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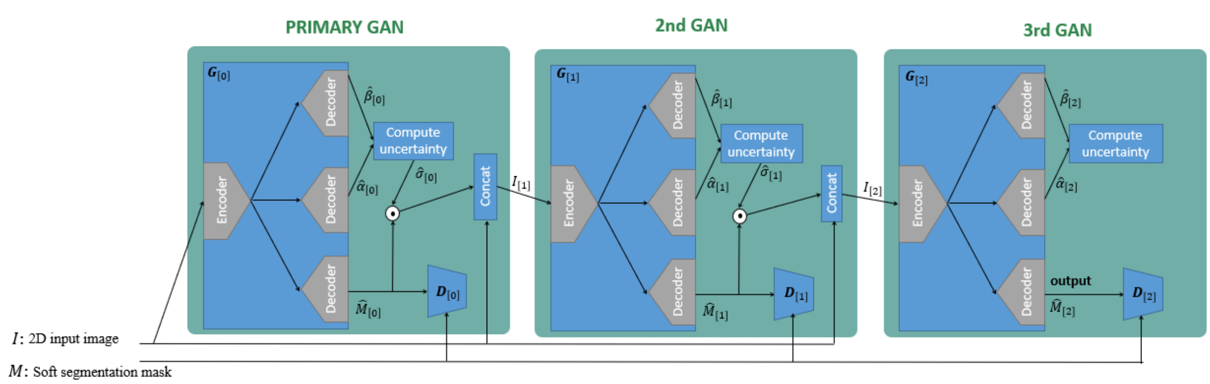
Method:

The uncertainty among different experts is modeled as probability maps and reflects the underlying graders' (dis-)agreement. Probability maps are soft segmentation masks which are the average of all segmentation masks annotated by experts. The network intends to produce soft segmentation masks.

We utilized the uncertainty-aware progressive GAN structure where the aleatoric uncertainty estimates as the guide to focus on improving the quality of different masks [1]. As shown in Figure, our network includes three sequential conditional GANs to produce the target uncertainty map i.e. soft segmentation mask (M) form the input 2D image (I). The generator of each stage ($G_{[s]}, s \in \{0,1,2\}$) produces the segmentation mask ($\widehat{M}_{[s]}$) as an uncertainty map besides aleatoric uncertainties ($\hat{\beta}_{[s]}, \hat{\alpha}_{[s]}$) to predict the optimal scale (α) and shape (β) of the generalized Gaussian distribution (GGD) for every pixel [1, 2]. The primary GAN takes the 2D input image ($I_{[0]} = I$), while subsequent GANs absorb outputs from the preceding GAN ($I_{[s]}, s \in \{1,2\}$). The uncertainty map serves as an attention mechanism to highlight the uncertain regions in the produced mask by the generator. All the discriminators ($D_{[s]}, s \in \{0,1,2\}$) are the patch discriminators from well-known pix2pix network [3] and generators are the modified U-Net [1, 4]. We further modified the loss function for the segmentation task with an additional soft dice score and consider it for estimating epistemic uncertainty. To compute $I_{[s]},\ s \in \{1,2\}$ see reference [1].

Our code and more information are available at https://github.com/mohaEs/UncertainyPGAN

Figure:



Loss functions:

Suppose K is the number of pixels in the image and k is the index over pixels. Then the loss for generator at stage $s \in \{0,1,2\}$ for each image is defined as:

$$L_{tot}^{G_{[s]}} = \lambda_1 L_{\alpha\beta}^{G_{[s]}} + \lambda_2 L_{adversarial}^{G_{[s]}} + \lambda_3 L_{soft\ dice}(\widehat{M}_{[s]}, M)$$

$$L_{adversarial}^{G_{[s]}} = fidelity\ loss\ (D_{[s]}(\widehat{M}_{[s]}), 1)$$

$$L_{\alpha\beta}^{G_{[s]}} = \frac{1}{K}\sum_{k=1}^{K}\left(\frac{|\widehat{M}_{[s]k} - M_k|}{\hat{\alpha}_{[s]k}}\right)^{\hat{\beta}_{[s]k}} - \log\frac{\hat{\beta}_{[s]k}}{\hat{\alpha}_{[s]k}} + \log\Gamma(\hat{\beta}_{[s]k}{}^{-1})$$

The loss of discriminator in each stage is as follow:

$$L_{adversarial}^{D_{[s]}} = fidelity\ loss\ (D_{[s]}(M), 1) + \ fidelity\ loss\ (D_{[s]}(\widehat{M}_{[s]}), 0)$$

Data Augmentation:

No augmentation used for training the networks.

Pre-processing:

The intensity values of each slice or 2D image is stretched such that the brightest pixel would be 255 and the darkest one be 0.

Label Processing:

As stated, the uncertainty map is assumed as the soft segmentation mask via averaging over the masks produced by ground-truth annotators.

Ensemble strategy:

As stated, the network architecture contains three sequential cGANs. It can be inferred as boosting strategy to calculate and reduce the uncertainties.

Limitation:

Our method works analyze the images and tasks only as 2D images and would not be practical for 3D tasks of the Qubiq. Modifying it with 3D convolution may increase results especially for tasks related to “brain tumor” which was multimodal and “Pancreas” which was 3D CT scans.

References:

[1] Upadhyay, U., Chen, Y., Hepp, T., Gatidis, S. and Akata, Z., 2021. Uncertainty-Guided Progressive GANs for Medical Image Translation. *arXiv preprint arXiv:2106.15542*.

[2] Upadhyay, U., Chen, Y., Akata, Z.: Uncertainty-aware generalized adaptive cycle-gan. preprint arXiv:2102.11747 (2021)

[3] Isola, P., Zhu, J.Y., Zhou, T., Efros, A.A.: Image-to-image translation with conditional adversarial networks. In: IEEE CVPR (2017)

[4] Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. In: MICCAI (2015)