1. Huber Loss

The loss function used for convexity, circularity, and count are modified versions of the Huber loss [1]. This loss has the general form of

$$H(R) = \begin{cases} \frac{1}{2} R^2, & \text{for } |R| \leq k \\ k|R| - \frac{1}{2} k, & \text{for } |R| > k. \end{cases}$$  \hspace{1cm} (1)$$

For small residuals $R$, this loss acts as $L_2$ loss, and for large residuals it acts as $L_1$ loss. We can find the gradient of this loss by differentiating with respect to the residual

$$\frac{dH}{dR} = \begin{cases} R, & \text{for } |R| \leq k \\ k * \text{sgn}(R), & \text{for } |R| > k \end{cases}$$  \hspace{1cm} (2)$$

2. Additional Qualitative Results

Here we present additional visual comparisons between our method and LC-FCN [2] on CRAID.

Figure 1: Qualitative comparison with SOTA methods on CRAID. Our method ($L_{Seg} + L_{Split} + L_{Convex}$) shows that using shape priors and better boundary and region selection allows robust segmentation and counting performance. Colors in prediction masks are random and are used to represent instances. Colors may repeat. Best viewed in color and zoomed.
Figure 2: Qualitative comparison with SOTA methods on CRAID. Our method ($\mathcal{L}_{Seg} + \mathcal{L}_{Split} + \mathcal{L}_{Convex}$) shows that using shape priors and better boundary and region selection allows robust segmentation and counting performance. Colors in prediction masks are random and are used to represent instances. Colors may repeat. Best viewed in color and zoomed.
References
