Colonoscopy polyp detection with massive endoscopic images

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Abstract We improved an existing end-to-end polyp detection model with better average precision validated by different data sets with trivial cost on detection speed. Our previous work on detecting polyps within colonoscopy provided an efficient end-to-end solution to alleviate doctor’s examination overhead. However, our later experiments found this framework is not as robust as before as the condition of polyp capturing varies. In this work, we conducted several studies on data set, identifying main issues that causes low precision rate in the task of polyp detection. We used an optimized anchor generation methods to get better anchor box shape and more boxes are used for detection as we believe this is necessary for small object detection. A alternative backbone is used to compensate the heavy time cost introduced by dense anchor box regression. With use of the attention gate module, our model can achieve state-of-the-art polyp detection performance while still maintain real-time detection speed.

Keywords Deep Learning · Polyp Detection · Colonoscopy · Endoscopy · Image analysis · Computer-aided diagnosis

1 Introduction

A study in 2020 [22] reports that mortality of colorectal cancer (CRC) has become the second most in US. And the global increasing trends of CRC might grow continuously over next decade and it is predicted to introduce 2.2 million new incidences by 2030 [1]. Nevertheless, figures in highly indexed HDI countries is relatively lower than those with medium HDI, partially due to the application of polypectomy [15].

Polys are some abnormal cells resides the intestine from colon surface, and are likely to develop into cancer tumors through time without any treatment.
Polypectomy is a surgical process of excision precancerous polys after their presence is detected. Therefore, as many researches suggested [7,24], early detection of polyps is important to prevent colon cancer. To date, colonoscopy or endoscopy are used to examine polyps condition from a patient’s colon, consequently, medical imagery are growing rapidly with the increasing popularity of these screening methods. However, doctors can not directly utilizing the abundance in existing visual dataset in increasing their diagnose ability, whereas more manual examination overheads are introduced. To this end, a fully automated detection system can be suggested to highlight potential region of interest. For this reason, [6] developed an end-to-end real-time polyp detection system which can be used to alleviate doctors’ cost while maintaining a stable detection performance. This proposed system features a end-to-end training pipeline with good performance on minor polyp object detection thanks to the adaption of RetinaNet [15] as a detector. However, as stated in [15], RetinaNet, is designed to be concise in order to highlights the performance gain comes solely from authors proposed focal loss and their underlying concepts.

General objects for detection task such as car, pedestrian or table which have defined outline or appearance which offers strong cues for neural network to learn. Polyps, on the other hand, have various sizes which scales from diminutive(< 5mm) to giant(> 30mm) [21] and present different appearances such as sessile or pedunculated [7]. This makes detecting polyps using a general-purpose oriented network more difficult and urges us to design a object-specific detector.

For this work, we collected two more datasets for testing with one of them being significantly more challengeable. According to our empirical test of RetinaNet [15] with our new test sets, we find the conciseness of such network design could result in a unreliable detection rate. We revisit the potential causes for performance degradation and some improvements has been proposed to maintain a comparable result when difficult sample is given. We propose new backbone and subnet architectural designs by incorporating dilated convolution, this allows network having larger receptive field with better multi-scale performance without increasing depth. To enhance the network in detecting various scale object, we also optimize the anchor configuration based on heuristic search and employ a attention gated function during feature fusion stage. Additionally, we further improved our detector by using different post-processing mechanism the Soft-NMS [4].

2 Object Detection

2.1 Multi-stage object detection

An object detection task aims at locating where an instance of object may exists. Detection algorithm predates the heavily use of deep learning era usually be referred as traditional detector. Many hand-crafted descriptors such
Colonoscopy polyp detection with massive endoscopic images

Fig. 1: Examples of possible polyp category within a frame: (a) sessile, (b) pedunculated or (c) multiple of them.

as HOG, SIFT are proposed to extract features over a sliding-window mechanism. The introduction of DPMs and its variants push the sliding-window to its peak by dominating PASCAL competition for many years. The throne of sliding-window based detectors are transferred after the resurgence of Deep Learning, where CNN based feature extraction shows prominent results. CNN based object detectors consists of two parts, feature extractor and regressor. Depending on how potential bounding box are generated, detectors will also be classified as one-stage or two-stage.

The two-stage paradigm can be simply summarized as set of candidate proposals are generated during the first stage, these proposals are regions that network believes to have object of interest. The second stage will refine these proposals to classify them into background and foreground. Selective Search network [27] first proposed this idea and it is surpassed by R-CNN [9] with the change of having CNN as the proposal classifier. R-CNN went through several upgrades in terms of both speed and accuracy. Fast R-CNN [8] uses feature map to generate region of proposals and RoI pooling to fix the input size, thus less convolution operations are required per image. Faster R-CNN [18] makes processing image faster by replacing the time-consuming selective search with Region Proposal Networks. Extensions in this paradigm based on faster R-CNN framework can be found in [34] [19] [20] with focus on achieving higher
accuracy. However, all these two-stage detectors are hardly meet the standard of real-time for video sequence.

Compared to proposal-based object detection network, single stage detector achieves higher frames per second (fps) with cost of accuracy. One stage detector uses anchor to replace the use of proposal. Anchor boxes differ proposals in a way of how they are generated, each box have predefined ratio and scale. Thus, anchor design introduce author’s prior toward the task they are addressing. Performance of early design of single-stage detector differs much to two-stage with focus on achieving higher speed with lost of accuracy. SSD [16] and YOLO [17] are typical instance in this era. One known issue barricading these networks achieving higher accuracy is the so-called class-imbalance problem where the classifier requires to process numerous background images but limited foreground images. This problem is studied in [15] with a feasible solution of using focal loss, it uses specific coefficients to prevent backgrounds overwhelms the classifier. Successors of single shot networks, such as EfficientDet and YOLOv4, both demonstrates comparable performance to those two-stage network while maintaining a optimal speed. These state-of-the-art designs either employ focal loss directly or creating dedicated structure to handle the class-imbalance problem.

2.2 Existing Polyp Detection Framework

Conventional polyp detection works uses engineered features such as color wavelet [12], elliptical shape [10], edge [28], valley and contour [2] to classify the presence of object within a given region. However, many hand-crafted descriptors are proposed to address specific detection issue thus, failed to be robust to variations of object in shapes, size, illumination etc.

In contrast to conventional approach, convolutional neural network gives unparalleled feature generalization ability with sufficient data availability makes CNN an ideal feature extractor for polyp detection task. Initial attempts of incorporating CNN into polyp detection task [25] uses engineering feature as candidate region, ensembled CNNs are used to extract robust feature out of polyps within these manual regions. In medical video domain, a 3D-CNN is favored by some researchers as it learns temporal information whereas 2d convolution only perceives spatial data. [31] proposed a 3D-FCN polyp detection framework, the learned spatio-temporal features from 3D convolution successfully reduced the variations of intra-class and intro-class within polyps. Convolution in 3D is essentially costly operation, though authors in [31] demonstrates their efforts in acceleration, structures like this are hardly a plausible choice for a real-time detection system. All these discussed polyp detectors above are applying non-linear function to feature map to generate a probability map which is thresholded to get precise location of object. In this regard, [32] propose to use SVM as a classifier on to a transfer-learned feature map to predict the presence of a polyp. While those anchor-based or proposals-based framework have achieved noticeable gains in object detection, most works aim at
Colonoscopy polyp detection with massive endoscopic images

Fig. 2: Overall pipeline demonstration for polyp detection

achieving higher results in finding general objects. Recently, researchers begin to adopt these popular frameworks into polyp analysis. \cite{8} uses jointly AlexNet and R-CNN for their autonomous polyp detection algorithm where they add additional pooling layer and use different optimization function to avoid over-fitting issue. In \cite{33}, three types of pooling layers – namely second-max pooling, second-min pooling and min-pooling – are added to SSD to improve detection result for small polyp. Authors in \cite{11} propose a two-stage polyp localization framework where the faster R-CNN is used to generate polyp proposals followed by a polyp segmentation stage. Semantics in both stages are shared thus assure the model’s performance.

Previous work in \cite{6} provide an end-to-end method, as given in \cite{2}, for detecting polyps where the input of colonoscopy content are feed directly into the system and precise location of polyps will then be presented as results. The overall pipeline of such system are organized as follows: an image data acquisition card is used to capture endoscope data and all data will be decoded into a RGB video sequence. The original input sequence consists of some undesired content: polyp-irrelevant and non-colorectal. Authors in \cite{6} trained two pre-process network to remove these elements.

Non-colorectal data is generated by improper use of endoscope where an operator does not start or end the acquisition at the appropriate time, therefore, results in unnecessary non-colorectal content being recorded. Author trained a classification network to differentiate the presence condition (internal or external) for each frame then follows a thresholding mechanism to smooth the inconsistency within consecutive frames. The output of threshold consist inside-body clip only and will be further pre-processed namely cutting, to remove the text box and other non-colorectal. The cutting process employs a manually-tuned binary mask representing the largest connected-component to preserve colorectal-only images. This will form the input data stream to our detection network.

The original method incorporate single stage RetinaNet\cite{15} as a detector. Although detecting polyp is a single object detection task, authors trained network with multiple classes where each category comes from different false positive instance. This indeed prone to work better but only in pre-defined situations since network trained in this way are based on assumption that
these defined classes are diverse enough to cover any class of object within colon.

3 Methods

An overview of our proposed polyp detector is given in \[3\]. We first show how our network architecture is designed including FPN and anchor configuration. We then describe other components which benefits in achieving higher detection accuracy.

3.1 Network design

RetinaNet is a famous one-stage object detector, it uses focal loss to address the common detection problem called class imbalance. Additionally, RetinaNet adopts a top-down Feature Pyramid Network (FPN) from \[14\] which extended a CNN with lateral connections to construct a pyramidal multi-scale feature architecture. Our baseline will follow the structure of RetinaNet, study of choosing optimal backbones ResNet-50 over VGG are discussed in \[6\]. The original structure of FPN used by RetinaNet consists of 5 stages from \(P_3\) to \(P_7\), each level can be used to detect object in different scales. Concretely, level \(P_3\) to \(P_5\) are obtained from the shortcut output of applying top-down and lateral connection to ResNet blocks \(C_3\) to \(C_5\). \(P_6\) is computed by 2-strided convolution on \(P_5\) and \(P_7\) is a down-sampled \(P_6\) activated by ReLu. Coarser level \(P_6\) and \(P_7\) which use for large object detection is computed based on \(P_5\) instead of feature learned by ResNet. Such design speeds up computation with trivial lost on detecting larger object. Our design, on the other hand, uses different method which will be discussed later to improve speed, therefore, all 5 levels will be computed in the same way as in \[14\].

3.2 Anchor optimization

Anchors with different sizes and ratios are generated on top of each pyramid level and feed into two subnets which are used to classify label and regress bounding box. Original anchor configurations uses sizes (32, 64, 128, 256, and 512) each size has three scales \((2^n, 2^n \times 2, 2^n \times 4)\) and three aspect ratios \((1 : 2, 1 : 1, 2 : 1)\). As the quality of anchors will have direct impact on detection, keeping default anchor settings might not possible to detect multiple polyps smaller than 32 within a frame. In this regard, we use differential evolution algorithm \[23\] to approximate optimal anchor configurations iteratively. Process of optimizing anchor configurations are detailed in \[35\], an object function which maximizes overlap area between anchor and object bounding box are optimized by a group of iteratively improved candidate solutions. We increase the number of anchors per level from 9 to 15 by having 5 aspect ratios so that each pyramid scale has denser anchor coverage. Unlike authors in
Fig. 3: An illustration of our architecture design: An image will first go to DetNet for feature extraction, the feature pyramid network is build upon on the output of DetNet as well as the residual blocks. The output of feature pyramid will be split into 4 stages and shared by two subnets.

All scales are optimized with their corresponding stride value associated. We use validation set to find optimal configurations, we eventually find the following anchor parameter combinations with scales (16 32 64 64 64) and ratios (0.481 0.741 1.0 1.349 2.078) fit our task best.

The figure 4 depicts the effect of anchor optimization. All boxes are centering at the object, after applying the optimized anchor parameters, each objects are associated with more boxes which also cover more area of polyps. The effects of having anchors like that is boxes are more likely to fit shapes that

3.3 Dilated Convolution

Previous sections briefly discussed how we get optimal anchor configurations, we increase the number of anchors for each pyramid scale to increase multi-object and finer object detection performance (boundary anchor). More anchor introduce heavier computation complexity which necessitate a efficient backbone design to even out the load from anchors. A traditional convolutional neural network reduces the resolution but increase the receptive field progressively. However, the very last feature map from CNN might be too coarse to be discernible. This issue is addressed by Dilated Residual Network (DRN) [30].
Fig. 4: example of anchor optimization. Anchor boxes on the left are the result of optimization, the ratio and sizes offer better coverage with GT label and more boxes are used.

A dilated convolution, also known as atrous convolution, is defined as \([29]\):

\[
(F *_{l} k)(p) = \sum_{s + lt = p} F(s)k(t)
\]  \( (1) \)

where \( l \) is the dilation rate. This operation introduces a space between values within the kernel (i.e., if we dilated a 3 by 3 convolution with rate of 2, then the resulting receptive filed size is equivalent to the ones of 5 by 5 convolution). One advantage of using dilation is that we can achieve same receptive field size but higher resolution with less parameters compare to its non-dilated counterparts. Thus, as reported in \([30]\), dilating the convolution layer can, to some extent, increase the performance without the need of increasing depth or complexity. Nevertheless, dilation is known to have gridding effect, an artifacts which occurs when sampling rate of dilation is lower than the frequency in feature map. As shown in Figure 5, a dilation with rate 2 could make output with a grided pattern. We adopt some preliminary degridding procedures as studied in \([30]\) \([26]\) by replacing the first global pooling layer with ResNet block and adding extra residual blocks with gradually decreasing dilation rate convolution. The overall structural design of our backbone is inspired by DetNet \([13]\), we replace the original bottleneck block \( C_{4} \) and \( C_{5} \) from ResNet-50 with the dilated bottleneck and 1x1 conv projection. On top up that, we applied the degridding mechanism to above structure and \( P_{6} \) are now computed directly from backbone. Figure below shows the de-gridded feature map.

3.4 Attention gated block

Applying attention gate to small and varying object has been proven to work according to \([35]\). It is a light-weight yet efficient accuracy-boosting mecha-
Colonoscopy polyp detection with massive endoscopic images

(a) gridded

(b) degridded

Fig. 5: Example of (a) gridded and (b) degridded feature map. Heat value in degridded feature map gives smoother spreads compare to its gridded map.

4 Experiments and results

For experiments, both training and testing are conducted on Nvidia GTX1080 Ti. Additionally, we use TensorFlow and Keras, the open-source deep learning frameworks to accompany our model’s implementation.

4.1 Datasets

We annotated our colonoscopy dataset for training and evaluation. It consists of 80k images from colonoscopy capture card output and follows the preprocessing procedures, this results in different pixel resolution ranging from $431 \times 368$ to $751 \times 641$. All images which are verified by our experienced gastroenterologist either contains our polyp annotations or not. We design and conduct several experiments to evaluate detection performance and details of experiment and result will be given in the following sections.
Table 1: Metrics for polyp detection

|         | Precision | Recall | F1   |
|---------|-----------|--------|------|
|         | $\frac{TP}{TP+FP}$ | $\frac{TP}{TP+FN}$ | $2 \times \frac{Prec \times Rec}{Prec + Rec}$ |

AP = $\int_0^1 p(r)dr$

Table 2: Polyp detection result tested on our dataset. Models are trained from scratch.

| Method                      | # of Pars | F1   | mAP  | Recall | Frame per Second |
|-----------------------------|-----------|------|------|--------|------------------|
| RetinaNet [6]               | 36.40M    | .821 | .869 | .814   | .0291s          |
| RetinaNet + AO              | 36.32M    | .825 | .888 | .833   | .0422s          |
| RetinaNet + AO + AG         | 36.39M    | .825 | .891 | .848   | .0422s          |
| RetinaNet + AO + AG + DilatedConv | 30.77M | .897 | .866 | .807   | .0198s          |
| RetinaNet + AO + AG + DilatedConv + Degrid | 34.77M | .901 | .901 | .807   | .0222s          |

4.2 Training and inference

We trained our network by following the strategies listed in [15]. We use adam as optimizer with weight decay 0.0001 and momentum 0.9, a focal loss and $L_1$ loss are used for training and box regression. Batch-size of 8 are used to for each epochs and group normalization with group size of 8 will be updated accordingly. All inputs are resized to 300x300 in accordance with size used in our previous work [6]. We also adopted flipping shearing for augmentation.

4.3 Polyp Detection Results

Our dataset is split into training, validation and testing with ratio of (7 : 2 : 1). All networks are trained from scratch as there is no pre-trained weights for our proposed architecture. The performance of polyp detection is evaluated quantitatively by the following metrics as shown in [1]. As a detection task, we use Intersection over union(IoU) to define a True Positive (TP) IoU of Ground truth(GT) and Prediction is greater than 0.5; otherwise, it is False Positive(FP). A False Negative(FN) is defined as count of the absence of the detection of a frame. Precision (Prec) describes the proportion of positive return is correct, while recall(rec) describes the proportion of real positive output is predicted correctly. F1 score indicates the balance between prec and rec. The area under the precision-recall curve $p(r)$ is the Average Precision (AP).

Table 2 shows the polyp detection result on our test set with various component incorporated. For this result, the backbone of RetinaNet is ResNet-50. DilatedConv indicates ResNet-50 are replaced by DetNet-59. From this
results, we can see the effect of adding each components, with the anchor optimization, the mAP increased by 2 percents but the processing speed drops significantly. We therefore changed the architecture of backbone to DetNet where less parameters are used without much performance drop. As discussed in the previous section, new backbone has a major issue named gridding effect. We observed that, the fix of such effect with attention module gives significant improvement without noticeable penalties on detection speed.

5 Conclusion and Future Work

In this paper, we extends our previous studies on designing an End-to-End polyp detection model. We discussed the potential reasons that cause our old model failed to give competitive results as before. We also showed that the original RetinaNet with ResNet-50 backbone can be further improved using a task-specific anchor optimization strategy. We plant in a attention gate module and design a de-gridded DetNet backbone to guarantee a real-time detection speed. Impressive results have been given on polyp detection based on our private dataset which exhibit the efficiency and generality of our improved model. Given the clinically available annotated dataset, the proposed method can be easily tuned and given fast inference, implying its applicability in many clinical practice.

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Conflict of interest

The authors declare that they have no conflict of interest.

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