Offset Curves Loss for Imbalanced Problem in Medical Segmentation

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Abstract: Medical image segmentation has played an important role in medical analysis and widely developed for many clinical applications. Deep learning-based approaches have achieved high performance in semantic segmentation but they are limited to pixel-wise setting and imbalanced classes data problem. In this paper, we tackle those limitations by developing a new deep learning-based model which takes into account both higher feature level i.e. region inside contour, intermediate feature level i.e. offset curves around the contour and lower feature level i.e. contour. Our proposed Offset Curves (OsC) loss consists of three main fitting terms. The first fitting term focuses on pixel-wise level segmentation whereas the second fitting term acts as attention model which pays attention to the area around the boundaries (offset curves). The third terms plays a role as regularization term which takes the length of boundaries into account. We evaluate our proposed OsC loss on both 2D network and 3D network.

Motivation

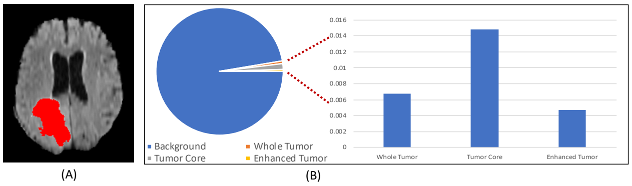
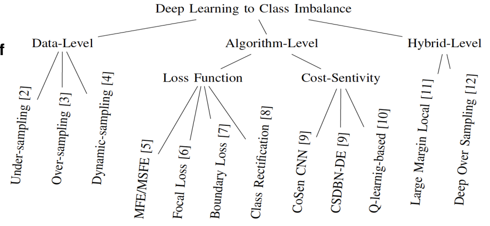
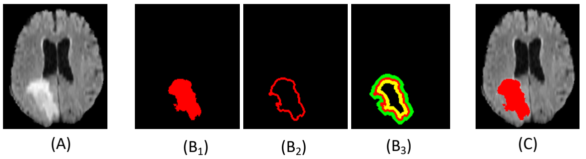


Fig. 1 an MRI slice visualizing a brain tumor. No. of brain tumor pixels: 1,410 (2.4%) and no. of brain pixels: 57,600(97.56%). (B): statistical information about the ratio between different classes in BRATS2018

Fig. 2 Summary of Deep Learning approaches to imbalanced-class data problem



Most DL-based segmentation have made use of common loss functions e.g., Cross-Entropy, Dice, and the recent Focal. These losses are based on summations over the segmentation regions and are restricted to pixel-wise setting. Not only pixel-wise sensitivity, these losses do not take geometrical information into account as well as are limited to imbalanced-class data. Furthermore, class imbalance is naturally existing in the medical imaging segmentation problem which is considered as pixel level, i.e. each pixel is classified as tumor/not tumor (brain tumor) or foreground (blood vessel) or background (retina). In most applications, the number of pixels in each class are unbalanced as shown in Fig.1. The literature review on imbalanced-class data problem is summarized as in Fig.2. Our proposed DL architecture with ***OsC loss*** for medical segmentation belongs to the second category where we pay attention on proposing an effective loss for imbalanced problem in medical segmentation. Our work aims at tackling those limitations by developing a new loss which takes into account both global and local information during learning including (i) lower feature level i.e contour; (ii) intermediate feature level i.e. narrow band around the contour; (iii) higher feature level i.e. area inside the contour as illustrated in Fig.3

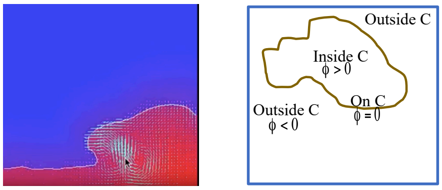


Given an image with imbalanced-class data (A), the proposed OsC loss focuses on three different levels of data: higher level feature - region(B$_1$), lower level feature - contour (B$_2$) and intermediate feature level - offset curves (B$_3$). The final segmentation is a combination of three different feature levels and shown in (C)

Proposed OsC Loss

Level Set used to **present complex function** (wave/fire surface)
Zero level set presents the **contour** of the object (wave/fire surface)

Fig. 3. Illustration of Zero Level Set



Level Set calculate the energy on the **entire image** domain
⇒ **Sensitive** for **imbalanced** classes => **Narrow Band**

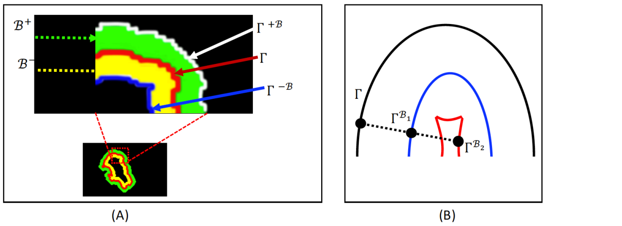


Fig. 3 (A): Illustration of inner band B$^-$ and outer bands B$^+$ of a contour T ; (B): Illustration of parallel curves theory with the main curve (black curve T) and its two parallel curves. Small translation B$_1$ yields regular curve (blue curve) whereas large translation B$_2$ yields a curve with singularities (red curve).

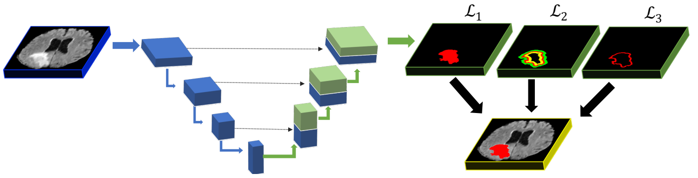
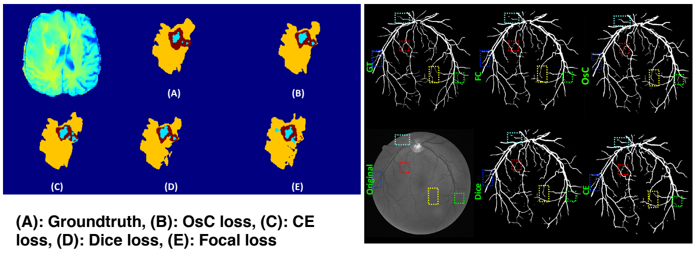


Fig. 5 our proposed OsC loss with Unet architecture

$$\mathcal{L}_1 = -\sum_{c=1}^{K} \mathbf{T}_o^c log \mathbf{P}_o^c \qquad \mathcal{L}_2 = \lambda_1 \sum_{x,y\in\mathcal{B}} |\mathbf{P}(x,y) - b^-|^2 H(\phi(x,y))$$

$$\mathcal{L}_3 = \sum_{x,y\in\omega} |\nabla \phi(x,y)| \qquad + \lambda_2 \sum_{x,y\in\mathcal{B}} |\mathbf{P}(x,y) - b^+|^2 (1 - H(\phi(x,y)))$$

Results



(A): Groundtruth, (B): OsC loss, (C): CE loss, (D): Dice loss, (E): Focal loss

TABLE I: Comparison on **DRIVE** dataset and **FCN**

Losses	DSC	Jac	Pre	Rec
CE	74.47	76.01	72.00	75.00
Dice	77.5	79.79	77.00	78.00
Focal	74.2	76.93	67.00	**83.00**
Ours	**78.5**	**80.1**	**79.00**	78.00

TABLE II: Comparison on **BRATS 2018** dataset and **FCN**

Losses	DSC	Jac	Pre	Rec
CE	77.3	73.1	76.66	79.00
Dice	76.31	71.84	75.00	76.33
Focal	72.45	67.76	68.00	77.33
Ours	**78.46**	**75.24**	**78.67**	**79.00**

TABLE III: Comparison on **DRIVE** dataset and **Unet**

Losses	DSC	Jac	Pre	Rec
CE	77.1	78.80	75.00	80.00
Dice	78.6	79.6	77.00	80.00
Focal	77.7	78.9	76.00	79.00
Ours	**79.3**	**81.2**	**78.00**	**82.00**

TABLE IV: Comparison on **BRATS 2018** dataset and **Unet**

Losses	DSC	Jac	Pre	Rec
CE	78.34	73.45	77.33	80.00
Dice	77.51	72.24	76.67	77.67
Focal	75.78	77.00	67.33	**86.00**
Ours	**79.78**	**80.33**	**78.33**	81.00