# 高光谱是什么 [>>](marginnote3app://note/B7EDE72A-13BA-4570-9294-7FCE6749A7F0)

## 高光谱遥感(hyperspectral remote sensing)又叫成像光谱遥感,是将成像技术和光谱技术相结合的多维信息获取技术(Goetz 等,1985)。 [>>](marginnote3app://note/57360C12-1533-45FF-B0AC-ADB8D98ABC17)

## 光谱遥感器能够同时获取目标区域的2维几何空间信息与1维光谱信息,因此高光谱数据具有“图像立方体”的形式和结构,体现出“图谱合一”的特点和优势(如图1所示)。高光谱图像中的每个像元记录着瞬时视场角内几十甚至上百个连续波段的光谱信息,其光谱分辨率在400—2500 nm波长范围内一般小于10 nm。将这些光谱信息作为波长的函数可以绘制一条完整而连续的光谱曲线,反映出能够区分不同物质的诊断性光谱特征,使得本来在宽波段多光谱遥感图像中不可探测的地物在高光谱遥感中能够被探测(童庆禧 等,2006a) [>>](marginnote3app://note/D3F56F51-962E-4411-BFD0-0F26EF19531E)

## 高光谱成像技术是一种图谱合一的新技术, 能同时检测到物质的内部信息和外部信息。光谱信息的提取分析方式有2 种:一是对采集到的所有波段进行分析;二是通过分析样本和光谱信息的关系, 提取与其相关的波长, 这种方法称为提取特征波长, 是指从原有的光谱数据中提取与样品化学物质相关的波长与波段[ [>>](marginnote3app://note/BED1A3FE-0EF1-4FF6-8130-6E0B4D7F07B5)

# 从噪声评估与数据降维方法、混合像元分解方法、图像分类方法、目标探测与异常探测方法 [>>](marginnote3app://note/B44A0752-D60E-4BDF-A742-F13EB62EE81C)

# 题制图的基础数据,在土地覆盖和资源调查以及环境监测等领域均有着巨大的应用价值。高光谱图像分类中主要面临Hughes现象(Hughes,1968)和维数灾难(Bellman,2015)、特征空间中数据非线性分布等问题。同时,传统算法多是以像元作为基本单元进行分类,并未考虑遥感图像的空间域特征,从而使得算法无法有效处理同物异谱问题,分类结果中地物内部易出现许多噪点。 [>>](marginnote3app://note/F4DA37FD-724E-4417-84F3-B6260114B849)

# 高光谱图像提供的精细光谱特征可以用于区分存在细微差异的目标,包括那些与自然背景存在较高相似度的目标。因此,高光谱图像目标探测技术在公共安全和国防领域中有着巨大的应用潜力和价值。高光谱图像目标探测要求目标具有诊断性的光谱特征,在实际应用中受目标光谱的变异性、背景信息分布与模型假设存在差异、目标地物尺寸处于亚像元级别等问题影响,有时存在虚警率过高的问题,需要发展稳定可靠的新方法。 [>>](marginnote3app://note/B838E4C5-BF0C-49BE-81E5-6C373A327251)

# 此外,高光谱遥感观测的目的是获取有用的目标信息,而不是体量巨大的高维原始数据,传统图像处理平台和信息提取方式难以满足目标信息快速获取的需求。尽管高性能处理器件的迅猛发展,为亟待解决的高光谱图像并行快速处理和在轨实时信息提取提供了实现途径,但也面临着一系列的关键技术问题。并行处理和在轨实时处理都需要对算法架构进行优化,同时要依据处理硬件的特点考虑编程方面的问题,此外,在轨实时处理还对硬件在功耗等方面提出了特殊的要求。 [>>](marginnote3app://note/DDE3CBED-5A59-4A82-9C8C-EC0363BD46CA)

# 高光谱图像波段多、数据量大,而且混合像元问题较为严重,且同物异谱影响明显,这都是信息提取研究需要解决的关键问题,概括为4个方面: [>>](marginnote3app://note/ED4B8997-8E4E-4E8F-8CEC-4A21BEDAB172)

# 光谱图像波段较多,相邻波段之间必然有着很强的相关性,这使得所观测到的数据在一定程度上存在冗余现象,而且数据量大,为图像的处理带来了压力,数据的膨胀导致计算机处理负荷大幅增加。另外,在高光谱图像数据获取过程中出现的噪声将会使图像中的光谱信息产生“失真”。因此需要进行数据降维,以压缩数据量和提高运算效率,同时可以简化和优化图像特征,并最大限度保留信号和压缩噪声。 [>>](marginnote3app://note/12B14713-AA2D-41B6-B801-9B089426FC74)

# 一个像元对应的瞬时视场内存在多种不同地物类型,该像元的光谱特征则由这些地物的光谱信息共同构成,由此产生了混合像元现象。 由于遥感器空间分辨率的制约,高光谱图像中普遍存在混合像元问题,这是制约分类精度提高和目标探测准确率的重要因素。为进一步挖掘像元内部信息,需要进行混合像元分解,发展描述光谱混合物理过程的数学模型以及求解模型的解混算法。 [>>](marginnote3app://note/CE700CEF-315E-4359-8589-C1B4D2AC6491)

# 利用高光谱图像进行地物精细分类是高光谱遥感技术应用的核心内容之一,分类结果是专 [>>](marginnote3app://note/E3FC0B5D-011C-4B96-A91E-B074354E0DC2)

# [>>](marginnote3app://note/68D5B1C0-CA44-4E6A-BD9F-20567F9E93D9)

# FPGA 能够应用于高光谱遥感图像的实时处理源于它灵活的设计方式和强大的面积-速度互换原则。Du和Qi(2006)在FPGA上实现了并行独立成分分析(pICA)算法,在此基础上研究了一个可重构的处理系统,并在高光谱图像处理上得以实现。何光林和彭林科(2009)基于FPGA实现基于奇异值分解(SVD)的高光谱图像数据降维方法,实验表明用这种方法降维后数据损失量非常小。Gonzalez和Woods(2010)讨论纯像元指数(PPI)算法在FPGA上实现的方法,高光谱图像解混可看做求解超定方程式,纯像元指数PPI的计算过程是复杂和耗时的,可以基于FPGA的硬件并行计算特性提高处理速率,并在Xilinx Vertex4 FPGA上实现了N-FINDR 算法,算法基于单形体的体积,反复迭代寻找构成单形体体积最大的像元组合即为提取的端元, 传统的N-FINDR算法处理时间很长,基于FPGA实现算法的硬件加速,达到实时处理(Gonzalez and Woods,2012),进一步使用FPGA实现了HySIME 算法,该算法是常用的有效的确认端元数量的算法,系统包括了DMA模块,同时使用了数据预获取技术,减少了等待数据输入造成的时延。 Lopez 等人(2012)对顶点成分分析算法(VCA)进行改进, 简化原始算法的计算过程,同时使其更加适合FPGA 进行快速并行处理,设计优化的MVCA算法,并利用Vertex 5 FPGA进行硬件实现。Chang等人(2013) [>>](marginnote3app://note/6239287B-4469-4B40-A978-973F3178F630)

# 顶点成分分析算法(VCA) [>>](marginnote3app://note/A0A25F9D-1ED5-44A9-B8B0-6790E7557676)

# 实现基于FPGA的实时快速单形体增长算法(RT- FSGA),该算法对传统的SGA算法进行改进,使用Woodbury等式简化矩阵行列式的计算,实现实时端元提取。Cervero等人(2015)提出一种动态可变的实时端元提取系统,该实验采用MVCA算法,并对具体实现方式进行优化,基于FPGA可重构的特征,根据数据的具体情况动态调整处理系统,避免了不必要的时间消耗,进一步提高了处理效率。 [>>](marginnote3app://note/E4E953F5-BFDF-4960-A73A-39E40A382FB1)

# 另外,在高性能计算领域,芯片研发逐渐向智能化方向发展,尤其是在基于深度学习方法的加速计算芯片领域,NVIDIA推出致力于人工智能和深度学习的Tesla P100以及面向深度学习的超级计 算 机 D G X - 1 。 I B M 发 布 基 于 脉 冲 神 经 网 络SNN(Spiking Neural Network)的类脑超级计算平台TrueNorth,其处理能力相当于1 600万个神经元和40亿个神经键,能耗仅为2.5 W(Merolla,2014)。 中国科学院计算技术研究所研制了面向机器学习的寒武纪神经网络计算专用加速芯片,寒武纪一 [>>](marginnote3app://note/D14BA38E-1783-4060-A752-13B19007C15D)

# 号主频为0.98 GHz,峰值性能达每秒4520亿次神经网络基本运算,65 nm工艺下功耗为0.485 W,面积3.02 mm 2(Chen,2014)。在若干代表性神经网络上的实验结果表明,平均性能超过主流CPU核的100倍,但是面积和功耗仅为1/10,效能提升可达3个数量级。可见,未来突破经典的存储和处理分离的冯诺依曼体系架构,发展支撑人工智能算法的高性能、低功耗芯片开始显示出巨大的潜力, 并将在高光谱图像信息提取领域发挥巨大的应用价值。 [>>](marginnote3app://note/45868CEE-C37C-4C29-9004-93F5679B003F)

# Group [>>](marginnote3app://note/47D1EDD4-5BB9-4B22-845B-FC9A0FA3841E)

## 基于FPGA的高光谱实时图像处理综述 [>>](marginnote3app://note/76A26D31-9788-4C7A-9676-8D7604E0BBD4)

### 假定 λ 表示可探测的波长范围,多光谱一般指的是光谱分辨率在波长的 1/10 数量级范围内(几十到几百纳米)的图像,而高光谱一般指的是光谱分辨率在波长的 1/100 数量级范围内(几纳米)的图像。 [>>](marginnote3app://note/1088616E-6343-4F9E-A446-4A1A9CB43C3A)

### 数据集 [>>](marginnote3app://note/94EDEBA4-295E-4D4A-B1FC-D9455E2AE9F9)

#### Foster [>>](marginnote3app://note/A91928FF-8D85-4051-BF0A-8AD12484AEF0)

#### University of Pavia [>>](marginnote3app://note/49BC3BA3-248B-471E-9E9C-D05F1A74185C)

#### CAVE [>>](marginnote3app://note/31A0A337-447E-4848-88D7-3840DDB8F040)

#### Harvard [>>](marginnote3app://note/E60B180C-20FA-4543-A0AD-BB9F17F8A67D)

### 高光谱图像的光谱范围可从可见光、近红外、中红外一直到远红外,光谱分辨率为纳米级别。 [>>](marginnote3app://note/0B77AC1F-E2B4-45F0-B440-55DB2689BF1F)

### 已有的光谱成像技术主要分为:摆扫式(whiskbroom) 、推扫式(pushbroom) 、凝视式(staring)以及快照式(snapshot) 。 [>>](marginnote3app://note/66E6EBDA-A453-408F-8E54-5BC6D76E4976)

### 因此,本文提出的高光谱图像超分辨处理算法,均通过利用卷积神经网络来学习光谱差或光谱间的映射关系,从而将这种映射关系用于指导输入图像的超分辨过程, 以达到保持光谱信息前提下空间分辨能力的提升,从而保证在原始地物中的光谱可分离性不被破坏,给后续的高光谱图像分类、目标检测等实际应用提供帮助。 [>>](marginnote3app://note/3E80251F-BAA5-40B9-A141-51ADCF1DDBBC)

这篇论文的意义

### 目标检测 [>>](marginnote3app://note/CB3D93D2-918D-4257-99A6-C3FDD5625127)

### 人脸识别 [>>](marginnote3app://note/5D7A9EF5-5705-4306-B7DE-2080AD4695A0)

### 图像去噪 [>>](marginnote3app://note/8FECFF74-2F19-4A9D-8189-FE9BE6F3A4DA)

### 分类 [>>](marginnote3app://note/751252F4-E750-4C64-AC95-3835515C540A)

### 降维 [>>](marginnote3app://note/0269D93C-470A-4D80-9F5D-64B657A09424)

### 特征提取 [>>](marginnote3app://note/50CF0703-8217-4619-BE22-0B9DBAC8F1B7)

### 我们提出的光谱差卷积神经网络(Spectral Difference Convolutional Neural Network,SDCNN)开创性地将卷积神经网络直接应用于高光谱图像的超分辨处理上,该光谱差卷积神经网络主要包含有卷积层和非线性层。不同于现有的高光谱图像超分辨方法,本章提出的 SDCNN 网络直接学习训练数据和标签之间的映射关系,且这种映射关系可以通过将误差反向传播的方式来直接进行端对端的训练, 从而对整个网络模型进行优化。 [>>](marginnote3app://note/830C0FA9-BAC7-4ED3-BF08-8CD0014BC577)

### 论文主要针对高光谱图像空间分辨率较低这一问题出发,对如何在保持光谱信息前提下的高光谱图像超分辨算法进行研究,并从主观的视觉重建效果以及客观的评价指标两个方面同时对算法进行性能评价。 [>>](marginnote3app://note/54AAA022-C6A6-49A5-A0D7-F4E9357EB1A5)

# 面向大米分类的高光谱特征波长提取方法\_赵刘 [>>](marginnote3app://note/0A2AF512-8947-44FF-B75B-8813D5FE562A)

## 摘要: 为了利用高光谱对不同类型大米进行快速有效分类, 首先采用高光谱成像系统在 400 ~ 1 000 nm 光谱区域获取大米图谱信息, 分别利用竞争性自适应重加权算法(competitive adaptive reweighted sampling, CARS)、 连续投影算法(successive projection algorithm, SPA)、 无变量信息消除法(uninformative variable elimination, UVE)、 随机蛙跳(shuffled frog leaping algorithm, SFLA)对大米波谱信息进行特征波长提取, 并利用提取的特征波长结合支持向量机( support vector machine, SVM)分类算法对 6 种大米进行品种鉴别。研究结果表明, 利用 SPA 选取的特征波长建立的分类模型识别率为 75. 00% ;利用 UVE 选取的特征波长建立的分类模型识别率为 77. 78% ;利用 SFLA 选取的特征波长建立的分类模型识别率为 52. 78% ;利用 CARS 选取的特征波长建立的分类模型识别率为 83. 33% ;利用全波段下的光谱信息建立的分类模型识别率达到 77. 78% 。表明利用 CARS 选取特征波长可以有效替代全波段信息进行大米品种分类。 [>>](marginnote3app://note/2A77CAAA-7466-4F55-9677-0A1A496324BF)

## 在 18 张样本的高光谱图像上选取每 1 粒大米作为 1 个ROI(感兴趣区域), 统计每个 ROI 得到 162 条光谱曲线( 图4)。通过 ENVI 软件导出光谱数据至 Matlab, 对获得的 400 ~ 1 000 nm 波长范围内的 162 × 339 个光谱数据进行后续分析。 [>>](marginnote3app://note/39488FE5-288D-4CE5-98A1-2A76B0104461)

## 竞争性自适应重加权算法(competitive adaptive reweighted sampling, CARS)、 连续投影算法(successive projection algorithm, SPA)、 无变量信息消除法(uninformative variable elimination, UVE)、 随机蛙跳(shuffled frog leaping algorithm, SFLA) [>>](marginnote3app://note/21C77361-2EC0-4C47-B226-105FBE3EE67B)

# 基于空谱联合特性的高光谱图像异常目标检测算法研究 [>>](marginnote3app://note/EFEF24C3-A904-4F7D-BF6A-36ED59DD33AE)

## [>>](marginnote3app://note/1F8F14E9-1B0B-4DC4-8E74-F886F5BEE1A9)

## 高维度和非线性是高光谱遥感图像的固有属性, [>>](marginnote3app://note/28FA58E3-1017-4952-9E87-98173A7A4B46)

# 空谱稀疏结构学习下的高光谱数据降维与分类技术研究 [>>](marginnote3app://note/B77EA801-6891-4074-A0DF-E1FA30951320)

## 谱、同谱异物的现象普遍存在 [>>](marginnote3app://note/427A1F4E-2AB3-4543-9B7F-AB15AD438AC6)

## 本文在“973”计划(非结构化环境的协同感知与高效目标相关信息获取, 2013CB329402) ,国家自然科学基金重大研发计划(基于稀疏特征的遥感信息高效感知与压缩,91438103)等项目的支持下,借鉴生物认知过程中稀疏感知与认知机理, 借助稀疏表征学习、 结构学习以及半监督学习等理论, 对高光谱遥感影像光谱约简与分类方法进行了研究。 [>>](marginnote3app://note/2156FEBD-E8C0-4791-9D4E-FAEC1BAA160C)

## 提出了基于光谱成对相似性的稀疏波段选择方法。 [>>](marginnote3app://note/73426682-5F93-43A7-BA39-16250451F233)

## 设计了基于空-谱压缩张量编码的稀疏波段选择算法。 [>>](marginnote3app://note/D57853D3-1911-4A5E-926B-33DA15291EEB)

## 设计了基于超像素张量稀疏编码的高光谱数据分类方法。 [>>](marginnote3app://note/66BB465C-B619-4FAD-B44E-33E054E03044)

## 高光谱数据不仅仅是一组光谱数据, 更是具有特定空间语义的图像数据。 [>>](marginnote3app://note/473554B3-33A6-40AA-B9D2-01BE00325F83)

## 设计了双几何低秩学习的高光谱数据分类方法。 [>>](marginnote3app://note/D04BF490-C516-4F96-BE99-8676331F7DC4)

## 设计了基于低秩结构正则的半监督子空间学习算法。 [>>](marginnote3app://note/DB39978A-9046-42BB-8003-52B4D456B935)

# 高光谱遥感影像处理中的若干关键技术研究 [>>](marginnote3app://note/FD2A2037-8DAE-43E0-A5C5-07E8E992BF77)

## 去噪、数据分析中的解混和分类三项关键技术展开研究 [>>](marginnote3app://note/72BBDA9C-7895-4DF4-93F5-B73226778871)

## Indian Pines [>>](marginnote3app://note/448BDCE6-D0FA-4C60-A5D0-1B1BBD97823C)

## Pavia University [>>](marginnote3app://note/7D9DC149-B593-4AA0-A3EA-4416EA88A3A5)

# 基于稀疏表达图的高光谱图像半监督分类方法研究 [>>](marginnote3app://note/ECC15C83-839F-4B50-852E-A92D9B432E43)

## 稀疏表达 [>>](marginnote3app://note/D05184EA-C662-4043-9299-1AC11E887C3C)

# 基于高光谱成像技术的滩羊肉新鲜度快速检测研究\_张晶晶 [>>](marginnote3app://note/CB314EAF-9D80-4683-BF30-C712E5652E3E)

## 采用X - Y共生距离( S P X Y) 法划分为校正集和预测集,分别选用多元散射校正( m u l t i p l i c a t i v e s c a t t e r c o r r e c t i o n,M S C) 、卷积平滑( s a v i t z k y - g o l a y, S G) 、标准变量变换( s t a n d a r d n o r m a l i z e d v a r i a t e,S N V) 、归一化( n o r m a l i z a t i o n) 、基线校准( b a s e l i n e) 五种方法对原始光谱数据进行预处理,优选出最佳预处理方法。采用竞争性自适应重加权法( c a m p e t i t i v e a d a p t i v e r e w e i g h t e d s a m p l i n g,C A R S) 和连续投影算法( s u c c e s s i v e p r o j e c t i o n s a l g o r i t h m,S P A) 分别提取了2 1个和6 个特征波长。为优化模型并提高其模型精度,采用S P A算法对C A R S所选特征波长进行二次提取,优选出1 4个特征波长。基于所提取的特征波长建立T V B - N浓度的P L S R模型,优选出S N V - C A R S - S P A - P L S R模型具有较高的预测能力( R2 c= 0 . 8 8,RM S E C= 2 . 5 1,R2 p= 0 . 6 5,RM S E P = 2 . 1 1) 。同时,建立了滩羊肉T V B - N变化与贮藏时间的动力学模型,并将优化后的光谱模型和动力学反应模型相结合建立了滩羊肉光谱吸光度值与贮藏时间的高光谱动力学模型,实现对贮藏时间的预测,并通过 P L S - D A判别模型对滩羊肉贮藏时间进行判别分析( 校正集判别准确率为1 0 0 %,预测集为9 7 %) 。研究表明,利用可见 / 近红外高光谱成像技术结合动力学和化学计量学方法以及计算机编程技术,可以有效地实现滩羊肉品质智能监控与质量安全快速无损分析,为开发实时在线检测装备提供理论参考。 [>>](marginnote3app://note/C220D41D-1A9B-4CD1-8B12-75ADD6F5E73E)

## C A R S提取特征波长 [>>](marginnote3app://note/ACE6D665-76CD-44F0-9473-0735A8F0AC6D)

## S P A算法选取特征波长 [>>](marginnote3app://note/42E31479-5EBF-45FF-913F-D9568350F933)

# 高光谱图像处理与信息提取前沿\_张兵 [>>](marginnote3app://note/D9FF0A1D-8E39-45DD-BB09-BBF071BEE323)

## 主成分分析是最基本的高光谱数据特征提取方法 [>>](marginnote3app://note/B801BF13-8D49-47DF-86FB-6E3367BFF5F9)

## 特征提取和波段选择。 [>>](marginnote3app://note/7D4D9B39-4AE4-4E04-A207-82F6E7C3FEB9)

## [>>](marginnote3app://note/E3601723-BC6C-4752-87B8-976DE1C6F76A)

## 特征选择的目的是选择原始高光谱数据的一个波段子集,这个波段子集能够尽量多地保留原始数据的主要光谱特征或者提高原始数据的地物类别可分性,也就是说要按照一定的标准选择一个最优的波段组合。所以波段选择问题实际上是一个组合优化问题,选择波段组合的标准也称为评价函数或者目标函数。 [>>](marginnote3app://note/9728C727-9861-4159-9AAD-8802B4309176)

## 目标函数 [>>](marginnote3app://note/561CDA4D-B370-4389-89F3-19AFB9F1C4F4)

## 可将波段选择算法分为监督的和非监督的两类 [>>](marginnote3app://note/77620283-7D68-4164-BEA1-1692375BAC84)

## 常用的非监督波段选择算法目标函数包括Bajcsy和Groves(2004)提出的信息熵、一阶光谱导数、二阶光谱导数方法,Du和Yang(2008) 提出的相似度以及Wang等人(2007)提出的单形体体积方法等。在监督波段选择算法中普遍采用的目标函数有离散度(Huang和He,2005)、Bhattacharyya 距离、Jeffries-Matusita距离、最小估计丰度协方差等(Chang 等,1999;Ifarraguerri和Prairie,2004; Yang 等,2011,2012;Wei 等,2012)。 [>>](marginnote3app://note/7EEBE431-5B12-45E5-9087-FEB5D1B5E65F)

## 波段选择算法中确定了目标函数以后,有效的搜索策略也是保证波段选择精度的重要因素。 [>>](marginnote3app://note/8606C384-C988-4764-B6CC-3FA9B5643752)

## 高光谱图像的混合像元分解有两个基本目的:确定组成混合像元的基本地物和计算各个基本地物在混合像元中所占比例。 [>>](marginnote3app://note/632CCE9A-49BD-4BC4-A93E-F04FEA994747)

## 端元提取(endmember extraction) [>>](marginnote3app://note/1DDC27E4-3704-4AD3-B4A2-FD43FF219A34)

## 丰度反演(abundance inversion) [>>](marginnote3app://note/28C32A0A-1D86-43E4-ABEF-726A281E82EA)

## 高光谱图像光谱混合模型可以分为线性光谱混合模型LSMM(Linear Spectral Mixing Moldel) 和非线性光谱混合模型NLSMM(Nonlinear Spectral Mixing Model)(张兵和孙旭,2015)。 [>>](marginnote3app://note/2B6896D6-B847-47CC-AD1A-6F66AA7A489D)

## 在软硬件结合方面。随着高光谱图像实时处理需求的增加以及移动计算、近似计算、专用计算芯片等计算前沿技术的发展(图12),将高光谱图像处理算法与计算硬件相结合,解决算法与计算架构的匹配优化问题,实现信息在高维特征数据中的“所见即所得”,使得高光谱成像系统从数据采集器转变为信息感知器,将成为高光谱图像处理未来的重要研究方向,也将极大地促进高光谱技术的普及和推广。 [>>](marginnote3app://note/10011399-8CED-4D86-8CE8-91BA92706163)

# 高光谱成像技术在食品品质无损检测中的应用\_刘建学 [>>](marginnote3app://note/A62B35E2-E46A-4700-9130-66B104090E15)

# Design of FPGA ICA for Hyperspectral Imaging Processing [>>](marginnote3app://note/9067FD09-3333-45A8-AB41-C44CD890EB7D)

# An FPGA Implementation of Parallel ICA for Dimensionality Reduction in Hyperspectral Images [>>](marginnote3app://note/FA74D3E5-CAEC-492E-AF31-8BD78A69B1C8)

## ICA is very time-consuming for high volume or dimension data set like hyperspectral images. [>>](marginnote3app://note/271356DE-EB9D-4EE4-8A67-CE4434749A97)

## [>>](marginnote3app://note/F6E8586D-8D7D-4A99-AE01-F6CCBD43EB6F)

# FPGA IMPLEMENTATION OF A MAXIMUM VOLUME ALGORITHM FOR ENDMEMBER EXTRACTION FROM HYPERSPECTRAL IMAGERY [>>](marginnote3app://note/01449381-6B10-4900-B3F1-B8817A980AFD)

# 基于FPGA实现卷积神经网络 [>>](marginnote3app://note/C017A297-5D0B-4B4F-AB8F-F7959E79F970)

# 一种FPGA实现的红外小目标检测算法\_王岳环 [>>](marginnote3app://note/30AE8124-7585-4DBD-954D-DC81CC5D9A27)

# 深度学习FPGA加速器的进展与趋势\_吴艳霞 [>>](marginnote3app://note/15F23D10-01B0-4E1E-9F48-BCDC9F7D38E0)

# 基于FPGA的卷积神经网络加速系统\_李小燕 [>>](marginnote3app://note/5EC85F09-FBAE-4FA3-AF4D-45FE327F4F34)

# 基于FPGA的硬件加速系统\_任卫欣 [>>](marginnote3app://note/AB5C3DBC-2BEC-48F1-925D-9FDF1E9CB60F)

# 基于FPGA的卷积神经网络卷积层并行加速结构设计\_陈煌 [>>](marginnote3app://note/5F214B09-FCC0-41A7-9D01-6D36627E03D2)

# 基于ARM\_FPGA平台的二值神经网络加速方法研究\_孙孝辉 [>>](marginnote3app://note/D05A0F1D-E82D-4446-BD95-E29B697DC28B)

# 基于GPU的高光谱图像分类研究及应用 [>>](marginnote3app://note/0DA4B6AD-17C3-4E87-BE75-62F34A25EF61)

## [>>](marginnote3app://note/F5ED9252-A126-4CF9-ACF5-8B8499265E8C)

## [>>](marginnote3app://note/65410638-0762-42E9-A582-9761E4F43615)

# 高光谱图像噪声分析与降噪模型概述\_李健 [>>](marginnote3app://note/3D0AF149-67FC-4661-903E-F63E59FE6C4E)

## 已经被广泛应用于不同土地覆盖类型的识别、采矿、军事侦察、城市规划等领域。 [>>](marginnote3app://note/70304015-39AB-46D3-AC68-52FDDBBC3286)

## 在采集数据图像时,原始数据图像经常会受到多种噪声的干扰,这些噪声影响了图像的可视效果,也降低了后续应用精度,因此,降噪成为分析高光谱图像的必要步骤。 [>>](marginnote3app://note/6E078731-ADBE-4ABC-BD86-9CB6020FEE52)

## 高光谱图像噪声主要由条带噪声、高斯白噪声、光子噪声等组成。另外,受观测条件和传感器故障的限制,噪声类型也是复杂多变的,通过量化一种噪声类型来对整个图像进行降噪建模很难实现,因此,通常会考虑两种噪声类型或混合噪声。 本文将对条带噪声和高斯白噪声进行分析,并总结降噪模型。 [>>](marginnote3app://note/6C24AB05-F106-467F-87FC-459F4780565B)

## 具体表现为:在一定方向上灰度值出现连续偏高或偏低的情况。 [>>](marginnote3app://note/AAAC54AC-770B-4415-BD95-7C67D79FC18F)

## 高斯白噪声指服从高斯分布,且每个波段上强度相同的噪声。 [>>](marginnote3app://note/EAC462FB-FD55-4BA4-B34C-53BF03577C8C)

## 条带噪声是 [>>](marginnote3app://note/F0C3D434-CDF3-4051-ACE1-705E3A473C66)

# 高光谱数据误差估计及降维方法研究\_孙墨寒 [>>](marginnote3app://note/0996070A-76DE-4485-B62B-792C9397C7D2)

# liu2019 [>>](marginnote3app://note/281F174B-7C69-4A43-8B03-D8EB1BBD1418)

## BASS Net [>>](marginnote3app://note/A3C67B25-F987-483B-B4D8-4C8DAE6E6328)

## HSI-CNN [>>](marginnote3app://note/72259272-F7A1-4459-A952-A72BDF5D0BE9)

## In order to address the above challenges and achieve fast processing speed on embedded devices, this work proposes a novel CNN architecture based on BASS Net [17], and our model is more hardware efficient for implementation on FPGAs while maintaining similar accuracy as the original BASS Net. [>>](marginnote3app://note/C764F58F-B8A4-4A06-917C-ED2CFF7463FA)

## FPGA by parallel processing, data pre-fetching and design space exploration. Compared to previous SVM-based FPGA accelerators, the proposed accelerator has almost the same scale of processing speed on the same scale of FPGA device, but provides a lot higher accuracy results. [>>](marginnote3app://note/7855457D-BB54-4538-BF89-766CCCDAB358)

# SVM-2016-FPGA [>>](marginnote3app://note/7DA15A0A-BCBD-49A7-B717-8BE9772ACB81)

## scalable [>>](marginnote3app://note/50A505BE-A83E-4A52-98BB-9C1947836FE4)

可扩展的

# SVM在高光谱图像处理中的应用综述\_王立国 [>>](marginnote3app://note/E9A65E69-BD21-4351-8EAD-A156B585075F)

## 波段选择、 据压缩、 光谱分类、 光谱端元选择、 光谱解混、 亚像元定位及异常检测等领域被广泛应用。 [>>](marginnote3app://note/2865088F-331D-4F41-B1FA-8C09ABF4CE75)

# 高光谱图像分类方法综述\_张建伟\_陈允杰 [>>](marginnote3app://note/EA158DAC-8482-4DDB-ACDD-DB8118752689)

# 深度学习在图像识别中的应用研究综述\_郑远攀 [>>](marginnote3app://note/1C31EA98-F8E6-4EFF-AD4D-79BEB2266DBE)

# 独立分量分析在高光谱遥感图像处理中的应用综述\_田野 [>>](marginnote3app://note/94392CA2-4880-40B3-BA6B-6D98818F0BF5)

# An SVM-based Hardware Accelerator for Onboard Classification of Hyperspectral Images [>>](marginnote3app://note/9CD6F622-2D50-4169-8F7E-3CD16202F25E)

# Machine\_learning\_based\_hyperspectral\_image\_analysi [>>](marginnote3app://note/2C503679-9DBC-453D-9607-93CB39007A2F)

# 实时图像处理-李聪 [>>](marginnote3app://note/A45ED9A1-D939-43CD-B3B2-4187A499F076)

# 深度迁移学习在高光谱遥感图像分类中的研究现状与展望\_刘小波 [>>](marginnote3app://note/DCD4CBD2-6D67-4F07-961B-8353917A6B94)

# 高光谱图像分类的研究进展\_闫敬文 [>>](marginnote3app://note/807D280C-8429-4BE1-BB12-A337C60F28E5)

# Zynq平台嵌入式本地光谱分离微型高光谱仪研制\_庞高峰 [>>](marginnote3app://note/83DD9CE9-1CF4-4286-917B-890A93E8B077)

# 一种改进的高光谱端元提取算法及其FPGA实现\_张锦涛 [>>](marginnote3app://note/443B01DD-5784-40F5-900F-38AB81624675)

# 深度迁移学习在高光谱图像分类中的运用\_王立伟 [>>](marginnote3app://note/78BEA820-E6F9-4B21-86F2-A7D1CE5CA2C1)

# 浅谈高光谱图像融合方法\_洪科 [>>](marginnote3app://note/17C874D8-CD14-4411-9E6B-4CCF8F82F56F)

# 基于LS\_SVM高光谱成像鱼新鲜度鉴别\_章海亮 [>>](marginnote3app://note/EF5BA476-C177-404B-89A8-E9AD015CF3EA)

# 基于随机森林算法的玉米品种高光谱图像鉴别\_邵琦 [>>](marginnote3app://note/A4FBC370-E8C7-42F3-AD2D-7667A4CCA1C9)

# 基于高光谱图像及深度特征的大米蛋白质含量预测模型\_孙俊 [>>](marginnote3app://note/504DBE1C-4D72-494C-B7A4-88763CE238B2)

# 基于高光谱成像技术的蓝莓果实成熟度识别研究\_英文\_马淏 [>>](marginnote3app://note/1036DB6C-51F2-4DE4-83EA-ED485B968882)

# 高光谱异常目标检测算法研究进展\_张炎 [>>](marginnote3app://note/B3100F43-9D20-4F5A-B701-62016D2C4696)

# 高光谱成像技术在肉品无损检测中的应用及进展\_张令标 [>>](marginnote3app://note/5EF59598-FE45-4612-A8DA-E9D359877191)

# 高光谱成像技术在农产品检测中的应用\_秦勤 [>>](marginnote3app://note/584529BC-A4C4-4961-B4FE-91AB116E6FD4)

# 高光谱成像的垃圾分类识别研究\_赵冬娥 [>>](marginnote3app://note/F52FE57E-EC7E-4353-956C-D6D64B239D36)

# 改进独立成分分析在高光谱图像分类中的应用\_赵慧洁 [>>](marginnote3app://note/9781301A-5A28-418A-92DF-4024DF98381A)

# 高光谱遥感影像处理 [>>](marginnote3app://note/8A19D9C9-6515-4FED-BA12-89DD13E3B953)

# 可重构神经网络加速器设计关键技术研究\_梁爽-魏少军-已读 [>>](marginnote3app://note/9431949B-22A6-456D-838D-9216555DD078)

## [>>](marginnote3app://note/71CE5727-EDFB-47E8-8705-2ADA337C572A)

# 深度学习在高光谱图像分类领域的研究现状与展望 [>>](marginnote3app://note/8C4FCAC6-7184-4811-9BDD-DEDB4A548593)

# 2019 A Comprehensive Survey on Graph Neural Networks [>>](marginnote3app://note/53C2A772-1C54-4A78-A3F2-9E109EA9D5AC)

## [>>](marginnote3app://note/0891F4F3-0AC6-40BE-B909-1CA7B1AC3077)

## The complexity of graph data has imposed significant challenges on existing machine learning algorithms. As graphs can be irregular, a graph may have a variable size of unordered nodes, and nodes from a graph may have a different number of neighbors, resulting in some important operations (e.g., convolutions) being easy to compute in the image domain, but difficult to apply to the graph domain. [>>](marginnote3app://note/7A705296-C9C6-419C-A7E9-D4EAEDCBFC8B)

## For example, a graph convolution can be generalized from a 2D convolution. As illustrated in Figure 1, an image can be considered as a special case of graphs where pixels are connected by adjacent pixels. Similar to 2D convolution, one may perform graph convolutions by taking the weighted average of a node’s neighborhood information. [>>](marginnote3app://note/65E78CC3-0327-411B-8B05-0B1574B68815)

## [>>](marginnote3app://note/857648A7-2713-4E42-B0D7-360987587BAE)

## four groups: recurrent graph neural networks, convo- lutional graph neural networks, graph autoencoders, and spatial-temporal graph neural networks. [>>](marginnote3app://note/BD9C80AF-3B30-4340-9838-A15B4AB6B756)

## ConvGNNs are divided into two main streams, the spectral-based approaches and the spatial-based approaches. [>>](marginnote3app://note/79016826-4536-4710-96DD-01780A73597B)

## pair-wise [>>](marginnote3app://note/6E8B9502-5CCA-4991-8B09-1D7D28AB005C)

## Model depth [>>](marginnote3app://note/9E95C563-0096-4456-96C7-B4DE620D7596)

## Scalability trade-off [>>](marginnote3app://note/01E34301-43F2-4C8F-B1AB-FA7E1593B1AD)

## Heterogenity [>>](marginnote3app://note/845361E5-C163-490D-BEDC-2D87FD87310A)

## Dynamicity [>>](marginnote3app://note/148ADB18-443C-42F7-8EDB-33DFD7F86801)

# 图神经网络综述 [>>](marginnote3app://note/A636A2C3-21AD-4E35-AD73-B47FCE1256B3)

## 核心在于图卷积算子的构建和图池化算子的构建 [>>](marginnote3app://note/3C7319E9-3FEB-47FA-8240-4356CC2B37F5)

## 图数据作为非欧空间数据, 不满足平移不变性, 即每个节点具有各异的局部结构. 而传统卷积神经网络中的基本算子: 卷积和池化, 依赖于数据的平移不变性. 此时如何在图数据上定义卷积和池化算子成为一个有挑战的工作. [>>](marginnote3app://note/E56255A7-5741-4F7B-852E-545A50896544)

## 近年来, 研究人员对图数据建模的关注逐渐转移到如何将深度学习的模型迁移到图数据上, 进行端到端的建模 [>>](marginnote3app://note/BCBC11B0-6BC3-428E-A83E-6CA8B8F3489D)

## 关注如何在图上构造深度学习模型. 借助于卷积神经网络对局部结构的建模能力及图上普遍存在的节点依赖关系, 图卷积神经网络成为其中最活跃最重要的一支 [>>](marginnote3app://note/F4DA78B3-7571-4482-A739-DD29040E85DD)

## 在建模图卷积神经网络时, 研究人员关注如何在图上构建卷积算子. [>>](marginnote3app://note/C5079AEB-C9C4-47AF-B71D-4E31A9D53CC4)

## 如何训练更高效的图卷积神经网络也受到广泛关注. [>>](marginnote3app://note/179C9546-65DA-4C1A-A1F1-2C3DC47AC76B)

## 可扩展性以及训练的速度 [>>](marginnote3app://note/08AEA7EE-A705-4DC0-B0E3-E8A3C92629F5)

## 池化算子作为卷积神经网络的主要组成部分, 作用是扩大感受野, 降低参数. 近期, 也有研究开始关注图上池化算子的构建. 图上池化算子主要用于图分类问题, 目的是学习到图的层级结构. [>>](marginnote3app://note/9C66E756-918A-44D4-8AD4-D718B1402CDD)

## 卷积算子和池化算子的构建 [>>](marginnote3app://note/5964119C-9863-4679-AF75-9FB1F889727E)

## 其中卷积算子的目的是刻画节点的局部结构, 而池化算子的目的是学到网络的层级化表示, 降低参数. [>>](marginnote3app://note/28A974E6-B625-4B7E-9BB5-2166214E7C1A)

## 谱方法 [>>](marginnote3app://note/3BDEE6EF-F501-4835-A749-D7E2E092A4A6)

## 空间方法两类 [>>](marginnote3app://note/CA73A2F9-45F2-419C-9E15-E0BC0E1DEEBE)

## 谱卷积神经网络 [>>](marginnote3app://note/4B739CAE-49AB-4449-BBDA-AA671CEBD021)

## 谱卷积神经网络将卷积核作用在谱空间的输入信号上, 并利用卷积定理实现图卷积, 以完成节点之间的信息聚合, 然后将非线性激活函数作用在聚合结果上, 并堆叠多层形成神经网络. 该模型不满足局部性, 使得谱卷积神经网络的局部性没有保证, 即产生信息聚合的节点并不一定是邻近节点 [>>](marginnote3app://note/9C5E5647-D075-473B-B8EA-85B98F4F25D0)

## 最近, 小波神经网络( GWNN)[ 2 1]提出用小波变换代替傅立叶变换实现卷积定理. [>>](marginnote3app://note/407CBC61-EF89-47CC-A0CB-163C2E8689FA)

## 好的性质 [>>](marginnote3app://note/6AF35A0F-D2B9-4F43-A266-1823D0F8C5E1)

## 切比雪夫网络和一阶图卷积神经网络着眼于参数化卷积核, 图热核网络着眼于低通滤波器 [>>](marginnote3app://note/4322725D-FD60-4325-9E0F-59FC4EA7507C)

## 通用框架 [>>](marginnote3app://note/1D1382B9-92A3-41E2-A929-1079259B04BD)

## 混合卷积网络(Mo N e t [>>](marginnote3app://note/34754B4C-E5A8-4CA1-8332-B1F3D95A490C)

## 平移不变性的缺失给图卷积神经网络的定义带来困难 [>>](marginnote3app://note/FEAE046B-8016-411F-B8E0-DE669F71E636)

## 近期, 注意力机制引起广泛关注, 图注意力网络( GAT) [>>](marginnote3app://note/8E7728C3-A382-4790-AE3C-3D1EEB7E8735)

## 图采样聚合网络 [>>](marginnote3app://note/A8B1AC39-A1CC-4FE1-AD7A-9EF03BF5F624)

## 这使得在大规模数据集上搭建图卷积神经网络成为可能. [>>](marginnote3app://note/F409BFE6-EBF1-430A-89BA-0FF9764EE583)

## 基于置信度的图卷积网络( C o n f GCN) [>>](marginnote3app://note/D8D8068C-2577-433A-91E4-F72A86E1A518)

## , 并指出GCN的本质是拉普拉斯平滑 [>>](marginnote3app://note/2C6D775E-6C17-4DAB-92E3-71F88F757804)

## 切比雪夫网络( C h e b y N e t [>>](marginnote3app://note/7203C94A-AF70-452A-A43E-E1AD45417B47)

## 于注意力机制的池化算子( [>>](marginnote3app://note/0324D788-D1FD-4DC1-AB53-0D7B5EE74436)

## 池化算子是为了学到图的等级结构, 进而完成图级别的任务 [>>](marginnote3app://note/ED0E109E-77F2-4F5F-8106-2D8A0867929D)

## 图卷积算子( 按特定权重聚合邻居节点的特征) 是图卷积神经网络空间方法的核心算子 [>>](marginnote3app://note/096A94FE-8C4C-4BE1-B610-6AB49C061C5B)

## G a r c i a等人[ 7 4]定义一个全连接的图, 其中节点是图片, 连边是图片和图片之间的相似度, 他们使用图神经网络对节点进行编码, 使用神经消息传播模型能够更好地利用图片之间的关联结构信息, 其在少样本、 半监督和主动学习等任务上取得了较好的实验结果 [>>](marginnote3app://note/7AE7BB05-2F84-406C-9DE6-CF4E8F6479FE)

## 谱方法 [>>](marginnote3app://note/8B55AC96-C5D6-4B70-817B-584C49BB7D85)

## 空间方法 [>>](marginnote3app://note/B028706B-F848-410D-864C-2961B576D137)

## 谱方法和空间方法 [>>](marginnote3app://note/1E73BAE9-9434-4CEC-BA59-F464666C175B)

## N e i g h b o rS a mp l i n [>>](marginnote3app://note/513EB8FC-95B9-4ACB-9DE0-D4C9257352EE)

## [>>](marginnote3app://note/0300EDAB-90F0-4D37-B756-7E392B9F5BE6)

# 福利：刘知远老师团队出版的一本GNN书籍-《Introduction to Graph Neural Networks》 [>>](marginnote3app://note/D5677DD7-635D-483C-B73B-B89CDA06AF8E)

## focus on node classification, link prediction, and clustering. [>>](marginnote3app://note/C428D1BB-4338-4B95-9FAE-B21046678105)

## However, CNNs can only operate on regular Euclidean data like images (2D grid) and text (1D sequence), which can also be regarded as instances of graphs. [>>](marginnote3app://note/B4D04E1C-E2A7-4FA0-8302-9F3F98D72D7D)

## Therefore, it is straightforward to think of finding the generalization of CNNs to graphs. [>>](marginnote3app://note/7E7FE0AA-64E3-4765-ABBE-DE10D6C08912)

## node2vec [>>](marginnote3app://note/370C459C-EF0B-41E8-9E5F-8355D040B3AF)

## DeepWalk [>>](marginnote3app://note/F3DE00E3-B957-419D-947C-56FE9DEFF193)

# 2020 DeepMap Learning Deep Representations for Graph Classification [>>](marginnote3app://note/750EDD42-E16C-42C3-B943-C3D9182880C5)

## mitigate [>>](marginnote3app://note/1A745E11-FFCA-4E76-A8C9-420F994056BA)

缓和

## spatially ordered, [>>](marginnote3app://note/851108F4-DEAF-4B67-B1FE-82FEA2DDE117)

## An image can be considered as a rectangle grid graph whose vertices represent pixels. [>>](marginnote3app://note/8965BA85-B286-4A51-90F4-A2B0D454747B)

## To make CNNs applicable to graphs, we first need to generate a vertex sequence for each graph such that the sequences are aligned across graphs. [>>](marginnote3app://note/22CAFD14-9BEC-42B6-8FAB-8D0F24054197)

## quantify the similarities of graphs [>>](marginnote3app://note/D1950D5F-5DC8-4EFD-A830-9E0098865A8F)

## positive-semidefinite [>>](marginnote3app://note/A5F2813E-F820-4C09-9237-7E3E946B7773)

半正定

## One problem in the effective implementation of this idea is that the sub- structures are not independent, which leads to high-dimensional feature space. In addition, graph kernels cannot capture the high- order complex interactions between vertices. [>>](marginnote3app://note/7C16C74D-8281-4BD3-882C-B28A50F2FC38)

## similarities [>>](marginnote3app://note/556B1107-76F4-4BCA-A1BD-5B78144901F1)

## R-convolution [>>](marginnote3app://note/720B5CE6-5E8B-4E7A-9A08-240BFE488AF2)

## graphlets [27], subtrees [29, 30], walks [34, 40], paths [4, 38], and then compare these substruc- tures from two graphs. [>>](marginnote3app://note/E3D0392A-880D-457B-902A-5F653E862568)

## are not independent. [>>](marginnote3app://note/5272FC61-68F2-4AFF-8E7A-90792A592222)

## hand-crafted features without considering the complex interactions between vertices. [>>](marginnote3app://note/FC7D1F29-EC91-4965-9795-29731F96D7C5)

## The learnt deep representation of a graph is a dense and low-dimensional vector that captures complex high-order interactions in a vertex neighborhood. [>>](marginnote3app://note/AD97A70C-9FE8-4151-805A-415870F7ED93)

## (1) Generate a vertex sequence for each graph such that the sequences are aligned across graphs. (2) Determine the receptive field for each vertex in the vertex sequence of each graph. [>>](marginnote3app://note/49400D4D-41E3-4D48-BB72-334624DCCEC3)

## eigenvector centrality [3] [>>](marginnote3app://note/AE4E7A93-155C-4E34-9495-F5028A982F2D)

## breadth-first search (BFS) method for constructing the receptive field for each vertex in the vertex sequence. [>>](marginnote3app://note/3A0D3E74-FF76-4F0C-B7DC-ABBF3B47653C)

## graphlet kernel (GK) [>>](marginnote3app://note/23C47E9C-FDE7-4E10-A550-974801710E52)

## Weisfeiler-Lehman subtree kernel [>>](marginnote3app://note/C7D9B6AC-EB2B-49B6-B596-CD5EEBFA9E97)

## isomorphic [>>](marginnote3app://note/40D87BBE-40CE-4234-8454-D18B68E63068)

同构的

## We first align vertices across graphs. Then, we build the receptive field for each vertex. [>>](marginnote3app://note/D6AB29FB-A9CF-4574-B703-E5215B946063)

## eigenvector centrality [>>](marginnote3app://note/E6E55398-18FC-49ED-AE09-0DD1EE417279)

## measure the importance of a vertex. [>>](marginnote3app://note/0A797D34-2AE5-4B7D-908D-F9B3B27F6733)

# 2020 Multiscale Dynamic Graph Convolutional Network for Hyperspectral Image Classification [>>](marginnote3app://note/A6C43565-60F9-4FE5-AFC8-1923428E458B)

## qualitative and quantitative aspects. [>>](marginnote3app://note/A73E31FC-E707-4546-B1A4-33C9A5DC9B33)

定性定量方面

## simple linear iterative clustering (SLIC) [>>](marginnote3app://note/B4801C9D-42C0-4DE8-A49A-5DCAE5241733)

## algorithm [65] [>>](marginnote3app://note/D4A61BB0-507A-42D0-AC2C-13934817F6D1)

## To address this problem, we adopt a segmen- tation algorithm named SLIC [65] to segment the entire image into a small amount of compact superpixels, [>>](marginnote3app://note/6652DEE6-A460-4098-A429-3054A32F71D5)

## Formally, an undirected graph is defined as G = (V, E), where V and E are the sets of nodes and edges, respectively. [>>](marginnote3app://note/6E7EC345-6BF1-4CB9-99AD-096C40E81DBC)

# 图卷积算法的研究进展 [>>](marginnote3app://note/6AE4C5D5-AACE-46A1-8903-143215279E34)

## 图节点的表示学习、 图节点的分类、 图上边的预测 ( 链接预测)、 图的分类等问题。 [>>](marginnote3app://note/6CC5FC30-1E6F-4878-BC02-1B0924FF3682)

## 目前图卷积算法主要是考虑如何将处理规则数据的卷积网络迁移过来。 [>>](marginnote3app://note/EF0E7C90-511E-4343-9E1E-A0EB9B617F7C)

## 对于像网格那样的规则数据, 由于有内在的序的关系, 很容易在同一模板上定义具有紧支撑的卷积算子。 然而, 图等不规则数据不具有这样序的关系, 因此无法在空间上定义这样的卷积算子。 [>>](marginnote3app://note/7177DBFA-8109-4642-AE51-D921C1493B99)

## 因此, 目前定义图卷积的一个主要思路是先将傅立叶变换推广到图结构数据上, 然后再根据卷积定理和逆傅立叶变换求得图谱卷积。 [>>](marginnote3app://note/B13909C9-6DCA-4603-9632-4FF66D43722C)

## 规则数据的卷积运算等价于相关性计算, 即中心点与周围网格数据的加权求和, [>>](marginnote3app://note/AD0FB66B-25EE-4938-BA8A-D780D997808F)

## 类似地可以将图上的卷积定义问题转化为图上相关性计算的定义问题, 对相关节点加权求和, 由此引出图上的空间卷积。 [>>](marginnote3app://note/5FDE4D03-80AD-4DB1-9F7D-3AE46A8C1F54)

## 层次聚类 [>>](marginnote3app://note/ED49AE2C-62F7-404B-BCD0-7D81F6248D50)

## Weisfeiler-Lehmance 测试 [>>](marginnote3app://note/FD491CAA-1E20-4B86-888E-0AE6B2548352)

## 图谱卷积 [>>](marginnote3app://note/791C6B0E-D01B-45EC-8C40-A7CC72911102)

## 空间卷积 [>>](marginnote3app://note/A1E3845B-83DB-4205-8FEE-7176ACF3E0AD)

## Spectral CNN[11] [>>](marginnote3app://note/C8756D62-9D48-493C-9F99-51878483FE6F)

## Chebyshev Spectral CNN[12] [>>](marginnote3app://note/5A118F01-5F49-4C33-935A-81CC45B4D176)

## CayleyNet[13] [>>](marginnote3app://note/C9E75602-C1EF-4620-8DC4-7B24E90D8476)

## Graph Convolutional Network (GCN)[14] [>>](marginnote3app://note/973D7A91-4EF0-4CAC-BE6A-B91AE7EA9800)

## GraphSAGE[16] [>>](marginnote3app://note/00A1CC3D-66FE-4761-805F-C984D6C1D602)

## Graph Attention Network[17] [>>](marginnote3app://note/B7B34CAF-3840-485C-9915-A069E0067219)

## [>>](marginnote3app://note/42D9109B-028C-4F03-A5CF-CA4B565EA51A)

# 图卷积神经网络理论与应用\_仝宗和 [>>](marginnote3app://note/E07F4FDF-F465-40F8-924E-72B2E94C1EF2)

# 2019 HOW POWERFUL ARE GRAPH NEURAL NETWORKS? [>>](marginnote3app://note/31E6F5EB-6856-4A06-8170-EC92DA72CC7A)

# 2016 Learning Convolutional Neural Networks for Graphs [>>](marginnote3app://note/C95E4B07-67C9-41DB-849F-27B734E32199)

## receptive fields [>>](marginnote3app://note/3C23F208-D4A0-4AE3-9215-D0E9148B74FE)

感受野

## PATCHY-SAN [>>](marginnote3app://note/BF0218E5-B136-49F3-BAD9-D99B03190A37)

## (i) Determining the node sequences for which neighborhood graphs are created and (ii) computing a nor- malization of neighborhood graphs, that is, a unique map- ping from a graph representation into a vector space rep- resentation. [>>](marginnote3app://note/CC8847B0-7E7A-4ADF-9F5D-87E74A1D8FD9)

## has several advantages [>>](marginnote3app://note/7019E50D-5427-4F70-84E1-41BA56348597)

## First, it is highly efficient, naively parallelizable, and applicable to large graphs. [>>](marginnote3app://note/BF4AB78B-2435-4319-86C4-6D4EF1A1DE34)

## Second, for a number of applications, rang- ing from computational biology to social network analysis, it is important to visualize learned network motifs (Milo et al., 2002). [>>](marginnote3app://note/F87F18BF-E3C4-418F-9FF0-416FCFAF5E68)

## Third, instead of crafting yet another graph kernel, PATCHY-SAN learns application dependent features with- out the need to feature engineering. [>>](marginnote3app://note/8FC5C3F2-593E-4EEC-AD72-02A77DC31B62)

## Moreover, the spatial order uniquely determines the nodes of each receptive field and the way these nodes are mapped to a vector space representation [>>](marginnote3app://note/FFB1A46E-14C4-473A-9FB1-A2F11E43B5FB)

## we need to determine for each graph (i) the se- quences of nodes for which we create neighborhoods, and (ii) a unique mapping from the graph representation to a vector representation such that nodes with similar structural roles in the neighborhood graphs are positioned similarly in the vector representation. [>>](marginnote3app://note/0D70DF38-0016-4208-863B-38F709BA6B22)

## applies the following steps to each graph: (1) Select a fixed-length sequence of nodes from the graph; (2) assemble a fixed-size neighborhood for each node in the selected sequence; (3) normalize the ex- tracted neighborhood graph; and (4) learn neighborhood representations with convolutional neural networks from the resulting sequence of patches. [>>](marginnote3app://note/DE004CE8-D0CF-4F33-A2EF-2231D21518A0)

# 2017 Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering [>>](marginnote3app://note/BD8026AD-AACE-4EE3-8F26-0DE91CC5DEE3)

## is the definition of localized graph filters [>>](marginnote3app://note/76E534C7-B547-456D-A904-02818F5CFBB0)

## three fundamental steps: [>>](marginnote3app://note/8A951FA6-EC0C-4E94-8A5F-B2E29626D3E3)

## two strategies to define convolutional filters; [>>](marginnote3app://note/14E66672-3706-47A5-998C-27FD11529698)

## spatial approach [>>](marginnote3app://note/63A3417B-007C-4A96-8CFE-FB234DFAA5C2)

## spectral approach [>>](marginnote3app://note/B06D3BA7-F169-40A8-8ADE-72BFB3DBB3CB)

## diagonalize [>>](marginnote3app://note/94E40764-C73D-4692-AB3F-D36B214BDCC1)

对角线化

## G = (V, E, W), where V is a finite set of |V| = n vertices, E is a set of edges and W ∈ Rn×nis a weighted adjacency matrix encoding the connection weight between two vertices. [>>](marginnote3app://note/7E1C8BE9-2762-4D72-A44B-6D0AA0743D9E)

## L = D−W [>>](marginnote3app://note/C3E234C9-8C62-4FB8-9E72-0FAEA1AE831F)

## x ∗G y = U((UTx) ? (UTy)) [>>](marginnote3app://note/0E0BBB9C-CF5B-4157-AC28-54AF3B5BCEAA)

## y = gθ(L)x = gθ(UΛUT)x = Ugθ(Λ)UTx. [>>](marginnote3app://note/D7A74107-C94E-4FF2-B2B2-ACB4BFB74E5D)

# 2017 A Generalization of Convolutional Neural Networks to Graph-Structured Data [>>](marginnote3app://note/C6690B1B-4E15-41FB-A44B-6F1CD7AF63CD)

## The main contribution of this work is a generalization of CNNs to general graph-structured data, directed or undirected, offering a supervised algorithm that in- corporates the structural information present in a graph. Moreover our algorithm can be applied to a wide range of regression and classification problems, by first estimat- ing the graph structure of the data and then applying the proposed CNN on it. [>>](marginnote3app://note/66531A60-BA1D-4FE4-8113-D90C1B551262)

## random walk [>>](marginnote3app://note/E2EFCD39-3CD4-4BF7-AE6E-27B0C5B41E0F)

## The fundamental hurdle [>>](marginnote3app://note/7D922F4E-1A5D-459F-875F-AD92408D5CAE)

基础障碍

## convolution operator. [>>](marginnote3app://note/BD3414DE-788B-43DB-A935-7EA2AD2DF444)

# Simplifying Graph Convolutional Networks [>>](marginnote3app://note/A8ECD9C3-FD79-47D6-83F6-5A43E7126A95)

## FastGCN. [>>](marginnote3app://note/AB217F42-0F05-4DBD-BEA1-67021B0A85C2)

# 2019 GraphACT- Accelerating GCN Training on CPU-FPGA Heterogeneous Platforms [>>](marginnote3app://note/B72B8BE3-8DE8-4DF4-AE3F-7E9D23416695)

## Operations of a graph convo- lutional layer are decomposed into two major steps, to (1) propagate information within the graph and (2) propagate information along the neural network layers. [>>](marginnote3app://note/D91418DC-6536-4CFC-B327-602702775D88)

## Memory access. [>>](marginnote3app://note/F3EC5FBC-5BF1-413A-8525-8D1B3BDC2B62)

## Computation. [>>](marginnote3app://note/3106CDD2-43B5-41E6-923B-47848DEEDEDC)

## Load-balance. [>>](marginnote3app://note/BC311450-6715-4681-A49E-CA89B5C5E141)

## Algorithm selection: By analyzing various GCN train- ing algorithms, we select a subgraph-based minibatch algo- rithm to significantly reduce CPU-FPGA communication. [>>](marginnote3app://note/DD443B7B-BE28-4FCD-907D-5DFC93ABB7CF)

## significantly reduces the number of on-chip operations and BRAM accesses on FPGA. [>>](marginnote3app://note/0F27F214-510B-4564-A06C-72D7D2F0E88B)

## We develop an accurate performance model for GraphACT. [>>](marginnote3app://note/C65BEEEF-8CA5-4A7B-8C10-13540753573E)

## GCNS require both sparse and dense matrix operations Apart from intensive computation, GCN accelerators need to ad dress issues such as irregular memory access and load-balance [>>](marginnote3app://note/E12C97F1-EE39-4C43-87E3-BC0883B05AAE)

## Apart from intensive computation, GCN accelerators need to ad- dress issues such as irregular memory access and load-balance. [>>](marginnote3app://note/03816F7E-9613-446F-85B1-8CED88A2D715)

## Many accelerator designs [7, 8, 16, 36, 41] have been proposed for traditional graph analytic problems, such as PageRank (PR), single source shortest path (SSSP) and breadth first search (BFS). [>>](marginnote3app://note/5F006045-D01F-4CE1-B73A-83AFA010276E)

## the first step is to reduce external memory communication via minibatches. [>>](marginnote3app://note/987BF4C3-D03F-4C94-A900-B05E3E781CA8)

## [34] [>>](marginnote3app://note/8F3F8B63-E89C-41D5-9E0B-EBE2A4B0D8DF)

## [5, 6, 14, 15, 34] [>>](marginnote3app://note/62ED88C1-5BE7-456E-8D29-78FDD8EA7D31)

## Computation-communication ratio of various train- ing algorithms [>>](marginnote3app://note/6D1CF218-1513-49ED-B141-88DF6E5EB06B)

## graph sampler [>>](marginnote3app://note/231336D2-3131-4564-83EF-3160F02665EF)

什么是graph sampler

## In this paper, we refer to block RAM and Ultra RAM by a general term “BRAM”. §Baseline code: https://github.com/ZimpleX/gcn-ipdps19, commit a6f531. ?GraphACT code: https://github.com/GraphSAINT/GraphAC [>>](marginnote3app://note/3499C1BC-CD66-4D2C-9E39-EFE119B2FBFE)

## propose a systolic array [>>](marginnote3app://note/5E70868C-FFDD-4390-AA96-293869495906)

## propose a light-weight pre-processing step [>>](marginnote3app://note/13CA30AE-CD10-4DEC-8736-5AF44E73CEFC)

## integrate the above optimizations into a complete hardware pipeline, and analyze its load-balance and resource utilization by accurate performance modeling. [>>](marginnote3app://note/C51C0C2B-398D-41BD-8B5A-423A5CF55F1F)

## The memory optimizations proposed in the above works do not directly apply to GCN accelerators. [>>](marginnote3app://note/DB5470A4-92BE-4352-9C00-64452B9D56E6)

## First of all, traditional graph analytics often propagate scalars along the graph edges, while GCNS propagate long feature vectors. Thus, although in both case memory accesses are irregular, the access patterns are very different Secondly, traditional graph analytics often propagate information [>>](marginnote3app://note/127586D3-3C7A-4E35-9426-A3214B99D94C)

## within the full graph, while GCNs propagate within minibatches. Thus, techniques such as graph partitioning may not be effective since minibatch size is much smaller than the full graph size. [>>](marginnote3app://note/60CA564C-C830-4587-B13E-007FC02C4BB6)

## negligible [>>](marginnote3app://note/8AAB7782-F504-4F54-B092-208BF89A2BA0)

Adj.可忽略不计

## he key to reduce redundancy is to identify sets of nodes ap- pearing frequently in the neighbor lists of v ∈ Vs. [>>](marginnote3app://note/F6E3F48B-F218-4F78-AAD3-DB402E413E84)

## Intuitively, the next step upon getting Sa is to extract the edges with largest weights, so that pre-computation of the correspond- ing vector sums reduces the most redundancy [>>](marginnote3app://note/C90AB6BB-1E8C-4DD1-96BD-FC0C344469EC)

## To avoid such useless pre-computation on x′′, a good solution is to find a maximum weight matching of Ga, so that the selected pairs imply high redundancy, and share no common nodes. [>>](marginnote3app://note/09937BDC-E0F6-47C9-A3A0-DDAAA7469F8D)

# 2020 Hardware Acceleration of Large Scale GCN Inference [>>](marginnote3app://note/48745C6D-D661-4FD8-98FE-CC8AD75D084A)

## 1) massive size of the input graph, 2) heterogeneous workload of the GCN inference that consists of sparse and dense matrix operations, and 3) irregular information propagation along the edges during the computation. [>>](marginnote3app://note/7A8D47B5-3C66-442B-813A-C8B62A1ADF15)

## sparsification [>>](marginnote3app://note/2BF61F6C-A249-4D72-A5F0-731D553F1B3B)

## node reordering [>>](marginnote3app://note/87720358-D8C9-4FEB-842A-328499FBFBB0)

## aggregation [>>](marginnote3app://note/0AF003DD-B373-429D-9744-6828F9BBFC57)

## transformation. [>>](marginnote3app://note/E484E39C-E244-4195-A976-919EB214448D)

## feature vector [>>](marginnote3app://note/ECB503CC-CE0B-40F7-B931-A7588538AAA5)

## 1) GraphACT focuses on accelerating one specific GCN train- ing algorithm–GraphSAINT [15], while our work proposes a generic method to accelerate GCN inference. [>>](marginnote3app://note/469B234F-9A40-4927-B2BA-8DD6090273B7)

## GraphACT targets at GCN training phase which uses mini-batch method. In each training epoch, a mini-batch subgraph is sampled from the full graph which can fit FPGA on-chip memory. Our work targets at GCN inference phase which is performed in full–batch manner. [>>](marginnote3app://note/E96619B9-299D-462B-9A33-4C4FC616A6A2)

# 2020 A Reconfigurable Convolutional Neural Network-Accelerated Coprocessor Based on RISC-V Instruction Set [>>](marginnote3app://note/A1CA50D7-646F-4141-9E90-A14CE73B52F0)

# GCN算法调研 - 王鹏 [>>](marginnote3app://note/FF4DF9EA-9B58-4E88-ACA9-A74761682046)

# 2020 Accurate, Efficient and Scalable Graph Embedding [>>](marginnote3app://note/A35A0181-87EB-4424-8B6D-1D564B0FC57D)

## In order to scale GCN to large graphs, the typical approach is to decompose training into “mini-batches” [>>](marginnote3app://note/9C53A568-C056-4248-A80B-D778E64E2478)

## Layer Sampling [>>](marginnote3app://note/6EC2D05F-8B11-4979-BF4B-7DB349BA5963)

# 2020 HyGCN- A GCN Accelerator with Hybrid Architecture [>>](marginnote3app://note/8BE20DEC-919F-4A58-BE8D-EAA99E9422D0)

## The convolutional layers occupy the major execution time of GCNs through two primary execution phases: Aggrega- tion and Combination [15, 40, 47]. [>>](marginnote3app://note/3BE141AC-4520-4D3A-8A83-F21B4A7D02BA)

# 基于RISC-V的图卷积异构可重构加速技术研究 [>>](marginnote3app://note/D2CA558F-66A9-4108-AA48-A05A02EDC795)

## 农产品检测 [>>](marginnote3app://note/3C8D93A5-02D5-447E-A66F-C508FA24C192)

## 高光谱 [>>](marginnote3app://note/F988806B-6246-48A4-A7E0-6CAA63FFA9DE)

### 意义 [>>](marginnote3app://note/AB3609B0-2D04-4552-AB6C-0CB05996DC71)

### 现状 [>>](marginnote3app://note/F7DC3E40-AD24-4AF3-AC1A-1235F5AFE790)

### 问题 [>>](marginnote3app://note/4D7CC1AA-67D0-4F1A-9E3A-B4D541C0D5A1)

## 图卷积 [>>](marginnote3app://note/CFF757DD-6443-49D1-8CC7-69077800441B)

### 意义 [>>](marginnote3app://note/63F0065D-70F5-4290-B923-EB0D7ED6019C)

### 现状 [>>](marginnote3app://note/CDD45BE4-33B7-4FB6-AC8A-1DAF0CFA478E)

### 问题 [>>](marginnote3app://note/5AED4DB7-A7CE-4B5B-8C6E-229847B66A8B)

## 可重构异构 [>>](marginnote3app://note/948A488E-A7BA-491E-B814-9233C01812EE)

### 意义 [>>](marginnote3app://note/806F30D4-A61A-44C4-8200-F7A0E08E0CB2)

### 现状 [>>](marginnote3app://note/61CC5E56-028A-44BC-AC79-3F6479A2D911)

### 问题 [>>](marginnote3app://note/4BAD69E3-4F83-451D-BA77-C4A6451CE2AF)

## RISC-V [>>](marginnote3app://note/86F50591-4063-4667-A8B8-57780875EA90)

### 意义 [>>](marginnote3app://note/B14D198E-25F8-4176-A8CF-2AE43B5F7A2E)

### 现状 [>>](marginnote3app://note/2CC654E2-63CF-4075-95A7-DEEAD5E60EF3)

### 问题 [>>](marginnote3app://note/3D65CC21-81F1-4C38-A51E-3FDF5A529255)

## 数据集 [>>](marginnote3app://note/94401DF6-2BF7-4EE5-B6BF-FFCA08544604)

### 图数据 [>>](marginnote3app://note/9A228010-7C1E-480A-9BED-E0293552CAC5)

#### datasets: Flickr, Reddit, Yelp. [>>](marginnote3app://note/26586442-3271-4983-B701-F2266BB76819)

#### [>>](marginnote3app://note/0BBCF291-9125-4AC4-A853-890EDBBE181B)

### 高光谱数据 [>>](marginnote3app://note/4543C1BD-4AF5-4597-AA73-4AAFC62098D0)

#### 遥感 [>>](marginnote3app://note/073ACC6D-A6FF-42B8-B967-0BF0E1252701)

##### Pavia University Dataset [>>](marginnote3app://note/145E785A-5A40-4A1F-8CCE-49626B5308CB)

###### PAVIA UNIVERSITY DATASET [>>](marginnote3app://note/48BFDB12-221A-4DC2-B408-123B81536443)

##### Houston2013 Dataset [>>](marginnote3app://note/1780FAA9-FECC-4638-9C23-7B8DCB3FC5FD)

###### HOUSTON2013 DATASET [>>](marginnote3app://note/BCB49B86-6CF6-4CC1-B968-B1D573463F97)

##### Indian Pines Dataset [>>](marginnote3app://note/53D4205C-A025-4B62-8657-1266A696385C)

#### 农产品 [>>](marginnote3app://note/4232D674-C8DF-4282-9491-49979AA819B8)

# 2020 Graph Convolutional Networks for Hyperspectral Image Classification [>>](marginnote3app://note/BD53EDCA-6636-4C00-993A-239BE793E40E)

## The high computational cost [>>](marginnote3app://note/4261FDA8-BAB7-4371-A4F0-95898D52A5C0)

## GCNs only allow for full-batch network learning, [>>](marginnote3app://note/B26D1356-5EA9-448C-A6B1-C225B2AE834E)

## miniGCNs [>>](marginnote3app://note/7881DC26-1DC4-4ECB-A0DB-146F4F0EF882)

## We develop three fusion schemes, including additive fusion, element-wise multiplicative fusion, and concate- nation fusion, to achieve better classification results in HS images by integrating features extracted from CNNs and our miniGCNs, in an end-to-end trainable network. [>>](marginnote3app://note/1A8F6246-3F15-4969-8030-B8F573C3A9CF)

## preliminaries [>>](marginnote3app://note/DCEF15AD-2765-44E6-8E5A-282C68E0A0AF)

## spectral domain. [>>](marginnote3app://note/EE560B30-EA3D-4B55-AE35-D232A3FE0FDA)

## Chebyshev polynomials [>>](marginnote3app://note/8E8BC080-F9CC-4ECB-9035-892863034699)

## INDIAN PINES DATASET [>>](marginnote3app://note/14304C08-BD5B-4CE6-93D8-144285E1D43C)

## Tensorflow platform [>>](marginnote3app://note/BF8DB38D-BA43-460B-A1D3-CC3F298ECA85)

## feature extraction (FE) [>>](marginnote3app://note/5C27B0BE-DAC7-4F06-8B73-CB8C83B8062F)

## morphological profiles (MPs) [>>](marginnote3app://note/1023DAEE-EE9B-4D98-AAEA-6F367F0411C5)

## attribute profiles [>>](marginnote3app://note/638306F2-B0C8-4590-B0A9-43FFC2F495FF)

## (both qualitatively and quantitatively) [>>](marginnote3app://note/D8E77BAD-ECC4-4E90-855E-25C6A131F536)

定性和定量

## preliminaries [>>](marginnote3app://note/DCF8BEED-60FC-4B2E-861B-0CFEE7FC19E3)

The preliminaries 论文正文前部分

## preliminaries [>>](marginnote3app://note/5D9FE765-F5AD-41D3-9C81-D3B6A95AE9C0)

## circumvent [>>](marginnote3app://note/0793BFCB-0F8E-46E4-9441-54C6F2B1ADE1)

circumvent  
circumvent

## circumvent [>>](marginnote3app://note/A2331827-74FC-4AC8-B8C4-DD8543D67E1D)

规避

## (in analogy to CNNs [>>](marginnote3app://note/019C0772-5058-41B8-B66F-B3C25A7272BE)

## inductive [>>](marginnote3app://note/05D36519-341B-44AB-A07C-7F741B683F97)

## cast [>>](marginnote3app://note/ADA2A2A6-2393-422C-82ED-B6CBA45D477E)

## proposition [>>](marginnote3app://note/F3946F5A-EAFB-4B14-AB8F-8CC9CA674453)

## [>>](marginnote3app://note/276B1AAB-727E-4486-B21D-10634BE5C39D)

## [>>](marginnote3app://note/9BA01746-726E-4CFF-B83F-26268189125F)

## reassembled [>>](marginnote3app://note/5D8F5532-E775-4FA7-993F-8BDC4756CC67)

重新组装

## additive (A) [>>](marginnote3app://note/36A7A1B1-45CF-4C6A-8A84-F6876F920DA7)

## , element-wise multiplicative (M) [>>](marginnote3app://note/38C80BEA-F0C2-4BDC-B950-428553B34D4F)

## concatenation (C) [>>](marginnote3app://note/02FD35B2-99FF-4556-87A8-30C149DCC034)

## [>>](marginnote3app://note/EF4B1AF7-36C7-4D85-8DD9-E45926DA770B)

## indices [>>](marginnote3app://note/B6E2D661-AD8C-4B51-86A2-3D737C84CC49)

指数

## Characterized by their rich and detailed spectral information, HS images allow discriminating the objects of interest more effectively (particularly those in spectrally similar classes) by capturing more subtle discrepancies from the contiguous shape of the spectral signatures associated to their pixels. HS imagery enables the detection and recognition of the materials on the Earth’s surface at a more fine and accurate level compared to RGB and multispectral (MS) data. However, the high spectral mixing between materials [5] and spectral variability and complex noise effects [6] bring difficulties in extracting discriminative information from such data. [>>](marginnote3app://note/A81405DA-F255-4332-B6DC-F574820318E7)

## [>>](marginnote3app://note/32DB04F6-56D9-492E-8D18-BAD8EE50E39C)

## three-fold [>>](marginnote3app://note/01A5B162-EAB8-4AAD-9A82-CAFF5A525C00)

## 33 [>>](marginnote3app://note/43909EAD-F5FF-4A5A-96AD-B41F1BB22349)

## [34] [>>](marginnote3app://note/90B6642B-AAB9-46F4-A359-EAE957EFCE69)

## 35 [>>](marginnote3app://note/837E7CE9-C10E-4A2B-A7CF-224282FF03BC)

# 2018 Adaptive Graph Convolutional Neural Networks [>>](marginnote3app://note/D37042AF-7683-4755-8E78-FCF950436C94)

# Graph Edge Convolutional Neural Networks for Skeleton-Based Action Recognition [>>](marginnote3app://note/B85E0282-BC60-4757-92DB-53A10F92456B)

# 2019 Graph Processing on FPGAs- Taxonomy, Survey, Challenges [>>](marginnote3app://note/F58983DE-98A4-4BC7-99EE-D9920B021D67)

## Field Programmable Gate Arrays (FPGAs) are integrated circuits that can be reprogrammed using hardware description languages. This allows for rapid prototyping of application-specific hardware. An FPGA consists of an array of logic blocks that can be arbitrarily rewired and configured to perform different logical operations. FPGAs usually use low clock frequencies of ≈100–200MHz, but they enable building custom hardware optimized for a given algorithm. Data can directly be streamed to the FPGA without the need to decode instructions, as done by the CPU. This data can then be processed in pipelines or by a network of processing units that is implemented on the FPGA, expressing parallelism at a massive scale. Another major advantage of FPGAs is the large cumulated bandwidth of their on-chip memory. Memory units on the FPGA, such as block RAM (BRAM), can be used to store reusable data to exploit temporal locality, avoiding expensive interactions with main memory. On a Xilinx Alveo U250 FPGA, 2566 memory blocks with 72 bit ports yield an on-chip bandwidth of 7 TB/s at 300 MHz, compared to 1 TB/s for full 256-bit AVX throughput at maximum turbo clock on a 12-core Intel Xeon Processor E5-4640 v4 CPU. In practice, the advantage of FPGAs can be much higher, as buffering strategies are programmed explicitly, as opposed to the fixed replacement scheme on a CPU. [>>](marginnote3app://note/21EC4E31-7534-4963-B04C-CA4B898C196B)

## Search (BFS) traversal [39], a fundamental graph algorithm, one accesses the neighbors of each vertex. In many graphs, for example various social networks, most of these neighborhoods are small (i.e., contain up to tens of vertices), while some are large (i.e., may even contain more than half of all the vertices in a graph). General purpose CPUs are not ideal for such data accesses: They have fixed memory access granularity based on cache line sizes, do not offer flexible high-degree parallelism, and their caches do not work effectively for irregular graph processing that have little or no temporal and spatial locality. GPUs, on the other hand, offer massive parallelism, but exhibit significantly reduced performance when the internal cores do not execute the same instruction (i.e., warp divergence), which is common in graphs with varying degrees. [>>](marginnote3app://note/6AF83E3A-5507-48B8-A886-C28D81658C4C)

## Connected Components [>>](marginnote3app://note/ABF48979-5F26-4405-A6EB-2FF09A97678C)

## strongly connected component [>>](marginnote3app://note/C225B03E-CFAE-4755-872B-12A8D51A649B)

## weakly connected component [>>](marginnote3app://note/EA9C3A2E-04BD-4827-8416-59B73F3BD787)

## Vertex-Centric Model. [>>](marginnote3app://note/C58DB527-274F-4329-B550-43C56287EF93)

## Edge-Centric Streaming Model. [>>](marginnote3app://note/1E112EAE-9AEA-45FF-B267-5C8E166FED90)

# 2020 FTRANS- Energy-Efficient Acceleration of Transformers using FPGA [>>](marginnote3app://note/CFE5003C-EE1A-4129-9792-DA20F69C24B4)

# 2020 Synetgy- Algorithm-hardware Co-design for ConvNet Accelerators on Embedded FPGAs [>>](marginnote3app://note/88CDA2F0-AAE7-4F2D-B8D3-7AEB872224BE)

## Synetgy, on the Ultra96 development board with Xilinx Zynq UltraScale+ MPSoC targeted at embedded applications. [>>](marginnote3app://note/68EFFE61-FA2E-4F4A-9624-0F34E59D46A9)

# 2018 A Survey of FPGA Based Deep Learning Accelerators- Challenges and Opportunities [>>](marginnote3app://note/429CB787-0F53-478E-8652-57E56F0E0918)

## software design [>>](marginnote3app://note/B6F4D5CB-86EC-47E7-8F80-A7E9E6ACCEE9)

## hardware design [>>](marginnote3app://note/06765A3C-0BF1-4C6C-ACC3-A023EF2E2A73)

## The primary goal of software design optimization is to reduce the computation or bandwidth requirements of the neural network model with keeping accuracy. [>>](marginnote3app://note/276E2758-F42F-41E6-A8C7-24FA86905C3E)

## CTC [>>](marginnote3app://note/820646E4-6F5F-47A5-8B2C-6A3186EC6F16)

## which are specific to each: accelerators for a specific application, accelerators for specific algorithms, accelerators for common features of algorithms, and general accelerator frameworks with hardware templates. [>>](marginnote3app://note/F8B94F07-8813-420B-94F5-01AFE4B6FE49)

## design accelerators are currently more common, [>>](marginnote3app://note/17A1E6A0-5919-40AB-95DE-CE254FC1D5BE)

## The improvement of hardware design mainly points to the characteristics of neural network algorithms to improve the existing logical unit structure so that it can execute deep learning algorithms efficiently and quickly. [>>](marginnote3app://note/793E9E26-B3D4-40CC-AAEC-41765DF4E557)

## In general, there are roughly three ways, which are optimization of algorithm procedure [2], data quantification and weight reduction [3]. The optimization of algorithm procedure is mainly for the characteristics of different neural network models, and the calculation process is simplified or transformed without affect- ing the result, thereby achieving the purpose of reducing the computation and reducing the bandwidth requirement. Data quantification is primarily the quantification of weights and neurons to reduce the bandwidth and storage requirements in neural network computing. Moreover, the last one, weight reduction, is to use a low-rank matrix to approximate the weight matrix so that the actual weight is reduced, reducing the total calculation of the model. [>>](marginnote3app://note/F76E7ACA-1B20-4A8E-B205-C94E3AEB923F)

## [28] [>>](marginnote3app://note/AE716966-70C2-4358-AC63-FA541AC76B8B)

## load- balanced sensing pruning method [>>](marginnote3app://note/927404EE-095F-43E4-9AC4-096353961432)

## The compressed model is then encoded and split into multiple PEs for paral- lelism, and a complex LSTM data stream is scheduled using a separately designed scheduler. Finally, an ESE hardware architecture that directly runs the sparse LSTM model is implemented. [>>](marginnote3app://note/2435713F-9173-4D4F-A22A-007430CC7DFB)

## roofline model [>>](marginnote3app://note/C05100E1-769F-4AC1-BEBD-78EAB7F388F9)

# A survey of FPGA design for AI aera [>>](marginnote3app://note/77AD7F1A-1326-4281-B737-2003F501B321)

# 基于FPGA的CNN算法加速\_邹虹 [>>](marginnote3app://note/41233D15-4E7C-407A-B19F-F80C987BA269)

# Gonzalez2018\_Article\_ANovelFPGA-basedArchitectureFo [>>](marginnote3app://note/1BF6F351-FC04-4D90-9931-86B22E6FFB4C)

# Wu2018\_Article\_FPGAImplementationOfCollaborat [>>](marginnote3app://note/336D7DF9-96AD-46AD-80F3-0E6F9773B5B3)

# Analyzing the Energy-Efficiency of Vision Kernels on Embedded CPU, GPU and FPGA Platforms [>>](marginnote3app://note/2924616C-59E7-4DF8-AC97-0EC45FAB3A34)

# 2019\_FPGA implementation of the principal component analysis algorithm for dimensionality reduction of hyperspectral images [>>](marginnote3app://note/8D0B106D-0106-4A7F-8D36-FF61B41274CB)

# 2019 A Survey of Convolutional Neural Networks on Edge with Reconfigurable Computing [>>](marginnote3app://note/045993EA-B428-4877-9813-C828F855F012)

## While advantageous, deep learning on edge is quite challenging because edge devices are usually limited in terms of performance, cost, and energy. Reconfigurable computing is being considered for inference on edge due to its high performance and energy efficiency while keeping a high hardware flexibility that allows for the easy adaption of the target computing platform to the CNN model. [>>](marginnote3app://note/C0AC1C55-0394-4C99-9762-87977DFDB67F)

## [>>](marginnote3app://note/3ED6D9F0-92AC-415C-8403-427CC0C4C2CD)

## A major issue is the inference latency that results from the delay to communicate with the server. [>>](marginnote3app://note/1FC32CC4-3FEF-491E-AF43-5823DA9AAF1D)

## computationally demanding and memory hungry [>>](marginnote3app://note/A60A4F0B-88DE-43A1-B7A6-7D396119826D)

## Another design option towards the implementation of deep neural networks in edge devices is the use of devices with better performance efficiency. Embedded GPUs (Graphics Processing Units), ASICs (Application Specific Integrated Circuits), and reconfigurable devices, like FPGAs (Field Programmable Gate Arrays), have already been explored as target devices for deep learning. ASICs have the best performance but have fixed silicon and thus are unable to follow the latest deep models due to long design cycles. On the other side, GPUs can follow the progress of deep models but are less power efficient than reconfigurable devices. Reconfigurable devices can be tailored for each specific model with a higher energy efficiency. [>>](marginnote3app://note/FD43700A-2C07-4E0E-9BC9-903B69D8C62B)

## [>>](marginnote3app://note/ED75F003-277E-4AE3-A3C8-2580E44FAAE2)

## coarse-grained [>>](marginnote3app://note/5E3450A4-2DB2-4F01-9B07-E930A13F3C8D)

## : (1) Data quantization and (2) data reduction. [>>](marginnote3app://note/77372CD8-6FD9-4061-8B53-116DE4999808)

# 遥感数据的边缘计算 [>>](marginnote3app://note/C45960F2-3815-40BD-B12A-D3367EB429AC)

## [>>](marginnote3app://note/596433DB-62C3-46AD-B61E-36630A703889)

# 2020 Deep Learning on Graphs- A Survey [>>](marginnote3app://note/ED2DFA1F-A852-48E3-A353-C6683CC936E4)

## ubiquitous [>>](marginnote3app://note/5BA5E6B2-58BE-4F24-92D8-A2C64E77559C)

## graphs1are ubiquitous in the real world, repre- senting objects and their relationships in varied domains, including social networks, e-commerce networks, biology networks, traffic networks, and so on. Graphs are also known to have complicated structures that can contain rich underlying values [5]. As a result, how to utilize deep learning methods to analyze graph data has attracted considerable research attention over the past few years. This problem is non-trivial because several challenges exist in applying traditional deep learning architectures to graphs: [>>](marginnote3app://note/5A4AEFB7-475D-4C95-B172-62843BEB3E81)

## • Irregular structures of graphs. Unlike images, audio, and text, which have a clear grid structure, graphs have irregular structures, making it hard to generalize some of the basic mathematical operations to graphs [6]. For example, defining convolution and pooling operations, which are the funda- mental operations in convolutional neural networks (CNNs), for graph data is not straightforward. This problem is often referred to as the geometric deep learning problem [7]. • Heterogeneity and diversity of graphs. A graph itself can be complicated, containing diverse types and properties. For example, graphs can be heterogeneous or homogenous, weighted or unweighted, and signed or unsigned. In addition, the tasks of graphs also vary widely, ranging from node- focused problems such as node classification and link predic- tion to graph-focused problems such as graph classification and graph generation. These diverse types, properties, and tasks require different model architectures to tackle specific problems. [>>](marginnote3app://note/22517BDD-ACD9-474F-8DC8-7928ADE66F17)

## Large-scale graphs. In the big-data era, real graphs can easily have millions or billions of nodes and edges; some well-known examples are social networks and e-commerce networks [8]. Therefore, how to design scalable models, preferably models that have a linear time complexity with respect to the graph size, is a key problem. • Incorporating interdisciplinary knowledge. Graphs are of- ten connected to other disciplines, such as biology, chemistry, and social sciences. This interdisciplinary nature provides both opportunities and challenges: domain knowledge can be leveraged to solve specific problems but integrating do- main knowledge can complicate model designs. For example, when generating molecular graphs, the objective function and chemical constraints are often non-differentiable; therefore gradient-based training methods cannot easily be applied. [>>](marginnote3app://note/0FDF9DDC-5B42-4CD8-BBB3-F62382DBA8CD)

# 2019 Deep Learning for Hyperspectral Image Classification- An Overview [>>](marginnote3app://note/762654E2-F45A-47CA-BE58-6BA54379DC6C)

# 2019-便携式近红外光谱仪研究进展\_刘建学 [>>](marginnote3app://note/4DBA57E9-632A-4493-ACEA-0953A5778308)

## 780 ~ 2 500 nm [>>](marginnote3app://note/31E6F706-A506-49C0-9A7A-B015706278C9)

## 将复色光色散成单色光是光谱仪的基础。 [>>](marginnote3app://note/E3536288-E53A-430A-BDB5-C807028614CB)

# Reconfigurable computing- a promising microchip architecture for artificial intelligence [>>](marginnote3app://note/C25549CF-8DA6-4AD4-B626-470BEDCA9950)

## From the perspective of computing performance, compared with single thread performance stagnation of general pur- pose processors (GPPS), reconfigurable computing may cus- tomize hardware according to application requirements, so as to achieve higher performance and lower energy consump- tion. [>>](marginnote3app://note/4AB14FC8-D120-4679-89D8-406AE6ACA083)

## Different from the traditional time domain programming computing mode, reconfigurable computing performs comput- ing on both temporal and spatial programmable architecture. Its connotation and implementation have been evolving with the progress of semiconductor technology and target applica- tions. Field-programmable gate arrays (FPGA), which was born in 1980s, is a typical reconfigurable microchip. It was de- veloped for logic emulation, but soon became widely used devices because its reconfigurability provides the possibility to implement various algorithms. By eliminating the instruc- tion fetch and decode of GPPs, FPGAs are much more en- ergy-efficient than GPPs. [>>](marginnote3app://note/39C5C2F9-9350-4812-8F63-27E7B82E537D)

## AI algorithms are still evolving, and one artificial NN (algorithm) only adapts to one application, so an ideal AI microchip must be able to adapt to the continu- ous evolution of algorithms, to support different artificial NNs according to requirements, and to switch between different ar- tificial NNs flexibly. Obviously, by enabling customization in computation pattern, computing architecture and memory hierarchy, microchips based on reconfigurable computing tech- nology might be able to efficiently support different NNs with high-throughput computations and communications. [>>](marginnote3app://note/18109012-B724-4B1F-A878-7C89BE5C5C8A)

## so an ideal AI microchip must be able to adapt to the continu- ous evolution of algorithms, to support different artificial NNs according to requirements, and to switch between different ar- tificial NNs flexibly. [>>](marginnote3app://note/1158766D-10D5-461E-8CFE-A51521DBD4C8)

## The latest de- velopment of AI researches require that AI microchips can also accelerate the newly emerging neural networks, such as graphical neural networks and memory networks. [>>](marginnote3app://note/4A6955AA-BEF7-40E3-BE7C-F16E4195EA5C)