FLATTENING SINGULAR VALUES OF FACTORIZED CONVOLUTION FOR MEDICAL IMAGES

Zexin Feng[1*], Na Zeng[1*], Jiansheng Fang[2], Xingyue Wang[1], Xiaoxi Lu[1], Heng Meng3†, Jiang Liu1†

[1]Research Institute of Trustworthy Autonomous Systems and Department of Computer Science and Engineering, Southern University of Science and Technology, Shenzhen, China
[2]Guangzhou Native-Stone Intelligent-Brain Technology Co., Ltd., Guangzhou, China
[3]Department of Neurology, The First Affiliated Hospital of Jinan University, Guangzhou, China

INTRODUCTION

- CNNs' potent representation enhances computer-aided medical image diagnosis. Hence, in assisting clinical decision-making practicality, it is **essential to effectively and efficiently deploy CNNs** for medical image processing (MIP) on devices with different computing capabilities.
- We count up the average skewnesses [1] of pixel distribution for two public datasets. As shown in Fig. 1, we found the **heavy skewness and high kurtosis** of medical images compared to the natural images.

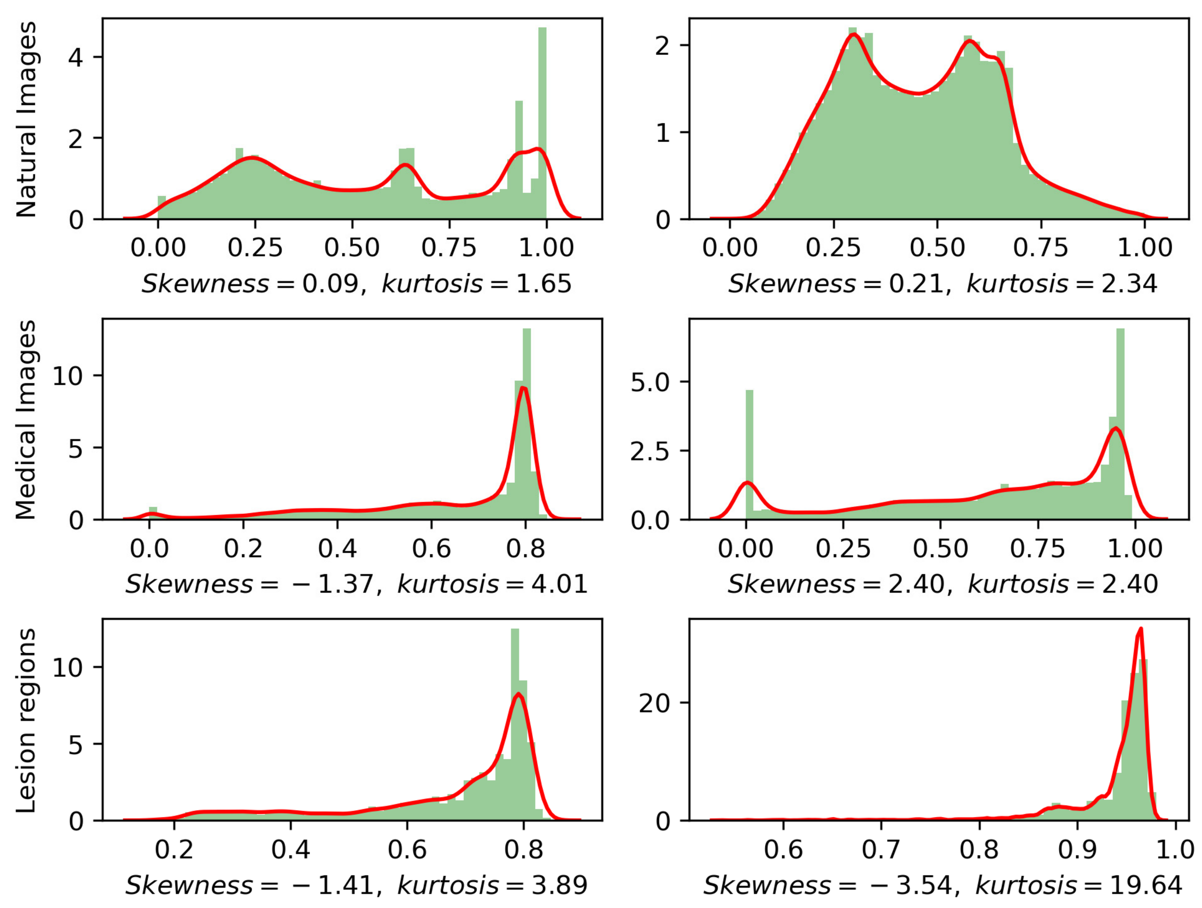

Fig. 1. Measures of skewness and kurtosis of data distribution.

- In this paper, **a novel Singular value equalization generalizer-induced Factorized Convolution** (SFConv) is proposed. With the purpose **of avoiding extra computation** from multiplying low-rank matrices, **two low-rank convolutions are employed** instead of a high-rank convolution for low-rank decomposition.
- We conduct experiments on Color Fundus Photography (CFP) and Optical Coherence Tomography Angiography (OCTA) datasets to demonstrate the effectiveness of our SFConv.

METHODOLOGY

- The SFConv utilizes two low-rank convolutions to achieve low-rank decomposition, thereby avoiding the decline of inference speed caused by matrix multiplication calculation.

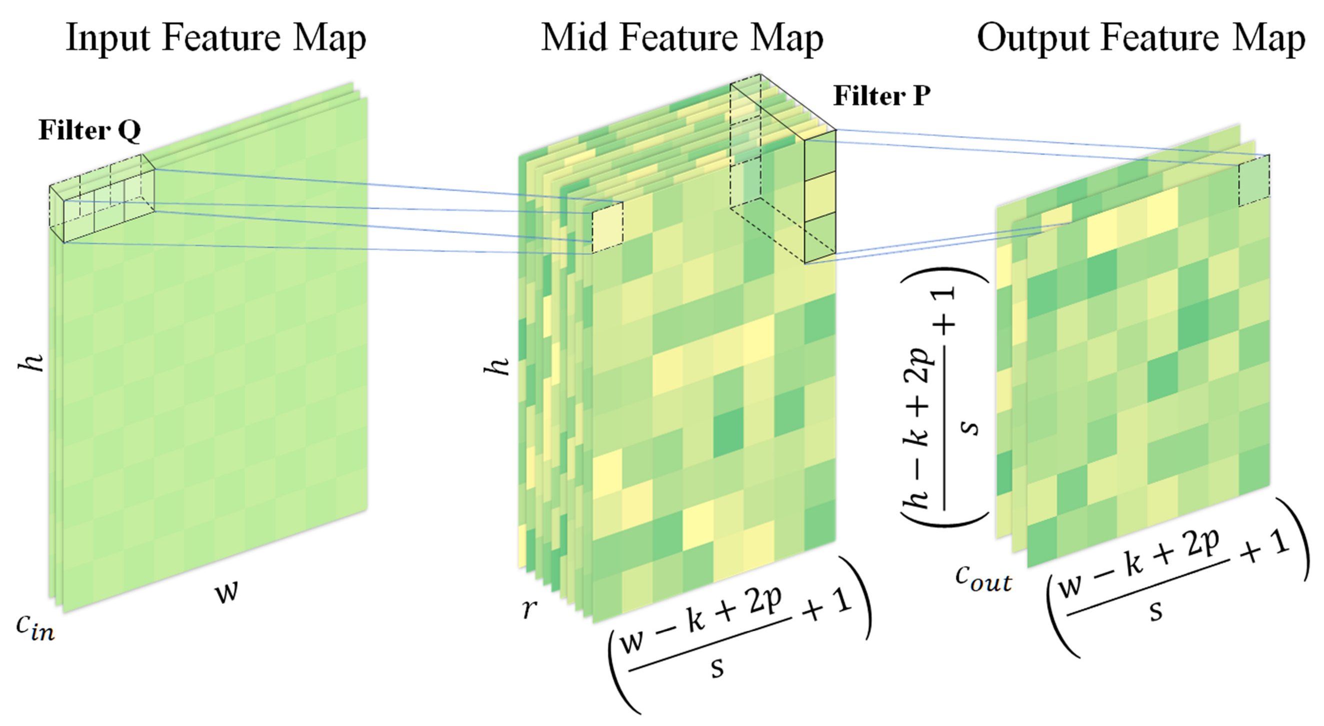

Fig. 2. Schematic diagram of SFConv, where s is stride, p is padding, w is width, h is height and k is the size of convolution kernel. The color shows the variance of weight parameters.

- We flatten singular values on two low-rank matrices of factorized convolutions by penalizing the KL divergence between weight distributions and uniform distribution. The KL regular term is expressed as follows:

$$\mathcal{L}_{\mathrm{KL}}=\sum_{i=1}^{c}\boldsymbol{F}_{\mathrm{KL}}(s_p^i,u_p^i)+\boldsymbol{F}_{\mathrm{KL}}(s_q^i,u_q^i)\quad(i=1,...,c),$$

where F_{KL} is the KL divergence, s_q and s_p represent the vectors composed of the singular values in diagonal matrix, u_p and u_q denote uniform distribution vectors with the same length with respect to s_q and s_p.

EXPERIMENTS

- We performs the diseases classification task on IDRiD dataset and vessel segmentation task on the SVC subset of ROSE-1.

Table 1. The classification results of different methods.

Methods	#.Params	FPS	FLOPs	ACC
Conv	11.22M	**222.23**	43.03G	0.8058
FConv [2]	2.78M	38.12	3.07G	0.7670
FConvSN [3]	0.40M	84.67	**2.78G**	0.7961
DPConv [4]	1.48M	204.27	105.11G	0.8155
SFConv w/o KL	0.27M	159.72	20.08G	0.7379
SFConv (ours)	**0.27M**	158.15	20.08G	**0.8582**

Table 2. The segmentation results of different methods.

Methods	#.Params	FPS	FLOPs	Dice
Conv	17.29M	**232.10**	57.99G	0.7476
FConv [2]	3.60M	73.30	0.21G	0.6770
FConvSN [3]	0.56M	76.22	**0.21G**	0.7503
DPConv [4]	2.03M	166.94	7.22G	**0.7738**
SFConv w/o KL	0.32M	155.65	3.08G	0.7327
SFConv (ours)	**0.32M**	156.57	3.08G	0.7652

- The KL regularization term successfully flatten the singular value of parameters in convolution matrix, as shown in Fig. 3.

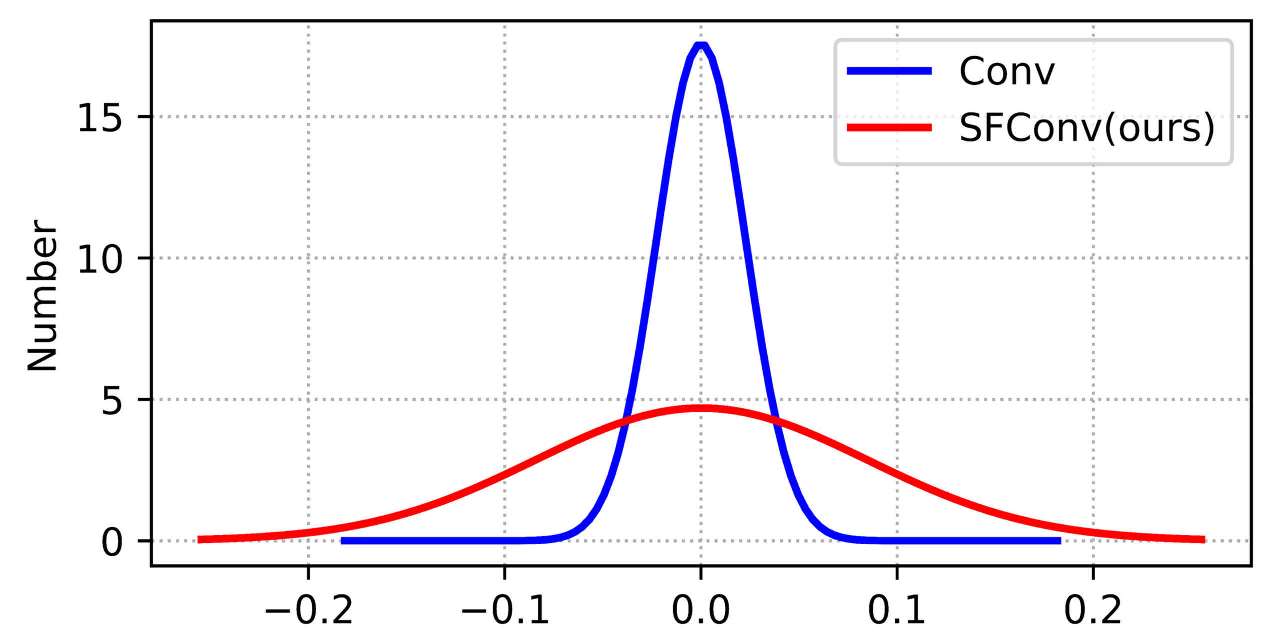

Fig. 3. Parameter distributions of the trained U-Net.

CONCLUSION

- As shown in Table 1 and Table 2, we see that SFConv has the lowest parameter quantity. This demonstrates that SFConv has powerful model compressing ability by factorizing convolutional layers.
- SFConv matches standard convolutions in performance with lower model complexity in both classification and segmentation tasks.
- The FPS of SFConv reaches 70% of the standard convolution, demonstrating that the two-step convolution strategy adopted by our SFConv avoids the decline of inference speed caused by matrix multiplication calculation.
- As shown in Fig.3, the parameter distribution of the network driven by SFConv has a larger variance. This shows that after equalizing the singular value distribution with the KL regularizer, the parameter distribution is wider. The information of the parameter matrix is no longer occupied by an excessively large singular value, so the performance of SFConv is significantly improved.

REFERENCES

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fengzx@mail.sustech.edu.cn
Mark4551124015
www.imed-lab.com