Pixel-Level Solar Filament Segmentation Based on Deep Learning

Gaofei Zhu, Ganghua Lin, Dongguang Wang, Suo Liu and Xiao Yang

Key Laboratory of Solar Activity, National Astronomical Observatories, Chinese Academy of Sciences, Beijing China;

Introduction

Solar filaments are the most obvious solar activity in the observation of Ha spectral line. They are the projection of prominences on the solar surface. So, they look like elongated dark ribbons with irregular edge on the brighter solar disk. Generally, their temperatures and densities are much cooler and denser, respectively, than the surrounding corona. In previous research work, we introduce the Dropout layers and interpolation method to improve the U-Net network. Even though the improved network can achieve an inspiring result, there are still some limitations in it. One of the most important points is that the network has the risk of falling into local optimum. In order to resolve this problem, we add several batch normalization layers after every max-pooling layer in the network, and the learning rate decline strategy is applied to the network. In section 2, we show the architecture of the proposed network. An example of solar filament segmentation result is given in section 3. In section 4, we draw the conclusion of our study.

Proposed Network

The U-Net network consists of two paths: a contracting and an expansive path. There are several down-sampling blocks (Figure 1) and several up-sampling blocks in the networks(Figure 2). As the previous improved network may trap the training model into local optimum, we introduce several batch normalization layers at end of the max-pooling layer in the first four down-sampling blocks. It aims to make the data have the mean of 0 and the variance of 1. Additionally, we use the learning rate decline strategy instead of a fixed learning rate. Therefore, the proposed method can effectively solve the problem of network falling into local optimum.

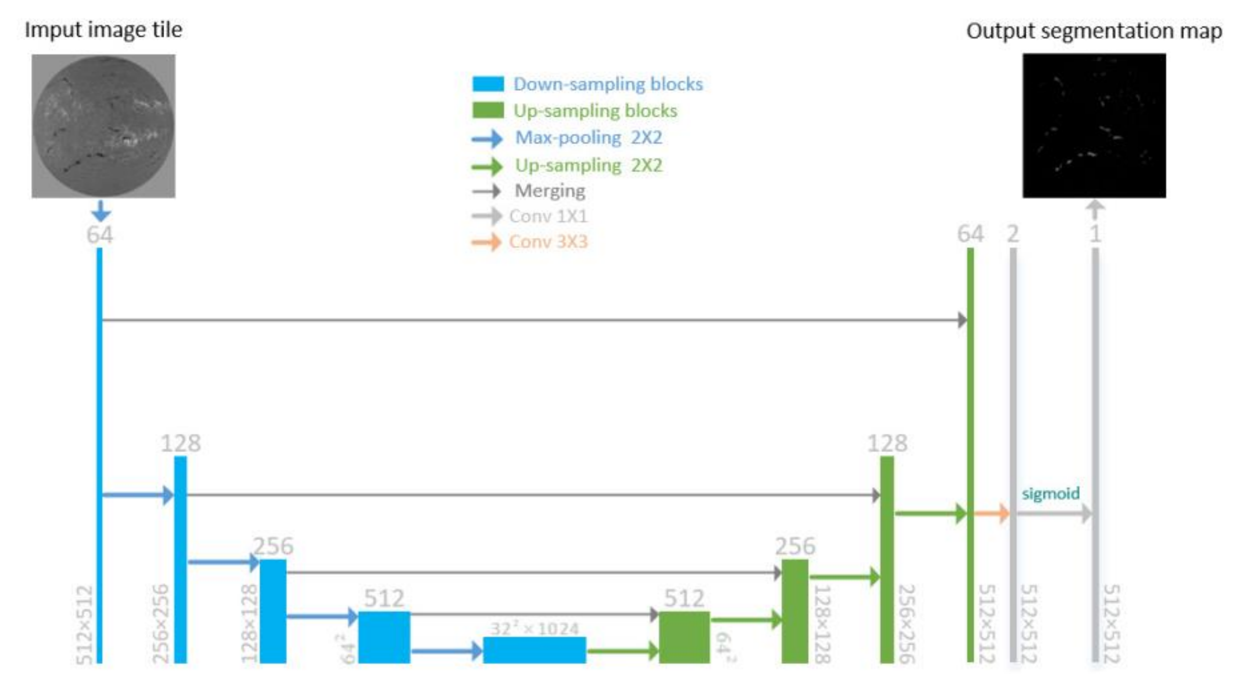

Figure 1. Architecture of the improved U-Net network. It contains a contracting path shown with blue and an expansive path with green. The number below each box represents the number of channels. The size of feature maps is provided at the left and right sides of the box. Each box contains more operations as shown in Figure 2.

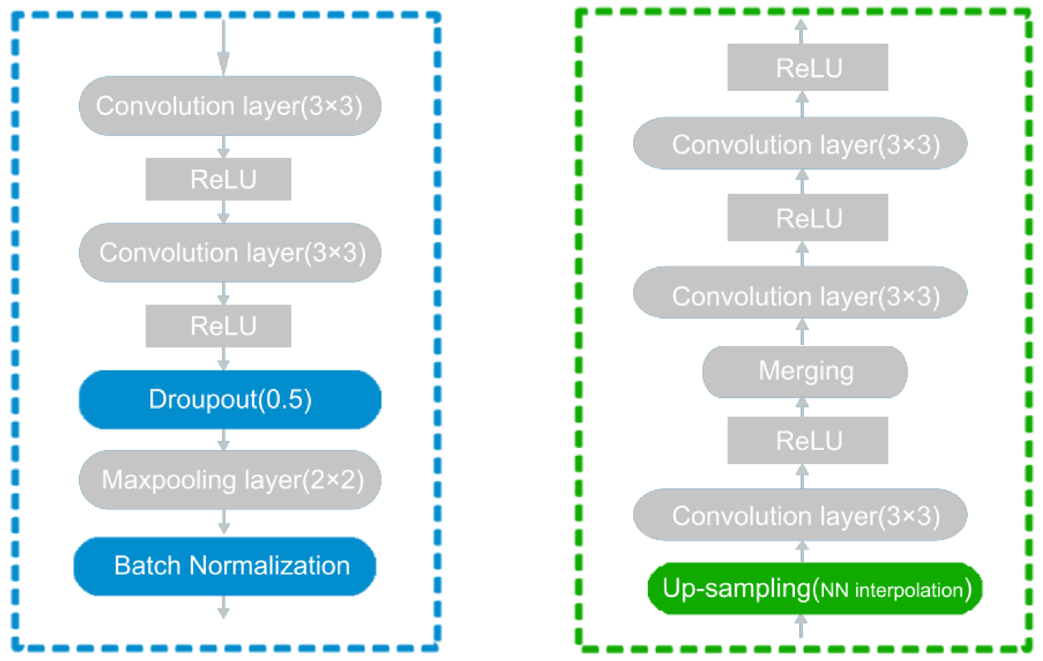

Figure 2. Figure 2. Architecture of each colored box as shown in Figure 1. Compared with the previous work, the batch normalization layers are added behind the max-pooling layers in the left panel.

The author who proposed the batch normalization uses the mean and variance of mini-batch as estimates of the mean and variance of the whole data set. The normalization process can be expressed by the following formula:

$$\begin{cases} \mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i \\ \sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i-\mu_B)^2 \\ \hat{x}_i = \frac{x_i-\mu_B}{\sqrt{\sigma_B^2+\varepsilon}} \\ y_i = \gamma\hat{x}_i + \beta \end{cases} \qquad (1)$$

where x_i represents the i-th value over a mini-batch, μ_B and σ_B^2 are the mean and variance of a mini-batch, respectively. γ and β are the parameters to be learned. The learning rate decline strategy can be given by:

$$\hat{l} = l * \frac{1.0}{1.0 + d * i} \qquad (2)$$

where $\hat{l}$ represents the learning rate updated after every epoch, l is the initial learning rate, d represents the decay parameter of the learning rate, i denotes the number of weight updated in each epoch.

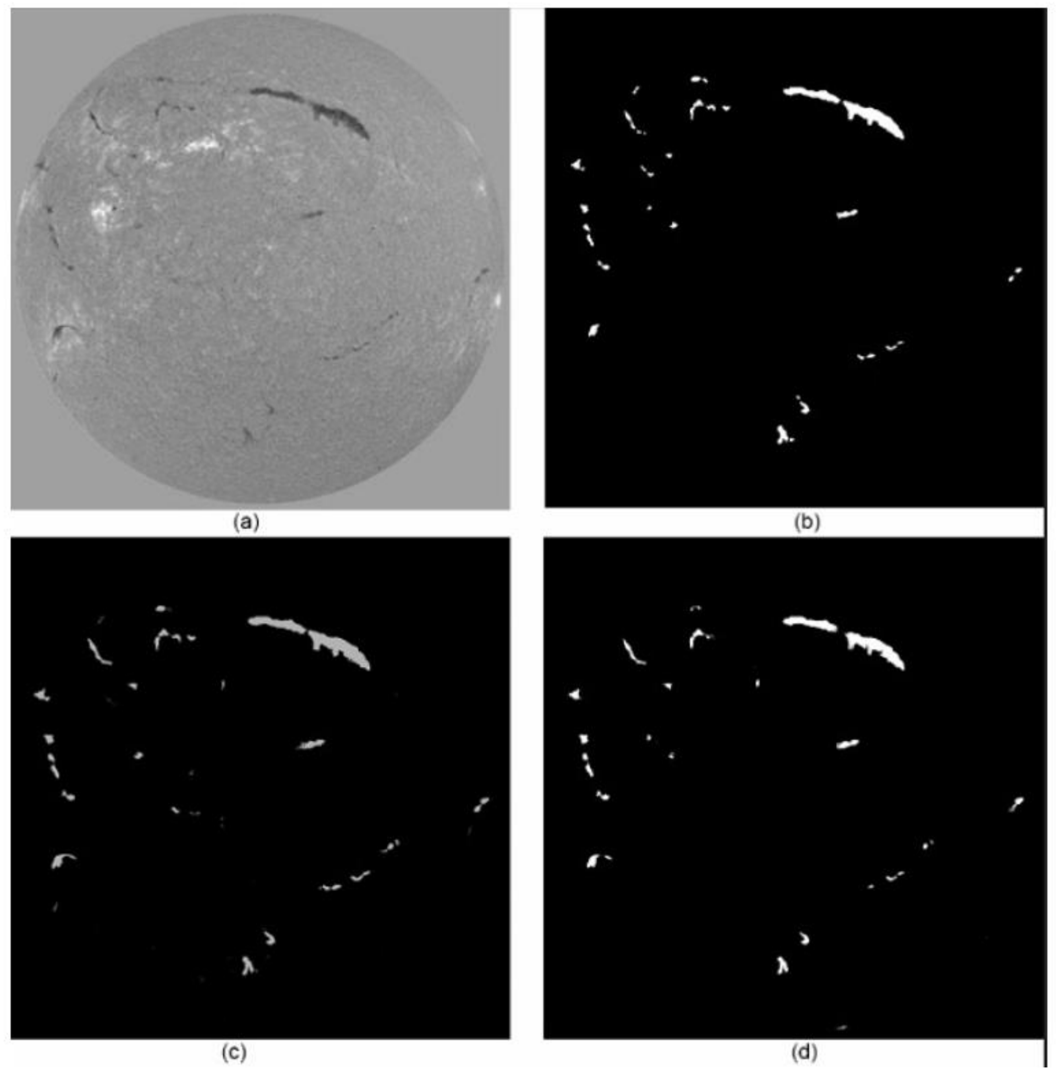

Figure 3. One example of segmentation result using the proposed network. (a) the preprocessed Ha image. (b) the ground truth. (c) the predict result using the previous improved network. (d) the predict result using the proposed network.

Experimental result

The proposed network can minimize the possibility of training model falling into local optimum and avoid model training failure. Figure (3) shows an example compared with the previous result. Figure (4) shows the decay curve of the learning rate during model training.

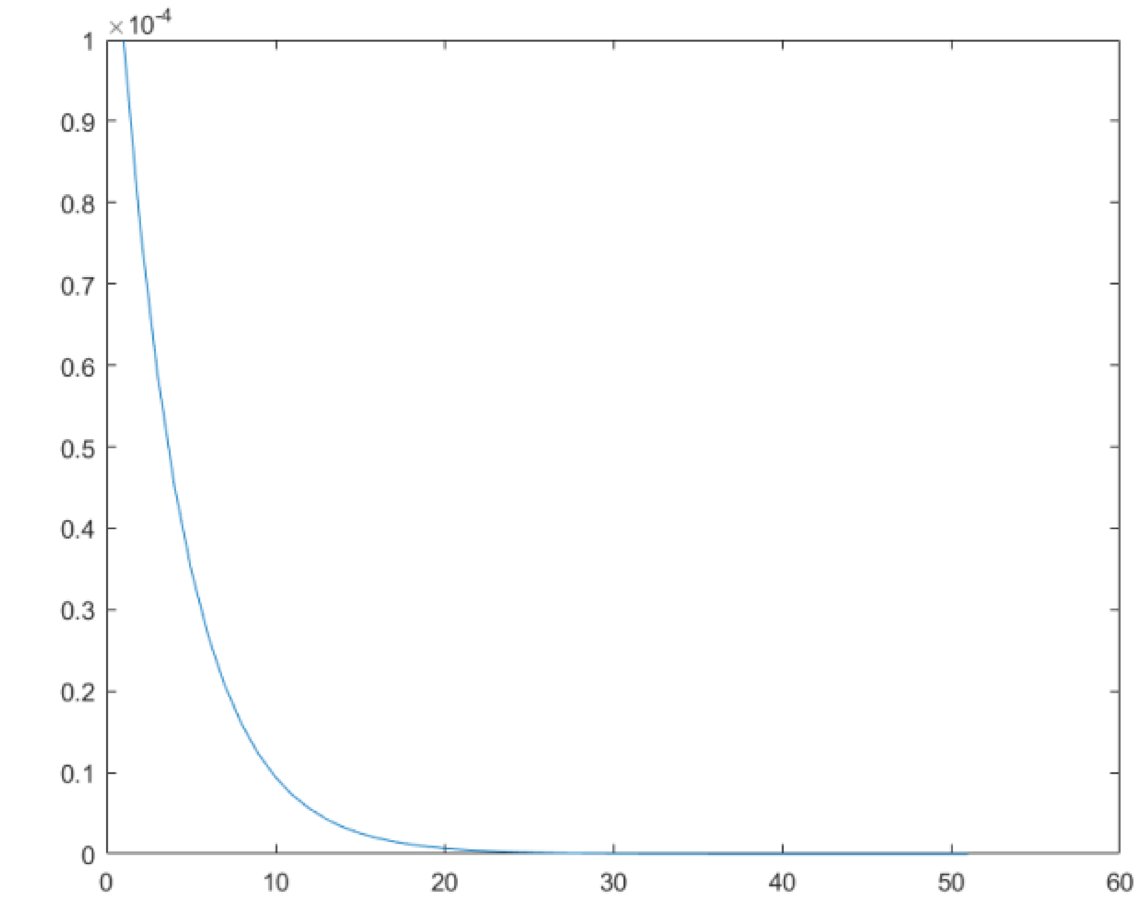

Figure 4. the decay curve of the learning rate of the proposed network.

Summary

We propose a better network for solar filament segmentation in Hα full-disk solar images. The proposed network not only reduces the possibility of falling into local optimum during the training process, but also improves the segmentation accuracy. The whole work is not finished yet. We need more experimental data to support our proposed method.

References

[1] Zhu, G., Lin, G., Wang, D. et al. Sol Phys, 2019
[2] S. Ioffe and C. Szegedy. ICML, 2015.