AUTOMATIC DATA AUGMENTATION VIA DEEP REINFORCEMENT LEARNING FOR EFFECTIVE KIDNEY TUMOR SEGMENTATION

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ABSTRACT

Conventional data augmentation realized by performing simple pre-processing operations (e.g., rotation, crop, etc.) has been validated for its advantage in enhancing the performance for medical image segmentation. However, the data generated by these conventional augmentation methods are random and sometimes harmful to the subsequent segmentation. In this paper, we developed a novel automatic learning-based data augmentation method for medical image segmentation which models the augmentation task as a trial-and-error procedure using deep reinforcement learning (DRL). In our method, we innovatively combine the data augmentation module and the subsequent segmentation module in an end-to-end training manner with a consistent loss. Specifically, the best sequential combination of different basic operations is automatically learned by directly maximizing the performance improvement (i.e., Dice ratio) on the available validation set. We extensively evaluated our method on CT kidney tumor segmentation which validated the promising results of our method.

Index Terms— Medical image segmentation, Data augmentation, Deep reinforcement learning

1. INTRODUCTION

Nowadays, to precisely and automatically delineate the boundary of different organs and tissues, deep learning-based medical image segmentation plays an essential role in computer-aided diagnosis. It is usually believed that when the enough delineated (or labeled) data is available during training, a desirable segmentation result could be expected by using deep learning based methods [1,2]. However, as a prerequisite, sufficient training data cannot always be guaranteed in real cases due to 1) limited access permission of medical images for privacy protection, and 2) intensive manual effort and high professional knowledge requirement for manual delineation. In this case, the performance degeneration usually happens when the trained model adapts to the testing data.

To overcome this challenge from limited data, existing methods intend to increase and diversify the available training images by generating new images from the original ones. This methodology, namely data augmentation, has shown its merits in improving the segmentation accuracy [13-15]. Typically, data augmentation performs some basic image pre-processing operations (e.g., flipping, cropping and warping) to generate additional training images on the original dataset. The improvement on segmentation tasks is validated by previous studies [6,7]. However, these methods are highly sensitive to the selection and magnitude of operations [8] which makes setting the optimal operations an ad-hoc task [9,10].

Besides, several works attempted to solve the data limitation problem by generating new samples on a simulated or learned data distribution. For example, Zach et al. [11] extended Mixup [12] to medical image segmentation by generating virtual data on the marginal region between two classes. With the same distribution of real and generated virtual data, the generative adversarial networks (GANs) were utilized to generate virtual images for boosting the performance in segmentation task [13-15].

Unfortunately, previous methods suffer from one major limitation: the data augmentation module and following segmentation module are trained in a separate way, where the result of the segmentation module cannot feedback to adjust the augmentation module. Thus, the optimal augmentation method is not guaranteed.

To solve the problem, training the augmentation and the segmentation module simultaneously is highly desired. However, the bottleneck of current data augmentation method is that the best operations of augmentation (i.e., to obtain the largest performance improvement) are hard to define. Regarding this challenge, we in this paper present a learning-based automatic data augmentation method for medical image segmentation, which introduces the deep reinforcement learning (DRL) to explore the most effective sequence of image pre-processing operations. The improvement of the segmentation module may directly influence the policy generated by the data augmentation module. By doing so, the agent can learn specific augmentation policy for each image, with a stable learned operation sequence. Please note that, the proposed method can combine the augmentation module and the subsequent segmentation module in an end-to-end manner.

Our contributions can be summarized in three-fold: (1)
We model data augmentation for medical image segmentation as a reinforcement learning problem to learn a data-specific augmentation policy. (2) A joint-learning scheme to integrate a hybrid architecture of Dueling deep Q-learning network (DQN) and a substitute segmentation module is developed where the learned policy directly optimizes the Dice ratio. (3) Taking the kidney tumor segmentation in CT images as an illustration, the results demonstrate the effectiveness of our method.

2. OUR METHODOLOGY

2.1. Preliminary

Reinforcement learning (RL) is one of the most representative machine learning paradigms for sequential decision-making problem [16]. To continuously interact with the environment, an agent learns the policy to make a sequential decision to maximize an accumulative reward. Mathematically, it can be formulated as a Markov decision process (MDP) \( M := (S, A, P, R, \gamma) \) where \( S \) is a finite set of states, \( A \) is a finite set of actions that allows the agent to interact with the environment, and \( P : S \times A \times S \rightarrow [0, 1] \) denotes the probabilities of state transition, respectively. \( R : S \times A \times S \rightarrow \mathbb{R} \) denotes the reward function which drives the action of the current agent. \( \gamma \in [0, 1] \) is the discount factor to control the importance of immediate versus future rewards [16].

During learning, the agent learns from experience to optimize its policy \( \pi : S \times A \rightarrow [0, 1] \). A widely-used form to represent the optimal policy could be the state-action value function \( Q(s, a) \) which is defined as the expected value of the accumulated reward at state \( s \) with taking action \( a \),

\[
Q(s, a) = E[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)]
\]

and can thus be solved iteratively as \( Q_{t+1}(s, a) = E[r + \gamma \max_{a'} Q_t(s', a')] \). The Q-function in Dueling DQN could be defined as follow:

\[
Q(s^i, a^i; \gamma, \omega, \sigma) = V(s^i; \gamma, \omega, \sigma) + C(s^{i+1}, a^{i+1}; \gamma, \omega, \sigma) - \frac{1}{|C|} \sum_{a^{i+1}} C(s^i, a^{i+1}; \gamma, \omega).
\]

More details could be referred to the original literature [18].

2.2. Proposed Method

We now discuss the technical details of our method. Given a training set \( X = \{(x_1, y_1), ..., (x_n, y_n)\} \), where \( x_i \) and \( y_i \) are the \( i \)-th CT image and its corresponding ground truth, respectively, we aim to 1) generate an augmented image \( x'_i \) according to \( x_i \), which is more effective to improve the segmentation results compared with \( x_i \), and at the same time 2) learn a robust segmentation module \( f \) trained with original and augmented training set.

As aforementioned, we propose to model joint data augmentation and segmentation as a sequential decision-making problem as illustrated in Fig. 1. Specifically, there are two sub-networks corresponding to the two modules in our method which include 1) a Dueling DQN and 2) a substitute segmentation network. Firstly, the Dueling DQN aims to decide a sequence of basic operations (i.e., actions) to augment the original CT image which could boost the performance of the following segmentation network in a best way which can be measured by the largest performance improvement. Afterwards, the substitute segmentation network is first magnified by the augmented samples and the performance of the current segmentation network is then evaluated on the

Fig. 1. The framework of our automatic data augmentation method for medical image segmentation. When randomly selecting a CT image and the corresponding mask from the training set, the initial state \( s^0 \) is the feature extracted from the CT image. The agent selects and performs an action on current CT image, and the processed image acts as the next input. This process is repeated until the agent decides to terminate this episode.

A joint-learning scheme to integrate a hybrid architecture of Dueling deep Q-learning network (DQN) and a substitute segmentation module is developed where the learned policy directly optimizes the Dice ratio.
validation set for reward calculation. The components of Dueling DQN are detailed as below.

2.2.1. States and Actions

Regarding that the original CT image \(x_i\) cannot be directly used as the state due to its high-dimensional representation, we define the state as the high-level feature extracted from \(x_i\) by a pre-trained segmentation model. This setting is more feasible and reasonable since pre-trained model could provide initial informative features. Here, we use U-Net \([12]\) as the state extraction network \(\phi\) to extract the \(t\)-step state \(s^t\) on \(x_i\) as \(s^t = \phi(x_i)\).

During the training procedure, the agent outputs an action \(a^t\) according to the current state \(s^t\). We formally define 12 types of basic actions including HF (horizontally flip the image), RT (rotate the image), CL/CR/CU/CD (crop from left, right, up and down), WP (warp the image), ZM (zoom in the original image into 1.1x), AN (add noise), LT (increase the brightness), DK (decrease the brightness) and TM (terminal this episode).

Specifically, we set the degree of RT to 30. For four crop operations (i.e., CL, CR, CU, CD), the step is set to 20, and the cropped image is resized as before. For AN, the Gaussian noise is added to the normalized image. For WP, the current image is distorted by the PiecewiseAffine operation in imgaug library. For LT and DK, the change magnitude is set to 0.1 (the value of each pixel is normalized in [0,1]).

2.2.2. Rewards

The reward is numerical feedback for each action performed by the agent. With the goal of learning the best augmentation policy, we measure the change of parameters in the segmentation module by the Dice ratio in the validation set \(Z\). \(Z = \{ (z_1, y_1), \ldots, (z_m, y_m) \}\), where \(z_i\) and \(y_i\) are the \(i\)-th CT image and its corresponding segmentation result in the validation set \(Z\), respectively, and \(m\) is the total number of samples.

Formally, the \(t\)-step reward \(r^t\) is defined as follows:

\[
r^t = \begin{cases} 
  d^t - d^{t-1}, & \text{if } t \text{ is not terminal} \\
  10(d^t - d^{t-1}), & \text{if } t \text{ is terminal}
\end{cases}
\]

(1)

where \(d^t\) donates the \(t\)-th step Dice ratio of the segmentation module in validation set defined as below:

\[
d^t = \frac{1}{m} \sum_{(x, y) \in Z} \frac{2|f(\theta_{X∪\{x_i\}}; z_j) ∩ y_j|}{|f(\theta_{X∪\{x_i\}}; z_j)| + |y_j|}
\]

(2)

where \(x_i\) denotes the augmented result after \(t\)-th transformation on the \(i\)-th image in training set instead of validation set. In Eqn. (2), \(f(\theta_{X∪\{x_i\}}; z_j)\) indicates the segmentation results of \(z_j\) by using the model trained on the training set \(X \cup \{x_i\}\) parameterized by \(\theta\). Typically, \(f(\theta_{X∪\{x_i\}}; z_j)\) is obtained by fine-tuning \(f(\theta_X; x_j)\) with \(x_i\).

2.2.3. Agent Learning and Exploiting

For action learning, we use multiple linear layers to approximate the state-action value function as the common representation of the optimal policy \([13]\). By using the state of each image as input, the corresponding output is the value of each action. The agent chooses the action with the largest calculated value.

For data augmenting, each sample is input into the environment and the agent performs sequential operations on it until it reaches the terminal state. We mix the generated images with original training images as the final augmented set. Thus, for a dataset of size \(N\), we generate a dataset of size \(2N\).

3. EXPERIMENTS

We now quantitatively and qualitatively report the results of our method. For the dataset, we use the CT kidney tumor
Table 1. The results on kidney tumor dataset.

| Method               | mIoU (%) | DSC (%) | PPV (%) | SEN (%) | CD (mm) | HD (mm) | ASD (mm) |
|----------------------|----------|---------|---------|---------|---------|---------|----------|
| Without Aug.         | 65.0     | 74.9    | 67.0    | 90.3    | 26.31   | 18.00   | 10.14    |
| Traditional Aug.     | 74.3     | 83.2    | 79.2    | 92.9    | 15.79   | 13.00   | 5.49     |
| VB-nets [19]         | 62.2     | 71.8    | 66.9    | 92.5    | 21.10   | 16.55   | 9.58     |
| Neff et al. [14]     | 47.4     | 57.6    | 51.3    | 88.6    | 53.09   | 28.00   | 17.53    |
| Shin et al. [15]     | 73.3     | 82.0    | 79.6    | 91.8    | 11.67   | 12.08   | 5.42     |
| Costa et al. [20]    | 53.1     | 62.7    | 56.6    | 91.4    | 34.80   | 22.00   | 13.23    |
| Our method           | 75.8     | 84.0    | 80.2    | 94.0    | 8.86    | 8.52    | 4.01     |

3.1. Setting

We randomly partitioned the dataset into training, validation and test subsets, which consist of 50, 5, and 13 different cases, respectively. The training and validation sets are used to learn the augmentation policy during training Dueling DQN. We set the comparison methods with the same size of augmented set in order for a fair comparison. Besides, the segmentation network structure was kept to be same when comparing with GAN-based augmentation methods. The performance was evaluated by training a segmentation model from scratch on the augmented set.

We used Adam [21] optimizer both for Dueling DQN and the segmentation module. For Dueling DQN, the initial learning rate was set to 0.001, the replay buffer was used. For the segmentation module, the initial learning rate was $2.5 \times 10^{-4}$ and dropped by $(1 - \text{epoch/epochs})^{0.9}$. The weight decay was set to $5 \times 10^{-4}$. The learning rate for fine-tuning segmentation module was $5 \times 10^{-5}$. The hype-parameters of all the experiments were set as the same to the proposed method for a fair comparison. We implemented our model with the PyTorch [22] Framework on three GTX 2080Ti GPUs.

3.2. Results

We employ the mean Interest of Union (mIoU), Dice ratio (DSC), positive predictive value (PPV), sensitivity (SEN), the median of centroid distance (CD) and Hausdorff distance (HD), and average surface distance (ASD) to evaluate the segmentation accuracy. Table 1 reports the results of these baselines. We can infer from the result that our method outperforms other methods in terms of mIoU, DSC, SEN, CD, HD and ASD. Also, we show some typical augmentation examples in Figure 2. It can be observed that HF is frequently selected during augmentation since flipping the image in a horizontal direction is widely used for medical image segmentation. Also, crop operations are useful to increase the size of foreground tumors. In addition, several segmentation results are reported in Figure 3 showing that our method is able to localize the tumor boundary more accurately than that of other baselines.

4. CONCLUSION

We propose a learning-based augmentation method to deal with the case of insufficient labeled images in CT kidney tumor segmentation. We model data augmentation as a sequential decision making problem, and utilize the DRL to search for the most effective sequence to augment each image automatically. Therefore, the result of the substitute segmentation module could return the feedback to adjust the augmentation method. To our knowledge, this is the first attempt to combine data augmentation and segmentation in an end-to-end manner. The results demonstrated the effectiveness of our method by comparing with the previous augmentation methods.

Our future directions include: 1) extending to other medical image segmentation tasks to validate the generalization of the proposed method [23,24], 2) combining with GAN-based methods [15,20] to increase the diversity of generated data.

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