

论文阅读0918

题目：

- 老年痴呆发病和性别没有显著关系
- 老年痴呆发病组中受教育年限低于4的更多
- CDT和 MMSE以及CAMCOG的联系很深
- CDT和MMSE以及CAMCOG联合起来做的话特异度更高
- CDT实验在低教育年限中的灵敏度和特异度更高，在高教育年限的低
- 因此CDT实验可以替代MMSE以及CAMCOG作为AD早期筛查的方法之一

题目: Object Counting and Instance Segmentation with Image-level Supervision

内容:文章面向领域是自然场景计数,即比人群计数更难一个等级.现有的图像级别的物体计数仅仅给出全局的物体数量并且需要依靠额外的实例级别的监督标签来确定物体的位置.

即标签应该是物体数量加各个物体的位置,也就是instance-level的.文章提出了一个image-level监督的方法可同时提供全局物体数量以及空物体的空间分布,后者通过构建一个目标标签密度图来实现.

根据心理学的研究,进一步减少imgae-level监督,通过使用受限的物体数量信息.

文章是一个提出image-level supervised density map来评估物体数量并进行实例分割的.

题目：GloU

内容：对目标检测网络损失函数的优化，原有loss function是针对bbox的坐标值进行l1-smooth或者L2损失函数计算。文章基于对iou的优化提出了giou，使用这个取代原有的l1/l2损失函数，在one-stage网络上获得了一定的提升。

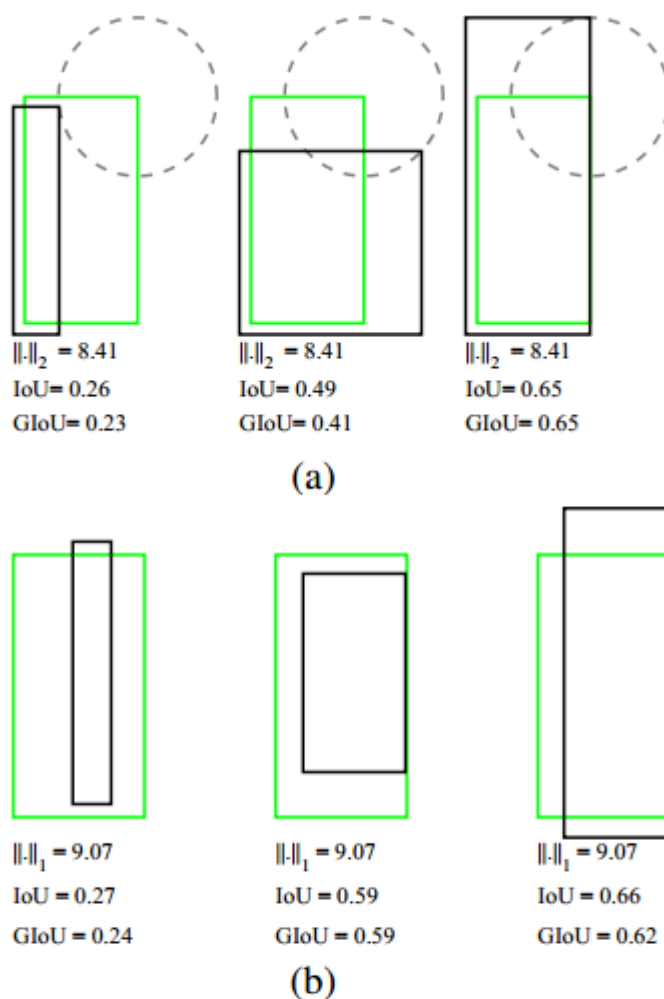


Figure 1. Two sets of examples (a) and (b) with the bounding boxes represented by (a) two corners (x_1, y_1, x_2, y_2) and (b) center and size (x_c, y_c, w, h) . For all three cases in each set (a) ℓ_2 -norm distance, $\|\cdot\|_2$, and (b) ℓ_1 -norm distance, $\|\cdot\|_1$, between the representation of two rectangles are exactly same value, but their IoU and $GIoU$ values are very different.

上图中可以看到，在 ℓ_2 相同的情况下，iou有较大差别。但iou也有两个问题：

- 检测框和gt不重合时，iou为零，无法反传
- 检测框和gt iou相同时，检测效果也有一定差异

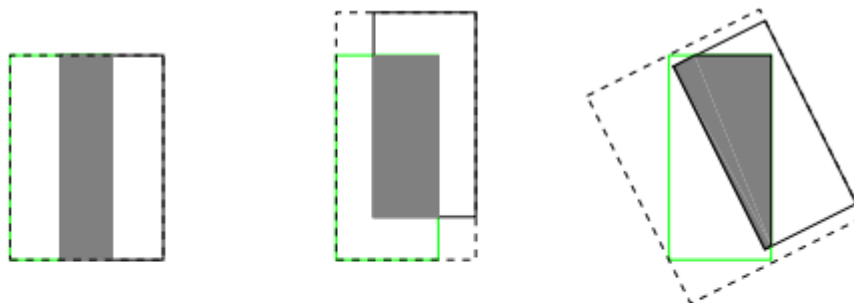


Figure 2. Three different ways of overlap between two rectangles with the exactly same IoU values, *i.e.* $IoU = 0.33$, but different $GIoU$ values, *i.e.* from the left to right $GIoU = 0.33, 0.24$ and -0.1 respectively. $GIoU$ value will be higher for the cases with better aligned orientation.

Algorithm 1: Generalized Intersection over Union

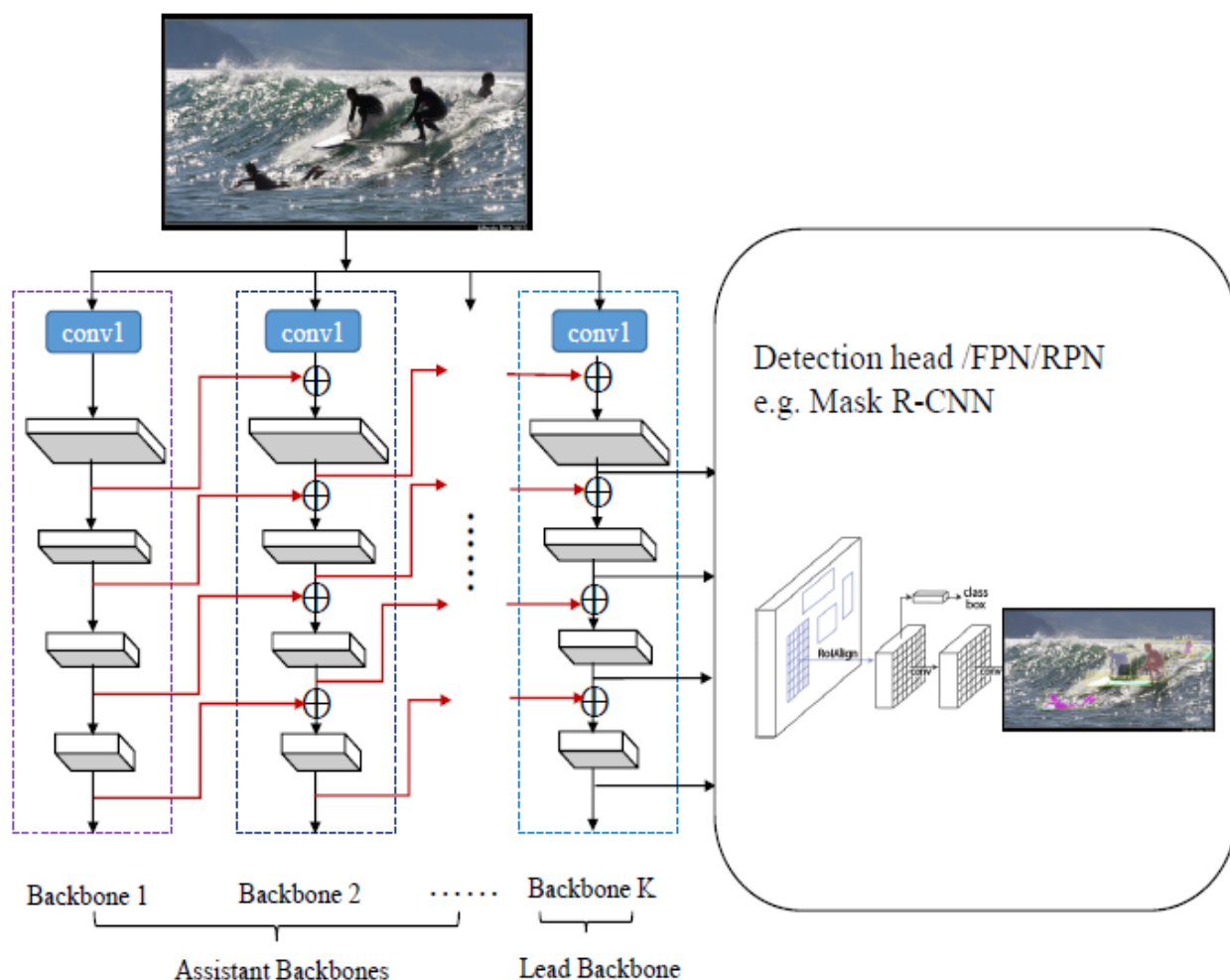
input : Two arbitrary convex shapes: $A, B \subseteq \mathbb{S} \in \mathbb{R}^n$

output: $GIoU$

- 1 For A and B , find the smallest enclosing convex object C ,
where $C \subseteq \mathbb{S} \in \mathbb{R}^n$
 - 2 $IoU = \frac{|A \cap B|}{|A \cup B|}$
 - 3 $GIoU = IoU - \frac{|C \setminus (A \cup B)|}{|C|}$
-

因此提出了giou。

题目：CBNet: A Novel Composite Backbone Network Architecture for Object Detection



多模型融合从而提升效果。优化的是目标检测网络的backbone

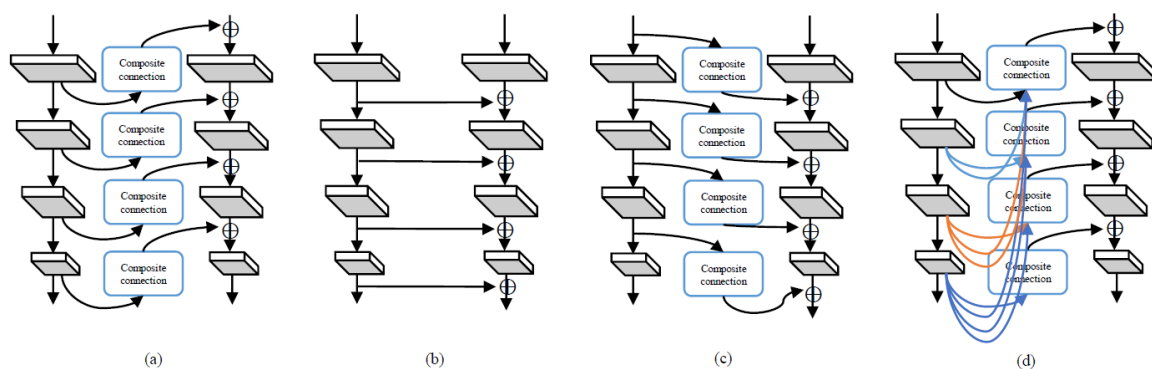


Figure 3: Four kinds of composite styles for Dual-Backbone architecture (an Assistant Backbone and a Lead Backbone). (a) Adjacent Higher-Level Composition (AHLC). (b) Same Level Composition (SLC). (c) Adjacent Lower-Level Composition (ALLC). (d) Dense Higher-Level Composition (DHLC). The composite connection denotes in blue boxes represents some simple operations, *i.e.*, element-wise operation, scaling, 1×1 Conv layer and bn layer.

作者尝试了以上四种连接，发现第一种效果最好。

| DB | Composite style | AP_{box} | AP_{50} | AP_{75} |
|----|-----------------|-------------|-------------|-------------|
| | - | 39.4 | 61.5 | 42.8 |
| ✓ | SLC | 38.9 | 60.8 | 42.0 |
| ✓ | ALLC | 36.5 | 57.6 | 39.6 |
| ✓ | ADLC | 40.7 | 61.8 | 44.0 |
| ✓ | AHLC | 41.0 | 62.4 | 44.5 |

最右边的lead backbone作为输出。效果的提升是否源于参数量的增加？这个可以尝试一下