第五届“中科星图杯”- 国际高分遥感图像解译大赛

面向海洋一号可见光图像中海冰目标监测技术

一种简单有效的二值分割方法

团队名称： deepjoker

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2023年3月18日

报告提纲

1 问题特性及数据处理方法

2 网络模型设计

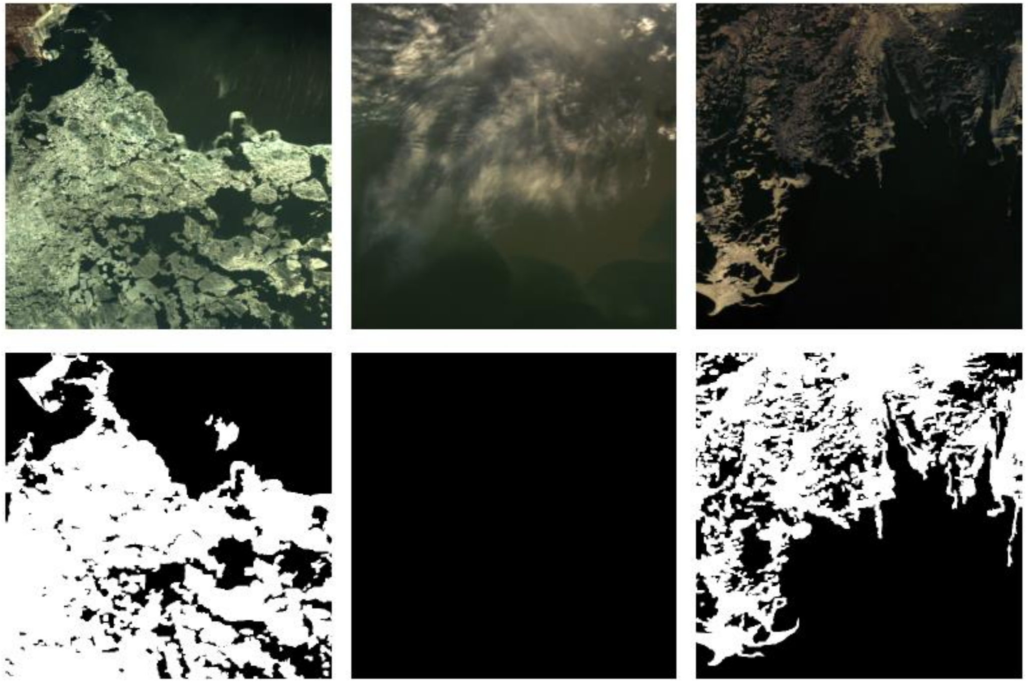
3 损失函数设计

4 精度及速度

问题特性

数据介绍：

- 海洋一号RGB光学数据
- 分辨率50m
- 场景覆盖我国渤海周边区域
- 二值分割：海冰像素值为255，背景像素值为0
- 图像尺寸：512-2048像素不等
- 数据量：共计2500余幅（训练集1500余幅，测试集1000余幅）

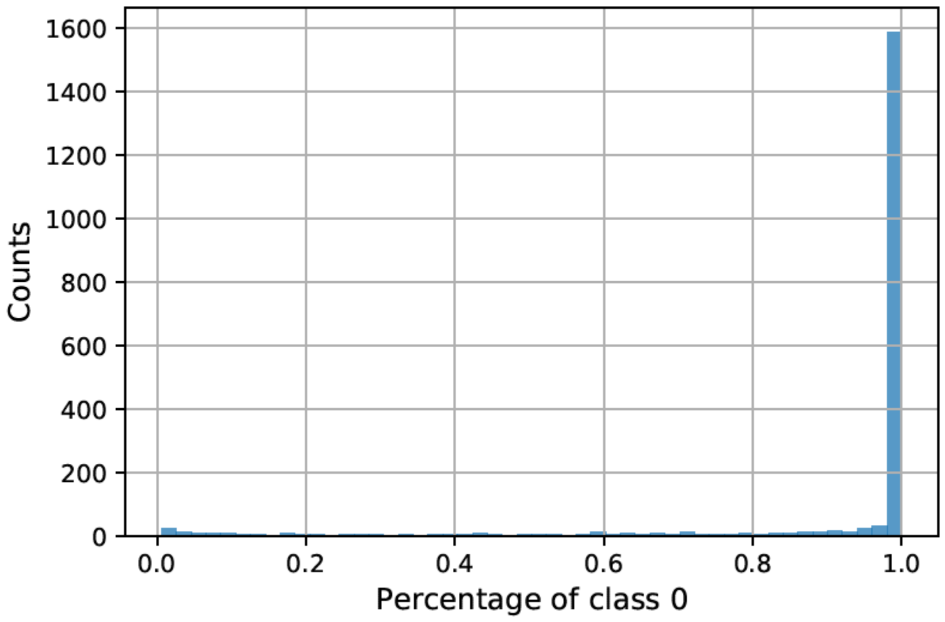


训练数据及真值

问题特性：

1. 目标形状不规则，细节信息丰富
2. 有些训练数据场景中不存在任何目标像素点

数据处理



训练数据中不存在目标像素的图像数量

↓

Dice分割损失函数梯度消失

数据增强方法：

- 水平翻转
- 随机90°旋转
- 归一化均值： 127.5， 方差： 31.875

数据读取：

- **NVIDIA Data Loading Library (DALI)**

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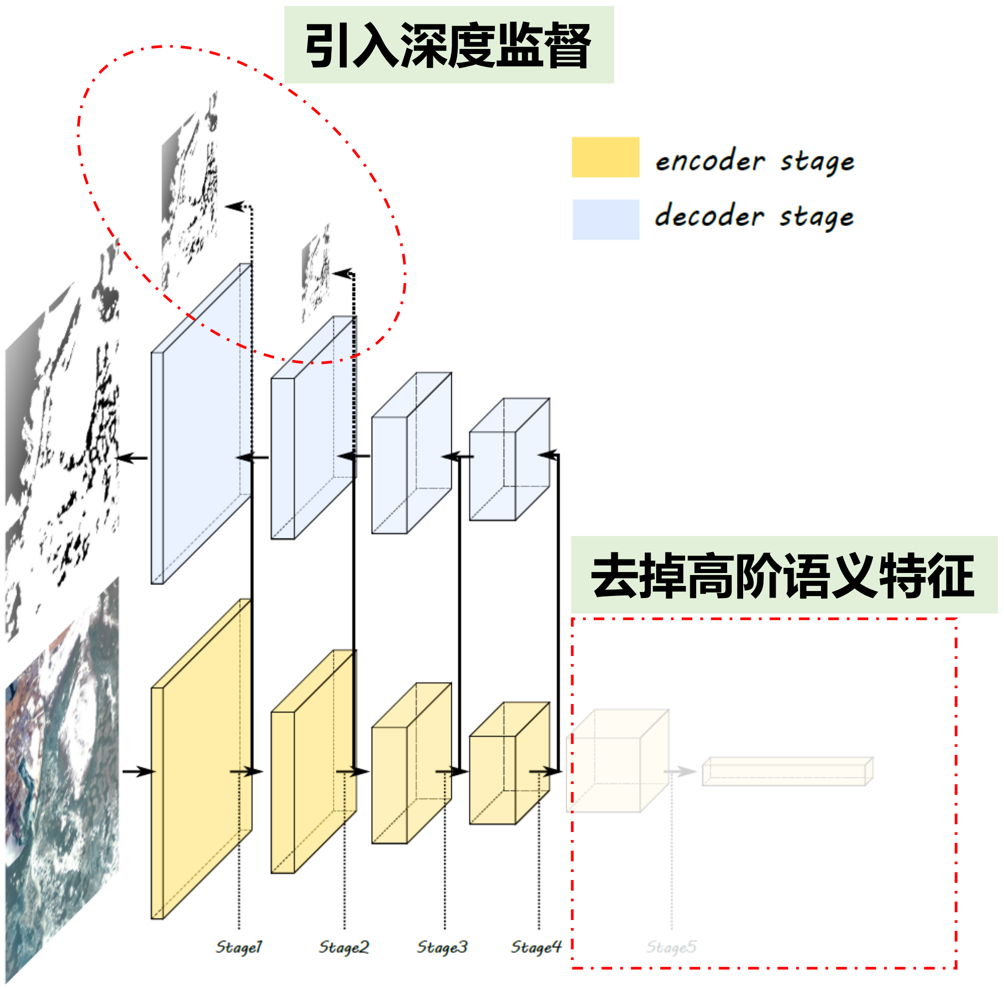
网络模型



类U-Net网络结构：

- 去掉 Stage 5，仅保留Stage1-4（**细节保持，轻量化**）
- Stage 1和2分别引入分割头进行深度监督 (**细节保持**)
- ImageNet预训练
- 骨干网络：Res2Net50， EfficientNet-B4， DPN （初赛）
  Efficientnet-Lite3（复赛）

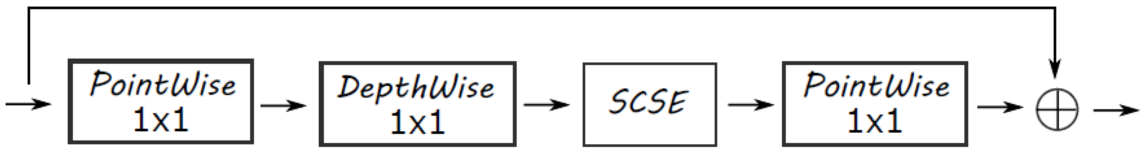
网络结构实现：

https://github.com/qubvel/segmentation_models.pytorch

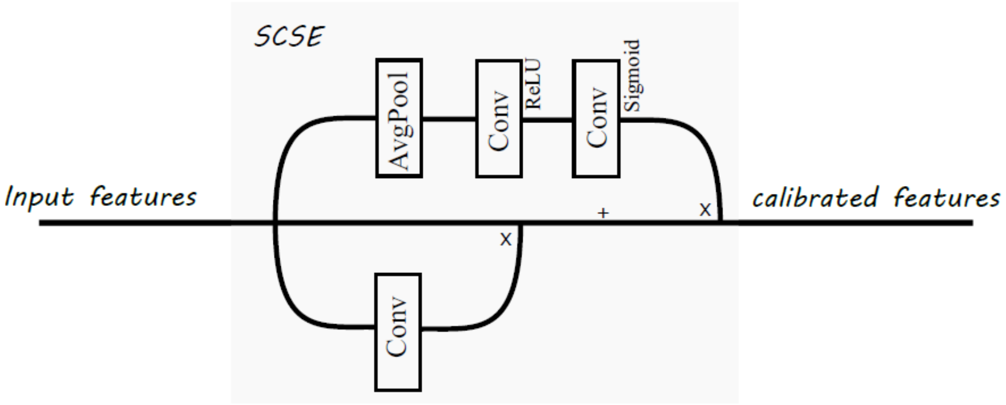
网络模型

解码器网络结构：

- SCSE [1]注意力
- 轻量化解码器卷积模块[2]



逐点逐通道的解码器卷积模块



SCSE

网络分割头输出：

- **逐类别(Class-wise)分割头**

背景类别概率（0-1） 目标类别概率（0-1）

[1] A. G. Roy, N. Navab, and C. Wachinger, "Concurrent spatial and channel 'squeeze & excitation' in fully convolutional networks," in International conference on medical image computing and computerassisted intervention. Springer, 2018, pp. 421–429.

[2] J. L. Silva, M. N. Menezes, T. Rodrigues, B. Silva, F. J. Pinto, and A. L. Oliveira, "Encoder-decoder architectures for clinically relevant coronary artery segmentation," arXiv preprint arXiv:2106.11447, 2021.

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损失函数

常用的分割损失函数：

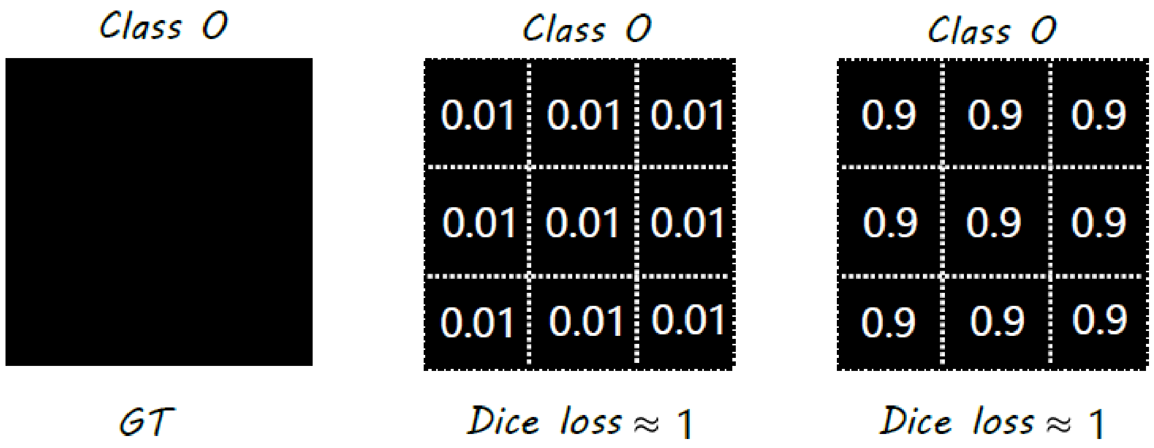
- **交叉熵（CE）**
- **Dice**

$$L_{\text{Dice}} = 1 - \frac{2\sum_i p_i y_i + \epsilon}{\sum_i y_i + \sum_i p_i + \epsilon}$$

若场景中不包含任何目标像素：

$$L_{\text{Dice}} = 1 - \frac{\epsilon}{\sum_i p_i + \epsilon}$$

$$\frac{\partial L_{\text{Dice}}}{\partial p_i} = \frac{\epsilon}{(p_i+\epsilon)^2}, \quad \forall y_i = 0$$



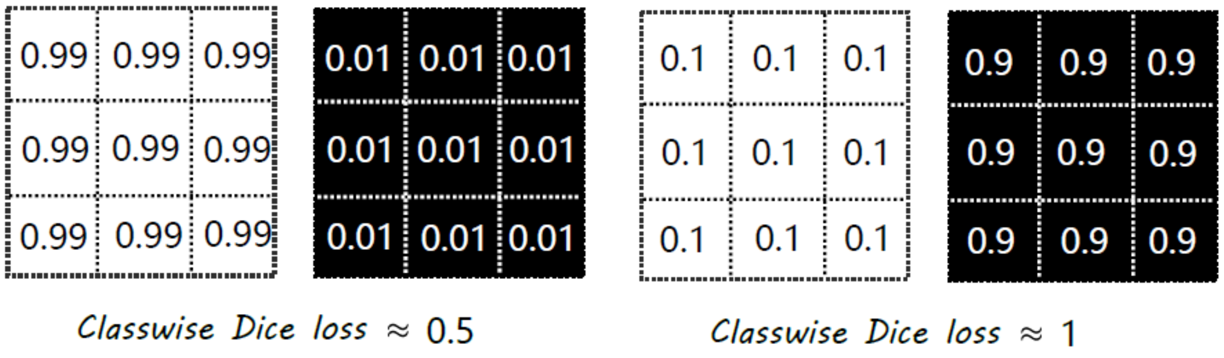
Dice分割损失函数梯度消失

损失函数

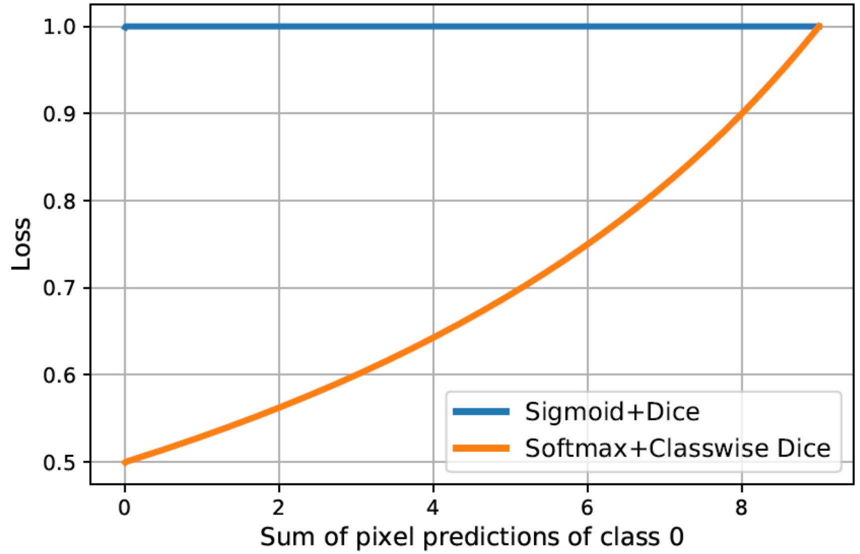
逐类别(Class-wise) Dice损失：

$$L_{\mathrm{Cls-Dice}} = 1 - \frac{1}{2}\sum_{c\in\{0,1\}} \frac{2\sum_i p_i^c y_i^c + \epsilon}{\sum_i y_i^c + \sum_i p_i^c + \epsilon}$$

$$\frac{\partial L_{\mathrm{Cls-Dice}}}{\partial p_i^c} = \frac{1}{2}\left(\frac{\epsilon}{(p_i^c+\epsilon)^2} - \frac{2+\epsilon}{(2-p_i^c+\epsilon)^2}\right), \quad \forall y_i^c = 0$$



解决Dice分割损失函数梯度消失问题



采用的联合分割损失函数：

- 交叉熵（CE）
- 逐类别(Class-wise) Dice损失
- 边界(Boundary)损失[3]

[3] A. Bokhovkin and E. Burnaev, “Boundary loss for remote sensing imagery semantic segmentation,” in International Symposium on Neural Networks. Springer, 2019, pp. 388–401.

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精度及速度：初赛（只看精度）

请于初赛截止前提交技术报告，否则排行榜成绩无效。

排名	队伍名称	提交次数	提交时间	运行时间	技术报告	分数
TOP1	glotwo 计图Jittor	35	2021-10-26 11:46:07	6033s	√	97.9354
TOP2	分割的都对 FUDAN EMWLAB...	31	2021-10-27 16:31:47	933s	√	97.9246
TOP3	deepjoker 老顽童	28	2021-10-26 21:17:16	136s	√	97.7907
4	宝略科技 宝略科技	33	2021-10-25 09:16:09	367s	√	97.7360
5	追风少年冲冲冲 致力于更好的利用...	23	2021-10-27 13:44:16	800s	√	97.7190
6	WIDEA RSIDEA：赵恒伟...	28	2021-10-27 15:55:18	2456s	√	97.6998
7	天竺鼠车车 天竺鼠车车	25	2021-10-27 16:24:01	607s	√	97.6956
8	BIT_505(James向前冲) 参赛队伍由BIT在...	4	2021-10-27 16:43:53	3495s	√	97.6534

总排名：第三

速度：第一

精度及速度：决赛（精度和速度同时考虑）

初 赛 决 赛

排名	队伍名称	提交次数	提交时间	算法精度	运行时间	时间得分	决赛分数
TOP1	BIT_505(James 向前冲)	13	2023-03-15 14:19:21	98.2718	27s	100	98.7903
TOP2	deepjoker	10	2023-03-15 14:34:58	98.2629	31s	99.2952	98.5726
TOP3	glotwo	12	2023-03-15 02:49:55	97.9076	28s	99.8238	98.4825
4	宝略科技	14	2023-03-15 15:36:37	98.4216	48s	96.2996	97.7850
5	分割的都对	11	2023-03-15 00:30:25	97.3555	54s	95.2423	96.7215
6	追风少年冲冲冲	10	2023-03-15 17:01:11	98.0576	96s	87.8414	94.9927
7	天竺鼠车车	15	2023-03-15 16:58:56	97.8134	108s	85.7269	94.1874
8	WIDEA	4	2023-03-14 19:09:04	98.3986	254s	60	86.8790

总排名：第二

技术成果发表及代码开源

技术成果发表在IEEE JSTARS专刊[3]：

2021 Gaofen Challenge on Automated High-Resolution Earth Observation Image Interpretation

方法实现将公布在以下GitHub存储库中:

https://github.com/jiankang1991/Challenge_ZhongKeXingTu5_Sea_Ice

Decoding the Partial Pretrained Networks for Sea-Ice Segmentation of 2021 Gaofen Challenge

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***Abstract*—Sea-ice segmentation is of great importance for environmental research, ship navigation, and ice hazard forecasting. Remote sensing (RS) images have been a unique data source for rapid and large-scale sea-ice monitoring. The 2021 Gaofen Challenge has offered a track of sea-ice segmentation based on optical RS images. For the initial competition, our team ranked 3rd place (deepjoker) in the accuracy leaderboard and the solution has been the most efficient algorithm to achieve a segmentation score above 97.79%. In this article, we briefly introduce our three strategies of the achievement including: 1) decoding the partial pretrained networks which can simultaneously capture the complex boundaries of sea ices and decrease the computational cost without the performance drop; 2) employing the classwise Dice loss for solving the gradient vanishing problem when most ground-truth maps are backgrounds; and 3) replacing the commonly exploited decoder with the one proposed by Silva *et al.* (2021). The main contributions are twofold: 1) an efficient and effective sea-ice segmentation method is proposed and 2) the gradient vanishing problem of binary Dice loss is investigated under some scenarios and solved by introducing its classwise version. Comparison and ablation experiments demonstrate the effectiveness of the proposed method with respect to other commonly adopted deep segmentation models.**

***Index Terms*—Gaofen (GF) challenge, gradient vanishing problem, sea-ice segmentation, semantic segmentation.**

I. Introduction

As THE effect of global warming, amounts of sea ices have disappeared in the past decades. Although the decreased sea-ice cover has led to the opening of new pathways for shipping, isolated and floating sea ices are still potential risks and hazards to the international shipping through those areas [1]. Compared to other sources of sea-ice images, such as phones, the nadir-looking from satellites has offered unique way for rapid and large-scale sea-ice monitoring through the acquired remote sensing (RS) images, as shown in Fig. 1. Therefore, segmenting sea ices from RS images is of great importance for ice hazard forecasting, ship navigation, environmental research, and other related topics [2].

The sea-ice segmentation aims at pixel-wisely labeling the sea-ice area with 1 and the background area with 0, which belongs to the binary segmentation problem. Conventional methods for segmenting sea ices are mostly model-driven, such as graph cut segmentation [3] on the back-scattering intensities from synthetic aperture radar (SAR) images [4], Markov random field segmentation based on image textures [5], and snake segmentation on detected ice pixels [6]. Although those methods have demonstrated prominent results for segmenting sea ices, they cannot effectively preserve the accuracy and efficiency as latest satellites provide more fine-grained and huge-volume RS images.

More recently, the fast development of deep learning methods, such as convolutional neural networks (CNNs), has significantly promoted the state of the art performances of RS imagery interpretation including sea-ice segmentation [7]–[17]. Based on CNNs, the key point for extracting sea ices is learning to discriminate pixels from sea ices and the background. The technical solution for solving such a binary segmentation problem is also general to other related tasks, such as building segmentation, cloud detection, and road extraction [18]–[22]. Commonly, the CNN models applied for the segmentation task are consisted of three parts: 1) CNN architectures, which decide the overall network construction; 2) encoders, which hierarchically encode multiscale features from the input images; 3) decoders, which decode the multiscale features into binary masks. For architectures, the most widely exploited ones include fully convolutional networks (FCN) [23], SegNet [24], UNet [25], DeepLab series [26], [27], etc. Researchers favor to choose the networks which achieve the state of the art performances on the ImageNet dataset [28], such as ResNets [29] and EfficientNets [30], as the encoders within segmentation architectures. To gradually increase the spatial dimensions of the encoded features, the upsampling operation and convolutional blocks are adopted in the design of decoder structures. In order to optimize the CNN

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[3] Kang, Jian, et al. "Decoding the partial pretrained networks for sea-ice segmentation of 2021 gaofen challenge." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 15 (2022): 4521-4530.

deepjoker参赛团队

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教育背景

- 2009.09-2013.07 哈尔滨工业大学 电子信息工程 学士
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- 2015.09-2019.09 慕尼黑工业大学 地球观测信号处理 博士
  导师：朱晓香教授

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个人主页

谢谢各位专家！敬请批评指正！