Sunspot Detection Method Based on LeNet-5 Convolutional Neural Network: Postprint

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Abstract

There exists a close relationship between sunspots and flare eruptions; therefore, timely and accurate detection of sunspots in full-disk images can provide a basis for flare forecasting. An automatic sunspot detection method based on the LeNet-5 convolutional neural network within a deep learning framework has been implemented. The main steps include: creating a sunspot sample database, training a fully convolutional neural network model Sunspotsnet, and detecting and marking sunspots in full-disk images. Experimental results demonstrate that this method can identify various types of sunspots in full-disk continuum images from SDO/HMI, particularly weaker magnetic pores (0.88 times the average photospheric intensity). The feasibility of employing deep learning-based methods for sunspot detection is confirmed, and the trained Sunspotsnet network model can be rapidly and effectively applied to sunspot detection.

Full Text

A Detection Method for Sunspots Based on LeNet-5 Convolutional Neural Network

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Abstract

Sunspots are closely associated with solar flare eruptions, making their timely and accurate detection crucial for providing a basis for flare forecasting. This paper implements a novel detection method for sunspots from SDO/HMI full-disk continuum images using a deep learning approach based on the LeNet-5 convolutional neural network. We construct a sunspot sample library and train a fully convolutional neural network model called Sunspotsnet, enabling automatic detection and annotation of sunspots in full-disk images. Experimental results demonstrate that this method can effectively detect various types of sunspots, particularly faint pores (with intensity as low as 0.88 times the average quiet-Sun intensity). The approach proves feasible for sunspot detection in full-disk continuum images using deep learning technology, with the trained Sunspotsnet model capable of rapid and effective deployment for sunspot detection tasks.

Keywords: Sunspot; deep learning; convolutional neural networks

1 Introduction

Sunspots represent typical manifestations of strong magnetic fields on the solar surface and are intimately linked to solar activity phenomena such as flares and coronal mass ejections. These activities can disturb Earth' s atmosphere, affecting short-wave radio communications and causing geomagnetic storms. Research indicates that sunspot groups are closely correlated with flare eruptions [1-3], and detecting sunspots can provide essential data for flare prediction. Therefore, accurate and timely sunspot detection is of paramount importance.

Current sunspot identification primarily relies on image processing techniques including morphological operations and wavelet analysis. For instance, reference [4] proposed automatic sunspot detection using morphological dilation and erosion, while references [5-7] employed morphological top-hat transforms with manually set thresholds. Reference [8] introduced a wavelet-based sunspot identification method, and reference [9] utilized level-set methods for sunspot detection and tracking. These approaches must address the solar limb-darkening problem and heavily depend on intensity and characteristic information of sunspots, generally requiring threshold-based methods for detection.

Deep learning [10] refers to a collection of algorithms that apply various machine learning techniques on multi-layer neural networks to solve problems in image processing, text analysis, and other domains. In recent years, it has achieved remarkable progress in speech recognition [11], natural language processing [12], and object recognition and classification [13]. Its core lies in deep feature learning, where hierarchical networks extract layered feature information, thereby solving the critical challenge of manual feature engineering. Convolutional neural networks (CNNs), which center on convolution operations, offer unprecedented advantages in feature extraction and model fitting compared to previous shallow machine learning models. By combining low-level features through convolution operations, CNNs can derive more abstract and essential high-level features, demonstrating excellent performance in processing information with complex structures.

Building upon the LeNet-5 CNN architecture described in reference [14], this paper trains a fully convolutional neural network model named Sunspotsnet and implements an automatic detection and annotation method for sunspots in full-disk images using deep learning.

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2 Convolutional Neural Networks and LeNet-5

Convolutional Neural Networks (CNNs) are particularly suitable for image object recognition. Their key characteristic is the automatic learning and extraction of image features from large datasets through multi-layer convolution operations. Strategies such as local connectivity and weight sharing effectively reduce the number of parameters in traditional deep network models, thereby decreasing network complexity. CNNs typically consist of three components:

(1) Convolutional Layers: These compute convolutions between input data and multiple filters, outputting feature maps (FMs). Each feature map comprises numerous neurons obtained by convolving a "receptive field" from the previous layer, adding biases, and passing through activation functions. Different convolution kernels extract different features from input data: low-level convolutions generally extract low-level features such as edges, line orientations, and colors, while high-level convolutions extract more abstract features like component shapes and combinations.

(2) Pooling Layers: Also known as subsampling layers, pooling layers are typically applied after convolutional layers to reduce feature map resolution, obtain spatial invariance, decrease data scale, and prevent overfitting. Common pooling methods include max pooling, average pooling, and stochastic pooling.

(3) Fully Connected Layers: After acquiring hierarchical features from data, fully connected layers integrate these features. The output of the final fully connected layer feeds into the output layer, which can be understood as a classifier. Commonly used logistic and Softmax regression functions compute probability distributions across neurons to complete classification tasks.

The LeNet-5 CNN, implemented in the Caffe framework, is an 8-layer network successfully applied to handwritten digit recognition. It comprises one input layer, one output layer, two convolutional layers, two pooling layers, and two fully connected layers. The first convolutional layer uses 20 kernels of size 5×5, followed by a 2×2 max pooling layer. The second convolutional layer employs 50 kernels of size 5×5, again followed by 2×2 max pooling. The first fully connected layer produces 500 neurons with ReLU activation for non-linear transformation. The second fully connected layer yields 10 neurons, with the final output layer using a Softmax function to produce 10 probability values for 10-class classification.

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3 Methodology

3.1 Data Collection

We utilize full-disk continuum images from the Helioseismic and Magnetic Imager (HMI) onboard the Solar Dynamics Observatory (SDO) satellite. Data from 2014 serve as the source for our sunspot sample library, comprising 4,789 sunspot samples and 197 background samples. We randomly select 80% of these samples as the training set and 20% as the validation set for network training. Additionally, we extract 100 different types of sunspot and non-sunspot data from full-disk images spanning 2011 to 2016 as an external test set. Following successful network model testing, we perform automatic sunspot detection on full-disk continuum images.

3.2 Sample Library Construction

Our proposed method consists of three main components: (1) extracting sunspot and background sample images to create a labeled sunspot sample library; (2) adapting the LeNet-5 architecture into a network model suitable for sunspot detection, followed by training and testing; and (3) after successful training, applying multi-scale scaling to input images, feeding them into the trained network to compute classification probabilities for candidate targets, filtering sunspots that meet threshold criteria, and performing annotation using non-maximum suppression.

The sample library requires two classes: sunspot samples and non-sunspot samples. For full-disk images, we apply morphological erosion and dilation operations followed by threshold-based extraction to locate sunspots. Based on sunspot positions and sizes, we crop square sunspot regions, resize them to 28×28 pixels (as shown in [Figure 1: see original paper]), and label them as class 1. Additionally, we manually augment the dataset with special sunspot samples, such as those very close to the solar limb, particularly small spots, or faint pores. We then crop background images without sunspots from various disk locations as class 0 samples. Finally, we convert these labeled samples (0 and 1) into LMDB format training and validation data files.

3.3 Sunspotsnet Network Architecture Design

The original LeNet-5 model outputs scalars through its final two fully connected layers, requiring input images to match the sample library dimensions (28×28). This prevents direct application to larger images. Two solutions exist: converting fully connected layers to equivalent convolutional layers after training, or adopting Fully Convolutional Networks (FCN). FCNs replace fully connected layers with convolutional layers—since neurons in both layer types compute dot products, they share the same functional form and can be interconverted [15]. We adopt the second approach, designing a fully convolutional network called Sunspotsnet, illustrated in [Figure 2: see original paper].

This network comprises 8 layers: an input layer, an output layer, four convolutional layers (conv1, conv2, conv3, conv4), and two pooling layers (pool1, pool2). With sample dimensions of 28×28, the first convolutional layer applies 30 kernels of size 5×5, producing 30 feature maps of size 24×24. A 2×2 max pooling layer then reduces these to 30 feature maps of 12×12. The second convolutional layer uses 50 kernels of size 5×5, generating 50 feature maps of 8×8, which are pooled to 50 feature maps of 4×4. The third convolutional layer corresponds to LeNet-5' s first fully connected layer, using 500 kernels of size 4×4 to produce 500 feature maps of 1×1, followed by ReLU activation for non-linear transformation. The fourth convolutional layer employs 2 kernels of size 1×1, yielding 2 feature maps of 1×1. Finally, a Softmax function produces pixel-level classification probabilities.

3.4 Sunspotsnet Training

Training CNNs involves optimizing the filters in each convolutional layer. Forward propagation algorithms (including convolution, pooling, etc.) compute classification probabilities and loss values, which are then fed back through the network via backpropagation to compute gradients for each layer. Optimization algorithms such as Stochastic Gradient Descent (SGD) continuously adjust filter weights to minimize the loss. We trained the network for 50,000 iterations, achieving perfect accuracy by iteration 5,000, indicating convergence.

3.5 Sunspotsnet Testing

After successful training, we tested the network using the test set, obtaining correct recognition results for all images. lists predicted probabilities and classification results for selected test images. Sunspots 1–7 exhibit label-1 probabilities exceeding 0.99, while sunspot 8, a very faint pore, shows a reduced probability of 0.76, yet all sunspots are correctly classified. For background images, non-disk and limb regions display high label-0 probabilities, whereas backgrounds 1 and 3, being very similar to faint pore samples, show relatively lower label-0 probabilities of 0.68 and 0.72, respectively. All background classifications are correct.

3.6 Full-Disk Image Sunspot Detection

Following successful model testing, we apply it to detect sunspots in full-disk images. Due to memory constraints and the blob data format limitations in the Caffe framework, we partition full-disk images into 1024×1024 sub-regions for detection. The process involves: (1) multi-scale transformation of the image, (2) inputting these into Sunspotsnet to compute probability matrices via forward propagation, (3) filtering regions exceeding a probability threshold and mapping coordinates back to the original image, and (4) applying non-maximum suppression (NMS) to annotate sunspot regions.

(1) Multi-Scale Transformation: Since sunspots vary significantly in size across full-disk images, we employ multi-scale scaling to generate images at different resolutions. Starting from the original size, we progressively downscale the image until the largest sunspot fits within a 28×28 window, ensuring detection of sunspots of all sizes. Based on the maximum sunspot size observed on October 24, 2014, during Solar Cycle 24, we downscaled full-disk images to a minimum resolution of 448×448.

(2) Probability Matrix Computation: Inputting scaled images into Sunspotsnet yields corresponding probability matrices through forward propagation.

(3) Sunspot Filtering: We filter candidate sunspots exceeding a probability threshold and compute their original coordinates based on scaling ratios.

(4) Sunspot Annotation: We apply NMS to annotate sunspots based on their coordinates. Since the same sunspot may be detected at multiple scales, producing multiple bounding boxes, NMS selects the highest-probability box within each local region while suppressing redundant boxes. This iterative process involves sorting all boxes by probability, starting with the highest-probability box, and discarding boxes with overlap exceeding a threshold (set to 0.01 in this work). The process repeats until all boxes are processed.

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4 Experimental Results

We tested our method on HMI full-disk continuum images containing various sunspot configurations: few sunspots, numerous sunspots, and complex sunspot position relationships. [Figure 3: see original paper] presents four local region cases with contrast-enhanced grayscale for clarity: (a) AR11147 region on January 20, 2011, 08:00 UT; (b) detection results for (a); (c) AR11203, 11204, 11205 regions on May 7, 2011, 12:00 UT; (d) detection results for (c); (e) AR11312 region on October 10, 2011, 20:00 UT; (f) detection results for (e); (g) AR11364 region on December 10, 2011, 08:00 UT; (h) detection results for (g). The method demonstrates excellent detection performance for both strong sunspots and faint pores, whether located near disk center or limb. Even very small, weak pores are accurately detected.

compares manual identification (including small pores) against our method for these four regions, listing total counts and missed detections. Careful verification reveals no false positives, only missed detections, yielding an approximately 80% detection rate. We also measured average quiet-Sun intensity in selected quiet regions and identified the weakest detected sunspot. The faintest manually identified pore has intensity approximately 0.90 times the quiet-Sun average, while our method detects pores as faint as 0.88 times the quiet-Sun intensity. [Figure 4: see original paper] shows that undetected sunspots are extremely small with intensities very close to the quiet-Sun average.

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5 Comprehensive Model Analysis

Parameter configuration critically affects CNN model performance, primarily including learning rate (base_lr), iteration count (iters), batch size (batch_size), kernel sizes, pooling kernel sizes, and feature map quantities. The learning rate controls convergence speed during deep learning, weighting the negative gradient during backpropagation. Excessively large values cause overshooting (divergence around extrema), while overly small values slow convergence. With 5,000 iterations, learning rates of 0.001 and 0.01 show similar time costs, but 0.001 yields lower accuracy due to insufficient updates. However, setting the learning rate to 0.02 or higher increases loss values, indicating a clear inflection point. Batch size determines the data volume per training step; larger values provide more accurate descent directions but increase computational time and memory consumption, while small values hinder convergence. A batch size of 500 significantly prolongs training time, especially when combined with a small learning rate. Our model achieves excellent results with a batch size of 10.

Given our small sample image size, kernel sizes of 3×3 or 7×7 show minimal difference. Pooling kernel size affects network depth: larger kernels reduce depth and cause excessive feature granularity changes, while smaller kernels increase depth and improve performance (ignoring overfitting). We use a pooling kernel size of 2 due to our small sample dimensions. Feature map quantity is also crucial: too few maps neglect influential classification features, while too many waste computational resources. Research suggests that pyramid-shaped feature map configurations (increasing layer by layer) more effectively balance computational resources and model performance than uniform distributions.

Considering these factors, we trained our network with base_lr = 0.01, batch_size = 10, kernel size = 5, pooling kernel size = 2, and feature map quantities of 30+50+500+2. We note that these parameters may not be globally optimal—a characteristic of CNNs where multiple satisfactory solutions exist.

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6 Summary and Outlook

This paper presents a Sunspotsnet fully convolutional neural network model trained under the deep learning framework based on LeNet-5, enabling automatic detection and annotation of sunspots in full-disk images. Testing on HMI full-disk continuum images demonstrates excellent detection performance, particularly for faint pores (down to 0.88 times quiet-Sun intensity) and limb sunspots. While parameter tuning is required during training, the trained model can be widely applied to sunspot detection tasks.

Current limitations include Caffe framework restrictions on image dimensions, low efficiency of sliding window search, and issues with image scaling and NMS strategies. Future work will focus on sunspot group classification and flare prediction using deep learning approaches.

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Note: Figure translations are in progress. See original paper for figures.