Shape-Preserving Embedding Technique for Binary Classification of Video Image of the Solar Surface

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Abstract

We study the embedding technique on the binary classification of video images as the explanatory variable. In this study, we assume the shape on video frame image has high sparsity and strong characteristic time evolution. In the embedding process, 2-dimensional image is resized keeping shape characteristics of the image and converted to a vector. The embedding allows dimensionality reduction from a 3-dimensional array (video image) as input data for machine learning to a 2-dimensional array of time sequences of embedded vectors. Using solar surface video images in the space weather field, we present evaluation experiments on multiple models with different embedding sizes, transformation formulas, and number of layers in the CNN.

Keywords: Embedding technique, Binary classification, Solar surface video images, Space weather

1. Introduction

Common applications of video analysis include object detection, object tracking, action recognition, and scene understanding. These applications are used in a wide range of fields, including security cameras, self-driving cars, sports analysis, and entertainment. Video analysis is achieved by combining the following typical deep learning algorithm methods:

- Convolutional Neural Networks (CNN) [1]: CNNs are used for image recognition in each frame to recognize objects in the video. It automatically learns local patterns in the image and is characterized by high discrimination performance.
- Recurrent Neural Network (RNN) [2], Long Short-Term Memory (LSTM) [3]: LSTM is suitable for learning time-series data and is good at capturing temporal changes in videos. It can effectively learn continuous changes of events in a video.
- 3D Convolutional Neural Network (3D-CNN) [4]: While a typical CNN learns local patterns on a 2D image, a 3D-CNN can learn local patterns on spatial and temporal axes simultaneously in a video.

For example, object detection and action recognition can achieve higher accuracy by recognizing objects in each frame using CNNs and capturing temporal changes using RNNs and LSTMs. On the other hand, 3D-CNNs can learn spatial and temporal information simultaneously, enabling more advanced analysis in video analysis.

Now we assume the object shape on video frame image has high sparsity and strong characteristic time evolution. In this case, the above-mentioned models have high computational costs. If each frame image (two-dimensional matrix) of the video is converted to a vector including the information of the space shape characteristic, this embedding allows dimensionality reduction from a 3-dimensional array (video image) as input data for machine learning to a 2-dimensional array of time sequences of embedded vectors.

In this study, we address the problem of a binary classification task using a video of the surface of the Sun. The structure of the radiation belts surrounding the Earth drastically changes due to solar activity [5]. In particular, the high-speed solar wind stream originating from recurrent coronal holes contributes to the abnormal increase of relativistic electrons in the outer radiation belts [6]. The location of coronal holes on the full disk of the Sun is strongly related to the dynamics of the radiation belts. The low-latitude coronal hole regions positively correlate with the high-speed solar wind stream associating with the relativistic electron enhancement of the radiation belts [7]. This suggests that the shape of coronal hole has high space sparsity on the task of the binary classification for the relativistic electron enhancement in the outer radiation belts using the solar surface image. In this paper, we propose a method for the vector embedding of solar coronal hole information. We also propose a binary classification model using the embedded coronal hole vector as the input data for estimating whether the relativistic electron enhancement of the radiation belts has occurred and evaluate the accuracy of our model.

2. Data

We used the two-dimensional extreme ultraviolet (EUV) images of the solar atmosphere (corona) taken by the Atmospheric Imaging Assembly (AIA) onboard NASA's Solar Dynamics Observatory (SDO) spacecraft [8]. The coronal holes appear dark in EUV SDO/AIA images. SDO/AIA 211Å images are used in this study to detect coronal hole regions (Fig. 1). The spatial and time resolution of AIA original image is 1024 × 1024 pixels and 15 minutes, respectively.

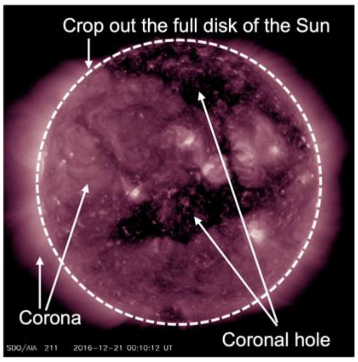

Fig.1 Example of SDO/AIA 211Å image.

For the relativistic electron flux in the Earth's outer radiation belt, the 1-minute averaged fluxes of electrons with energy >2 MeV measured by the spacecraft of the Geostationary Operational Environmental Satellite (GOES) series, GOES-15 satellite. Since the GOES-15 satellite rotates with the earth, the relativistic electron flux data shows the daily fluctuations (Fig. 2). The relativistic electron flux reaches its absolute maximum when the satellite approaches noon. In this study, when the >2 MeV electron flux exceeds 10,000 [particles/(cm^2 s sr)], we assume that an abnormal increase in the relativistic electron flux in the radiation belt has occurred.

The time interval analyzed in this paper ranges from January to December 2016, containing the declining phase (from the maximum to minimum solar activity) of Solar Cycle 24. The coronal holes generally appear with a high frequency during the declining phase. We consistently take the ratio of training and testing samples to be 11 : 1 for all models presented throughout the paper. The datasets from January to October 2016 are used as the training samples, while the datasets from November to December 2016 are used as the testing samples.

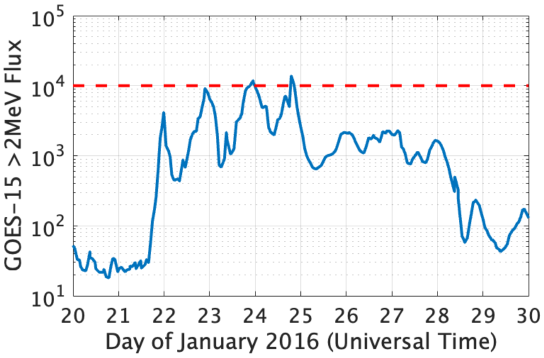

Fig.2 Example of the time-series data of GOES-15 >2 MeV electron flux.

3. Methodology

The proposed model consists of three main processes: (1) SDO/AIA images preprocessing, (2) embedding to coronal hole vectors, and (3) binary classification prediction model (Fig. 3).

3.1. *SDO/AIA images preprocessing*

To remove the non-sun areas from each frame image of the SDO/AIA video, a size-optimized circular mask is used to crop out the full disk of the sun. We assume the full disk of the Sun always locates in the center of the solar frame image (Fig. 1).

The binarization processing is applied to the masked solar frame image to divide the coronal hole regions and the corona regions. First images are converted to gray scale. Next, the pixel values in the image are converted to white if the pixel value is equal to or greater than the threshold (50), and to black if the pixel value is less than the threshold. Since coronal holes appear dark in the SDO/AIA 211Å image, black pixel areas indicate coronal hole area (Fig. 3).

3.2. *Coronal hole vector*

Here, we define the two-dimensional array of SDO/AIA images converted into a one-dimensional vector as a “corona hole vector”. The embedding process into a corona hole vector consists of two steps: image resizing and vectorization. First, the SDO/AIA binary image (1024 × 1024 pixels) is divided into $n \times n$ grids. In this process, each grid is quantified as a coronal hole region or a non-coronal hole region according to the ratio of black pixels contained in each grid. Then the $n \times n$ array is converted to a vector, size $(n \times n, 1)$.

We propose two methods for the quantification of coronal hole region in each grid: (method A) Presence/Absence method, and (method B) Occurrence ratio method.

(A) Presence/Absence method

If the ratio of black pixels to the total number of pixels in a grid is greater than the threshold (10% in this paper), the value 1 is embedded, otherwise 0 is embedded. Consequently, a one-hot vector is generated.

(B) Occurrence ratio method
The ratio of black pixels in each grid is embedded in the vector elements.

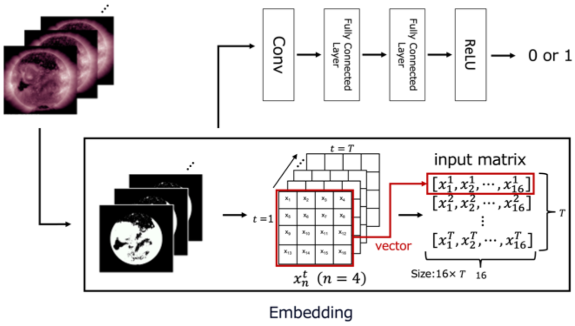

Fig.3 Coronal hole-related radiation belt electron enhancement binary classification using deep convolutional neural networks.

3.3. *Binary classification prediction model*

We propose the binary classification model for predicting the 1-day ahead relativistic electron enhancement based on coronal holes appearing in the past 5-day (120 h) SDO/AIA video images. The explanatory variable is a time series array of coronal hole vectors, size $(n \times n, T)$ and the objective variable is a label (1 or 0) indicating whether there is a relativistic electron enhancement in the radiation belts. T is the number of frame image of SDO/AIA video. The original SDO/AIA video frames are taken every 15 minutes. In this paper, we used 1-hour SDO/AIA video frames as the training samples to reduce the computational costs. Consequently, T is 120 for 5-day SDO/AIA video images.

For the binary classification task, such as the relativistic electron enhancement/non-enhancement classification, we prepare the positive/negative label data from the data of GOES-15 >2 MeV electron flux by defining the positive class (e.g., enhancement) and negative class (e.g., non-enhancement). The labels are given by

$$the\ label = \begin{cases} 1, & E \geq 10^4 \\ 0, & E < 10^4 \end{cases}, \qquad (1)$$

where E is the absolute maximum of daily GOES-15 >2 MeV electron flux [particles/(cm^2 s sr)]. $The\ label = 1$ indicates the relativistic electron enhancement occurs, while $the\ label = 0$ notes the non-enhancement of relativistic electron flux in the radiation belts. The architecture of our model is shown in Fig. 3. The binary cross-entropy loss (BCELoss) is used as the loss function, and the Adam optimizer with a learning rate of 0.0001 is employed. The batch size is set to 16, and the number of epochs is 300.

3.4. *Evaluation Metric: F$_1$ score*

The F$_1$ score is a performance metric for classification and is calculated as the harmonic mean of a model's precision and recall. F$_1$ score is given by

$$F_1 score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (2)$$

4. Results and Discussion

We trained models with the following different parameters of the network: two types of embedding method (method A, method B) and the split size ($n = 4, 8$) of the coronal hole vector, the length ($T = 120, 72$) of the time series of the coronal hole vector, the kernel size (3× 3, 7×7) and the number of layers of convolution neural network. Table 1 compares the F$_1$ score of 10 models to evaluate the suitable parameters of the classification model of the relativistic electron enhancement.

Table 1. Classification Results

Model	Coronal hole vector	n	T	Kernel size	Conv Layer	F$_1$ score
1	A	4	120	3 × 3	Conv1	0.2545
2	B	4	120	3 × 3	Conv1	0.5574
3	A	4	120	7 × 7	Conv1	0.5676
4	B	4	120	7 × 7	Conv1	0.3673
5	A	8	120	3 × 3	Conv1	0.3333
6	B	8	120	3 × 3	Conv1	0.3448
7	A	4	72	3 × 3	Conv1	0.3333
8	B	4	72	3 × 3	Conv1	0.3881
9	A	4	120	3 × 3	Conv5	0.4722
10	B	4	120	3 × 3	Conv5	0.2979

For the method of the coronal hole vector, the models (model 2, 6, and 8) with the Occurrence ratio method b shows higher accuracies than the Presence/Absence method A. This result suggests that the coronal hole vectors based on the Occurrence ratio method B contain more information on the two-dimensional features of coronal holes than the method A and the models can be trained effectively even with a simplified architecture. On the other hands, the coronal hole vectors based on the Presence/Absence method A lack information about the structural characteristics of the coronal holes compared to the method B and therefore require a more complex architecture model. The small number of split size and length is also suitable to the present task which is the binary classification model requiring the simple network architecture. The 5-day coronal hole vector models show good performances than the 3-day model. This suggests that 5-day model trained the dependency of the sequence of coronal hole structure.

The kernel size is also important of the complexity of the model. The results (model 3, 4) show the small kernel size such as 3 × 3 is suitable to the coronal hole vector based on the Occurrence ratio method B. This vector essentially has the spatiotemporal structure of the coronal hole and allows the small kernel size of the convolution. Thus, the model 4 resulted into the low F_1 score than model 3. In addition, the deep network (model 10) is not suitable to the coronal hole vector based on method B. The results support the idea that the adequate embedded vector allows the simple network requiring the non-deep convolution neural network.

5. Conclusion

We proposed the embedding technique on the binary classification of video images as the explanatory variable. In this study, we assume the object shape on video frame image has high sparsity and strong characteristic time evolution. We demonstrated the two embedding methods based on the spatiotemporal structure of the object shape. Our embedding method allows dimensionality reduction from a 3-dimensional array (video image) as input data for machine learning to a 2-dimensional array of time sequences of embedded vectors. Finally, a few potential limitations for the prediction model need to be considered. Future work will concentrate on the construction of the binary classification model with higher accuracy to predict the relativistic electron enhancement based on coronal holes appearing in SDO/AIA video images.

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