下的奖励曲线

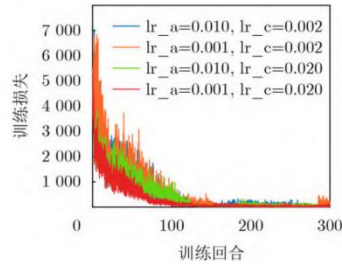


图6 不同学习率下的损失值曲线

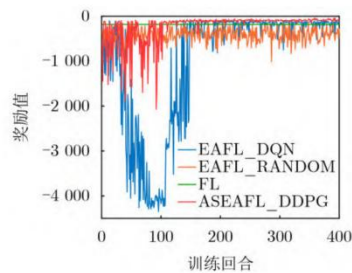


图7 不同算法奖励值

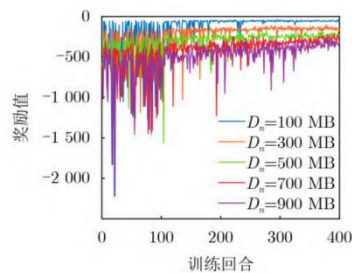


图8 本文算法在不同样本数据量下的奖励值曲线

配不合理时，难以辅助落后设备完成局部模型训练，此时较大的训练数据量将导致联邦学习出现较大的时延，因而奖励值曲线波动值变大。

鉴于各算法在训练回合达到400后趋于收敛，本文使用第400次学习的结果作为各算法的辅助训练决策。在不同MEC算力下，各算法的系统训练时延如图9所示。由图9可知，当边缘服务器的算力增加时，FL算法因不接受辅助训练而无训练时延的变化，EAFL_RANDOM算法的训练时延随机变化，ASEAFD_DDPG和EAFL_DQN算法的训练时延减小。但在相同的MEC算力下，ASEAFD_DDPG总能得到比EAFL_DQN算法更小的系统训练时延。

不同辅助带宽下各算法的系统训练时延如图10所示。由图10可知，当边缘服务器和设备间通信带宽增大时，FL算法因不接受辅助训练而无训练时延

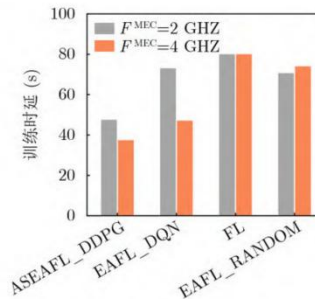


图9 不同MEC算力下的系统训练时延

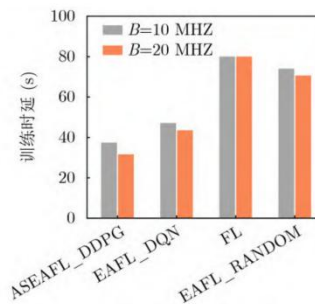


图10 不同辅助带宽下的系统训练时延

的变化，EAFL_RANDOM算法的训练时延随机变化，ASEAFD_DDPG和EAFL_DQN算法的训练时延减小。但在相同的通信带宽下，ASEAFD_DDPG总能得到比EAFL_DQN算法更小的系统训练时延。

总之，所提算法合理地分配辅助资源，并对模型进行自适应剪枝，降低了设备开销，减少了掉队设备，因此获得了模型精度和系统训练时延两方面性能的提升。另外，该框架使得联邦学习的设备选择不再受制于设备资源情况，而可以选择具有不同数据统计特征的设备终端，这有利于提升模型在非独立同分布数据上的精度。

5 结束语

本文构建了联合边缘辅助训练和模型自适应稀疏的联邦学习架构。首先，建立了边缘辅助训练的资源分配优化模型并使用深度强化学习理论求解。其次，在联邦系统中，联合优化的资源分配决策和全局自适应稀疏算法，提高了模型精度并降低了系统时延。具体来说，边缘服务器的引入减小了联邦学习系统时延，给予掉队设备继续参与联邦训练的机会，保证了模型的精度；全局模型自适应稀疏算法进一步减少了设备的开销，避免了设备掉队现象。本文框架尤其适合部署于依据非系统异构性标准选

择聚合设备(如高模型贡献率或随机设备选择策略等)的联邦学习中。这是因为上述联邦学习场景存在较普遍的掉队者问题,而本文架构有效减少了设备掉队情况,同时允许高模型贡献率的设备连续参与多轮联邦训练,减少了中央服务器频繁的设备选择开销。本文所提联邦学习架构具有较实际的应用价值,进一步,在资源受限的联邦学习中边缘服务器可以执行如部分辅助训练、分割模型训练等更多样灵活的模型更新任务。

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Adaptively Sparse Federated Learning Optimization Algorithm Based on Edge-assisted Server

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Abstract:

Objective Federated Learning (FL) represents a distributed learning framework with significant potential, allowing users to collaboratively train a shared model while retaining data on their devices. However, the substantial differences in computing, storage, and communication capacities across FL devices within complex networks result in notable disparities in model training and transmission latency. As communication rounds increase, a growing number of heterogeneous devices become stragglers due to constraints such as limited energy and computing power, changes in user intentions, and dynamic channel fluctuations, adversely affecting system convergence performance. This study addresses these challenges by jointly incorporating assistance mechanisms and reducing device overhead to mitigate the impact of stragglers on model accuracy and training latency.

Methods This paper designs an FL architecture integrating joint edge-assisted training and adaptive sparsity and proposes an adaptively sparse FL optimization algorithm based on edge-assisted training. First, an edge server is introduced to provide auxiliary training for devices with limited computing power or energy. This reduces the training delay of the FL system, enables stragglers to continue participating in the training process, and helps maintain model accuracy. Specifically, an optimization model for auxiliary training, communication,

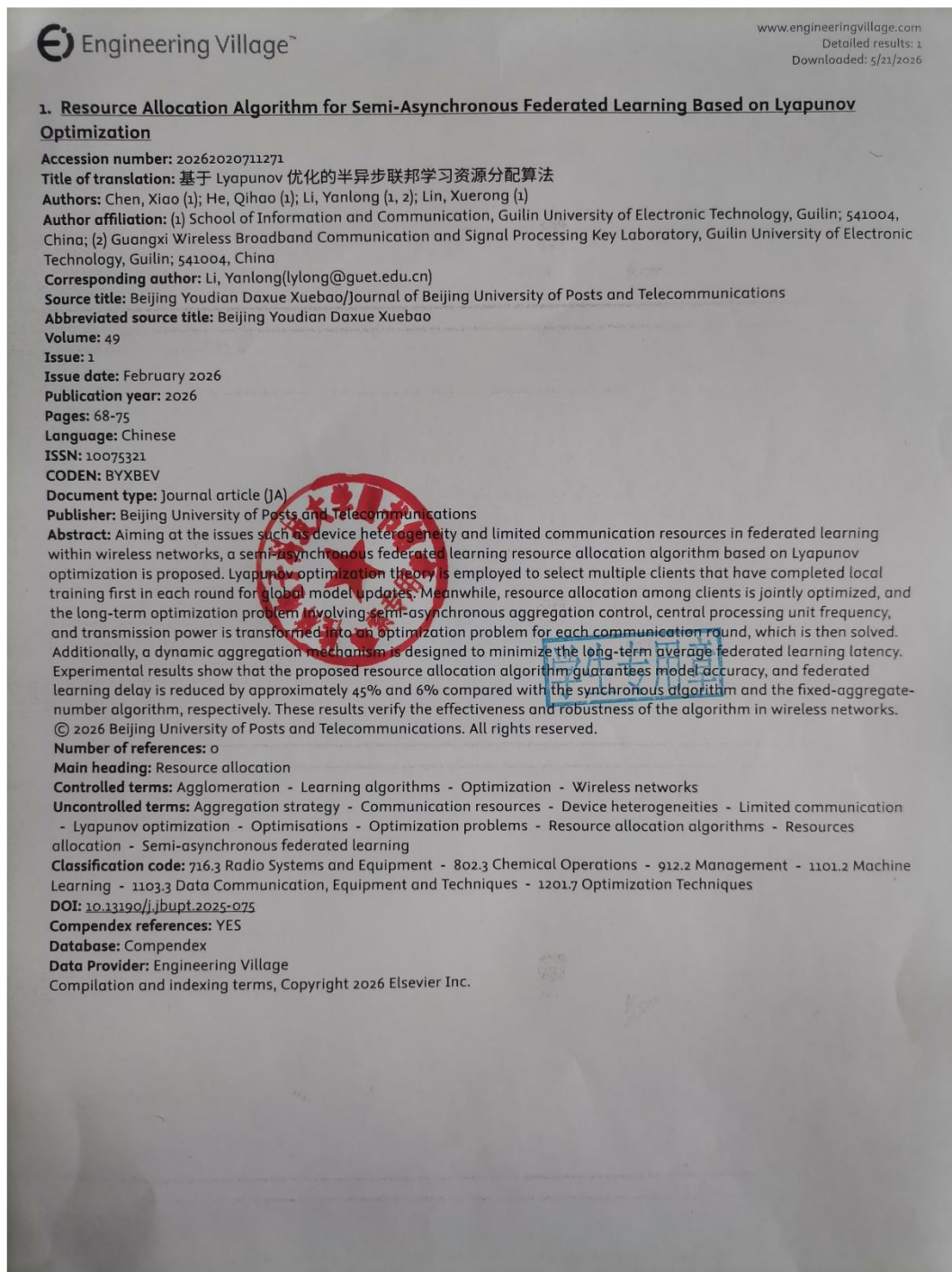
and computing resource allocation is constructed. Several deep reinforcement learning methods are then applied to obtain the optimized auxiliary training decision. Second, based on the auxiliary training decision, unstructured pruning is adaptively performed on the global model during each communication round to further reduce device delay and energy consumption.

Results and Discussions The proposed framework and algorithm are evaluated through extensive simulations. The results demonstrate the effectiveness and efficiency of the proposed method in terms of model accuracy and training delay. The proposed algorithm achieves an accuracy rate approximately 5% higher than that of the FL algorithm on both the MNIST and CIFAR-10 datasets. This improvement results from low-computing-power and low-energy devices failing to transmit their local models to the central server during multiple communication rounds, reducing the global model's accuracy (Table 3). The proposed algorithm achieves an accuracy rate 18% higher than that of the FL algorithm on the MNIST-10 dataset when the data on each device follow a non-IID distribution. Statistical heterogeneity exacerbates model degradation caused by stragglers, whereas the proposed algorithm significantly improves model accuracy under such conditions (Table 4). The reward curves of different algorithms are presented (Fig. 7). The reward of FL remains constant, while the reward of EAFL_RANDOM fluctuates randomly. ASEAFD_DDPG shows a more stable reward curve once training episodes exceed 120 due to the strong learning and decision-making capabilities of DDPG and DQN. In contrast, EAFL_DQN converges more slowly and maintains a lower reward than the proposed algorithm, mainly due to more precise decision-making in the continuous action space and an exploration mechanism that expands action selection (Fig. 7). When the computing power of the edge server increases, the training delay of the FL algorithm remains constant since it does not involve auxiliary training. The training delay of EAFL_RANDOM fluctuates randomly, while the delays of ASEAFD_DDPG and EAFL_DQN decrease. However, ASEAFD_DDPG consistently achieves a lower system training delay than EAFL_DQN under the same MEC computing power conditions (Fig. 9). When the communication bandwidth between the edge server and devices increases, the training delay of the FL algorithm remains unchanged as it does not involve auxiliary training. The training delay of EAFL_RANDOM fluctuates randomly, while the delays of ASEAFD_DDPG and EAFL_DQN decrease. ASEAFD_DDPG consistently achieves lower system training delay than EAFL_DQN under the same bandwidth conditions (Fig. 10).

Conclusions The proposed sparse-adaptive FL architecture based on an edge-assisted server mitigates the straggler problem caused by system heterogeneity from two perspectives. By reducing the number of stragglers, the proposed algorithm achieves higher model accuracy compared with the traditional FL algorithm, effectively decreases system training delay, and improves model training efficiency. This framework holds practical value, particularly for FL deployments where aggregation devices are selected based on statistical characteristics, such as model contribution rates. Straggler issues are common in such FL scenarios, and the proposed architecture effectively reduces their occurrence. Simultaneously, devices with high model contribution rates can continue participating in multiple rounds of federated training, lowering the central server's frequent device selection overhead. Additionally, in resource-constrained FL environments, edge servers can perform more diverse and flexible tasks, such as partial auxiliary training and partitioned model training.

Key words: Federated Learning (FL); Edge server; Adaptive sparsity; Deep reinforcement learning; Unstructured pruning

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基于 Lyapunov 优化的半异步联邦学习资源分配算法

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摘要: 针对无线网络中联邦学习面临的设备异构性、通信资源受限等问题,提出了基于 Lyapunov 优化的半异步联邦学习资源分配算法。该算法通过 Lyapunov 优化理论选择每轮率先完成本地训练的多个客户端参与全局模型更新,同时联合优化客户端的资源分配,将半异步聚合控制、中央处理器频率与发射功率的长期优化问题转化为每个通信轮次的优化问题并求解,进一步设计动态聚合机制,最小化了长期平均联邦学习时延。实验结果表明,所提资源分配算法在保证模型精度的同时,较同步算法和固定聚合数量算法分别降低了约 45% 和 6% 的联邦学习时延,验证了该算法在无线网络中的有效性和稳健性。

关键词: 半异步联邦学习; 资源分配; Lyapunov 优化; 聚合策略

中图分类号: TP181

文献标志码: A

Resource Allocation Algorithm for Semi-Asynchronous Federated Learning Based on Lyapunov Optimization

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Abstract: Aiming at the issues such as device heterogeneity and limited communication resources in federated learning within wireless networks, a semi-asynchronous federated learning resource allocation algorithm based on Lyapunov optimization is proposed. Lyapunov optimization theory is employed to select multiple clients that have completed local training first in each round for global model updates. Meanwhile, resource allocation among clients is jointly optimized, and the long-term optimization problem involving semi-asynchronous aggregation control, central processing unit frequency, and transmission power is transformed into an optimization problem for each communication round, which is then solved. Additionally, a dynamic aggregation mechanism is designed to minimize the long-term average federated learning latency. Experimental results show that the proposed resource allocation algorithm guarantees model accuracy, and federated learning delay is reduced by approximately 45% and 6% compared with the synchronous algorithm and the fixed-aggregate-number algorithm, respectively. These results verify the effectiveness and robustness of the algorithm in wireless networks.

Key words: semi-asynchronous federated learning; resource allocation; Lyapunov optimization; aggregation strategy

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随着无线网络感知和计算能力的提升,智能设备数量的高速增长产生了大量的数据,充分利用这些数据将极大地促进无线网络为智能设备提供安全、高效的服务。然而,传统的集中式学习会导致数据传输负载过重以及隐私数据的泄露^[1],实际运用到机器学习训练任务的数据相对有限且多数以数据孤岛的形式存在。因此,分布式训练的联邦学习应运而生,其允许设备完成训练过程而无需将原始数据上传至服务器^[2]。目前,联邦学习已在移动云计算、工业互联网、物联网和端对端通信等领域中取得了广泛的应用^[3]。但在无线网络中,部署联邦学习需要考虑以下现实挑战:一是设备异构性,各种边缘设备具有不同的数据量、计算能力及信道状态;二是通信资源有限,服务器与客户端之间频繁模型传输会消耗大量的通信带宽,网络易出现拥塞现象^[4]。

上述问题不仅会导致同步联邦学习中算力强的节点总是等待算力弱的节点,造成计算资源和时间的浪费^[5],还会使得异步联邦学习中存在陈旧的模型更新,降低训练精度^[6]。半异步联邦学习凭借高效的训练框架,能够有效应对以上挑战^[7],其中聚合服务器捕获并存储率先上传的局部模型,随后在特定的时间段内完成聚合,反复迭代直至模型收敛。

自半异步联邦学习框架提出以来,学者持续致力于提升其在无线网络中的应用性能,研究主要集中于聚合策略与优化方案的设计^[8]。Nguyen 等^[9]提出了缓冲异步聚合机制,当 K 个梯度更新上传至特定缓冲区时,服务器执行全局聚合操作。Chen 等^[10]利用多臂老虎机算法识别客户端计算与通信能力,据此动态分配本地更新次数,同时设计两种半异步聚合规则,分别为自适应更新和固定更新。He 等^[11]建立基于历史参与次数的陈旧模型筛选策略,服务器按设备历史参与次数排序,优先选择参与次数少的设备模型进行聚合。Xu 等^[12]通过基于区块链的领导节点选举机制和审计机制设计半异步聚合算法。上述文献中的聚合策略依赖系统状态的历史信息,当无线网络突发波动时系统无法实时调整,可能导致低质量的模型参数聚合以及模型陈旧性问题。Ao 等^[13]提出了半异步联邦拆分学习框架,该框架支持个性化模型拆分与半异步聚合,并设计 Lyapunov 虚拟队列优化训练能耗。Sun 等^[14]基于 Lyapunov 优化框架,将模型陈旧性约束转化为队列稳定问题,动态调整每轮聚合客户端数。上述文献

中的队列机制仅将 Lyapunov 队列控制作为约束条件嵌入算法流程,并未充分发挥其在无线网络排队问题的优势。

针对上述问题,笔者联合考虑了无线半异步联邦学习网络中每轮的聚合策略和各设备中央处理器(CPU, central processing unit)频率与发射功率的控制问题。该问题的目标是在长期功率消耗约束下最小化联邦学习时延,并考虑到客户端设备的异构性,提出了基于 Lyapunov 优化的半异步联邦学习资源分配(L-SAFLRA, Lyapunov-based semi-asynchronous federated learning resource allocation)算法。该半异步联邦学习的聚合策略为每轮服务器聚合率先完成训练并上传的多个客户端,并为参与该轮聚合的客户端分配 CPU 频率和发射功率。将 Lyapunov 优化与半异步联邦学习相结合,将长期优化问题分解为每轮确定性问题,不仅确保队列稳定和长期功率约束满足,还以较低的计算复杂度保障联邦学习模型的收敛。

1 系统模型

在无线网络中设计一个新颖的半异步联邦学习框架,该框架由 K 个异构无线客户端和 1 个服务器构成,如图 1 所示。

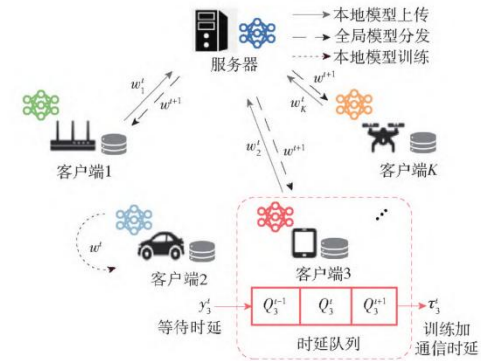


图 1 半异步联邦学习系统框图

在每轮训练中,服务器优先聚合最快完成本地训练并上传局部更新的客户端,且根据每轮系统状态动态调整聚合数量。而未及时完成训练的客户端将在后续轮次中继续参与训练。此机制通过缓解同步机制中等待最慢客户端引起的资源浪费,同时避免完全异步机制可能引发的模型陈旧性偏差。在所提框架中,每个客户端 $k \in \{1, 2, \dots, K\}$ 均具有

本地数据集 $D_k = \{(x_k^i, y_k^i)\}$, 其中 x_k^i 和 y_k^i 分别为客户端 k 的第 i 个样本及其对应标签, $|D_k|$ 为客户端 k 本地数据集的样本数量。

1.1 学习模型

所提半异步联邦学习框架假设共进行 ϕ 轮全局迭代, 在每个客户端 k 上执行机器学习任务。进一步引入 $j_k(x_k^i, y_k^i, w_k^t) = \frac{1}{2}(x_k^{iT} w_k^t - y_k^i)^2$ 为数据样本 i 的损失函数, w_k^t 为客户端 k 在训练轮次 $t = 0, 1, \dots, \phi - 1$ 中的学习模型, 该损失函数捕获了模型预测值与标签之间的差距。因此, 客户端 k 的损失函数可以定义为

$$J_k(w_k^t) = \frac{1}{|D_k|} \sum_{i=1}^{|D_k|} j_k(x_k^i, y_k^i, w_k^t) \quad (1)$$

客户端 k 的本地模型更新方式为

$$w_k^t = w_k^{t-1} - \eta \nabla J_k(w_k^{t-1}) \quad (2)$$

其中: η 为预定义的学习率。

1.2 功率消耗模型

在所提框架下, 每个客户端的功率消耗由本地训练功率消耗和模型上传功率消耗两部分组成。将服务器在训练轮次 t 分配给客户端 k 的 CPU 频率定义为 f_k^t , 则进行一次本地训练的功率消耗计算可以表示为 $G_k^{t,lr} = \gamma (f_k^t)^3$, γ 为客户端的电容系数^[3]。将 p_k^t 定义为服务器在训练轮次 t 分配给客户端 k 的发射功率, 则上传本地模型的功率消耗为 $G_k^{t,up} = p_k^t$, 因此, 训练轮次 t 期间客户端 k 的功率消耗为

$$G_k^t = G_k^{t,lr} + G_k^{t,up} \quad (3)$$

1.3 时延模型

客户端 k 处理单位数据样本所需要的 CPU 周期数为 C_k , 则进行一次局部梯度计算的本地训练时延可以表示为

$$\tau_k^{t,lr} = \frac{C_k |D_k|}{f_k^t} \quad (4)$$

当本地训练完成后, 客户端通过正交频分多址 (OFDMA, orthogonal frequency division multiple access) 将其局部更新上传至服务器。总可用带宽为 B , 假定该带宽在每一训练轮次期间平均分配给所有客户端。因此, 在每轮客户端 k 所分配到的带宽可以表示为 $B_k = \frac{B}{K}$ 。

根据香农公式, 将本地模型的上传速率定义为 $r_k^t = B_k \log \left(1 + \frac{p_k^t h_k}{B_k N_0} \right)$, 其中, h_k 为客户端与服务器之

间的信道增益, N_0 为噪声功率谱密度。则模型上传时延为

$$\tau_k^{t,up} = \frac{Z}{r_k^t} = \frac{Z}{B_k \log \left(1 + \frac{p_k^t h_k}{B_k N_0} \right)} \quad (5)$$

其中: Z 为机器学习模型大小。

所以客户端 k 的训练加通信时延为训练时延与上传时延之和, 即

$$\tau_k^t = \tau_k^{t,lr} + \tau_k^{t,up} \quad (6)$$

所提框架假设服务器端具有较强的计算能力和较大的存储空间, 与局部训练过程相比, 可以忽略服务器端的聚合时延和聚合功率消耗, 以及服务器向客户端分发全局模型的时延与功率消耗。

将 M^t 定义为训练轮次 t 的聚合数量, 则在每一训练轮次中, 服务器优先聚合前 M^t 个完成训练并上传的客户端, 无需等待所有客户端的局部训练进程, 所以每轮联邦学习时延取决于当前轮次最后一个完成训练并上传的客户端总时延, 即

$$\tau^t = \max_{k \in \{1, 2, \dots, K\}} \{a_k^t \tau_k^t\} \quad (7)$$

其中: 将 $a^t = \{a_1^t, a_2^t, \dots, a_K^t\}$ 定义为训练轮次 t 的聚合策略, $a_k^t = 1$ 表示客户端 k 在训练轮次 t 参与全局聚合, 否则, 则相反。则该轮次的参与聚合的客户端数量为 $M^t = \sum_{k=1}^K a_k^t$ 。

综上, 半异步联邦学习框架的训练过程示例如图2所示。假设该框架由1个服务器和4个客户端构成, 训练之初, 服务器向4个客户端发送初始全局模型 w^0 , 并为4个客户端分配当前的 CPU 频率 $f^1 = \{f_1^1, f_2^1, f_3^1, f_4^1\}$ 和发射功率 $p^1 = \{p_1^1, p_2^1, p_3^1, p_4^1\}$ 。各个客户端利用其自身数据集训练当前全局模型, 轮次1中客户端1和客户端3先完成训练并上传局部更新 w_1^1 和 w_3^1 , 服务器执行聚合操作。客户端3在客户端1之后上传, 则轮次1的联邦学习时延 τ^1 为

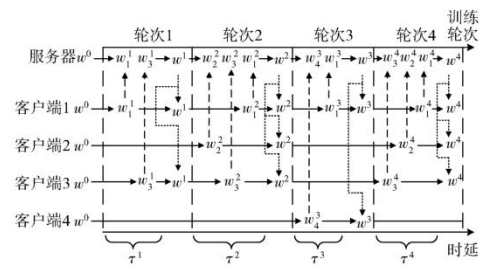


图2 半异步联邦学习过程

客户端 3 训练时延与上传时延之和 $\tau^1 = \tau_3^{1,lr} + \tau_3^{1,up}$ 。轮次 2 开始前服务器向客户端 1 和 3 分发聚合了 w_1^1 和 w_3^1 的全局模型,并为客户端 1 和 3 分配 CPU 频率 $f^2 = \{f_1^2, f_3^2\}$ 和发射功率 $p^2 = \{p_1^2, p_3^2\}$ 以进行新一轮次的训练。轮次 2 中客户端 1、2、3 分别完成训练并上传其局部更新,且该轮次客户端 1 最后一个上传,则轮次 2 的联邦学习时延 τ^2 为客户端 1 训练时延与上传时延之和为 $\tau^2 = \tau_1^{2,lr} + \tau_1^{2,up}$ 。

1.4 问题描述

在无线网络中,客户端资源的异构性直接导致训练与上传时延的不均衡,可通过动态聚合策略优先选择快速客户端优化时延,规避同步等待损耗。在无线网络资源受限的情况下,客户端功率消耗与 CPU 频率、发射功率分配强相关,以时延为目标并联合调控计算资源与通信参数,在功率消耗约束下实现效率最大化。通过有限训练轮次内的优化,最小化联邦学习时延。基于上述定义,考虑了一个关于联邦学习时延的优化问题,该问题通过联合优化 CPU 频率和发射功率的控制与聚合策略,最大程度地减少系统时延:

$$\begin{aligned} \text{P1: } \min_{f^t, p^t, a^t} & \frac{1}{\phi} \sum_{t=1}^{\phi} \tau^t \\ \text{s. t. C1: } & \max_{k \in \{1, 2, \dots, K\}} \{a_k^t \tau_k^t\} = \tau^t \\ \text{C2: } & a_k^t \in \{0, 1\} \\ \text{C3: } & \sum_{k=1}^K G_k^t \leq G^{\text{total}} \\ \text{C4: } & f_k^{\min} \leq f_k^t \leq f_k^{\max} \\ \text{C5: } & p_k^{\min} \leq p_k^t \leq p_k^{\max} \end{aligned} \quad (8)$$

其中:约束 C1 表示每轮时延由当前训练轮次参与全局聚合的最慢客户端决定。约束 C2 表示客户端是否被选中参与聚合, $a_k^t = 1$ 表示客户端 k 在训练轮次 t 参与全局聚合,反之亦然。约束 C3 表示处在无线网络中的客户端每轮学习受到总功率消耗上限 G^{total} 的限制,即每轮所有客户端的功率消耗总和不得超过。约束 C4 表示任意客户端 k 的 CPU 频率存在上界 $f_k^{\max}$ 与下界 $f_k^{\min}$ 。约束 C5 表示任意客户端 k 的发射功率存在上界 $p_k^{\max}$ 与下界 $p_k^{\min}$ 。约束 C4 和约束 C5 中的上下界由客户端的硬件能力和通信标准共同决定,旨在保证优化结果在实际系统中的可行性。

2 随机优化理论问题转换

由于平均时间优化目标和多客户端累计功率消

耗的限制,优化问题 P1 的本质是长期多目标约束下的动态决策问题,对其直接解决是不可行的。为了解决这一问题,将问题 P1 转换为一系列的子问题,且该方案不依赖于任何先验信息。

2.1 Lyapunov 优化

通过应用 Lyapunov 优化理论^[15]和队列控制技术的引入来实现这种转变。该方法可将复杂的长期随机优化问题分解为实时优化问题,无需系统随机性的先验知识即可平衡多约束耦合,并保证系统在无线网络场景中的性能。为了应对时延约束,将各个客户端的训练加通信时延及其等待时延(此轮参与聚合的最慢客户端的训练加通信时延与自身训练加通信时延的差值),构造成 Lyapunov 实际队列:

$$Q_k^{t+1} = \max(Q_k^t - \tau_k^t, 0) + y_k^t \quad (9)$$

其中: y_k^t 为客户端 k 的等待时延,且任意客户端 k 的队列初始条件均为 $Q_k^1 = 0$ 。

以图 2 为例,在轮次 1 中客户端 1 和客户端 3 参与此轮聚合,且客户端 3 在客户端 1 后上传,则该轮次客户端 1 的等待时延 $y_1^1 = \tau^1 - \tau_1^1 = \tau_3^1 - \tau_1^1$,由于客户端 3 没有等待任何客户端,其等待时延为 0。轮次 1 中客户端 2 和客户端 4 都未完成训练,则其等待时延 $y_2^1 = y_4^1 = 0$,但客户端 2 和客户端 4 在此轮的训练加通信时延为轮次 1 的联邦学习时延,即 $\tau_2^1 = \tau_4^1 = \tau^1$ 。各个客户端根据式(9)分别使用对应的等待时延和训练加通信时延更新 Lyapunov 队列。轮次 2 中客户端 1、2、3 参与此轮聚合,此时客户端 2 在轮次 2 中的训练加通信时延为其完整进行一次局部训练和模型上传的时延之和与上一轮次联邦学习时延的差值, $\tau_2^2 = \tau_2^{1,lr} + \tau_2^{1,up} - \tau^1$ 。由于该轮次客户端 1 最后完成上传,则客户端 2 在此轮的等待时延为 $y_2^2 = \tau^2 - \tau_2^2 = \tau_1^2 - \tau_2^2$ 。后续轮次,以此类推。

为了维持队列的平均速率稳定性, Lyapunov 函数构建为

$$L(Q^t) = \frac{1}{2} \sum_{k=1}^K (Q_k^t)^2 \quad (10)$$

其中: $Q^t = \{Q_1^t, Q_2^t, \dots, Q_K^t\}$ 表示所有队列。引入连续轮次之间 Lyapunov 函数的差异,称为 Lyapunov 漂移,以衡量预期的队列变化:

$$\Delta(Q^t) = E\{L(Q^{t+1}) - L(Q^t) | Q^t\} \quad (11)$$

为了限制该时延队列的增长并最大程度地降低成本函数,将目标函数映射为惩罚函数并整合到 Lyapunov 漂移中。因此,漂移加成本函数定义为

$$\Delta(Q^t) + VE\{\tau^t | Q^t\} \quad (12)$$

其中: $V > 0$ 为权衡参数, 用于平衡最小化目标函数和满足队列稳定之间的权衡。根据上式可得, 该优化目标仅涉及当前训练轮次 t , 这表明原始优化问题 P1 可以在每轮迭代求解的基础上转化为实时问题。

通过每个轮次的控制决策最小化漂移加惩罚项, 将队列积压始终推向较低的拥塞并保持网络的稳定性。首先计算 Lyapunov 漂移的上界:

$$\begin{aligned} \Delta(Q^t) &\triangleq E\{L(Q^{t+1}) - L(Q^t) | Q^t\} \leq \\ &\frac{1}{2} \sum_{k=1}^K E\{(Q_k^t - \tau_k^t + y_k^t)^2 - (Q_k^t)^2\} \leq \\ &\frac{1}{2} \sum_{k=1}^K E\{(y_k^t - \tau_k^t)^2 + 2Q_k^t(y_k^t - \tau_k^t)\} \leq \\ &A_1 + \sum_{k=1}^K E\{Q_k^t(y_k^t - \tau_k^t)\} \end{aligned} \quad (13)$$

其中: A_1 为常数, 取值为 $\frac{1}{2} \sum_{k=1}^K E\{(y_k^t - \tau_k^t)^2 | Q^t\}$ 的上界。Lyapunov 优化理论的应用提供了有关漂移加惩罚函数上限的相关引理, 通过在上式两侧添加目标函数, 可以获得漂移加惩罚函数的上界:

$$\begin{aligned} \Delta(Q^t) + VE\{\tau^t | Q^t\} &\leq \\ A_1 + VE\{\tau^t | Q^t\} + \sum_{k=1}^K E\{Q_k^t(y_k^t - \tau_k^t) | Q^t\} &\leq \\ A_2 + VE\{\tau^t | Q^t\} + \sum_{k=1}^K E\{Q_k^t \tau^t | Q^t\} \end{aligned} \quad (14)$$

其中: A_2 为常数, 取值为 $\sum_{k=1}^K E\{(y_k^t - \tau_k^t)^2 | Q^t\} - 2 \sum_{k=1}^K E\{Q_k^t \tau_k^t | Q^t\}$ 的上界。

由上式可得, Lyapunov 漂移项加系统目标函数有确定性上界, 对于原优化等式, 不是通过直接对其最小化, 而是对其确定性上界进行最小化。将漂移加惩罚项上界与优化变量无关的项去除, 得到新的优化目标, 得出优化问题的转化:

$$\begin{aligned} \text{P2: } \min_{f^t, p^t, a^t} &\left(\sum_{k=1}^K Q_k^t + V \right) \tau^t \\ \text{s. t. } &\text{P1: C1} \sim \text{C5} \end{aligned} \quad (15)$$

该问题为一个混合整数问题, 直接解决难以实现。利用交替迭代的思路, 先固定聚合策略 a^t , 对于任意给定的 a^t , 由于客户端的训练时延和上传时延随 f_k^t 和 p_k^t 的变化呈现凸函数特性, 每轮时延为参与聚合的客户端总时延的最大值作为目标函数符合凸优化理论, 且总功率约束为线性约束。将 P2 的目标函数转化为一个与客户端 CPU 频率和发射功率相

关的凸函数:

$$\begin{aligned} \text{P3: } \min_{f^t, p^t} &\left(\sum_{k=1}^K Q_k^t + V \right) \tau^t \\ \text{s. t. } &\text{P1: C3} \sim \text{C5} \end{aligned} \quad (16)$$

2.2 问题求解

在问题 P3 中, 仅对参与聚合的客户端进行 CPU 频率和发射功率的分配, 不参与聚合的客户端则沿用上一轮的 CPU 频率和发射功率继续完成训练。可以通过拉格朗日乘子法解决凸优化问题 P3, 分别有效获取所选客户端的最优 CPU 频率和发射功率。

由于每一轮次的联邦学习时延取决于参与聚合的最慢客户端, 则其余参与聚合的客户端的训练加通信时延不超过当前轮次的联邦学习时延, 引入 $\lambda_k \geq 0$ 为客户端 k 的时延约束乘子。对应约束 C3, 引入 $\mu \geq 0$ 为总功率约束乘子。通过求解拉格朗日函数, 分别得到 CPU 频率和发射功率的最优解分别为

$$\begin{aligned} (f_k^t)^* &= \\ \begin{cases} \min \left(f_k^{\max}, \max \left(f_k^{\min}, \sqrt{\frac{\lambda_k C_k |D_k|}{3\mu\gamma}} \right) \right), & a_k^t = 1 \\ f_k^{t-1}, & a_k^t = 0 \end{cases} \end{aligned} \quad (17)$$

$$\begin{aligned} (p_k^t)^* &= \\ \begin{cases} \min \left(p_k^{\max}, \max \left(p_k^{\min}, \frac{bN_0}{h_k} \left(\frac{\lambda_k h_k Z}{\mu b^2 N_0 \ln 2} - 1 \right) \right) \right), & a_k^t = 1 \\ p_k^{t-1}, & a_k^t = 0 \end{cases} \end{aligned} \quad (18)$$

建立了最优的 CPU 频率和发射功率, 优化问题 P2 转换为仅关于聚合策略 a^t 的函数:

$$\begin{aligned} \text{P4: } \min_{a^t} &\left(\sum_{k=1}^K Q_k^t + V \right) \tau^t \\ \text{s. t. } &\text{P1: C1} \sim \text{C2} \\ \text{C3: } &f_k^t = (f_k^t)^*, p_k^t = (p_k^t)^* \end{aligned} \quad (19)$$

解决问题 P4 的直接策略是遍历所有可能的聚合数量选择方案, 然后选择目标函数最小的方案。通过交替迭代的方式求解原联合优化问题 P2, 将原混合整数规划问题分解为一系列易于求解的凸优化子问题, 并在一个有限的离散空间中进行搜索, 得出 CPU 频率、发射功率以及聚合策略这三者的最优解。

2.3 最优性分析

考虑到最小化平均时延成本和满足总功率消耗

上限约束之间的权衡,对 L-SAFLRA 算法的最优性进行了分析。

定理 1 假设每个客户端 k 的等待时延与队列积压存在上界,即 $y_k^{\max} \geq y_k^t, Q_k^{\max} \geq Q_k^t$,则平均时延成本函数满足:

$$\frac{1}{T} \sum_{t=1}^T E\{\tau^t | Q^t\} \leq \frac{A_3}{V} + \psi^* \quad (20)$$

其中: A_3 为常数,取值为 $A_1 + \sum_{k=1}^K Q_k^{\max} \max(y_k^{\max} - \tau_k^t)$ 的上界; ψ^* 为优化问题 P1 的最优解。

定理 2 假设每轮联邦学习时延存在上界与下界,即 $\psi^{\min} \leq \tau^t \leq \psi^{\max}$,存在变量 $\varepsilon > 0$,使得客户端的时延队列满足:

$$\frac{1}{T} \sum_{t=1}^T \sum_{k=1}^K E\{Q_k^t | Q^t\} \leq \frac{A_1 + V(\psi^{\max} - \psi^{\min})}{\varepsilon} \quad (21)$$

定理 2 表明,时延队列的积压是有界的,即所有队列在联邦学习迭代期间保持平均速率稳定。定理 1 和定理 2 的证明过程可参考 Lyapunov 优化理论^[15]。

3 仿真结果与分析

3.1 实验设置

通过使用 Matlab 机器学习工具箱进行手写数字识别及图像分类任务。对于手写数字识别,每个客户端使用改良国家标准与技术研究院(MNIST, modified national institute of standards and technology)数据集^[4]训练由 50 个神经元组成的前馈神经网络。对于图像分类任务,每个客户端使用加拿大高级研究所-10 类(CIFAR-10, canadian institute for advanced research-10 classes)数据集^[5]训练卷积神经网络,以验证所提 L-SAFLRA 算法在更复杂场景下的有效性。

每个客户端 k 的数据集大小 $|D_k|$ 在 $[300, 500]$ 区间内分布,呈现数据不平衡特性。服务器与每个客户端 k 之间的信道增益 h_k 也呈现出异构性,其值在 $-20 \sim 14$ dB 之间分布。客户端总数设置为 10 个,共执行 150 轮全局迭代,其他关键参数如表 1 所示。

为了证明所提算法的优势,引入以下算法作为对比算法:①同步算法,所有客户端均参与训练且同时参加全局聚合^[2];②固定聚合数量算法,每轮参与全局聚合的客户端数量是固定的,设定每轮聚合

表 1 仿真参数

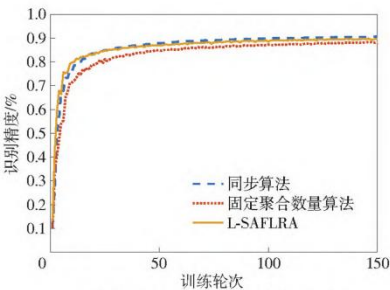
参数	取值
$N_0 / (\text{dBm} \cdot \text{Hz}^{-1})$	-100
B / MHz	1
Z / MHz	1
$f_k^{\min} / \text{GHz}$	1
$f_k^{\max} / \text{GHz}$	2.5
$p_k^{\min} / \text{W}$	0.01
$p_k^{\max} / \text{W}$	0.1
$G^{\text{total}} / \text{W}$	10
γ	10^{-28}
V	100

数量为客户端总数的一半^[9]。

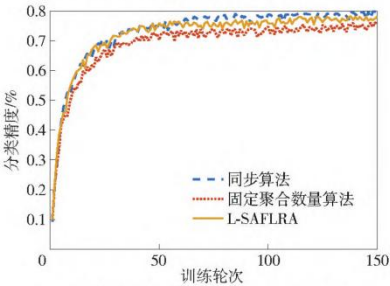
2 种对比算法中,每个客户端的资源分配均采用未做优化的 CPU 频率和发射功率,其值分别与 L-SAFLRA 算法第一个训练轮次的 CPU 频率和发射功率相等,且固定该资源分配执行每一轮次的训练。

3.2 仿真结果分析

图 3 所示为所提的 L-SAFLRA 算法和对比算法在 MNIST 和 CIFAR-10 数据集上的识别精度与分类精度随训练轮次的变化。可见,L-SAFLRA 算法在 2



(a) 在 MNIST 数据集上的识别精度对比



(b) 在 CIFAR-10 数据集上的分类精度对比

图 3 各算法在 2 个数据集上的精度对比

个数据集上的性能表现接近于同步算法,略高于固定聚合数量算法,且 L-SAFLRA 算法较快达到收敛状态。这是因为 L-SAFLRA 算法通过优化每轮每个客户端的资源分配与聚合策略,在每轮参与聚合数量不一致的情况下,达到了所有参与训练的客户端全局聚合的性能。固定聚合数量算法虽减少了等待时延,但因聚合数量固定,可能纳入性能较差的客户端模型,导致模型更新有效性下降,因此精度始终低于其他两种算法。

L-SAFLRA 算法和对比算法的联邦学习时延随训练轮次的变化如图 4 所示。可见,L-SAFLRA 算法的时延表现更高效,因为所提算法无需等待所有客户端完成训练并上传才执行聚合操作,这极大降低了设备、环境异构性的影响。通过 Lyapunov 优化,根据系统状态灵活调整聚合策略,避免了因固定聚合数量导致的资源浪费。结合图 3 可知,L-SAFLRA 算法在达到与同步算法相近性能的同时,降低了约 45% 的联邦学习时延。L-SAFLRA 算法与固定聚合数量算法相比,所耗时延降低约 6%,能更快地达到收敛且性能更好。

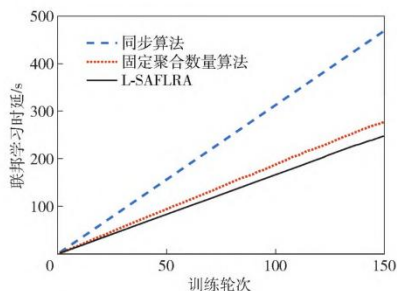


图 4 不同算法的联邦学习时延

每轮参与全局聚合的客户端数量如图 5 所示。可见,L-SAFLRA 算法每轮参与全局聚合的客户端数量呈动态变化,该算法优势在于每轮聚合数量不是固定的,而是通过 Lyapunov 优化根据每轮系统状态、信道条件、功率消耗等联合优化得出。

不同的信道条件对平均联邦学习时延的影响如图 6 所示。随着信道质量变差,模型上传时延增大,导致平均联邦学习时延增大。然而即便在极端信道条件下,时延的增长幅度仍较为平缓,这是因为 L-SAFLRA 算法通过 Lyapunov 优化动态提升发射功率补偿信道损耗,缓解极端信道对时延的影响,验证了 L-SAFLRA 算法在信道突变与极端条件下的鲁

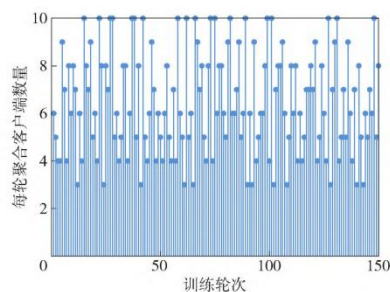


图 5 每轮参与聚合客户端数量

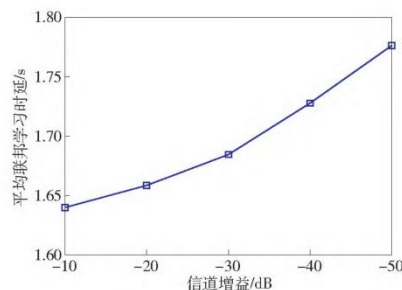


图 6 不同信道增益下的平均联邦学习时延对比

棒性。

不同的 Lyapunov 参数 V 对所提 L-SAFLRA 算法平均联邦学习时延和平均队列积压的影响如图 7 所示。可见,随着 V 的增大,L-SAFLRA 算法优先最小化当前轮次时延,使联邦学习时延减少,但会造成整体队列积压的增大,这是因为过度追求低时延可能导致部分客户端因资源分配不足而使得其余客户端积累等待时延。合理调整参数 V ,可以有效平衡即时成本优化与系统长期稳定性。当 V 取值为 100 时,L-SAFLRA 算法可以在降低联邦学习时延和保持队列稳定之间取得有效平衡。图 7 也验证了定理 1 和定理 2 对平均时延和时延队列的最优性分析。

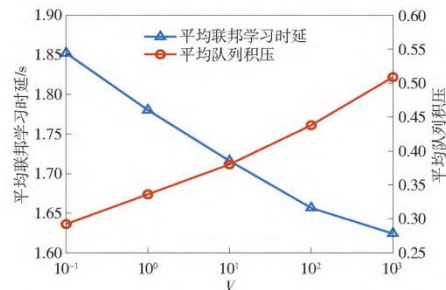


图 7 平均联邦学习时延和平均队列积压随参数 V 的变化

4 结束语

笔者提出了半异步联邦学习资源分配算法, 该算法通过动态调整每轮聚合的客户端数量并联合优化客户端的 CPU 频率与发射功率分配, 在无线网络中实现了低时延、高能效的模型训练。L-SAFLRA 算法基于 Lyapunov 优化框架, 将长期功率约束与时延均衡问题转化为在线决策, 优先聚合最快完成训练的客户端, 有效缓解了同步机制的资源浪费与异步机制的模型陈旧性问题。实验结果表明, 相比传统同步算法与固定聚合数量算法, L-SAFLRA 算法在保证模型精度的同时大幅降低了联邦训练时延, 且 Lyapunov 队列稳定性验证了系统的长期可靠性。未来可探索将强化学习、差分隐私技术、数字孪生等方法与半异步联邦学习资源分配相结合, 提升大规模无线网络的半异步联邦学习可扩展性与鲁棒性。

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Review

Fundamentals, Key Technologies and Networking of Ultraviolet Non-Line-of-Sight Scattering Communication: A Review

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Abstract

Traditional wireless communication signals are often susceptible to physical obstructions and background noise in complex geographical environments or adverse weather conditions, hindering stable and reliable data transmission. Ultraviolet communication (UVC) offers a compelling solution; its unique scattering mechanism and low background noise characteristics facilitate robust communication under non-line-of-sight (NLOS) conditions. At present, there remains a relative lack of comprehensive reviews spanning UVC, including fundamental theory, physical devices, channel models and networking technologies. This review synthesizes the current state of global research, providing a systematic overview of the background, advantages and application scenarios of UVC. It examines the hardware characteristics of light sources and detectors, evaluates NLOS scattering channel models, analyzes key signal processing techniques, including modulation/demodulation, coding/decoding and multiple-input multiple-output technology. Furthermore, this review conducts an in-depth analysis of multi-user networking protocols and three-dimensional topology control mechanisms. Finally, it identifies the prevailing technical challenges and outlines promising directions for future development.

Keywords: ultraviolet communication; non-line-of-sight; scattering mechanism; multi-user networking



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1. Introduction

With the advent of the information age, the explosion of daily human information has driven the rapid development of communication technologies. While modern systems have achieved significant milestones in transmission speed and coverage, maintaining robust, high-quality connectivity in complex or hostile environments remains a formidable challenge. Conventional radio frequency (RF) communications are increasingly hindered by electromagnetic interference (EMI), stringent licensing requirements, and the escalating scarcity of available spectrum [1]. Similarly, although visible light communication (VLC) offers high bandwidth and capacity, its efficacy is inherently limited by a strict reliance on line-of-sight (LOS) links and high susceptibility to ambient light interference and physical obstructions. Infrared (IR) communication, while cost-effective and hardware-simple, suffers from intense solar interference in outdoor settings, restricting its utility

primarily to short-range, indoor LOS scenarios [2]. In contrast, ultraviolet communication (UVC)—leveraging its unique low solar background noise and potent scattering properties—presents unparalleled advantages for robust, non-line-of-sight (NLOS) connectivity in challenging environments. Consequently, UVC is rapidly emerging as a pivotal research frontier for next-generation wireless communication systems [3–6].

Ultraviolet (UV) radiation encompasses electromagnetic waves with wavelengths ranging from 10 nm to 400 nm. Current academic research predominantly focuses on the deep ultraviolet (UV-C) band, specifically the 200–280 nm range [7,8], as illustrated in Figure 1. Due to the intensive absorption by the stratospheric ozone layer, solar radiation in the UV-C spectrum is effectively filtered before reaching the Earth’s surface. This phenomenon creates a “solar-blind” window where background noise is negligible, significantly enhancing signal-to-noise ratios [9]. Furthermore, the interaction between UV light and atmospheric constituents, such as gas molecules and aerosols, induces strong scattering effects. This mechanism facilitates NLOS communication, enabling robust data transmission even in the presence of physical obstructions and eliminating the requirement for precise pointing and tracking. As depicted in the schematic of Figure 2a, even over distances of several kilometers, the inherent scattering properties of atmospheric particles enable UV signals to bypass obstacles. Simultaneously, the pronounced atmospheric attenuation limits signal propagation to localized areas, inherently providing a low probability of interception (LPI) and a low probability of detection (LPD). These physically rooted characteristics endow UVC with its core competencies: exceptional security and high operational flexibility. Moreover, UVC facilitates robust connectivity in electromagnetically sensitive or silent states, such as underground mines, where traditional radio frequency (RF) signals are restricted or prone to severe interference. It also demonstrates significant potential for collaborative formation networking, as illustrated by the application scenarios in Figure 2b,c.

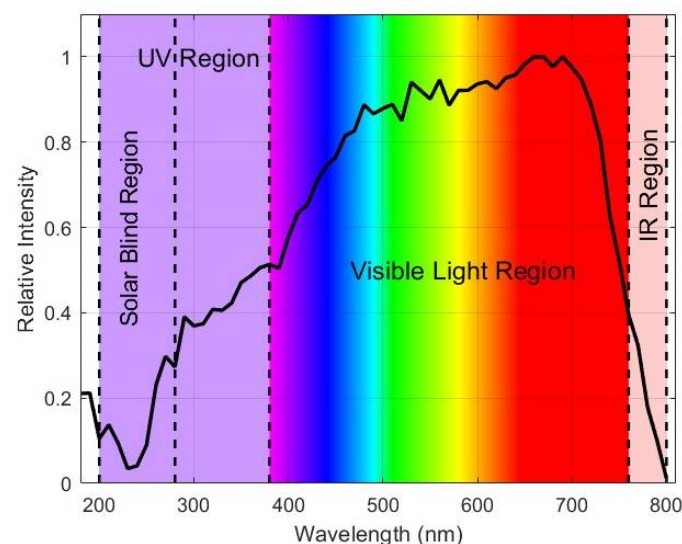


Figure 1. Solar spectrum.

Based on the aforementioned attributes of NLOS transmission, robust security, and high interference immunity, UVC holds immense potential across a diverse range of critical sectors. Within industrial paradigms, such as smart factories and large-scale workshops, UVC facilitates stable connectivity for autonomous systems, remaining impervious to intense electromagnetic interference and physical obstructions [10]. In contested or radio-denied environments, unmanned aerial vehicle (UAV) swarms can leverage UVC networking to ensure real-time data synchronization and the reliable exchange of flight

commands [1,11]. Furthermore, in Intelligent Transportation Systems (ITS), UVC enables vehicles to rapidly exchange kinematic data including velocity and heading, thereby mitigating collision risks through enhanced situational awareness. In the defense sector, UVC stands as a premier candidate for covert tactical communications. Personnel equipped with portable or helmet-mounted UVC terminals can securely transmit intelligence and operational directives while maintaining strict radio silence, thereby minimizing the risk of compromising their tactical positions. Figure 3 is a schematic diagram of the deployment of UVC in cities.

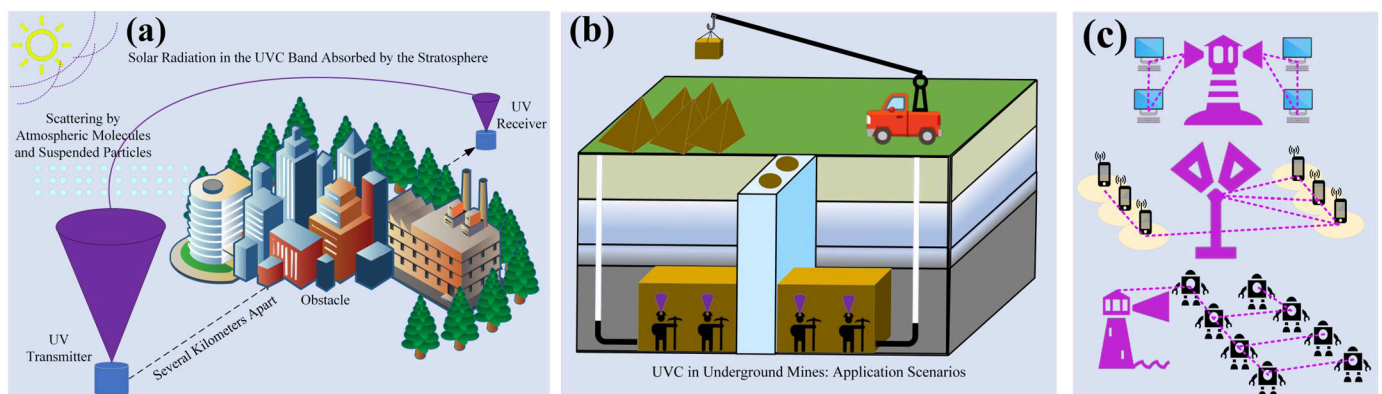


Figure 2. Typical application scenarios of UVC: (a) Schematic of solar-blind UVC based on atmospheric scattering for NLOS connectivity; (b) UVC implementation in electromagnetically sensitive underground mines with RF constraints; (c) Deployment of UVC for collaborative formation networking and coordination among high-mobility platforms.

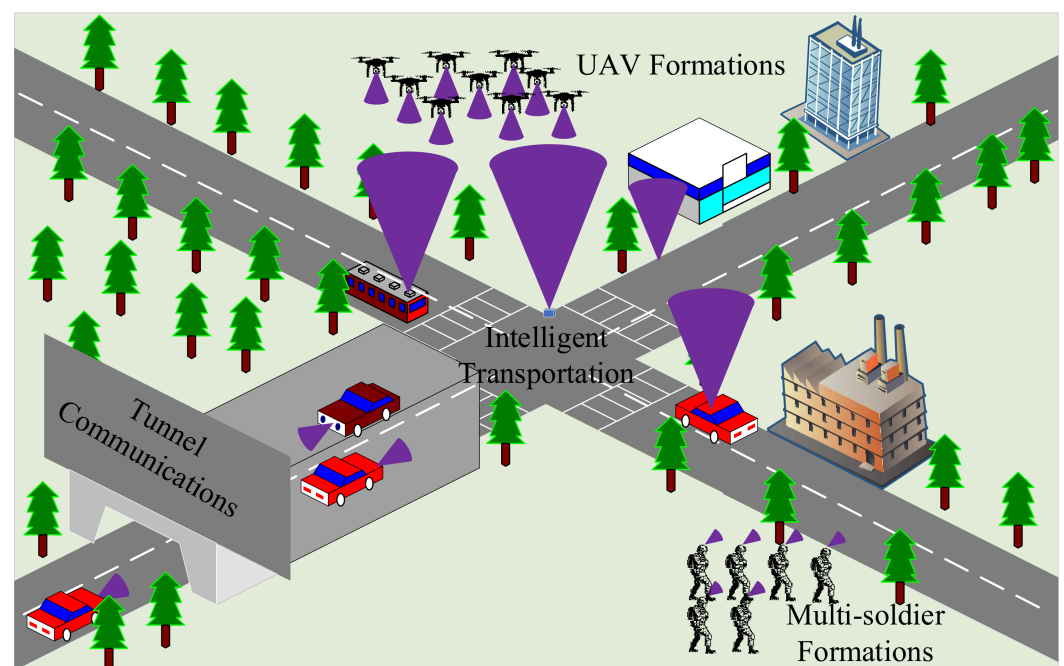


Figure 3. Schematic diagram of UVC application scenarios.

Despite its technical merits, radiation in the UV-C band presents inherent photobiological hazards to human eyes and skin. Consequently, the deployment of UV light sources must strictly adhere to exposure limits prescribed by international regulatory bodies, such as the International Commission on Non-Ionizing Radiation Protection (ICNIRP) and the International Electrotechnical Commission (IEC). In UVC system design, a critical challenge lies in reconciling the need for maximized transmission power and

extended range with stringent safety constraints. To resolve this trade-off, communication performance can be optimized via adaptive power control strategies or the integration of ultra-sensitive photodetectors [12], ensuring robust connectivity while maintaining a safe operational environment.

The remainder of this paper is structured as follows. Section 2 reviews the evolution and global research status of UVC. Section 3 presents the specifications and performance of advanced light sources and detectors. Section 4 investigates NLOS scattering channel models and key influencing factors. Section 5 focuses on physical layer optimizations, comparing modulation, coding, and equalization techniques for UV signals. Section 6 extends to multi-user networking, covering multiple access protocols and 3D topology control. Section 7 concludes by identifying technical bottlenecks and outlining future directions for next-generation UVC systems.

2. Current Research Status of Ultraviolet Communication

2.1. International Research Status

The origins of UVC research can be traced back to approximately 1940, when researchers in the United States initiated fundamental theoretical studies on ultraviolet light sources, detectors, and optical filters [9]. Over the subsequent half-century, spurred by rapid technological evolution and the strategic exigencies of modern warfare, the U.S. Navy began exploring the practical utility of ultraviolet light for robust communication systems.

Research on hardware systems is the core premise underpinning UVC systems, and this section begins with the introduction of this part. In 1968, researchers at the Massachusetts Institute of Technology (MIT) constructed an experimental ultraviolet scattering communication system [13]. The transmitter leveraged a xenon flash lamp paired with a searchlight reflector, while the receiver employed a photomultiplier tube (PMT) and a pulse counter. Theoretical analysis and system calibration were conducted over a 26 km link. The study demonstrated that approximately 300 photons per pulse could be detected under clear weather conditions, thereby validating the feasibility of UV scattering for medium-range communication and establishing a rigorous system calibration framework.

In 1986, Geller et al. conducted field trials at the San Diego Naval Base, establishing a UVC link over an initial distance of 0.75 km [14]. The system was designed to support both LOS and NLOS communication modes. Experimental evaluations demonstrated that at a data rate of 2400 bps and a bit error rate (BER) of 10^{-5} , the system could achieve a maximum communication range of 3 km in LOS configuration and 1 km in NLOS scenarios.

Entering the 21st century, GTE Corporation introduced a mercury-lamp-based UVC system (253.6 nm) utilizing PMT detection [15]. This architecture enabled NLOS links of 1–2 km and directional LOS links of 5–10 km via atmospheric scattering. The research highlighted the system's robust anti-interference and covertness properties, maintaining a BER of 10^{-6} at 4800 bps for distances up to 10 km, further proving the technical viability of UVC for long-range tactical applications.

The Defense Advanced Research Projects Agency (DARPA) catalyzed significant advancements by initiating the Semiconductor Ultraviolet Optical Sources (SUVOS) and Deep Ultraviolet Avalanche Photodetectors (DUVAP) programs in 2002 and 2007, respectively [9]. In 2004, BAE Systems developed a solar-blind UVC system utilizing LEDs developed under the SUVOS program and a quantum-noise-limited photon-counting receiver. Experimental results indicated that the system could achieve NLOS communication over several hundred meters at data rates in the hundreds of kbps with a BER below 10^{-7} , while LOS links reached kilometer-scale distances at Mbps rates. Subsequently, researchers at MIT conducted a series of trials using 274 nm solar-blind LEDs and channel photomultiplier (CPM) tubes [16]. To overcome the power limitations of individual devices, a large-scale LED

array comprising 10 modules (totaling 240 units) was employed in 2005; this configuration achieved an optical output power of 45 mW, facilitating a 200-bps link over a 100 m range.

In 2007, at the MILCOM annual conference held in Florida, BAE Systems unveiled a handheld UVC prototype based on ultraviolet light-emitting diode (UV LED) arrays [16]. The device was powered by eight AA batteries and was capable of facilitating point-to-point (P2P) voice communication, demonstrating the potential for portable, tactical ultraviolet networking in the field. During the same period, the U.S. Army Research Laboratory (ARL), in collaboration with the University of California, conducted extensive research on LED-based solar-blind NLOS communication. In 2008, Chen et al. from the University of California constructed an experimental solar-blind NLOS system utilizing deep UV LED sources and PMT receivers [17]. Their study systematically investigated various elevation angle configurations, including symmetric pairs (θ_T , θ_R) of (30°, 30°) and (45°, 45°), as well as asymmetric settings of (45°, 30°) and (30°, 45°). The experimental results demonstrated that a BER below 10^{-4} could be achieved within a 100 m range at a signal-to-noise ratio (SNR) of 15 dB. This work validated the feasibility of LED-based solar-blind UVC for short-range, covert NLOS applications.

In 2010, Chen and Xu at the University of California developed an experimental platform to measure the NLOS UVC channel impulse response (CIR) [18]. The setup employed a 266 nm Q-switched fourth-harmonic Nd:YAG pulsed laser as the source, paired with a high-speed PMT receiver and a solar-blind filter. Their research systematically quantified the effects of transceiver elevation angles, beam divergence, receiver field-of-view (FOV), and baseline distance on pulse broadening. The experimental results indicated that the pulse width increases approximately linearly with elevation angles, FOV, and communication distance, while remaining relatively insensitive to variations in the beam divergence angle. Specifically, over distances ranging from 10 m to 100 m, as the elevation angles increased from 10° to 90°, the full width at half maximum (FWHM) of the pulse expanded from approximately 20 ns to 1100 ns. This corresponded to a significant reduction in channel bandwidth from 50 MHz to 0.9 MHz, providing foundational channel characterization data for UVC system optimization. Subsequently, the team further extended their research to explore medium access control (MAC) protocols for outdoor wireless optical networks [19].

In 2020, researchers at the King Abdullah University of Science & Technology experimentally validated the feasibility of NLOS optical communication in turbid underwater channels using a 377 nm UV laser and a PMT receiver [20]. The study demonstrated that in water with an extremely high attenuation coefficient, a data rate of 85 Mbit/s could be achieved. Notably, even under conditions of complete transceiver misalignment, the system maintained a throughput of 72 Mbit/s. These results prove that UV scattering can effectively mitigate the stringent pointing and tracking requirements typically associated with underwater wireless optical communication (UWOC).

At the 2022 International Conference on Unmanned Aircraft Systems (ICUAS), Horyna from the Czech Technical University proposed and implemented a scheme integrating optical communication into a relative positioning system for unmanned aerial vehicles (UAVs) [21]. The architecture utilizes UV LEDs as transmitters and a UV-sensitive camera—equipped with a wide-angle lens and a UV bandpass filter—as the receiver. By employing a 4D Hough Transform for the simultaneous processing of multiple signals, the system achieves integrated local-area communication and positioning without relying on radio frequency (RF) links. Experimental results in both simulated and real-world environments demonstrated that the system maintains a data rate of at least 15 bps over a range of 17–20 m, with the BER kept within 20%. Furthermore, the framework successfully enabled

heading consensus and collaborative mission execution in multi-UAV formations through optical signaling.

At the 2023 IEEE Research and Applications of Photonics in Defense Conference (RAPID), Kirste et al. presented high-performance UV-C optoelectronic devices based on the AlGaIn material system grown on aluminum nitride (AlN) substrates [22]. This suite of hardware includes 265 nm UV LEDs with output powers exceeding 100 mW and solar-blind avalanche photodiodes (APDs) featuring a quantum efficiency (QE) of 70–80% and a gain of approximately 10^5 . Their research suggests that, by leveraging high-power emission, high-sensitivity detection, and intrinsic solar-blind characteristics, these devices are poised to enable NLOS UVC over ranges of 2–5 km. Consequently, this work establishes a critical hardware foundation for the development of covert, interference-resistant short-range wireless optical communication systems.

In 2025, simulation studies at the University of Rome mainly focused on the performance disparities between underwater UVC and VLC [23]. The simulation results indicated that in a pure seawater channel with a 30 m link distance and 10 W transmit power, the Signal-to-Interference-plus-Noise Ratio (SINR) of ultraviolet light at 360 nm was 4–15 dB higher than that of VLC. Furthermore, the UVC system sustained a spectral efficiency of 1 b/s/Hz using binary modulation at a distance of 170 m, effectively demonstrating its inherent solar-blind advantage against ambient sunlight interference in underwater environments.

Channel modeling is the core theoretical foundation for accurately characterizing UV optical transmission characteristics and quantifying system performance boundaries. In 2012, Kashani at McMaster University, Canada, conducted a theoretical analysis and numerical optimization of free-space optical (FSO) communication systems employing serial and parallel relaying schemes [24]. Based on the lognormal turbulence channel model, the study derived analytical expressions for outage probability and proposed an optimization methodology for relay node positioning. These findings provided important theoretical insights into enhancing the reliability and coverage of optical links in turbulent environments.

In 2017, Uysal's research team in Turkey investigated multi-hop NLOS UVC systems employing decode-and-forward (DF) relaying [25]. Utilizing a log-normal turbulence channel model, they derived—for the first time—the closed-form probability density function (PDF) for turbulence fading and the analytical expression for the outage probability in NLOS links. The research demonstrated that for a 1000 m link at a BER of 10^{-6} and constant transmit power, adding a single relay node yielded a 7.4 dB performance gain, whereas a second relay provided negligible further improvement. Consequently, the study concluded that increasing the number of relay nodes does not inherently guarantee performance enhancement, as overall system efficacy is governed by other configuration parameters.

2.2. Research Status in China

Compared with international research, research on UVC in China started relatively late. Major contributors to this field include the Beijing Institute of Technology, National University of Defense Technology, Chongqing University, Xi'an University of Technology, Beijing University of Posts and Telecommunications, Nanjing University of Posts and Telecommunications, and the University of Science and Technology of China. Key research institutes, most notably the Institute of Semiconductors of the Chinese Academy of Sciences, have also played a pivotal role. Domestic research focuses predominantly on the theoretical foundations of NLOS UVC, the development of atmospheric scattering models, and the characterization of hardware components.

Research on UVC hardware systems in China has undergone rapid development. At the beginning of the 21st century, Beijing Institute of Technology pioneered the field of UVC in China by developing one of the first hardware platforms [15]. Utilizing low-pressure mercury lamps as emitters and GBD-152 photomultiplier tubes (PMTs) as detectors, they achieved NLOS connectivity over distances up to 1330 m. In 2012, Guo et al. constructed a UVC system using a UV laser source and implemented a real-time 4-PPM (Pulse Position Modulation) scheme via a Field-Programmable Gate Array (FPGA) [26]. Their experimental results showed that despite a low pulse repetition frequency (PRF) of only 20 kHz, the system successfully achieved a data rate of 40 kbps with a BER under 10^{-4} , effectively overcoming the bandwidth limitations typically imposed by low-PRF sources.

In 2015, Huang et al. established an omnidirectional UVC testbed using UV LED arrays and PMTs [27]. By designing specialized omnidirectional optical antennas for both transmission and reception, the system achieved a data rate of 115.2 kbps over a 100 m range with a BER superior to 10^{-5} . Notably, the measured received SNR showed high consistency with channel model simulations based on the Monte Carlo method, further validating the accuracy of domestic scattering models.

The National University of Defense Technology began the study on UVC in 2000. Jia leveraged frequency loading technology and a half-bridge series resonant circuit to achieve an integrated design for light source excitation and information modulation in 2003 [28]. The experimental results demonstrated that this system successfully increased the baud rate to 9600 Baud, effectively overcoming the limitations of conventional designs where excitation and modulation were separate. This work laid a crucial foundation for the practical deployment of UVC. Two years later, to address the low communication rates caused by the “self-trapping” effect in mercury lamps [29], Jia proposed a high-speed UVC system based on low-pressure iodine lamps. The system achieved a communication rate of 48 kbps over short distances, ten times that of the GTE system reported in 2000, representing a leading performance in the industry at that time.

Chongqing University has made notable contributions to the advancement of UVC hardware systems. In 2007, Lan developed a solar-blind UVC system utilizing an 8 W quartz UV germicidal lamp as the light source [30]. The modulation circuitry was designed around an L6574 electronic ballast chip, incorporating a 4N25 optocoupler for signal isolation and level shifting. Experimental results demonstrated successful data transmission at 1200 bps over an outdoor range of 50 m, establishing a foundational framework for research into solar-blind UV voice communication. Subsequently, Professor Xiao Shali’s team developed a novel solar-blind UV voice communication architecture [31]. In 2010, the group introduced a UV LED-based system with a 10 m communication range. Two years later, they implemented an FPGA-based demodulation method that facilitated connectivity over 5 m [15]. This system achieved a bit rate of 9.6 kbps with a BER of 1% for coded communication, and reached 115 kbps for uncoded transmission.

Xi’an University of Technology, led by Zhao Taifei’s research group, has conducted extensive and productive investigations into UVC technologies. In 2011, Zhao developed a comprehensive wireless optical communication system utilizing solar-blind UV LEDs and OOK modulation [32], followed by rigorous performance evaluations across diverse environmental conditions. The findings indicated that the system BER correlates positively with transmission distance and data rate, while lower background interference significantly enhances performance; furthermore, the study confirmed that relaying mechanisms effectively extend the communication range.

In 2017, the University of Science and Technology of China achieved a significant breakthrough in UVC hardware. Wang et al. developed a real-time NLOS UVC system based on a 266 nm solid-state laser with an output power of 200 mW [33]. This experimental

setup successfully attained a data rate of 400 kbps over a 500 m transmission range, while maintaining a frame error rate (FER) below 10^{-5} . This work represents a landmark achievement, effectively pushing the boundaries of both transmission distance and data throughput in UVC systems.

Nanjing University of Posts and Telecommunications has made significant progress in UVC hardware. In 2023, Qi et al. developed a full-duplex deep ultraviolet (DUV) communication system using a 275 nm DUV LED array as the light source [34], complemented by solar-blind filters and a central processing unit. The transmitter and receiver were integrated into a single package, enabling simultaneous and independent data transceiving. Experimental results demonstrated that at a 10 Mbps transmission rate over a 7 m distance, the system achieved a coverage area of 46 m² with a packet loss rate (PLR) of 1.28% in daylight environments, successfully supporting real-time video transmission and file sharing.

Two years later, Qi designed and implemented a Mobile Full-Duplex Deep Ultraviolet Communication (MDUVLC) system featuring integrated visual tracking [11]. The system utilized a 275 nm DUV LED array for the transmitter and an Avalanche Photodiode (APD) with a solar-blind filter for the receiver. RS coding and OOK modulation were implemented via FPGA, while dynamic target tracking was achieved through a camera and a 3-axis gimbal. Experimental results indicated that the system maintained real-time video communication between a UAV and a ground vehicle over a 12 m distance at 10 Mbps, with a PLR of 1.51%. This work successfully established an all-optical communication network integrating underwater, terrestrial, and space domains, validating its anti-interference and full-duplex capabilities on mobile platforms.

In 2025, Wang et al. from the University of Science and Technology of China developed a LOS UVC system utilizing a wide field-of-view (FOV) LED array as the light source [4]. The transmitter consisted of nine 370 nm UV LED chips with a beam angle of 60°, while the receiver incorporated a PMT and a 370 nm bandpass filter. Indoor experimental results verified that the BER remained below the forward error correction (FEC) threshold within a transceiver angle range of $\pm 60^\circ$. In outdoor field tests, the system achieved a data rate of 1.25 Mbps over a distance of 1131 m using OOK modulation and FEC coding. With zero bit errors recorded over a transmission of 65,536 bits, the study demonstrated the feasibility of reliable, kilometer-level UVC without the need for precise alignment, facilitated by wide-FOV LED arrays.

Research institutions in China have also conducted significant studies on UVC. In 2024, Zhao Yingkai from the Institute of Semiconductors, Chinese Academy of Science, proposed and validated a UV weak-light communication system based on 4-level frequency shift keying (4FSK) modulation and a photon-counting algorithm [35]. The system utilized a 254 nm low-pressure mercury lamp as the transmitter and a Hamamatsu H10720-210 PMT as the detector. By employing an FPGA for photon counting, frequency detection, and clock synchronization, the design addressed the high sensitivity requirements of conventional FSK schemes. Experimental results showed that in NLOS scenarios with a 20° elevation angle and 3–4 m obstacles, the system achieved 5 kbps at 65 m with a BER of 7.52×10^{-4} . In LOS conditions, the BER remained below 10^{-5} within 400 m and was approximately 10^{-4} at 700 m.

In the same year, Jiao Yu from the Institute of Semiconductors, Chinese Academy of Science, proposed a scheme to optimize OOK modulation by adjusting the signal duty cycle to mitigate the increased BER caused by the LED trailing effect [36]. A channel model incorporating path loss and the LED trailing effect was established, and BER expressions for various duty cycles were derived. Using a 100 mW 265 nm UV LED array, a 262 nm filter, and a PMT receiver, field tests were conducted at distances of 500–700 m and rates

of 150–300 kbps. The results indicated optimal duty cycles of 48%, 47%, and 45% for 150 kbps, 200 kbps, and 300 kbps, respectively. The study verified that reducing the duty cycle effectively suppresses BER degradation due to the trailing effect in high-speed communication, enhancing overall UV system performance.

In the field of channel modeling, researchers in China have also achieved a series of relevant research accomplishments. Beijing University of Posts and Telecommunications has also made significant contributions to the physical layer technologies and channel modeling of UVC. In 2012, Han et al. developed a dual-PMT diversity reception experimental system using an array of 36 UV LEDs (265 nm) [37]. By employing an equal gain combining (EGC) algorithm, they theoretically modeled and experimentally validated diversity reception for NLOS UVC at data rates ranging from 2.4 to 9.6 kbps. Their experimental results showed that at a BER of 10^{-4} , the dual-diversity system achieved communication distances of 70–160 m, yielding a performance gain of approximately 2.5 dB over a single-receiver setup and effectively enhancing system transmission performance.

Building on this, Han proposed a photon-tracing-based Monte Carlo simulation method in 2013 to establish an NLOS UVC channel model that accounts for multiple scattering effects [38]. Using a 265 nm source with 43 mW transmit power at 5 kbps, the simulation indicated that a dual-receiver configuration could reduce path loss by approximately 3 dB compared to a single receiver. At a constant BER, the dual-receiver setup significantly extended the communication range. The high degree of consistency between the simulation results and outdoor experimental trends further validated the reliability of the MC model for predicting diversity-reception channel characteristics.

To address the research gap in channel modeling for NLOS UVC in mobile scenarios, Song Peng from Xi'an Polytechnic University proposed a single-scattering channel model based on the Monte Carlo method in 2022 [39]. This model was designed to evaluate the impact of the relative movement speed and direction of communication terminals on the system impulse response. Simulation results—conducted under parameters of a 500 m transmission distance, 30° elevation angles for both transmitter and receiver, a 3° beam divergence half-angle, a 15° receiver FOV half-angle, and speeds ranging from 5 to 100 m/s—indicate that transmission distance remains the dominant factor influencing system response. This conclusion holds true across coplanar, non-coplanar, and varying height scenarios, providing a solid theoretical foundation for the design and analysis of mobile UVC systems.

Networking is the core link to promote UV optical communication technologies from point-to-point link verification to large-scale practical scenario deployment. In 2024, Zhao introduced a UVC-assisted coalition capture algorithm for UAV formations [40]. By integrating an optimal coalition generation strategy with a Voronoi partition-based area minimization strategy, the algorithm leverages onboard hemispherical UV LEDs to facilitate secure and interference-resistant information sharing and cooperative decision-making within the swarm. Simulation results conducted in a $1\text{ km} \times 1\text{ km} \times 1\text{ km}$ 3D space demonstrated that, compared to traditional area minimization strategies, this algorithm reduces average energy consumption by 12.73% and average iterations by 27.49% during multi-target capture missions, significantly enhancing the operational efficiency of collaborative UAV formations.

Ultraviolet Positioning (UVP) and Integrated Ultraviolet Communication and Positioning (IUCaP) represent cutting-edge research directions in the field of UV. Yuan proposed a UV NLOS positioning method based on a two-photon counting receiver [41]. In this method, the transmitter azimuth angle is first obtained by solving the intersection line between the transceiver coplanar plane and the ground plane, using the receiving azimuth angle corresponding to the maximum received power; subsequently, the transceiver dis-

tance, as well as the elevation angle and azimuth angle of the transmit beam, are solved based on the power constraint equation. Performance verification results demonstrate that, under a typical transceiver geometric configuration within a 100 m range, the proposed method achieves a positioning distance error of less than 2 m and a transmitter azimuth estimation error of less than 2° . Subsequently, the same team upgraded the two-photon counting receiver to a linear array consisting of three or more receivers, and proposed corresponding positioning methods for two typical spacing configurations between adjacent receivers [42]. The results show that when the transmit elevation angle is greater than 30° and the spacing between adjacent receivers exceeds 2 m, the proposed method can still maintain the aforementioned performance. In addition, the adoption of three receivers can completely eliminate the multi-solution problem in positioning and achieve acceptable positioning accuracy.

However, existing studies on UVC and UVP have largely been conducted independently of one another. In [43], the authors systematically established the technical framework of Integrated Ultraviolet Communication and Positioning (IUCaP), comprehensively elaborated its system-level gain and collaborative gain, and devised a universal system architecture for IUCaP. The results demonstrate that the communication-centric Integrated Transceiver Geometric Design (ITGD) scheme, which adopts a low transmit elevation angle and vertical receiving architecture, enables multi-user high-speed communication with low path loss. In contrast, the positioning-centric ITGD scheme, which employs a vertical transmit configuration and low receive elevation angle architecture, achieves omnidirectional uniform signal coverage and superior positioning accuracy. UVC frame-level a priori information assistance can proportionally reduce positioning latency by narrowing the angle search space, while UVP-assisted predictive link tracking can significantly mitigate the link misalignment probability of mobile nodes.

This section systematically reviews the Chinese and international research progress in the field of solar-blind UVC. Existing studies have achieved significant improvements in core performance indicators such as communication rate, transmission distance, and system reliability. However, scattered experimental data fail to intuitively reflect the inherent logic of technological iteration and performance evolution. To clearly present the performance evolution context of representative systems, this paper standardizes and compares the core parameters of the aforementioned key studies, as shown in Table 1.

Table 1. Performance Parameter Comparison of Representative Systems.

Year	Core Technical Solution	Transmission Distance (m)	Communication Rate	BER Threshold	Ref
2008	Deep UV LED sources, PMT receivers, various elevation angle configurations	100	—	$<1 \times 10^{-4}$ (SNR = 15 dB)	[17]
2010	266 nm Q-switched fourth-harmonic Nd:YAG pulsed laser, high-speed PMT receiver, solar-blind filter (channel impulse response measurement)	10–100	—	—	[18]
2023	275 nm DUV LED array, solar-blind filters, integrated transceiver, full-duplex communication	7	10 Mbps	Packet Loss Rate (PLR) = 1.28% (daylight environment)	[34]
2024	254 nm low-pressure mercury lamp, PMT detector, 4FSK modulation, photon-counting algorithm, FPGA	NLOS: 65; LOS: 700	5 kbps	NLOS: 7.52×10^{-4} ; LOS: $<1 \times 10^{-5}$ (400 m), $\sim 1 \times 10^{-4}$ (700 m)	[35]
2025	275 nm DUV LED array, APD receiver, RS coding, OOK modulation, FPGA	12	10 Mbps	PLR = 1.51%	[11]

It should be noted that the performance metrics presented in the comparative table are highly dependent on specific experimental conditions. Key influencing factors include types of light sources and detectors, atmospheric conditions (e.g., daylight background), and modulation and demodulation schemes. To ensure the comparability of the data presented in this review, we have explicitly distinguished between LOS and NLOS scenarios, BER and PLR, and annotated all special experimental conditions in the table. Readers are advised to fully consider these contextual factors when interpreting and comparing the performance of different systems.

3. Ultraviolet Light Sources and Detectors

The preceding section reviewed domestic and international research progress in UVC, covering theoretical studies, channel modeling, transmission attenuation characteristics, and signal processing schemes. These investigations have established a solid foundation for understanding the physical mechanisms of UVC. However, for the outstanding characteristics described in theoretical models, such as NLOS performance and strong resistance to interference, to truly move beyond the laboratory and adapt to complex and ever-changing real-world environments, a transition from theory to practice must be achieved [44]. The performance ceiling of an efficient and stable UVC link is often directly constrained by the manufacturing processes and physical specifications of its core components. Therefore, Chapter 3 shifts focus from abstract theoretical derivations to concrete engineering implementations, analyzing the core physical hardware architecture of UVC systems and exploring the evolution of UV light source technologies at the transmitter end, as well as performance breakthroughs in high-sensitivity detectors at the receiver end.

A typical UVC system consists of a transmitter module and a receiver module. In consideration of the inherent characteristics of UVC, the transmitter design should account for transmission power, form factor, thermal performance and portability, while the receiver design prioritizes high sensitivity and compactness [45]. Because UV light undergoes significant attenuation as it propagates through the atmosphere, the transmission power at the transmitter cannot be increased indefinitely without exposing the human body to excessive UV radiation. Therefore, optical antennas must be installed at both the transmitter and receiver ends to extend the communication range. The design of the transmitter's optical antenna should minimize the divergence angle as much as possible to reduce losses, while the design of the receiver's optical antenna should maximize the field of view to enhance gain. In addition, the receiver should incorporate a filter tailored to the light source's wavelength band to block out background light and improve the signal-to-noise ratio.

Figure 4 shows a schematic diagram of a UVC system. The transmitter end employs a transmitter information processing module to preprocess raw source data, including format conversion and source coding, to generate a digital baseband signal suitable for transmission, which is then modulated onto a carrier waveform. The signal is subsequently amplified by an LED driver to power the UV light source in the transmission optical system, converting the electrical signal into a UV light signal, which is emitted into free space as UV light that is invisible to the human eye. The receiver collects and filters out background noise through its optical system, extracting the valid UV light signal. This signal is then converted into a weak electrical signal by the photoelectric conversion module, which also amplifies and shapes it. Subsequently, the receiver's information processing module performs demodulation, channel decoding, and format restoration to recover the original digital baseband signal. Finally, the restored source information is output, completing the entire ultraviolet light communication process.

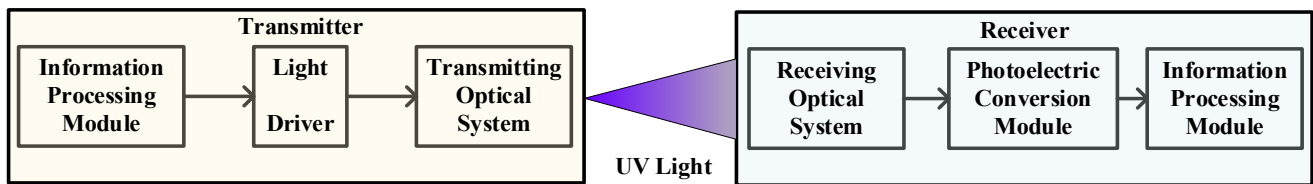


Figure 4. Schematic diagram of a UVC system.

3.1. Light Source

UV light sources are key to the development of UVC technology. Traditional UV light sources include xenon flash tubes, low-pressure mercury lamps, and UV lasers. The light radiation from a xenon lamp is produced by thermal excitation of a high-temperature arc and the recombination of positive and negative ions, resulting in a very intense continuous spectrum, with UV radiation covering the wavelength range of 200–400 nm [46]. Conventional gas-filled mercury lamps generate UV radiation through mercury vapor discharge. High-pressure gas-filled mercury lamps feature high power density, a wide power range, and large output power; their spectral energy distribution spans the mid-ultraviolet, long-ultraviolet and visible light regions. In contrast, the UV spectral energy output of low-pressure gas-filled mercury lamps is largely concentrated at 254 nm, within the mid-ultraviolet region. UV lasers typically employ fourth-harmonic Nd:YAG lasers, sapphire lasers, or copper vapor lasers [47]. UV lasers generally have a power output of less than 1 W and exhibit excellent directional radiation characteristics, with their energy concentrated solely in a specific beam direction. However, high-power UV lasers are not only expensive and bulky, but their core technologies are still in the developmental stage. Therefore, for free-space communication, which involves LOS and directional constraints, UV lasers are currently unable to meet the required performance standards. Most of these light sources are bulky, inefficient, and have narrow bandwidths, making them unsuitable for use as communication light sources.

Semiconductor UVC light-emitting diodes (LEDs), with their compact size, low cost, and high bandwidth, have greatly advanced the development of UVC technology [12]. Since the beginning of the 21st century, countries and regions such as the United States, China, Japan [48], and Europe have conducted extensive research on ultraviolet light sources.

Compared with conventional mercury lamps and UV lasers, UV LEDs exhibit remarkable differences in four key performance dimensions. In terms of modulation bandwidth, UV LEDs can reach the megahertz (MHz) level. By contrast, mercury lamps only achieve a bandwidth in the hertz (Hz) to kilohertz (kHz) range, while UV lasers deliver a bandwidth spanning from kHz to MHz [49]. Regarding operational lifetime, UV LEDs can reach 20,000 to 50,000 h, whereas mercury lamps have a service life of approximately 8000 to 12,000 h [50], and UV lasers mostly feature a lifetime ranging from several thousand hours up to 10,000 h. In terms of power consumption, the wall plug efficiency of UVC LEDs in the 275–285 nm wavelength range is approximately 10–15%, that of low-pressure mercury lamps is about 30–40% [51], and that of lasers is about 0.2–5%. In terms of cost, mercury lamps have the lowest upfront purchase cost. The total cost of ownership (TCO) of UV LEDs continues to decline yet remains slightly higher than that of mercury lamps, while UV lasers incur the highest cost along with expensive maintenance overheads.

The optical output power and bandwidth of a UV light source are key parameters that determine the performance of communication systems. The light output power (LOP) of the light source largely determines the communication distance and is directly related to the external quantum efficiency (EQE). The EQE represents the proportion of charge carriers injected into the device that are converted into UVC photons emitted by the LED; it

can be calculated as the product of the internal quantum efficiency and the light extraction efficiency [52]. The EQE of conventional UVC LEDs typically ranges from 1% to 3%, with luminous intensity at the milliwatt level.

A single 15 mW 285 nm micro-LED can achieve a data rate of 6.5 Gbps over a transmission distance of 10 m, while maintaining a data rate above 1 Gbps at a distance of 116 m. In contrast, multi-milliwatt UVC LEDs only support low-speed transmission within a 20 m range [53]. On the other hand, increasing the -3 dB bandwidth from 150 MHz to 600 MHz can boost the communication data rate from 1 Gbps to 4.6 Gbps [53]. Therefore, high output power serves as the fundamental basis for realizing long-distance, large-coverage communication, and high bandwidth is the prerequisite for achieving high-rate data transmission. The two parameters must be collaboratively co-optimized to meet the requirements of practical applications.

A summary of related research on traditional UV LED-based communication is provided in Table 2 [54].

Table 2. Performance of Conventional LEDs for Ultraviolet Communication.

Year	Wavelength/nm	Power/mW	Bit Error Rate	Rate/kbps	Line of Sight	Distance/m	Ref
2006	274	4.5 (10 piece)	—	2.4	NLOS	11	[55]
2009	270	—	10^{-4}	100		11.46	[56]
2011	270	0.32 (Single)	7.0469×10^{-4}	115.2		4.5	[32]
2012	—	43 (36 piece)	10^{-4}	2.4	LOS	—	[37]
2014	265	1–10	10^{-3}	500	LOS	27.5	[57]
2015	—	30	<0.01	—	NLOS	24	[57]
2017	294	190 μ W (7 V)	2.8×10^{-4}	71,000	LOS	—	[58]
2018	280	3–5 (mW/cm ²)	—	2,080,000	LOS	1.5	[59]
2021	276.8	0.854	2.86×10^{-3}	2,000,000	LOS	0.5	[60]
2023	266	16 (4 piece)	$<10^{-3}$	100,000	NLOS	40	[61]
2025	275	—	$<10^{-3}$	2000	LOS	122	[62]

Reference [59] utilized commercial 280 nm LEDs combined with Tomlinson-Harashima Precoding (THP) and 4-level Pulse Amplitude Modulation (PAM-4) to achieve error-free transmission at rates up to 1.6 Gbps over a 1.5 m LOS link. The system's 3 dB bandwidth was 153 MHz, primarily limited by the LED devices. In the absence of solar interference, the effective data rate reached 2.08 Gbps. Even under direct noon sunlight, the receiver maintained an effective rate of 1.66 Gbps with a BER below the FEC threshold. These experimental results demonstrate that solar-blind UVC possesses exceptional anti-interference capabilities in strong background light environments, offering a viable, low-cost, and high-speed solution for outdoor optical communication in the 5G era.

3.2. Detector

Since the energy of UV radiation is extremely weak by the time it reaches the detector after traveling long distances and undergoing multiple scatterings, PMTs with a UV window are detection devices with ultra-high sensitivity; traditional PMTs offer the advantages of low dark count rates and high gain, but they are bulky. Solid-state detectors, such as AlGaIn-based and SiC-based APDs [63], can meet basic requirements for sensitivity, selectivity, speed and stability. Additionally, other alternative materials, such as MgZnO and Ga₂O₃, are available.

PMTs are the earliest and most widely used detectors in UVC applications. They feature extremely high sensitivity, low dark current, high gain and a large detection area, making them particularly suitable for detecting extremely weak light signals [3]. However, PMTs are bulky, fragile, and expensive, requiring the use of solar-blind filters, which hinders system miniaturization. Moreover, their typical bandwidth is only around 50 MHz, making it difficult to satisfy high-speed communication requirements. Xing et al. constructed a 2×2

MIMO system using two independent PMTs with a bandwidth of 5 MHz [64]; Meng et al. constructed a four-receiver SIMO system using equal-gain combining (EGC) technology, which significantly improved BER performance under weak signal conditions [64].

With advancements in semiconductor technology, Si- and SiC-based PIN diodes and APDs are gradually replacing PMTs [3]. SiC PIN detectors exhibit high responsivity and ultra-low dark current within the 200–400 nm range, making them ideal for UV detection. Meanwhile, Si APDs offer high bandwidth (above 400 MHz) and high gain, suitable for high-speed communication links. AlGaIn-based APDs, leveraging the tunable bandgap of the material, possess an inherent solar-blind advantage without requiring additional filters. Furthermore, the Separate Absorption and Multiplication (SAM) design enables high gain and low-noise performance, showing great potential for integration. Shao et al. realized an AlGaIn APD with a gain as high as 1.2×10^4 and a peak responsivity of 0.15 A/W at 280 nm [65].

In the field of emerging detectors, materials such as Ga₂O₃, ZnO-Ga₂O₃ heterostructures, and MgZnO have become intensive research focal points. With a wide bandgap of 4.9 eV, Ga₂O₃ is inherently suitable for solar-blind detection, and its heterostructure-based devices have already demonstrated high responsivity [3]. Specifically, an Au-Ga₂O₃-Au detector fabricated by Hu et al. achieved its peak responsivity at 255 nm [66]. Furthermore, ZnO-Ga₂O₃ core-shell APDs have exhibited exceptional responsivity and detectivity with microsecond-level response times. For instance, Zhao et al. developed a core-shell APD with a peak responsivity of 1.3×10^3 A/W, a record-high detectivity of 9.91×10^{14} cm·Hz^{1/2}/W, and a response time of 20 μs [67].

For MgZnO, the bandgap can be precisely tuned by modulating the Mg content. Metal-Semiconductor-Metal (MSM) structured devices have shown responsivities in the order of 10^4 A/W at 276 nm, indicating superior detection performance. Alema et al. reported a device with a responsivity as high as 1.8×10^4 A/W at 276 nm, attributed to the asymmetric barriers within the MSM structure [68]. Collectively, UVC detectors are transitioning from traditional PMTs to semiconductor-based alternatives (e.g., SiC PIN, Si APD, and AlGaIn APD) to satisfy the systemic demands for miniaturization, high bandwidth, and low power consumption.

In the performance analysis of photodetectors, dark current noise, shot noise, and thermal noise collectively determine the SNR and the minimum detectable optical power. PIN photodetectors have no internal gain, where thermal noise is dominant under low optical power conditions, thus requiring pairing with a low-noise amplifier (LNA) [69]. APDs suppress thermal noise via avalanche multiplication, yet their excess noise factor amplifies shot noise and dark current. The optimal multiplication factor must be selected with a deliberate trade-off, and it exhibits strong temperature sensitivity [70]. PMTs feature ultra-high gain with an excess noise factor close to unity, and can operate in the single-photon counting mode under ultra-weak light conditions. However, their key limitations lie in dark current (especially ion feedback in the ultraviolet band) and the requirement for a complex high-voltage power supply [71].

The performance of UV detectors is poised for further optimization, enabling the design and fabrication of devices that surpass the capabilities of traditional bulk-material-based counterparts. The key performance metrics for these detectors are summarized in Table 3. The parameters were measured under standard laboratory conditions. Currently, catalyzed by innovative device architectures based on low-dimensional solid materials, self-powered photodetectors, and plasmonic enhancement technologies, a multitude of novel UV photodetection concepts is emerging [72]. Furthermore, emerging wide-bandgap materials, represented by Ga₂O₃ and MgZnO, have demonstrated significant advantages

in solar-blind detection. Although their fabrication processes are still in the nascent stages, these materials are expected to become the ideal choice for future UVC detectors.

Table 3. Performance of Ultraviolet Detectors.

Detector	Spectral Range (nm)	Responsivity (A/W)	Response Time (ns)	Dark Current (nA)	Ref
PMT	110–1100	~10 ⁵	1–15	2–30	[3]
SiC PIN	200–400	0.085–0.13	~10	—	[3]
Si PIN	200–1100	~0.38	6–50	~10	[3]
AlGaIn PIN	220–280	~0.15	~6.5	—	[73]
Si APD	260–1100	0.24–0.5	—	1–100	[3]

This section reviewed the evolutionary history and current research status of UV light sources and detectors, delineating their technological trajectories and contemporary research frontiers. By comparing the critical performance parameters of various devices, this work establishes a comprehensive theoretical foundation for component selection and system design in subsequent ultraviolet communication developments.

4. Ultraviolet Non-Line-of-Sight Scattering Channel Models

The UV-C band within the solar spectrum is heavily absorbed by the stratospheric ozone layer as it penetrates the atmosphere. This absorption ensures that negligible solar radiation reaches the Earth’s surface, creating a solar-blind region. Consequently, UVC systems can achieve a superior SNR even with relatively weak signals due to the nearly non-existent background noise. However, the NLOS UVC channel is highly complex, with transmission quality strictly dictated by atmospheric physical conditions. Therefore, a systematic analysis of the fundamental elements and physical characteristics of channel modeling is essential to accurately evaluate communication performance.

4.1. Factors Influencing Channel Modeling

The troposphere contains fluctuating concentrations of gaseous molecules and aerosol particles. Under diverse meteorological conditions, such as clear sky, rain, fog and dust, the concentration and physical state of these aerosols vary significantly, directly modulating the scattering distribution as well as attenuation magnitude of UV light during propagation. The atmospheric impact on solar-blind UV light is primarily characterized by the synergistic effects of absorption and scattering induced by both gaseous constituents and aerosol particles.

Simultaneously, atmospheric turbulence is a critical factor. Turbulence triggers random fluctuations in the refractive index, leading to intense intensity fluctuations at the receiver, known as the scintillation effect [5]. Experiments have shown that models integrating classical turbulence theory with Monte Carlo simulations can effectively characterize irradiance fluctuations under both strong and weak turbulence conditions using probability density functions.

4.1.1. Atmospheric Absorption

Atmospheric absorption is primarily caused by gas molecules. In the UV-C band, strong ozone absorption is the main reason for the extremely low background noise near the surface and the rapid attenuation of UV signals along the transmission path. The attenuation of light due to absorption is classically described by the Beer-Lambert Law [74]:

$$I(d) = I_0 e^{-k_a d}, \quad (1)$$

where I_0 is the initial transmitted intensity, $I(d)$ is the intensity after transmission distance d , and k_a is the atmospheric absorption coefficient. On a microscopic level, the absorption coefficient is determined by the absorption cross-sections and number densities of the various absorbing gases. In UV channel modeling, the absorption coefficient and the total scattering coefficient together constitute the total atmospheric extinction coefficient.

4.1.2. Atmospheric Scattering

Scattering is the physical basis for NLOS UVC. Based on the relative size of suspended particles compared to the UV wavelength, scattering is categorized into Rayleigh scattering and Mie scattering.

Rayleigh Scattering: Caused by gas molecules (e.g., O_2 , N_2) much smaller than the UV wavelength. Its energy distribution is relatively uniform and symmetric between the forward and backward directions. The normalized scattering phase function is given by [75]:

$$P_{Ray}(\theta) = \frac{3[1 + 3\gamma + (1 - \gamma) \cos^2 \theta]}{16\pi(1 + 2\gamma)}, \quad (2)$$

where θ is the scattering angle. γ denotes the molecular depolarization factor for atmospheric Rayleigh scattering. Under standard atmospheric conditions, $\gamma \in [0, 0.035]$ holds for both general theoretical research and practical engineering implementations. Specifically, $\gamma = 0$ corresponds to the theoretical limit of classical Rayleigh scattering theory for ideal isotropic spherical molecules, whereas $\gamma = 0.035$ represents the upper bound of this parameter in extreme atmospheric environments with high water vapor content and abundant polar molecules. For research in the field of UVC and UVP, the widely adopted typical value of γ is 0.017. Rayleigh scattering is strongest in the forward and backward directions and weakest at the sides.

Mie Scattering: Caused by aerosol particles (e.g., fog, dust and pollutants) with sizes comparable to or larger than the UV wavelength. Unlike Rayleigh scattering, Mie scattering exhibits strong forward-scattering characteristics. Due to the complexity of the rigorous Mie theory based on Maxwell's equations, the Henyey-Greenstein (H-G) model is commonly used for approximation [76]:

$$P_{Mie}(\theta) = \frac{1 - g^2}{4\pi} \left[\frac{1}{(1 + g^2 - 2g \cos \theta)^{3/2}} + f \frac{0.5(3 \cos^2 \theta - 1)}{(1 + g^2)^{3/2}} \right], \quad (3)$$

where g is the asymmetry parameter ($g \in [-1, 1]$). $g > 0$ indicates dominant forward scattering (typically 0.6–0.9 for atmospheric aerosols), $g = 0$ represents isotropic scattering, and $g < 0$ indicates dominant backward scattering. θ is the scattering angle.

4.1.3. Composite Phase Function

In real atmospheric environments, neither Rayleigh nor Mie scattering alone can accurately describe photon angular deflection because the atmosphere is a mixed medium. Therefore, a composite phase function must be introduced. This function uses the scattering coefficients of both particles as weights to perform a weighted linear summation [77]:

$$P_{comp}(\theta) = \frac{k_s^{Ray}}{k_s} P_{Ray}(\theta) + \frac{k_s^{Mie}}{k_s} P_{Mie}(\theta), \quad (4)$$

where k_s^{Ray} is the Rayleigh scattering coefficient, k_s^{Mie} is the Mie scattering coefficient, and $k_s = k_s^{Ray} + k_s^{Mie}$. This mechanism provides strong environmental adaptability: in clear high-altitude conditions, k_s^{Ray} dominates and the function degrades to a Rayleigh-

like symmetric distribution; in adverse weather like fog or sandstorms, k_s^{Mie} dominates, resulting in a sharp forward-scattering peak.

4.1.4. Atmospheric Turbulence

Irregular fluctuations in local atmospheric physical properties—specifically temperature, pressure, and wind speed—induce stochastic variations in the atmospheric refractive index [78]. As signal light propagates through such an atmospheric channel, turbulence causes phenomena such as beam divergence, distortion, and wandering [79], which leads to intensity scintillation and jitter at the receiver [5,80]. Under weak turbulence conditions, the Rytov solution of the wave equation is employed to characterize these scintillation effects based on the log-amplitude variance of the received wave.

For a plane wave propagating over a channel of length L , the log-amplitude variance $\sigma_\chi^2(L)$ is defined as [81]:

$$\sigma_\chi^2(L) = 0.56 \left(\frac{2\pi}{\lambda} \right)^{7/6} \int_0^L C_n^2(x) (L-x)^{5/6} dx, \quad (5)$$

where λ represents the wavelength and C_n^2 denotes the atmospheric refractive index structure constant.

For a spherical wave, the log-amplitude variance is given by [81]:

$$\sigma_\chi^2(L) = 0.56 \left(\frac{2\pi}{\lambda} \right)^{7/6} \int_0^L C_n^2(x) \left(\frac{x}{L} \right)^{5/6} (x-L)^{5/6} dx. \quad (6)$$

In short-range weak turbulence scenarios, a higher refractive index structure constant (indicating increased turbulence intensity) surprisingly results in a lower system BER. This phenomenon occurs because intensified atmospheric turbulence enhances the scattering capability of the medium, allowing a greater fraction of scattered signals to be captured by the receiver. This effectively reduces path loss and subsequently improves the BER performance.

4.2. Analytical Channel Models

Analytical models formulate NLOS scattering into closed or semi-closed integral expressions, typically categorized by single-, double-, or triple-scattering orders. These models offer transparent physical insights and high computational efficiency, often providing path loss estimates within seconds. However, their applicability is frequently constrained by specific geometric configurations and the inherent complexity of higher-order scattering. In particular, as second- and third-order scattering involve mathematically intensive multiple integrals, many analytical channel models primarily focus on single-order scattering to maintain a balance between computational tractability and fundamental accuracy.

4.2.1. Single-Scatter Model in Cartesian Coordinates

The single-scatter model is defined by scenarios where a photon is received by the detector after undergoing exactly one scattering event. Figure 5 illustrates the parameter definitions for the single-scatter geometric model. φ_1 and θ_1 represent the divergence angle and elevation angle of the transmitter (Tx) beam, respectively; φ_2 and θ_2 denote the field of view (FOV), divergence angle, and elevation angle of the receiver (Rx); V signifies the common volume where the FOV and beam overlap; and r is the baseline distance between the transmitter and receiver.

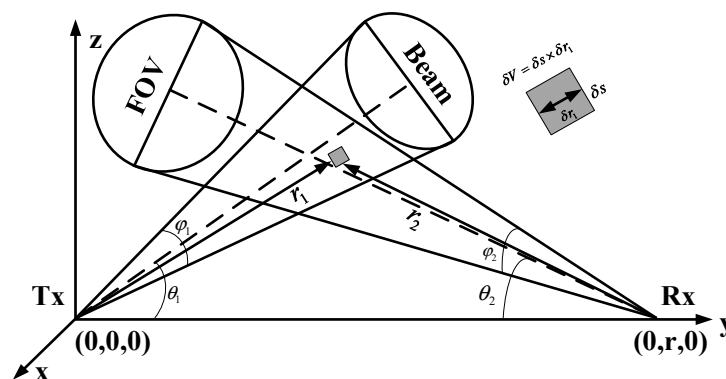


Figure 5. Parameter definition of a single-order scattering geometry model.

Let δV be an arbitrary differential volume element within the common volume V , be the distance from the Tx to σV , r_2 be the distance from δV to the Rx, θ_s be the angle between r_1 and r_2 , and ζ be the angle between r_2 and the FOV central axis. The optical power received by the Rx, scattered from all differential elements within the common volume, can be expressed as [82]:

$$P_{r,1} = \int_V \frac{P_t A_r k_s P(\cos \theta_s) \cos \zeta}{\Omega_t r_1^2 r_2^2} e^{-k_e(r_1+r_2)} \delta V, \quad (7)$$

in this expression, P_t is the transmitted optical power, A_r is the active area of the receiver, Ω_t is the solid angle of the transmitter, k_s is the atmospheric scattering coefficient, k_a is the absorption coefficient, and $k_e = k_s + k_a$ is the extinction coefficient. $P(\cos \theta_s)$ represents the phase function jointly determined by Rayleigh and Mie scattering [83].

4.2.2. Single-Scatter Model in Ellipsoidal Coordinates

Following the analysis of scattering models in Cartesian coordinates, the single-scatter model based on ellipsoidal coordinates offers an alternative perspective. In 1979, Reilly established a transmission model for single scattering of wireless UV light through the atmospheric channel using ellipsoidal coordinates [84]. Building on this, Luetggen utilized the focal properties of ellipses to propose an NLOS coplanar single-scattering model, as illustrated in Figure 6. Here, F_1 and F_2 serve as the two foci of the ellipse with a focal length of r , β_s represents the scattering angle, and ψ_1 and ψ_2 are the two focal angles of the ellipsoid.

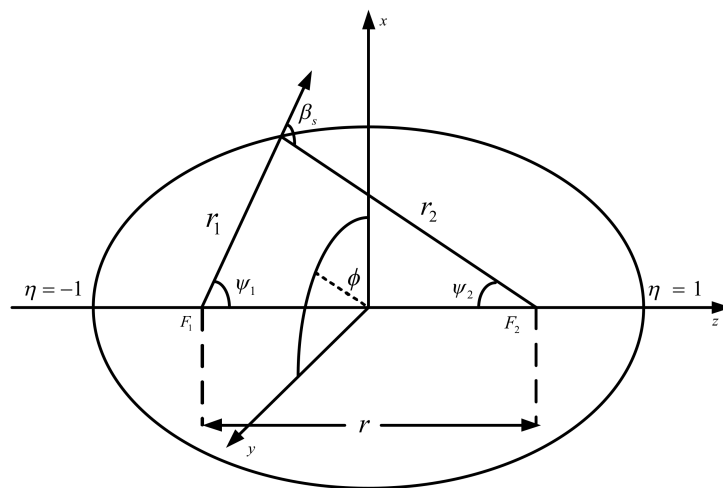


Figure 6. Parameter definition of a single-order scattering geometric model under ellipsoidal coordinates.

The parameters ξ and η are defined as follows [85]:

$$\xi = \frac{r_1 + r_2}{r}, 1 \leq \xi \leq \infty, \quad (8)$$

$$\eta = \frac{r_1 - r_2}{r}, -1 \leq \eta \leq 1. \quad (9)$$

Consequently, within the ellipsoidal coordinate system, the focal angles can be expressed through these parameters as:

$$\cos \psi_1 = \frac{1 + \xi\eta}{\xi + \eta}, \quad (10)$$

$$\sin \psi_1 = \frac{[(\xi^2 - 1)(1 - \eta^2)]^{\frac{1}{2}}}{\xi + \eta}, \quad (11)$$

$$\cos \psi_2 = \frac{1 - \xi\eta}{\xi - \eta}, \quad (12)$$

$$\sin \psi_2 = \frac{[(\xi^2 - 1)(1 - \eta^2)]^{\frac{1}{2}}}{\xi - \eta}, \quad (13)$$

$$\cos \beta_s = \frac{2 - \xi^2 - \eta^2}{\xi^2 - \eta^2}. \quad (14)$$

The elegance of this model lies in placing the transceiver at the foci of the ellipse. Assuming the scattering point lies on the ellipse significantly simplifies the calculation of the system's impulse response, facilitating a more convenient derivation of path loss.

In [86], the authors propose a non-direct-view ultraviolet single scattering path loss model based on spherical coordinates, which can handle non-coplanar geometric scenarios with arbitrary orientation of the transmitter and receiver. Simulation results show that the model is highly consistent with the Monte Carlo results under parameters such as wavelength 260 nm, communication distance 10–100 m, divergence angle 30°, and field of view 40°.

4.2.3. Single-Order Scattering Model with Reflection from Obstacles

To enhance the practical utility of channel modeling, researchers have integrated obstacle effects into idealized single-scatter frameworks. In [87], the authors established an analytical diffused-LoS model accounting for factors such as obstacle dimensions, positioning, and transceiver height differentials; this approach reduced computational time by approximately 93% compared to Monte Carlo methods while demonstrating that diffused-LoS scenarios provide superior path loss and BER performance over traditional NLOS links. Furthermore, for NLOS environments involving rectangular obstacles, a simplified single-scatter path loss algorithm was proposed in [88]. Simulation results confirm that obstacle reflections significantly mitigate path loss, and the simplified model maintains high precision with a computational complexity far lower than that of conventional Monte Carlo photon-tracing techniques.

4.3. Probabilistic Channel Models: Monte Carlo Method

The Monte Carlo simulation model builds probability models for photon emission, transmission, scattering, and reception. By tracing a large number of photons, it calculates the path loss and impulse response [89].

Figure 7 illustrates the parameter definitions for the Monte Carlo geometric model [89]. In this configuration, the receiver (Rx) is positioned at the origin (0, 0, 0), while the

transmitter (Tx) is located on the y-axis at $(0, r, 0)$. The angles θ_0 and φ_0 denote the zenith and azimuth angles, respectively, of a photon at the moment of emission from the Tx. The distance traveled by the photon after leaving the i -th scatterer (where $i = 0$ corresponds to the photon leaving the emitter) is given by the following equation:

$$d_i = -\frac{\ln(1 - \text{rand}(1))}{k_s}. \quad (15)$$

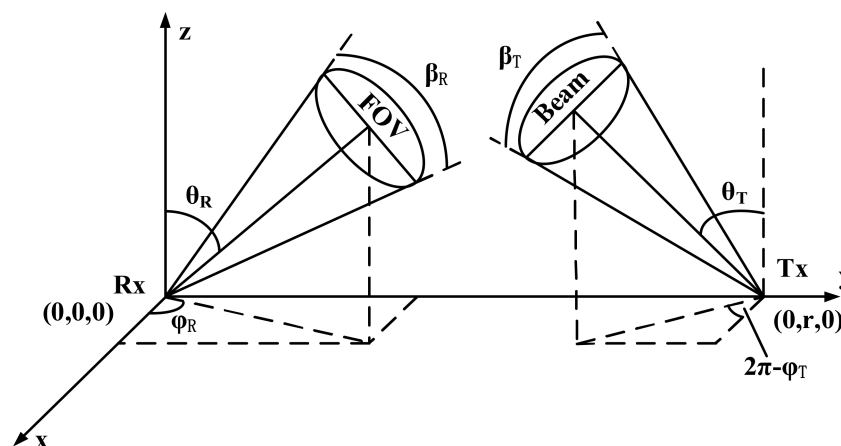


Figure 7. Parameter definitions for the Monte Carlo geometric model.

Assuming a uniform light source distribution, the initial emission direction of a photon is determined by the following equations [89]:

$$\theta_0 = \arccos\{1 - \text{rand}(1)[1 - \cos\left(\frac{\beta_T}{2}\right)]\}, \quad (16)$$

$$\varphi_0 = 2\pi\text{rand}(1), \quad (17)$$

where $\text{rand}(1)$ is independent random variables uniformly distributed on $[0, 1]$.

The direction of the photon changes after being scattered by the scatterer. Let (θ_i, φ_i) represent the angle by which the photon deviates from its original propagation direction after the i scattering, and satisfy the probability density function $f(\theta_i, \varphi_i) = P(\theta_i, \varphi_i) \sin \alpha$, where $P(\theta_i, \varphi_i)$ is the phase separation function. Then (θ_i, φ_i) can be generated by the following two equations [89]:

$$\theta_i = F^{-1}(\text{rand}(1)), \quad (18)$$

$$\varphi_i = 2\pi\text{rand}(1), \quad (19)$$

where $F(\theta_i)$ is the marginal probability distribution function of $f(\theta_i, \varphi_i)$ with respect to θ_i .

After each scattering, if the photon is within the receiving field of view (FOV), the probability of the photon being received by the detector is calculated. Assuming the solid angle formed by the i scattering point and the receiving surface is Ω_i , the coordinate vector of the scattering point is r_i , and the angle between the original direction of the photon and r_i is θ_{r_i} , then the i order scattering and receiving probability of the photon at this time is [89]:

$$p_{r,i} = \begin{cases} p_{s,i-1} e^{-k_a d_{i-1}} P(\theta_{r_i}, 0) \Omega_i e^{-k_a |r_i|}, & r_i \in \text{FOV} \\ 0, & r_i \notin \text{FOV} \end{cases}, \quad (20)$$

where $p_{s,i-1}$ is the survival probability before the i scattering. The survival probability of the photon is updated after each reception judgment as [89]:

$$p_{s,i} = p_{s,i-1} e^{-k_a d_{i-1}} (1 - P(\theta_{r_i}, 0) \Omega_i). \quad (21)$$

The Monte Carlo process of a single photon is shown in Figure 8.

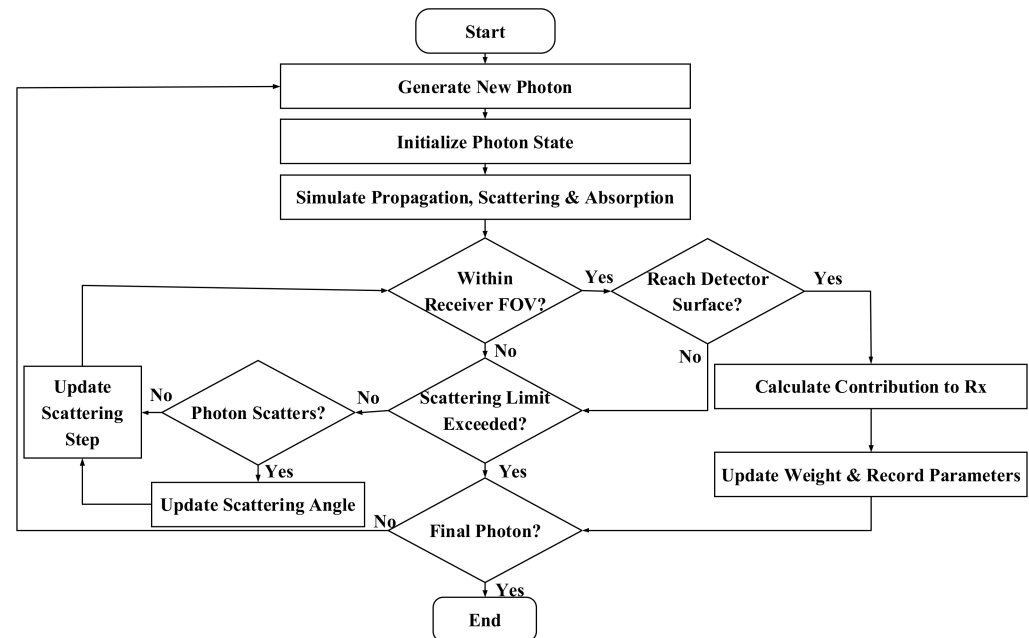


Figure 8. Flowchart of the Monte Carlo process for a single photon.

Figure 9 presents the experimental results obtained via the aforementioned Monte Carlo simulation, with the core benchmark parameters adopted in the simulation listed in Table 4. The simulation results demonstrate that the path loss of the UV NLOS communication link exhibits a significant monotonically increasing trend with the increase in communication distance. For a fixed communication distance, both increasing the transmitter beam divergence angle and widening the receiver FOV can effectively reduce the link path loss.

Table 4. Core Simulation Parameters of UV NLOS Communication Channel.

Symbol	Parameter Description	Value
θ_T	Transmitter Zenith Angle	30°
θ_R	Receiver Zenith Angle	30°
β_T	Transmitter Beam Divergence Angle	7°
β_R	Receiver Field of View (FOV)	20°
λ	Optical Wavelength	266 nm
k_a	Atmospheric Absorption Coefficient	$0.802 \times 10^{-3} \text{ m}^{-1}$
k_{s_ray}	Rayleigh Scattering Coefficient	$0.266 \times 10^{-3} \text{ m}^{-1}$
k_{s_mie}	Mie Scattering Coefficient	$0.284 \times 10^{-3} \text{ m}^{-1}$
g	Mie Scattering Asymmetry Parameter (Henyey-Greenstein)	0.72
γ	Rayleigh Scattering Anisotropy Factor	0.017
f	Mie Phase Function Correction Factor	0.5

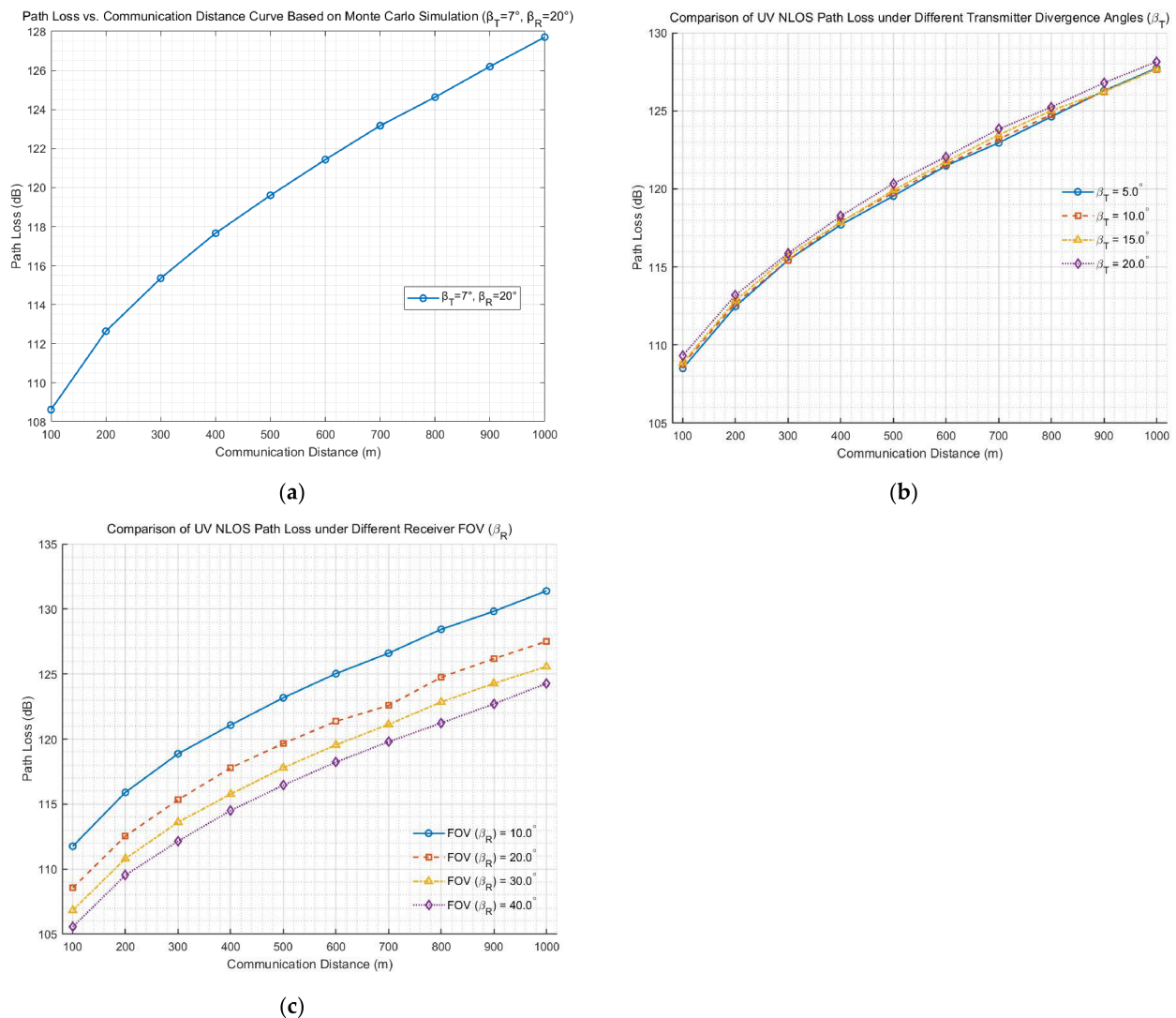


Figure 9. Path loss curves versus communication distance based on Monte Carlo simulation: (a) Fixed divergence angle and field of view (FOV); (b) Different divergence angles; (c) Different FOV.

This section systematically analyzes the critical issues of UV channel modeling. First, it elucidates core physical mechanisms such as atmospheric absorption and scattering to clarify the underlying patterns of transmission loss and perturbation. Subsequently, it categorizes and discusses mainstream modeling methodologies, including analytical approaches and probabilistic Monte Carlo simulations. The established analytical framework and modeling taxonomy provide a robust theoretical foundation for subsequent link performance evaluation, transmission scheme optimization and simulation verification.

5. Ultraviolet Signal Processing Technology

5.1. Modulation and Coding Technologies

In UVC systems, modulation techniques are critical for determining data transmission rates and bandwidth requirements [90]. Selecting an appropriate modulation scheme optimizes signal attenuation characteristics, power utilization and spectral efficiency [75]. Essentially, optical modulation involves embedding information onto optical waves at the transmitter, which is subsequently recovered through detection and demodulation at the receiver [91].

On-Off Keying (OOK) modulation is a special form of Amplitude Shift Keying (ASK) and a fundamental method of optical intensity modulation. Compared with OOK modula-

tion, pulse-phase modulation (PPM) is threshold-free, exhibiting stronger anti-interference performance against inter-symbol interference and enabling further interference suppression via soft demodulation. Based on the number of pulses, it can be divided into single-pulse (LPPM), multi-pulse (MPPM), and differential pulse (DPPM) position modulation. Differential pulse position modulation (DPPM) transmits information by the number of time slots between adjacent pulses, while digital pulse interval modulation (DPIM) uses the number of empty time slots between adjacent pulses to transmit information.

Figure 10 compares the average normalized transmit power of four modulation modes—OOK, DPPM, DPIM, and PPM—at different modulation orders M . The normalized power of OOK modulation is constant at 1.0, independent of the modulation order; the normalized power of DPPM, DPIM, and PPM all decrease significantly with increasing modulation order M ; when the modulation order is 6, PPM has the lowest average normalized transmit power. This figure provides a power efficiency basis for selecting modulation schemes in optical communication systems.

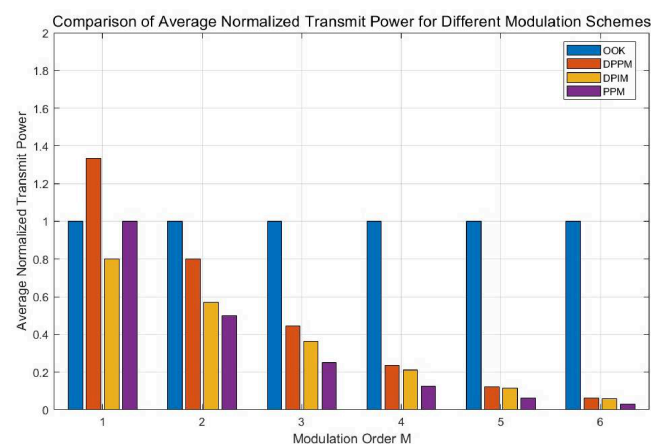


Figure 10. Comparison of normalized transmit power mean for different modulation modes.

In [92], the limited transmission distance of NLOS UVC is addressed by theoretically modeling and numerically analyzing the node isolation probability in serial multi-hop networks. Using a single-scattering path loss model together with OOK and PPM modulation formats, the study derives analytical expressions for the node isolation probability and investigates the effects of node density, data rate, transmit power, and transceiver geometry on network connectivity. Under the conditions of 50 mW transmit power, 100 kbps data rate, 10^{-3} BER performance, 30° transceiver elevation angle, and 10° beam divergence angle, as well as receiver field of view, covering a 10 km service range requires approximately 1400 nodes (OOK) and 700 nodes (PPM), respectively. This demonstrates that PPM modulation significantly reduces the required node density, providing a theoretical basis for the deployment of ultraviolet multi-hop networks.

In [93], BER expressions for OOK and PPM modulations under weak turbulence are derived based on the NLOS UVC model, and a simulation model for helicopter landing guidance using UV light is established. Simulation results show that PPM significantly outperforms OOK in terms of BER, with higher modulation orders yielding better performance. The system BER decreases with increasing transmit power, beam divergence angle, and receiver field of view, but increases with longer communication distance and larger transceiver elevation angles. This study provides theoretical and simulation support for enhancing the anti-interference capability of UVC systems for helicopter landing assistance in atmospheric turbulence.

References [58,94] adopt an Orthogonal Frequency Division Multiplexing (OFDM) modulation scheme combined with QAM, where the OFDM signal is superimposed with a DC bias to drive a 294 nm UVB LED. The system uses 2048-point OFDM symbols with 25 information subcarriers and adaptively selects the QAM order based on channel conditions. Under perfect alignment between the transmitter and receiver, 8 QAM is employed, achieving a data rate of 71 Mbit/s. When an angle exists between the transmitter and receiver, the system switches to 4 QAM or 2 QAM to maintain the BER below the forward error correction threshold (3.8×10^{-3}).

OOK, PPM, Frequency Shift Keying (FSK) and OFDM are four widely employed modulation schemes in ultraviolet UVC systems. In terms of BER performance, PPM eliminates the need for threshold-based detection, achieving the optimal BER performance under identical transmit power and channel conditions. OFDM effectively mitigates frequency-selective fading through orthogonal subcarrier multiplexing, while FSK conveys information via multi-frequency carriers, both delivering moderate BER performance. OOK relies on threshold-based detection, resulting in the poorest BER performance under the same operating conditions.

In terms of implementation complexity, OOK features a simplified architecture, with only on-off control of the optical source required at the transmitter and threshold-based detection at the receiver, thus presenting the lowest hardware and software implementation complexity. PPM requires a stringent time slot and symbol synchronization, and FSK imposes high requirements on optoelectronic devices, leading to moderate implementation complexity for both schemes. OFDM necessitates a complete set of modules for Inverse Fast Fourier Transform/Fast Fourier Transform (IFFT/FFT) processing, carrier synchronization, channel estimation and equalization, along with matched peak-to-average power ratio (PAPR) suppression algorithms, resulting in significantly higher implementation complexity than the other three schemes.

In terms of spectral efficiency, OFDM fully leverages the limited modulation bandwidth of UV LEDs via orthogonal subcarrier multiplexing, achieving the highest spectral efficiency among the four schemes. OOK has no redundant time slot overhead, outperforming PPM and FSK in spectral efficiency at the same symbol rate. FSK requires reserved guard bands for multi-carrier transmission, leading to relatively low spectral utilization. PPM encodes information through the time slot position of optical pulses, where redundant time slot overhead grows exponentially with the increase in modulation order, causing a sharp degradation in spectral efficiency and rendering it the lowest among the four modulation schemes.

For the core characteristics of ultra-low received optical power and scarcity of valid photon counts in the weak photon-counting scenario of UVC, there are distinct differences in the applicability characteristics of Reed-Solomon (RS) codes, Low-Density Parity-Check (LDPC) codes, and Polar codes. RS codes can effectively combat burst errors induced by atmospheric turbulence and photon count fluctuation, yet exhibit inferior performance to LDPC codes and Polar codes in single-photon-level ultra-low SNR scenarios. LDPC codes can fully exploit the soft count information from single-photon detection via iterative soft decoding, and still achieve remarkable coding gain under ultra-low received optical power, while suffering from the drawback of high decoding complexity at large code lengths. Polar codes outperform LDPC codes in error correction performance in single-photon-level ultra-low SNR scenarios, while their performance advantage is insignificant at short code lengths, and their maturity in engineering applications lags behind that of LDPC codes.

In UVC systems, pulse broadening and noise severely degrade system performance. In [95,96], the authors introduce LDPC codes under the single-scattering model, significantly improving both BER performance and communication distance under the same

modulation scheme; at a BER of 6.5×10^{-6} , the coded sequence achieves approximately twice the communication distance of the uncoded case. In [97], the authors employ a 36-element 265 nm UV LED array and FPGA-based coding modulation to compare RS(18,10) and LDPC(960,480) codes. Experimental results show that at a BER of 10^{-3} , RS codes and LDPC codes extend the communication distance by an average of 32% and 78%, respectively. At a transceiver elevation angle of 30° , the uncoded distance is about 6 m, increasing to about 9 m with RS coding and about 11 m with LDPC coding, demonstrating the significant gain of LDPC codes. In [98], the authors develop a Monte Carlo-based UV scattering channel model and a 2×2 UV MIMO experimental platform to verify 2/4/8-PPM schemes. It compares the BER performance of 1×1 , 2×1 , and 2×2 PSP-OSTBC + 4-PPM systems under various transmission distances and transceiver elevation angles. The results indicate that the proposed scheme features low decoding complexity, significantly enhances channel capacity, diversity gain, and coding gain, and makes the system insensitive to path loss and elevation angle variations. The 2×2 configuration achieves the best performance, and higher-order 8-PPM outperforms 4-PPM and 2-PPM. This work provides experimental and theoretical support for the practical implementation of optical MIMO in UV scattering channels.

5.2. MIMO Technology

Multiple-Input Multiple-Output (MIMO) is a technology that uses multiple antennas simultaneously at the transmitting and receiving ends. It has two core functions. First, it transmits the same information through multiple antennas and combines diversity combining technology to achieve spatial diversity, effectively mitigating channel fading, lowering the BER, and improving system reliability. Second, it achieves spatial multiplexing by transmitting different data streams in parallel through multiple antennas, significantly increasing the system transmission rate and capacity without expanding bandwidth or raising transmission power [99].

In UV NLOS scattering channels, channel spatial correlation imposes a significant limitation on the performance gain of MIMO systems. UV NLOS communication relies on atmospheric scattering to achieve signal transmission, where the angular spread of the channel is determined by the geometric parameters of the transceiver. When the system is configured with small antenna element spacing, narrow beam divergence angle or narrow FOV and large transceiver elevation angles, strong correlation is presented among multi-antenna sub-channels, resulting in a marked degradation of the MIMO system's diversity gain, BER performance, and channel capacity gain. In practical deployment of UVC systems, increasing antenna spacing and optimizing optical parameters can effectively mitigate channel spatial correlation and enhance MIMO system performance.

In [100,101], spatial diversity techniques for NLOS UVC are studied from a theoretical perspective. The BER performance of SISO, SIMO and MISO schemes under a log-normal turbulence channel model is analyzed in [100]. The results show that at a communication distance of 1000 m and the BER of 10^{-6} , using two and three receivers provides signal-to-noise ratio gains of 4 dB and 5.5 dB, respectively, outperforming the multi-transmitter schemes. In [101], the authors address Gamma-Gamma turbulence fading by employing a dual-branch switch-and-stay combining (SSC) diversity technique, deriving analytical expressions for outage probability and average symbol error probability (ASEP). It is found that dual-branch SSC improves system performance by approximately 7 dB compared to no diversity, and that channel correlation degrades performance, while a higher switching threshold reduces diversity gain.

Hardware implementation and experimental validation are addressed in [37,102]. In [102], the authors adopt spectral-amplitude coding on a broadband UV light source,

and employ two PMTs at the receiver for linear combining and demodulation, achieving a favorable trade-off between performance and computational complexity. In [37], the authors build an experimental platform with a 36-element 265 nm UV LED array and dual PMTs, validating the feasibility of equal-gain combining (EGC) diversity reception through outdoor experiments. The measured results indicate that diversity gain depends on receiver spacing and transceiver elevation angles, and are compared with theoretical predictions.

5.3. Equalization Technology

In the field of UVC, equalization technology is a critical technical approach to break through the inherent bandwidth bottleneck of UV LED devices and mitigate the dispersion effects of atmospheric scattering channels. In [60], targeting the high-frequency attenuation characteristics of a 276.8 nm DUV micro-LED, the authors proposed a frequency-domain single-tap pre-equalization scheme tailored for 16-ary quadrature amplitude modulation orthogonal frequency division multiplexing (16-QAM-OFDM) systems. Through inverse compensation of the measured full-link frequency response and optimization of weighting coefficients, this scheme achieves an optimal trade-off between high-frequency gain compensation and noise amplification. Experimental results demonstrate that this scheme extends the available system bandwidth from 340 MHz to 500 MHz, achieves a maximum transmission rate of 2 Gbps over a 0.5 m free-space link (a 47% improvement compared with the non-pre-equalized scheme), and maintains support for 0.82 Gbps high-speed communication at a 3 m transmission distance. These findings fully validate the remarkable performance gain enabled by pre-equalization technology in high-speed UVC systems.

While mainstream linear adaptive equalization algorithms, including least mean square (LMS), recursive least square (RLS), and minimum mean square error (MMSE), can only compensate for linear channel distortion, they exhibit extremely weak fitting capability for the strong nonlinear characteristics of UVC scattering channels. Accordingly, modern equalization technologies have increasingly advanced into the field of deep learning. In [103], the authors proposed an end-to-end blind equalization scheme based on a hybrid long short-term memory-deep neural network (LSTM-DNN). With an integrated design of “temporal feature extraction and nonlinear distortion compensation”, this equalizer achieves significant performance enhancement, with an average BER reduction of 67.8% and an average mean square error (MSE) reduction of 70.8% over the entire SNR range of 0 dB to 20 dB. This scheme provides critical theoretical and experimental support for the design of high-speed, high-reliability UVC systems.

6. Networking Technologies

As research progresses, UVC is evolving from traditional point-to-point physical-layer transmission towards multi-node, large-scale self-organising networks [104]. The focus of research into UV networking technologies has shifted from simple channel modelling to protocol design and system architecture optimisation at the network layer. Overall, current research primarily concentrates on addressing three key challenges: first, the issues of spatio-temporal desynchronization and deaf nodes caused by directional transmission and reception; second, collision conflicts arising from high path loss in scattering channels and multi-node concurrency; third, the maintenance of three-dimensional dynamic topologies posed by mobile nodes such as UAVs. To address these challenges, researchers have achieved significant breakthroughs in three key areas: neighbour discovery mechanisms, media access control (MAC) protocol design, and three-dimensional mobile node architectures.

6.1. Multi-User Channel Modeling

The mathematical modeling of multi-user systems can be generally divided into four stages [105]: three-dimensional geometric modeling of multi-user systems, link channel path loss modeling, quantitative receiver-side modeling of multi-user interference (MUI), and performance boundary modeling of multi-user systems. In the first stage, the spatial coordinates of each user node are uniformly defined, and a unified spatial geometric framework for multi-node networking scenarios is constructed. In the second stage, the path loss of all links is calculated. In the third stage, the calculated path loss of the target link and each interference link is substituted into the receiver photon counting model, respectively, to complete the quantitative conversion from single-link attenuation to total received interference. In the fourth stage, the optimal decision threshold at the receiver is solved, and the system BER is calculated.

It is assumed that OOK modulation is adopted, and the receiver is equipped with a photon-counting PMT, where the number of photons arriving at the receiver within each modulation symbol interval follows a Poisson distribution. The first two stages are consistent with the modeling process of conventional single-link systems. In the third stage, the average photon number of the target signal at the receiver is defined by the formula [105]: $\lambda_S = \frac{\eta_1 \eta_2 P_t}{L_{Tx} R_{bTx} h \nu_S}$, where η_1 is the photoelectric conversion efficiency of the PMT, η_2 is the optical filter efficiency, P_t is the transmit power of the target transmitter (Tx), R_{bTx} is the bit rate of the target link, h is Planck's constant, and ν_S is the optical frequency of the target signal. The average photon count of the total multi-user interference (MUI) at the receiver is defined by the formula: $\lambda_i = \sum_{j=1}^K \frac{\eta_1 \eta_2 P_{ij}}{L_{Ixj} R_{bIxj} h \nu_i}$, where K is the total number of interfering user nodes in the network, P_{ij} is the transmit power of the j -th interfering node, L_{Ixj} is the path loss from the j -th interfering node to the receiver (Rx), R_{bIxj} is the bit rate of the j -th interfering node, and ν_i is the optical frequency of the interfering signal. In the fourth stage, the optimal decision threshold for the receiver to distinguish between binary "0" and "1" symbols is defined by the formula: $m_T = \left\lceil \frac{\lambda_S}{\ln(1 + \lambda_S / \lambda_i)} \right\rceil$. The system BER is constructed by the formula: $P_e = \frac{1}{2} \sum_{k=0}^{m_T} \frac{(\lambda_S + \lambda_i)^k e^{-(\lambda_S + \lambda_i)}}{k!} + \frac{1}{2} \sum_{k=m_T+1}^{\infty} \frac{\lambda_i^k e^{-\lambda_i}}{k!}$.

In multi-user UVC, MUI has emerged as a core challenge. Conflicts originally confined to the time-frequency domain have been extended to the spatial collision domain formed by the overlapping coverage of communication links. Meanwhile, the analytical scope has been expanded from point-to-point BER to network coverage and connectivity, while the receiver architecture has evolved from single-signal demodulation to array-based space division multiple access (SDMA) and multi-user detection (MUD). This gives rise to the critical challenge of effectively suppressing multiple access interference and coordinating multi-node access over strong-scattering, power-constrained channels, and has spurred a series of technological innovations, including collision-free medium access control (MAC) protocols integrating graph theory and cross-layer design, receiver array-based SDMA with successive interference cancellation (SIC) detection, as well as beamforming and power optimization schemes.

6.2. Ultraviolet Neighbour Discovery and Link Establishment Mechanisms

Neighbour discovery is the first step in ultraviolet self-organising networks. As ultraviolet networks typically employ directional transmission, omnidirectional reception, or directional/directional modes, misalignment of transmission and reception beams between nodes is common, resulting in prolonged neighbour discovery delays. Wang proposed a leader-based neighbour discovery protocol [106]. By designating a node as the leader to sequentially perform neighbour discovery, this approach avoids the conflict issues associated with random access. Furthermore, to enhance fairness, the protocol balances the number

of times each node acts as the leader via a leader table and incorporates a counter-based mechanism to determine when to terminate the discovery process. Verification via OPNET simulation demonstrated that this protocol can reduce neighbour discovery time by over 90%. The study also analysed the impact of parameters such as the number of nodes and the number of transmission directions on discovery performance, providing an important reference for UV network design.

With the maturity of UAV combat technology, UAVs in practical operational scenarios are frequently subjected to the adverse impacts of multiple factors, including complex atmospheric conditions and EMI, resulting in degraded intra-formation communication efficiency. Zhao designed a spherical ultraviolet LED communication node model [107], as shown in Figure 11, based on the characteristics of near-line-of-sight ultraviolet communication during the initial phase of three-dimensional formation assembly for UAV fleets. This paper proposes a handshake interaction framework incorporating random probabilities and a token-derived random avoidance algorithm to address the issues of channel conflicts and neighbour discovery efficiency during the neighbour discovery process. Compared to traditional single-token or simple random backoff schemes, this algorithm achieves clock synchronisation through dynamic token derivation, thereby significantly balancing channel collisions and discovery efficiency. The proposed algorithm offers a novel solution for neighbor discovery in UAV formations.

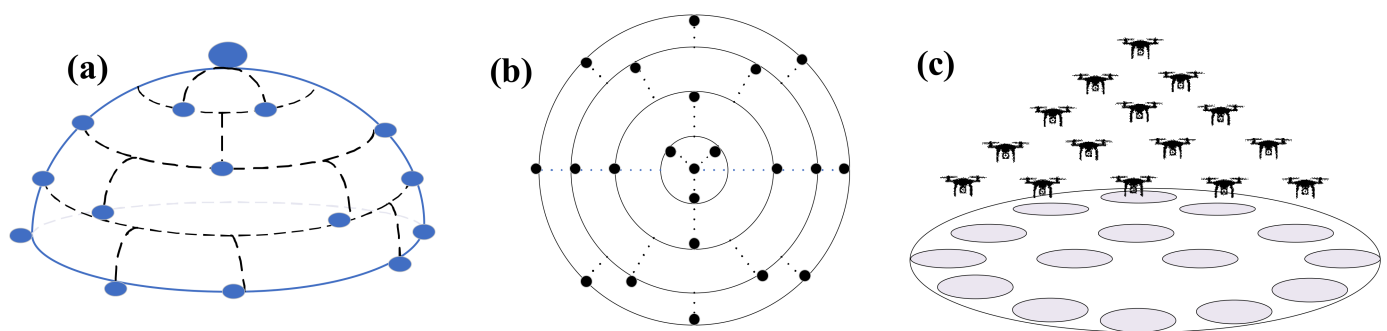


Figure 11. Model of nodes with non-uniform longitudinal and lateral distribution: (a) side view; (b) top view; (c) physical schematic diagram.

Wang, starting from the characteristics of the physical layer, proposed a UVCN–NDA-based method for ultraviolet cooperative networks [108]. By dynamically adjusting the bit transmission time to establish a neighbour table and selecting the shortest transmission path between nodes for frame transmission, this approach avoids unnecessary forwarding, thereby reducing the network’s power consumption. In a 16-node simulation, the UVCN–NDA protocol achieved a neighbour discovery probability of 1 and a channel collision probability of 0 by the 16th time slot. Under full network load and a maximum hop count of 9, UVCN–NDA reduced average power consumption by approximately 86.2% and increased overall throughput by approximately 52% compared to BST. In a physically constructed 7-node network, a 265 nm wavelength LED (single-chip optical power 100 mW, six-sided emission) and an H10721-110 photomultiplier tube (paired with a 10 nm bandwidth, OD4 cutoff depth filter) were used. with a terminal in a hexahedral configuration (diagonal 20 cm, height 10.5 cm, side length 10 cm), and a maximum communication distance of 50 m. Only R1 participates in data relaying; R2 and R4 receive data but do not forward it; R3, R5 and R6 have no data input whatsoever, fully realising the shortest-path relaying.

Five neighbor discovery algorithms, including asynchronous probabilistic scanning, are collectively discussed in [107,108]. Figure 12 presents a comparison of their key performance metrics. The bar chart represents the average neighbour discovery time, while

the line chart represents the channel collision probability. It can be seen that the newly proposed token derivation and bit-sharing techniques significantly reduce collisions whilst improving the success rate.

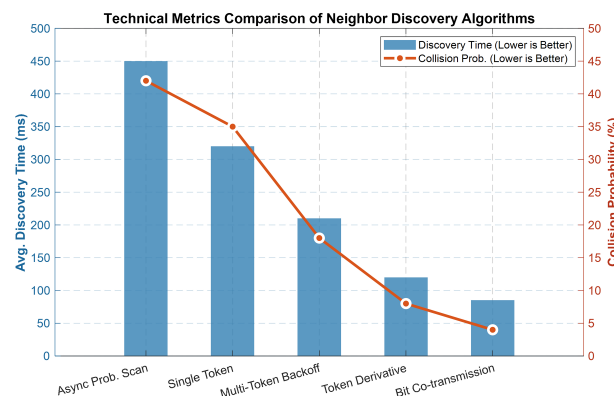


Figure 12. Comparison of key metrics for different neighbour discovery mechanisms (discovery time vs. conflict probability).

6.3. Multiple Access and Media Access Control (MAC) Protocols

During concurrent transmission by multiple nodes, scattered UV signals are highly prone to overlap, leading to decoding failures. The design of the MAC protocol directly determines the network's throughput and resource utilisation.

The CSMA-based UVOC-MAC protocol developed by the University of California (Riverside) is tailored for NLOS ultraviolet transmission, full-duplex communication, and multi-rate operation [19]. It fully exploits the potential of spatial multiplexing, reducing the collision probability by 50% compared to traditional protocols and increasing throughput by up to fourfold. Support for full-duplex operation results in a 377.26% increase in throughput compared to pure half-duplex mode (full-duplex is supported only when the beam angle is $\leq 40^\circ$). Without UVOC-MAC, the collision probability is 70.59% with an average of 7 neighbours and an SIR of 10 dB; after adopting the protocol, the collision probability under high-rate priority sorting drops to 19.83%, and under path loss priority to 23.61%. Compared to traditional protocols, the collision probability is reduced by approximately 50%, although the conflict rate remains extremely high under heavy load.

Li from the Engineering University of the PLA Army proposed an Ultraviolet Lossless Contention MAC (UVLLC-MAC) protocol [109]. This MAC protocol is based on the superposition logic of ultraviolet power, transforming traditional destructive collisions into analysable lossless contention. It effectively reduces collision losses in multi-node contention access and fundamentally alters the collision handling mechanism, with the network's peak normalised throughput increasing by 77.8% compared to Slot ALOHA. In a practical physical setup with four nodes, full-duplex communication with one-hop reachability was achieved, with an effective communication rate of approximately 115 kbps, which is essentially consistent with the 100 kbps set in the simulation, thereby validating the protocol's actual throughput performance. Latency is inversely proportional to node priority. Under light load, the average network latency stabilises at 25 ms; under medium load with a cache capacity of 5: the average latency for nodes A, B and C is below 200 ms, whilst the lowest-priority node D has a latency of 410 ms; Under heavy load: the rate of delay increase for low-priority nodes is significantly higher than that for high-priority nodes, and can only meet the requirements of low-real-time communication. Although this protocol can achieve lossless contention to a certain extent, with stable performance for high-priority nodes suitable for the transmission of critical information, network fairness is

poor. The throughput of low-priority nodes decreases significantly, latency rises sharply, and the data loss rate is relatively high.

Ren from the University of Science and Technology of China evaluated the system through network model-based simulations, taking into account node mobility, node tracking and UV link gain, and combined this with beam tracking to optimise multiple access for directional UVC [110]. Under high transmission demand, CSMA-A's throughput growth virtually stagnates due to the significant resources consumed by control frames, whilst CSMA-B and CSMA-C continue to show steady growth. CSMA-C, lacking RTS/CTS control frames, exhibits the greatest increase in throughput. Furthermore, CSMA-C directly replaces control frames with data transmission and PN broadcast relaying, whilst utilising PN relaying as implicit acknowledgement, eliminating the need for additional ACK frames and thereby further reducing channel overhead. As CSMA-C lacks the pre-emptive RTS/CTS collision avoidance mechanism, direct collisions occur when multiple stations transmit data simultaneously; the resource overhead per collision is slightly higher than in CSMA-A/B (though the overall resource overhead is lower due to the absence of control frames).

Li from the Naval Aviation Engineering College, based on a vertical transceiver model for ultraviolet light communication, selected central nodes to radiate to adjacent cells using a weighted algorithm that takes power factors into account [111]. By employing a segmented time-slot method to allocate different time-slot segments to adjacent cells, they enabled nodes in more distant cells to reuse time slots, thereby resolving the conflict between an increasing number of nodes and a limited number of time slots. Compared to TDM, this method reduces message queuing delay by 4 ms when the number of network nodes is 40, increases link utilisation by 2.7%, and boosts network throughput by 1.8 kbps.

Pan designed and demonstrated an NLOS UVC network [112]. He developed a multi-node transmission protocol based on time-division multiple access (TDMA) that supports beacons, as well as protocols for beacon transmission, beacon reception, time compensation and slot conversion on a field-programmable gate array (FPGA) board based on a master-slave architecture. The master node periodically sends beacon signals to the slave nodes to implement the TDMA protocol. During outdoor field tests within a transmission range of 110 m × 90 m, the real-time communication throughput of this UVC network reached 800 kbps; the system utilised OOK modulation with a base transmission symbol rate of 2 Mbps, and the throughput was 40% of the symbol rate, primarily due to transmission resources being occupied by guard intervals in slot allocation and beacon control slots. Although the synchronisation error was reduced to the 50-nanosecond range after time compensation, the system was still unable to completely eliminate synchronisation errors, necessitating the design of a relatively long guard interval (29,124 symbols) to avoid slot collisions; this is also a significant cause of channel resource wastage.

Li proposed the Ultra-Violet Random Access Cooperative Networking Protocol (UVCN-TDMA) based on Time Division Multiple Access (TDMA), which integrates the advantages of synchronous and asynchronous MAC protocols and utilises the characteristics of the ultraviolet physical layer to design a cross-layer frame structure [113]. Through Markov chain analysis of node buffer queue changes, they derived formulas for queue length and average queuing delay. Simulations demonstrate that, through dynamic slot allocation, this protocol achieves higher throughput, lower latency, and lower packet loss rates than traditional TDMA. The study also investigates the impact of maximum buffer capacity and burst traffic on network performance.

Wang conducted research targeting the critical challenges in UVC, including severe path loss, the restriction of existing MAC protocols to only small-scale UV networks, and the scarcity of tailored protocols for large-scale distributed networks [114]. Based on a lossless contention mechanism and a bit-synchronous transmission relay scheme,

a neighbor discovery algorithm with low control overhead was designed to enable all nodes to construct a network-wide topology matrix. By innovatively decoupling channel contention from data transmission, a space division multiplexing (SDM)-enabled MAC protocol via dynamic subnet division was proposed, which forms multiple interference-free subnets through lossless contention and achieves parallel data transmission. This study analyzed the impacts of factors including node density on network performance, and indicated that further optimization of the protocol is required in conjunction with mobile scenarios and the energy efficiency requirements of UAV platforms.

As shown in Figure 13, based on the quantitative comparison results of the core performance metrics (throughput, delay, and control overhead) of the MAC protocols with normalized processing, it can be seen that the throughput of the traditional CSMA/CA protocol increases first and then decreases with rising load, while its delay and control overhead deteriorate significantly with the increase in node number. The traditional TDMA protocol presents balanced performance but suffers from insufficient flexibility in topology adaptation. Lossless contention protocols including the improved TDM and UVLLC-MAC can achieve low-delay and high-throughput transmission, but are prone to resource waste in scenarios with large-scale node deployment. Relying on space division and sectorized directional transmission, the SDM-MAC protocol maintains optimal throughput, delay and control overhead performance across the entire load range, exhibiting the most prominent comprehensive performance advantages.

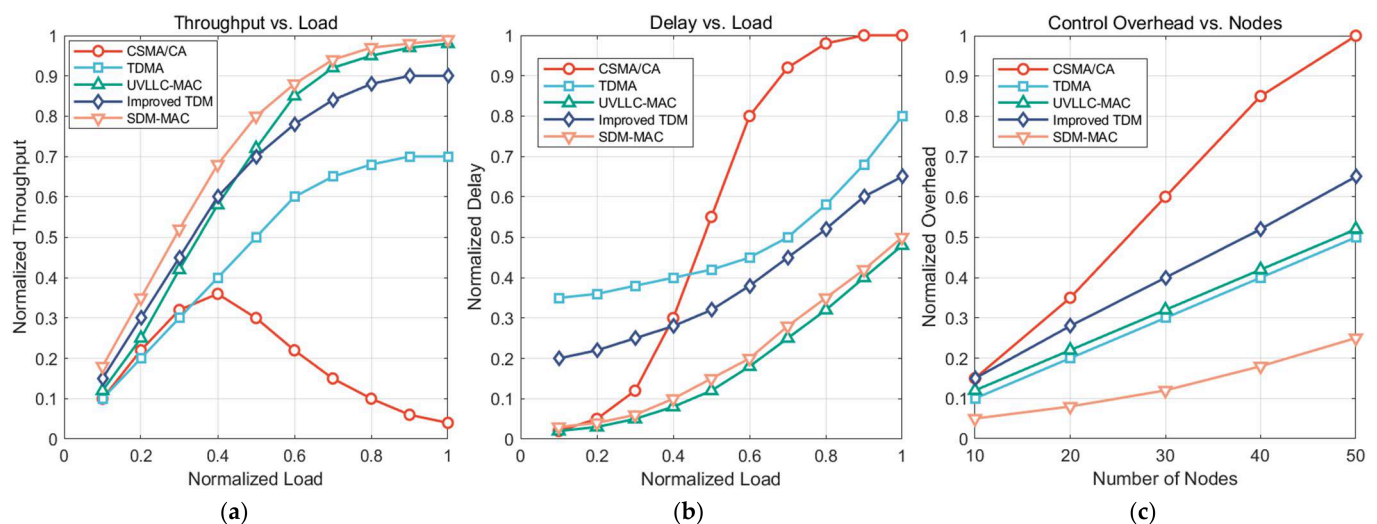


Figure 13. Performance comparison of different MAC protocols: (a) normalized throughput versus normalized load; (b) normalized delay versus normalized load; (c) normalized control overhead versus number of nodes.

In terms of scenario adaptation, for low-to-medium mobility scenarios with small-to-medium node scale, including static sensor networks and mobile emergency rescue networking, the improved TDM or UVLLC-MAC protocol is applicable, which can strike a balance between implementation complexity and transmission reliability. For high-mobility, large-scale node deployment scenarios such as high-density UAV swarms and space-air-ground heterogeneous collaborative networking, the SDM-MAC protocol can accurately adapt to dynamic topology changes and effectively avoid channel collisions, making it the optimal adaptation scheme. For confidential short-range networking scenarios, multi-channel encryption scheduling can be integrated based on the SDM-MAC protocol to simultaneously meet the requirements of communication concealment and multi-user parallel transmission.

6.4. Three-Dimensional Topology Control and Dynamic Mobile Architecture

The transition from early two-dimensional sensor networks to real-world three-dimensional UAV networks places stringent demands on node hardware architecture and topological dynamics.

Zhao systematically evaluated the impact of parameters such as transmission power [115], transmit/receive elevation angles and data rates on the coverage, connectivity and survivability of three-dimensional UAV networks (UVNNS), providing theoretical support for non-uniform deployment. The 3D region spans $200 \times 200 \times 200 \text{ m}^3$ and is divided into $20 \times 20 \times 20$ sub-regions, categorised into four priority levels based on deployment difficulty. Compared with the Random Deployment Algorithm (RDA), under conditions of $P_e = 10^{-1}$ (OOK + Poisson model), a transmission vertex angle of 60° and a reception vertex angle of 70° , UVNNS coverage improved by an average of over 5.01% and deployment costs were reduced by an average of over 3.11%. The convergence times for both methods increased with rising node density, and the average convergence time for UVNNS was significantly longer than that of RDA.

Although UV light offers the advantage of NLOS communication, beam pointing adjustments are still required in mobile networks. Song designed a mobile node device that combines transmission and reception functions, integrating an Acquisition, Pointing and Tracking (APT) method [116]. Through Monte Carlo simulations, the intricate relationship between node rotation speed and acquisition time was revealed, providing critical insights for the hardware architecture design and networking protocols of high-mobility platforms. Experimental results from outdoor NLOS UVC experiments indicate that the code rate curves obtained in the experiments follow the same trend as the simulation results. When the transmission power is 50 mW, the maximum deflection angle for NLOS communication is set to 6° , and the BER is 10^{-5} , the transmission code rate at the transmitter can reach 1.64×10^6 Baud.

Based on [115,116], a comparison chart was produced showing how the probability of connectivity varies with node movement speed under different node architectures. The results indicate that as node movement speed increases, the probability of network connectivity decreases gradually for all three schemes. Furthermore, at the same speed, the probability of connectivity is highest for directional mobile nodes using APT tracking, followed by nodes with three-dimensional omnidirectional LED arrays, whilst traditional two-dimensional/unidirectional nodes exhibit the lowest probability. Figure 14 shows the results of a comparison of connectivity performance in three-dimensional mobile self-organising network topologies.

Unlike the omnidirectional static coverage described above, Ren adopted a model in which secondary nodes track the primary node unidirectionally [110]. Directional protocols under this dynamic topology not only reduce the interference range but also significantly enhance link gain, representing another efficient evolutionary direction for mobile ad hoc networks.

Based on a comprehensive analysis of the latest literature, the development of wireless ultraviolet light communication networks has moved beyond the stage of verifying fundamental principles. Future trends clearly point towards: integrating lossless optical power superposition and spatial division multiplexing (SDM) at the physical layer; utilising dynamically derived tokens or beacons at the data link layer to enable ultra-low-latency neighbour discovery and MAC scheduling; and at the network layer, relying on intelligent nodes equipped with APT tracking and three-dimensional transmission-reception models to adapt to highly dynamic mobile platforms such as UAVs. The deep, cross-layer integration of these three elements will form the core technological foundation of future tactical-level, all-weather covert communication networks.

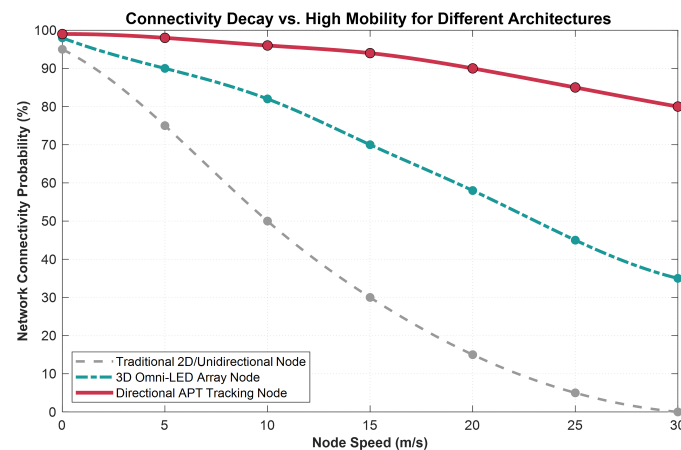


Figure 14. Comparison of connectivity performance in 3D mobile ad hoc network topologies (probability of connectivity as a function of mobility speed/distance).

7. Challenges and Future Trends

This study provides a systematic review of the evolution, underlying physical mechanisms, and core network architectures of UVC. As a highly promising specialized communication modality, UVC offers irreplaceable advantages in environments characterized by severe electromagnetic interference or requirements for strict covertness. These advantages stem from the negligible background noise in the solar-blind band, robust NLOS scattering characteristics, and an inherent low LPI. Currently, the field is in a pivotal transition phase, moving from theoretical validation toward engineering applications in complex, real-world scenarios.

7.1. Key Challenges

While UV communication demonstrates unique strengths in specific scenarios, transitioning from theoretical proof-of-concept to large-scale field deployment still faces several rigorous challenges.

- **Hardware Limitations:** Current mainstream semiconductor UV light sources, such as UV LEDs, continue to suffer from low photoelectric conversion efficiency and limited luminous power. Breakthroughs in novel wide-bandgap semiconductor materials and advanced device packaging structures are urgently required. Simultaneously, there remains significant potential to improve the detection sensitivity of existing UV detectors, including APDs and PMTs.
- **Channel Modeling Complexity:** Although numerous researchers have proposed various single and multiple scattering models, achieving an ideal balance between computational efficiency and accuracy remains difficult in extreme meteorological conditions (e.g., thick fog, heavy haze or dust) or field environments containing irregular dynamic obstacles. Furthermore, stochastic fluctuations in the refractive index caused by atmospheric turbulence lead to intense scintillation effects at the receiver. More refined models are necessary to accurately describe the transient influence mechanisms of turbulence across different altitudes and weather conditions.
- **Signal Processing Constraints:** NLOS UVC channels are characterized by severe path loss and multipath delay spread. Under such harsh transmission conditions, conventional modulation and channel coding techniques often lack sufficient spectral efficiency and error correction capabilities [117]. Additionally, further advancements are needed in weak signal acquisition, equalization algorithms to mitigate inter-symbol interference (ISI), and fundamental signal processing technologies.
- **Networking and Multi-node Coordination:** In collaborative multi-node networks, multiple access technologies (including TDMA, SDMA, CDMA, FDMA and WDMA)

tailored to the wide-angle scattering properties of UV light remain in the exploratory stage. The absence of a mature protocol architecture limits network concurrent capacity and the ability to suppress co-channel interference. Moreover, most existing network protocols are based on static or quasi-static topologies, providing insufficient support for nodes with high 3D mobility, such as UAV swarms. Because UVC relies on scattering, reducing mutual interference between nodes in dense distributed networks at both the protocol and physical layers remains a formidable challenge.

7.2. Future Outlook

The unique NLOS, high-security and anti-electromagnetic interference properties of UVC position it for significant growth within future ubiquitous networks. The technology is advancing from theoretical simulation to engineering implementation and from isolated links to intelligent heterogeneous networks.

In terms of application scope, UVC is expected to expand into diverse fields, including emergency lifeline support in extreme environments, secure inter-platform communication for aircraft, and high-precision assisted landing systems for aerial vehicles. Regarding architectural evolution, cross-band heterogeneous fusion will become a dominant trend. By leveraging the synergy between UV, RF and VLC, researchers aim to construct resilient, all-weather “Space-Air-Ground-Integrated” systems.

Furthermore, the integration of deep learning and artificial intelligence (AI) algorithms for adaptive equalization of complex nonlinear channels and intelligent topology optimization will grant UVC systems enhanced self-sensing as well as self-healing capabilities. These advancements will enable UVC to play a critical strategic role in the future special-purpose communication landscape of the Internet of Everything.

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(一) 一种水下全双工 LED 光成像 MIMO 实时通信系统及方法，
第二.

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