

Postprint: Solar Filament Detection Method Based on Improved VNet

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Date: 2021-03-04T00:00:00+00:00

Abstract

Solar filaments serve as tracers of the solar atmospheric magnetic field, and their accurate detection is of paramount importance for solar magnetic field research. To address the issues of low detection accuracy, misdetection, and missed detection of weak and small filaments in existing filament detection methods, this paper proposes a solar filament detection method based on an improved VNet network. First, a solar filament dataset is constructed using H full-disk images from the Big Bear Solar Observatory combined with magnetograms. Second, in the downsampling part of the VNet network, inception modules are adopted to fuse features from feature maps at different scales, while an attention mechanism is incorporated to enhance the semantic information of filament regions in the feature maps. Finally, a deep supervision module is introduced in the upsampling part to better preserve the detailed features of solar filaments. To validate the algorithm's performance, this study employs a dataset comprising 191 H full-disk images, which includes a total of 3,372 filaments. The algorithm achieves an average accuracy of 0.9883 and an F1-score of 0.8385 on the test dataset. Experimental results demonstrate that the proposed method can effectively identify filaments in H full-disk images.

Full Text

Solar Filament Detection Based on an Improved VNet

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Abstract

Solar filaments serve as tracers of magnetic fields in the solar atmosphere, and their accurate detection is of paramount importance for solar magnetic field re-

search. Existing filament detection methods suffer from low accuracy, misdetection, and missed detection of weak and small filaments. To address these issues, this paper proposes a solar filament detection method based on an improved VNet network. First, we constructed a solar filament dataset using H α full-disk solar images from the Big Bear Solar Observatory combined with magnetogram data. Second, we incorporated Inception modules in the downsampling path of VNet to fuse features from different scales, while adding an attention mechanism to enhance semantic information of filament regions in feature maps. Finally, we introduced a deep supervision module in the upsampling path to better preserve fine-grained filament details. To validate the algorithm's performance, we employed a dataset of 191 H α full-disk images containing 3,372 filaments. The proposed method achieved an average accuracy of 0.9883 and an F1-score of 0.8385 on the test set. Experimental results demonstrate that this approach can effectively identify filaments in H α full-disk solar images.

Keywords: filament detection; solar filament dataset; VNet; Inception; deep supervision; attention mechanism

Solar filaments consist of low-temperature, high-density plasma in the solar corona, appearing as filamentary structures near the solar disk center [1]. These features vary in scale and activity, with different filaments eventually disappearing or erupting. Filament eruptions are closely associated with solar flares, coronal mass ejections, and magnetic storms. Intense filament activity can eject plasma that reaches Earth within days, affecting the magnetosphere and potentially causing communication equipment damage, service interruptions, and aviation navigation failures [2]. Furthermore, filaments typically appear above polarity inversion lines in the photospheric magnetic field, making their study crucial for understanding solar magnetic field evolution. As a fundamental prerequisite for such research, accurate filament detection holds significant scientific importance.

Based on the characteristic that optically thick filament material absorbs substantial photospheric background radiation while emitting very little, solar filaments observed in the H α band appear darker than the surrounding background. Building upon this principle, numerous scholars have developed automated filament detection methods that can be categorized into three main approaches: (1) **Threshold-based methods.** For instance, Gao et al. [3, 4] employed global thresholding and region growing algorithms for automatic filament detection. Fuller and Abouadarham et al. [5-7] improved upon Gao's work by using local thresholds instead of global thresholds to address limb darkening and non-uniform brightness in full-disk images. Qu [8] utilized Canny edge detection followed by morphological erosion and dilation to identify filaments. While computationally efficient and requiring no manually labeled datasets, these methods often misidentify noise points and dark background regions as filaments, resulting in low precision. (2) **Machine learning methods.** Zharkova et al. [9, 10] applied artificial neural networks for filament detection, scanning pixel-by-pixel

through predefined windows to identify filaments against various backgrounds. These methods reduce dependence on image normalization and leverage prior knowledge for efficient feature extraction and fast model training. However, they suffer from poor generalization, ineffective modeling of complex filament structures, and insensitivity to weak and small filaments, leading to fragmented detections and missed detections. (3) **Deep learning methods.** Deep learning approaches excel at learning image features and have achieved considerable success in astronomical image processing [11-12]. For example, Salasa [13] applied Mask R-CNN for filament detection using H α full-disk images from the Indonesian National Institute of Aeronautics and Space, with ResNet-101 and Feature Pyramid Networks as the backbone. Zhu [14] employed a UNet-based deep learning network for solar filament recognition using H α full-disk images from the Big Bear Solar Observatory, incorporating Dropout layers in the downsampling path and replacing transposed convolutions with linear interpolation in the upsampling path. Compared to machine learning methods, deep learning eliminates the need for manual feature engineering, automatically learning filament characteristics and details from labels, thereby achieving higher generalization and robustness. Nevertheless, these methods face challenges with inaccurate labeling, where sunspots and noise points in the labels interfere with feature extraction, resulting in imprecise models. The UNet architecture's limited feature extraction capability during downsampling leads to loss of filament details, while the upsampling process only refines the final output without adequately training intermediate feature maps, causing fragmented detections, missed weak filaments, and false positives from background regions.

To address these limitations and enable the network to learn more accurate filament features, we present the first dataset that combines solar magnetograms with manual filament annotation. We perform preprocessing steps including brightness normalization and denoising before training. We adopt the VNet architecture [15], which demonstrates strong anti-interference capabilities and effectively suppresses background influence on detection results. To fully extract filament details, we propose improvements to VNet that enable more precise detection of weak and small filaments. Our main contributions are: (1) We created a solar filament dataset* by incorporating solar magnetograms. Compared to existing datasets, our approach uses contemporaneous magnetogram magnetic field distributions to eliminate sunspots and noise while preserving weak filaments, resulting in more accurate labels. (2) We integrated Inception modules [16] in the downsampling path to extract multi-scale features, introduced an attention mechanism [17] to suppress interfering background features, and incorporated a deep supervision module [18] in the upsampling path to fuse features from different depths, thereby improving detection accuracy.

Experimental results demonstrate that our method achieves high-precision solar filament detection.

1.1 Data Preprocessing

The filament dataset comprises $H\alpha$ full-disk solar images from the Big Bear Solar Observatory. Since the observatory is ground-based, variations in Earth-Sun distance, temperature, humidity, and wind cause the solar disk to appear off-center in images. Additionally, atmospheric effects and instrumental factors introduce noise and brightness non-uniformity. These issues can negatively impact detection accuracy and recall. To address them, we first employ Hough circle detection and least-squares fitting to determine the solar center and radius. We calculate the offset between the image center and solar disk center, then translate the solar disk to the image center. When the two methods differ by more than 5 pixels, manual adjustment is performed. The solar 轮廓 is obtained and pixels outside the 轮廓 are set to gray to avoid interfering with network training. Second, we use a total variation model to remove background noise. Finally, we enhance image contrast to highlight filament features by clipping extreme pixel values and redistributing the remaining pixels proportionally. The preprocessed images are shown in [Figure 1: see original paper], where filaments in Figure 1(b) become more prominent after preprocessing.

1.2 Dataset Construction

Data is the lifeblood of deep learning. Filament segmentation algorithms based on deep learning require accurately labeled data to learn filament features and continuously adjust network parameters. Inaccurate labeling can prevent model convergence and yield imprecise results, potentially underperforming traditional threshold segmentation methods. The currently public solar filament dataset from the National Astronomical Observatories of China [14] uses $H\alpha$ full-disk images from the Big Bear Solar Observatory but employs threshold-based segmentation for annotation. This approach incorrectly labels sunspots and small noise points while missing weak filaments, causing the network to extract erroneous features and resulting in missed detections and false positives. [Figure 2: see original paper] illustrates common issues in this dataset: red boxes in Figures 2(a) and 2(c) show sunspots and weak filaments in full-disk images, while corresponding labels in Figures 2(b) and 2(d) contain sunspot mislabeling and missed weak filaments (red boxes) along with noise points (yellow boxes).

To improve training accuracy and model performance, we created and released a solar filament dataset comprising $H\alpha$ full-disk images and binary filament masks. The $H\alpha$ images were captured by the Big Bear Solar Observatory between 2010 and 2020. Filaments have a close relationship with magnetic fields, existing above polarity inversion lines where radial magnetic fields transition between positive and negative polarities in the photosphere [19]. Sunspots, conversely, reside in regions of single polarity. Leveraging this characteristic, we used contemporaneous magnetograms from the Global Oscillation Network Group (GONG) at the National Solar Observatory to identify polarity inversion lines (the intersection of black and white regions in Figure 3: see original paper). Combining magnetogram information with filament brightness and texture fea-

tures, we manually annotated filaments using the LabelMe tool while excluding sunspot interference. In Figure 3: see original paper, red lines indicate annotated magnetic neutral lines; the region corresponding to the red box in Figure 3: see original paper shows no polarity inversion, confirming the absence of a filament. Our dataset contains 191 full-disk $H\alpha$ images with 3,372 filaments of various morphologies. Training images (146) were selected from 2013-2014 when filament activity was high and features were most complete, while test images (45) were taken from other years.

Fausto Milletari et al. [15] proposed VNet for medical image segmentation. Since both medical images and solar filaments share characteristics of high labeling costs and limited training samples, VNet's ability to train effective models with small datasets makes it suitable for this application. Additionally, VNet's residual connections in both downsampling and upsampling paths mitigate gradient vanishing in deep networks, and its strong anti-interference capability effectively suppresses background influence on filament detection results. Therefore, we adopted an improved VNet architecture for solar filament detection.

The VNet architecture consists of downsampling and upsampling paths, as shown in [Figure 4: see original paper]. The downsampling path extracts image features through five convolutional units, each comprising convolutional layers, pooling layers, and activation functions. Convolutions use $5 \times 5 \times 5$ kernels with padding of 2 and stride of 1. Pooling layers reduce parameters, memory usage, and accelerate training. The activation function is PReLU [20], and residual learning structures in convolutional blocks alleviate gradient vanishing. The bridge between downsampling and upsampling paths uses skip connections that fuse feature maps from the downsampling path with upsampled feature maps before convolution, preventing feature loss and preserving target location and edge information.

2.1 Improved VNet Network

While the original VNet effectively suppresses background interference, the varying scales of filaments make it difficult to extract features from weak and small structures, leading to detail loss and fragmented detections. To address these issues, we propose an improved VNet-based filament detection algorithm. The network architecture, shown in [Figure 5: see original paper], maintains VNet's fundamental structure while incorporating three key improvements: Inception modules in the downsampling path to learn multi-scale features, attention mechanisms in the second and third upsampling convolutional units to better utilize contextual information and enhance semantic information of filament regions, and a deep supervision module in the upsampling path to fully extract solar filament features. These enhancements enable the network to extract filament features more comprehensively and improve detection precision.

2.2 Inception Module

Solar filaments exhibit significant scale variations, making kernel size selection challenging. Large filaments can reach 100 pixels in length with globally distributed information requiring large kernels, while small filaments of approximately 10 pixels have localized information better suited to smaller kernels. To extract more effective features while reducing parameters, input images first pass through Inception modules [16] that increase convolutional unit diversity. Large kernels are preceded by 1×1 convolutions for dimensionality reduction, enabling multi-scale feature fusion that improves computational resource utilization, enhances network performance, and mitigates overfitting [see original paper], operates multiple filter sizes (1×1 , 1×1 , 3×3 , 5×5) at the same level. The 1×1 convolutions before branch accelerates training and improves feature robustness. Finally, feature maps from different kernels are fused to enhance network generalization.

2.3 Attention Mechanism

Repeated convolution operations during downsampling cause loss of filament edge and detail information. Although VNet uses skip connections to preserve some information, different spatial locations contain information of varying importance and should be weighted accordingly. We incorporate a spatial attention mechanism [17] during feature extraction to enhance filament features while suppressing irrelevant background information.

As shown in [Figure 7: see original paper], the feature map from the second downsampling convolutional unit undergoes both max and average global pooling operations. Max pooling highlights filament features, while average pooling captures global information. The pooled feature maps are concatenated along the channel dimension, followed by 1×1 convolution with non-linear activation and a sigmoid function to generate spatial attention weights. The sigmoid function prevents excessive sparsity and overly large weight coefficients. The resulting weight coefficients are multiplied with the input feature map to produce an enhanced feature map. The spatial attention mechanism can be expressed as:

where M_c represents the generated spatial attention map, c denotes feature map channels, MLP indicates a multi-layer perceptron, σ represents the sigmoid activation function, and $AvgPool$ and $MaxPool$ denote average and max global pooling operations, respectively. This attention mechanism enables the network to focus on filament features while suppressing background noise, improving detection accuracy for weak and small filaments.

2.4 Deep Supervision

Lee et al. [18] proposed Deeply-Supervised Nets (DSN) to provide supervision for earlier layers and ensure effective overall network training. We employ deep supervision to adjust parameters at each feature map layer, enabling both output and hidden layers to learn as many detailed features as possible for more

precise training of upper layers.

The deep supervision module is illustrated in [Figure 8: see original paper]. Each upsampling stage includes an additional branch that upsamples different-scale feature maps to the original image size, producing maps map1, map2, map3, and map4, which are then fused. By supervising feature maps at different scales, each scale learns the most accurate features, thereby improving detection accuracy.

3.1 Training Details

All experiments were conducted on a Windows 10 system using the Keras deep learning framework. Hardware specifications included an Intel Core i7-7800X 3.50GHz CPU, GTX Titan X GPU, and 32GB RAM. We used our custom filament dataset with preprocessed images, comprising 146 pairs of training images and labels. During training, batch size was set to 2 with 300 steps per epoch. The training schedule planned for 200 epochs with early stopping if loss did not decrease for 10 consecutive epochs. The initial learning rate was 0.0001, halved if loss remained stagnant for 3 epochs. Training terminated at epoch 151. The loss curve in [Figure 9: see original paper] shows decreasing loss with fluctuations that gradually stabilize.

For optimization, we adopted the Adam optimizer [21], which computes adaptive learning rates for different parameters during training. This approach benefits network optimization for large-scale parameter problems with minimal memory requirements.

3.2 Data Augmentation

Limited training samples are a primary cause of overfitting in deep learning. Since manual annotation of solar filament images is costly and datasets are small, we used Keras' s ImageDataGenerator to augment training images through rotation, vertical flipping, and translation. This expanded the 146 original image pairs into 26,648 training samples, enhancing model generalization and robustness.

3.3 Loss Function

In solar filament detection, filaments occupy only approximately 5% of the H α full-disk image area, causing the loss function to easily fall into local minima and bias predictions toward the background, leading to missed detection of weak filaments. To address this severe foreground-background pixel imbalance, we employ a Dice coefficient-based loss function [15] for model optimization, defined as:

where P and G represent predicted filament regions and ground-truth labels, respectively; $\Delta(P)$ and $\Delta(G)$ denote pixel counts in predicted and labeled re-

gions; and $Smooth = 0.001$ prevents division by zero. Lower Dice values indicate higher detection accuracy.

3.4 Evaluation Metrics

Effective evaluation metrics are essential for assessing filament detection performance. Comparing detection results with ground-truth labels yields four outcomes: True Positive (TP) for correctly detected filament pixels, False Positive (FP) for incorrectly detected filament pixels, True Negative (TN) for correctly detected background pixels, and False Negative (FN) for incorrectly detected background pixels, as shown in .

From these results, we calculate three performance metrics: accuracy (Acc), recall, and precision. Accuracy measures the proportion of correctly classified pixels in the entire image. Recall measures the proportion of correctly detected filament pixels among all actual filament pixels. Precision measures the proportion of correctly detected filament pixels among all detected filament pixels. The F1-score provides a comprehensive evaluation of precision and recall, ranging from 0 to 1. Our calculation methods are summarized in .

3.5 Experimental Results

3.5.1 Comparison Before and After Improvement To demonstrate the advantages of incorporating Inception modules with attention mechanisms in the downsampling path and deep supervision in the upsampling path, we evaluated original and improved VNet networks on the test set against manually annotated labels. compares the original VNet, Inception-VNet, Attention-VNet, and our final improved VNet. The original VNet achieved 0.9661 accuracy and 0.8168 F1-score, effectively detecting prominent filaments but missing weak ones. Our improved VNet reached 0.9883 accuracy and 0.8385 F1-score, showing significant F1 improvement by extracting weak filament information more effectively during downsampling.

[Figure 10: see original paper] displays local regions containing weak filaments magnified $2.5\times$. Comparing our method with ground-truth and original VNet results reveals that while original VNet suppresses background interference, it shows low accuracy for weak filaments with missed detections. Our improved network, with Inception modules and attention mechanisms enhancing feature extraction, and deep supervision fusing multi-scale features with final predictions, preserves detail features and maintains weak filament continuity while resisting background interference.

3.5.2 Comparison with Different Algorithms To further validate our method' s performance on solar filament images, we compared it against Zhu et al.' s UNet-based method [14] and a ResNet-UNet variant with dense skip connections for enhanced detail capture. summarizes the results. UNet achieved 0.9587 accuracy and 0.7834 F1-score but suffered from interference by dark background

regions and noise, showing weak anti-noise capability. ResNet-UNet, with dense skip connections for enhanced feature fusion, achieved 0.9598 accuracy and 0.7947 F1-score but exhibited lower precision, indicating excessive sensitivity that misidentified dark background regions as filaments. Our method achieved 0.9883 accuracy and 0.8385 F1-score, surpassing both UNet and ResNet-UNet in accuracy and achieving a superior F1-score.

[Figure 11: see original paper] provides visual comparisons on solar filament images. Weak filaments in red boxes in Figure 11: see original paper are partially detected by traditional threshold methods Figure 11: see original paper but suffer from severe background noise interference. UNet Figure 11: see original paper reduces background noise but misses weak filaments. ResNet-UNet Figure 11: see original paper detects more weak filaments through enhanced feature extraction but still misses low-contrast regions. Our improved VNet Figure 11: see original paper effectively completes solar filament detection with superior performance, stability, and anti-interference capability, demonstrating advanced capability in detecting weak filaments even in complex backgrounds.

Conclusion

This study addresses limitations in existing solar filament detection by creating a new dataset that combines magnetograms to eliminate sunspot and noise interference while preserving weak filaments, enabling networks to learn precise filament information. To tackle background interference and weak filament loss, we improved VNet by: (1) introducing Inception modules to capture multi-scale information and improve computational resource utilization; (2) incorporating attention mechanisms to enhance filament features while suppressing background noise; and (3) implementing deep supervision to ensure accurate feature learning at all scales, thereby improving detection accuracy. Evaluation metrics confirm significant performance improvements with our method. Future work will focus on developing efficient detection models using limited training images.

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Funding: National Natural Science Foundation of China (12063002, 11873027).

Received: 2021--; Revised: 2021--

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