OfGAN: Realistic Rendition of Synthetic Colonoscopy Videos

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Introduction

Background:

In medical imaging, annotating real data is a challenging and tedious task. However, machine learning methods have to inference on patient-specific data.

Motivation:

To gain labelled "real" datasets, we can transform the synthetic data into realistic ones meanwhile keep the annotation unchanged. In this paper, we try to do the realistic rendering on synthetic colonoscopy videos basically on this idea.

Related work:

Previous works [20, 29] achieve good performance on image-to-image translation in general image. However, simply applying the methods on colonoscopy videos leads to bad results.

Challenges:

- Hard to transform domain and keep temporal consistency simultaneously.
- Large domain gap makes the training much harder.
- Must be robust to avoid training a second model for a single simulator.

Contributions:

1. Optical Flow GAN (OfGAN): Our proposed OfGAN is able to transform the domain while keeping the temporal consistency of colonoscopy videos and rarely influencing the original optical flow annotation.
2. Real-enhanced Colonoscopy Generation: Our method can be incorporated in a colonoscopy simulator to generate near-infinite real-enhanced videos.
3. Qualitative and Quantitative Evaluation: The model is evaluated on our synthetic and a CT colonoscopy dataset [23] qualitatively and quantitatively.

Method

Our model is a GAN-based model, which consists of two key components:

- **Temporal Cycle Structure**

Compared with CycleGAN [29] which forms a circle only on a single time step, we force a temporal mapping chain (forward cycle) as :

$$s_n \xrightarrow{G_{next}} R'_{n+1} \xrightarrow{G_{self}} S^{rec}_{n+1}$$

where the subscript indicates the number of continuous frames, prime indicates "transformed", "rec" indicates "reconstructed". In the novel mapping chain, the generator G_{flow} has to predict the next frame meanwhile doing the domain transformation.

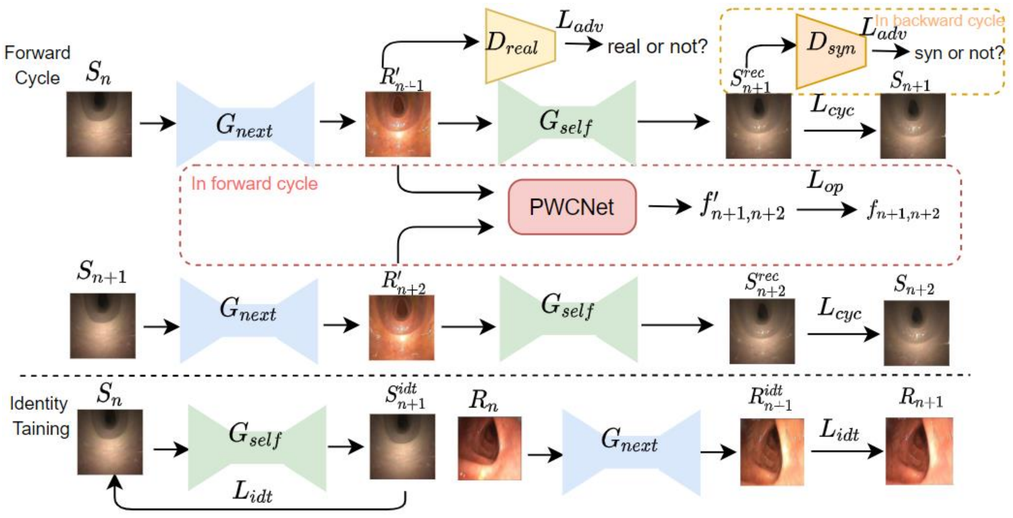

Fig.1: Forward cycle and identity loss of OfGAN. G_{next} transforms the input to the next frame of the target domain. It is trained by the temporal-consistent loss which forces the reserved generation (G_{self}) to be same as the ground-truth synthetic frame.

- **Optical Flow Loss**

we force the G_{next} to learn the underlying optical flow so that we have $f'_{n,n+1} \approx f_{n,n+1}$ where $f_{n,n+1}$ means the ground truth optical flow between the n-th frame and n+1-th frame and f', is the optical flow of the transformed version. We utilized a pretrained PWC-Net [27] for optical flow estimation.

Datasets

State of the art CSIRO simulator:

- Synthetic videos, consists of 8000 video frames with ground truth optical flow from 5 different simulated colons which were generated by a variety of possible camera motion. 2000 frames from two unknown synthetic colonoscopy videos were used for test.
- A Published CT colonoscopy dataset [23]

Real video:

- Real videos, consists of 1472 video frames (after cleaning) captured from patients by our specialists.

Experiments and Results

Qualitative evaluation:

It measures if the transformed frame looks much more like real ones while, on the other hand, it evaluating if it contains less noise. This evaluation is on the baseline model (CycleGAN) and our model testing on both our synthetic dataset and the public CT dataset.

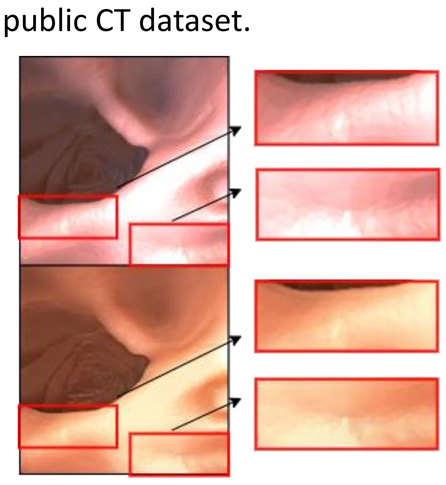

Fig.2: Qualitative evaluation of CT colonoscopy outputs, CT input (top), and our transformed results (bottom).

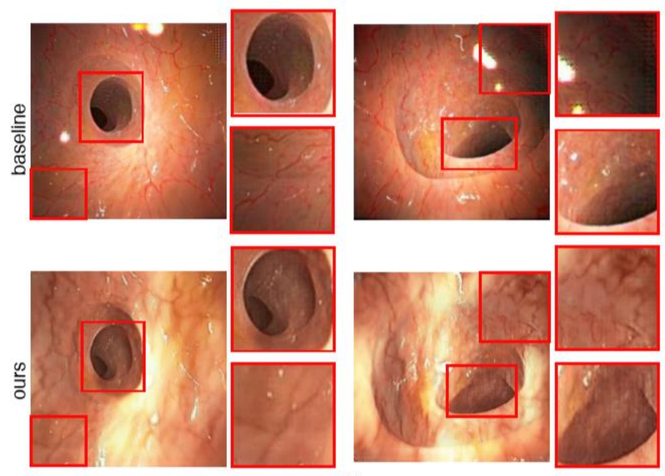

Fig.2: Qualitative assessment of the selected frame between two selected pairs from the baseline (top) and our method (bottom). Zoomed zones come from the detail inside the nearby red rectangles.

Quantitative evaluation:

It quantifies the performance by using a joint metric (DTS) of the spatial and the temporal dimension. We weighted four well-known losses, E_{gt} (AEPE to ground truth), E_{pred} (AEPE to estimated), L_{perc} (Perceptual loss), L_{style} (Style loss).

These metrics are normalized on 36 test cases with different hyper-parameters. The smaller the DTS, the better the performance.

$$DTS = \frac{3}{8}\mathrm{N}(E_{gt}) + \frac{1}{8}\mathrm{N}(E_{pred}) + \frac{1}{4}\mathrm{N}(L_{perc}) + \frac{1}{4}\mathrm{N}(L_{style}) + 0.5$$

Approach	E_{gt}	E_{pred}	L_{perc}	L_{style}(1e-3)	DTS
Synthetic	0	0.15	3.31	11.19	1.47
baseline	1.27	**0.24**	2.53	3.22	0.37
Cycle + op	1.53	0.81	2.43	2.82	0.40
Temp w/o op	2.85	2.35	**2.39**	**2.37**	0.77
Sig = 5	**1.19**	0.36	2.47	2.96	0.31
Sig = 0.1	1.22	0.31	2.49	2.64	**0.27**

Tab.1: "cycle + op" and "temp w/o op" are two setting for ablation study. Our full model is the last two with different sigmas (weight of optical flow loss).

For GIF and MP4, we highly recommend you to visit https://www.boblog.wiki/project/OfGAN.html

Summary

Conclusions: The transformed dataset by our proposed OfGAN has outstanding temporal and spatial quality, which can be used for data augmentation, domain adaptation, and other machine learning tasks to enhance the performance.

Limitations: The performance might reduce if it fails to transform a frame correctly in a sequence. This can cause a dramatic effect on generating long videos. We will verify our model on other styles of datasets in the future.

FOR FURTHER INFORMATION

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