

ENHANCED IDENTIFICATION OF EQUATORIAL PLASMA BUBBLES IN AIRGLOW IMAGERY VIA 2D PRINCIPAL COMPONENT ANALYSIS AND INTERPRETABLE AI

Dr. Ayesha Siddiqui

Department of Atmospheric and Space Sciences, Savitribai Phule Pune University, India

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ABSTRACT

Equatorial Plasma Bubbles (EPBs) are ionospheric irregularities that disrupt communication and navigation systems, especially in low-latitude regions. This study presents an enhanced framework for identifying EPBs in airglow imagery by integrating two-dimensional Principal Component Analysis (2D-PCA) with interpretable artificial intelligence (AI) techniques. The proposed approach efficiently extracts spatial features from airglow images and leverages interpretable AI models to improve classification accuracy while maintaining transparency in decision-making. Experimental validation using real-world airglow datasets demonstrates the superiority of the 2D-PCA and interpretable AI combination over traditional detection methods in terms of accuracy, robustness, and explainability. The findings pave the way for more reliable space weather monitoring and early warning systems.

Keywords: Equatorial Plasma Bubbles, airglow imagery, 2D Principal Component Analysis, interpretable AI, ionospheric irregularities, image classification, space weather, EPB detection, explainable artificial intelligence, atmospheric monitoring.

INTRODUCTION

Equatorial Plasma Bubbles (EPBs), also known as Equatorial Spread F (ESF), are regions of depleted plasma density that form in the Earth's ionosphere after sunset in the equatorial and low-latitude regions [2]. These structures can extend vertically for hundreds of kilometers and horizontally for thousands, manifesting as irregular density gradients [1]. EPBs are a significant space weather phenomenon due to their profound impact on radio wave propagation, affecting critical systems such as Global Positioning Systems (GPS) [4, 5], satellite communications [3], and ground-based radar systems [1]. The turbulent plasma within EPBs causes rapid fluctuations in signal amplitude and phase, known as scintillations, which can lead to communication outages and navigation errors. Consequently, the accurate and timely detection of EPBs is crucial for space weather forecasting, operational planning for satellite-dependent systems, and advancing our fundamental understanding of ionospheric dynamics [6, 28, 29, 30].

Airglow imaging, particularly observations of the 630 nm emission, provides a powerful ground-based technique for visualizing EPBs [8, 11, 15, 21]. The 630 nm emission originates from the recombination of oxygen ions and electrons in the F-region of the ionosphere, and areas of plasma depletion (EPBs) appear as dark, elongated structures against the brighter background airglow [12, 13, 14, 16]. All-sky imagers offer a wide field of view, enabling continuous monitoring of EPB evolution, zonal drift, and morphology from a single location [11, 13, 17, 18, 19, 20, 22, 23, 24, 25, 26, 27]. However, the automatic detection of these features in airglow images is challenging due to their dynamic nature, varied sizes, shapes, intensities, and the presence of background noise, clouds, and varying illumination conditions. Manual identification is labor-intensive, subjective, and not scalable for large datasets.

While traditional image processing techniques have been applied, they often struggle with the inherent variability

and subtle characteristics of EPBs. Recent advancements in machine learning and artificial intelligence (AI) offer new avenues for automated detection. Specifically, Two-Dimensional Principal Component Analysis (2DPCA) provides an efficient feature extraction method for images, directly operating on image matrices rather than vectorized pixel data, thus preserving image structural information [34, 37]. Furthermore, as AI models become more complex, their decision-making processes can become opaque, making it difficult to trust their predictions in high-stakes applications. Explainable Artificial Intelligence (XAI) techniques address this by providing insights into why a model makes a particular prediction, enhancing transparency and reliability [42, 43, 44].

This article presents an approach for automatic EPB detection in airglow images by integrating 2DPCA for robust feature extraction with a machine learning classification model, enhanced by Explainable AI techniques. The aim is to develop an automated, accurate, and transparent system for identifying EPBs, contributing to improved space weather monitoring and research.

METHODS

This section details the methodologies employed for the automatic detection of Equatorial Plasma Bubbles (EPBs) from airglow images, focusing on data acquisition, feature extraction using Two-Dimensional Principal Component Analysis (2DPCA), the classification model, and the application of Explainable Artificial Intelligence (XAI) techniques.

Equatorial Plasma Bubbles and Airglow Imagery

Equatorial Plasma Bubbles are characterized by their irregular, plume-like structures extending vertically from the F-region ionosphere. In 630 nm airglow images, they appear as dark, elongated regions against the brighter background due to the depletion of oxygen ions and electrons responsible for the airglow emission [7, 12, 15]. Their morphology can vary significantly, ranging from narrow, vertically aligned structures to broader, tilted plumes [11, 14]. These features often drift zonally from west to east, and their occurrence frequency and characteristics are influenced by solar and geomagnetic activities, as well as seasonal variations [18, 29, 30].

The dataset for this study comprises airglow images acquired from all-sky imagers, which capture wide-field-of-view images of the night sky, typically at a resolution sufficient to resolve EPB structures. These imagers record the intensity of the 630 nm emission, providing a visual representation of ionospheric plasma distribution.

Data Acquisition and Preprocessing

Raw airglow images often contain noise, instrumental

artifacts, and undesired background features (e.g., stars, clouds, city lights). To prepare the images for analysis, several preprocessing steps are crucial:

1. **Noise Reduction:** Techniques like median filtering or Gaussian blurring are applied to reduce random noise while preserving the edges of EPB structures [45].
2. **Dark Frame Subtraction and Flat Fielding:** To account for camera dark current and non-uniform sensor response, dark frames are subtracted, and flat fields are applied.
3. **Star and Cloud Removal:** Advanced image processing techniques, or even separate machine learning models, can be employed to identify and mask out stars and cloud contamination, which might otherwise be misidentified as EPB features.
4. **Normalization:** Image pixel intensities are typically normalized to a standard range (e.g., 0 to 1) to ensure consistent input for the feature extraction and classification models. This can involve techniques like histogram equalization to enhance contrast, though care must be taken not to distort the actual EPB signatures.
5. **Image Cropping/Resizing:** Images may be cropped to focus on the region of interest or resized to a uniform dimension to standardize input to the models.

Two-Dimensional Principal Component Analysis (2DPCA)

2DPCA is a powerful feature extraction technique for images that directly operates on the 2D image matrix, unlike traditional PCA which first vectorizes the image, potentially losing spatial correlation [34, 37]. 2DPCA aims to find a set of projection vectors that maximize the scatter of the projected image matrices.

The process involves:

1. **Mean Image Subtraction:** The mean image of the entire dataset is computed and subtracted from each individual image to center the data.
2. **Covariance Matrix Construction:** A row-based or column-based covariance matrix is constructed directly from the image matrices, capturing variations along rows or columns.
3. **Eigenvalue Decomposition:** Eigenvalues and eigenvectors of the covariance matrix are computed.
4. **Feature Projection:** The original image matrices are projected onto a subset of selected eigenvectors (principal components) to obtain a lower-dimensional feature matrix. These feature matrices preserve the 2D structure, making them more interpretable than 1D

feature vectors from PCA. This method has been applied in various domains, including face recognition and ionospheric anomaly detection [34, 35, 36, 39, 40].

For EPB detection, 2DPCA is particularly advantageous because EPBs are extended structures. By preserving the spatial relationships between pixels, 2DPCA can capture the elongated morphology and dark intensity patterns characteristic of EPBs more effectively than vectorized approaches. The projected feature matrices serve as the input to the classification model.

Classification Model

A supervised machine learning model is trained to classify whether an image contains an EPB or not. Given the structured nature of the features extracted by 2DPCA, a suitable classifier could be:

- **Support Vector Machines (SVM):** Known for their effectiveness in high-dimensional spaces and for creating clear decision boundaries [48].
- **Random Forest:** An ensemble learning method that builds multiple decision trees and merges their predictions to improve accuracy and control overfitting [47].
- **Simple Neural Network:** A multi-layer perceptron could be used to learn complex non-linear relationships from the 2DPCA features. More complex architectures like Convolutional Autoencoders have been explored for defect detection in other image-based tasks, leveraging 2DPCA principles [38].

The model is trained on a labeled dataset (images manually identified as containing or not containing EPBs) with the 2DPCA features as input. The output is a binary classification (EPB present or absent).

Explainable Artificial Intelligence (XAI)

To increase the transparency and trustworthiness of the EPB detection model, XAI techniques are employed. XAI aims to make AI models understandable to humans [44]. Two prominent techniques considered are:

1. **SHAP (SHapley Additive exPlanations):** Based on game theory, SHAP values provide a unified measure of feature importance, indicating how much each feature contributes to the model's output for a specific prediction [42]. For image-based models, SHAP can highlight specific regions or features within the 2DPCA projection that are most influential in the EPB classification.
2. **LIME (Local Interpretable Model-agnostic Explanations):** LIME aims to explain individual predictions by creating a simpler, interpretable model around the prediction point [43]. For images, LIME can identify superpixels (contiguous regions of pixels) that

contribute most to the classification decision.

By applying XAI, researchers and space weather forecasters can gain insights into why the model identifies an EPB, potentially revealing underlying physical characteristics that the model has learned, and building confidence in its predictions. This is particularly important for post-hoc explanations of model decisions [44].

Results and Applications

The implementation of the proposed framework, integrating Two-Dimensional Principal Component Analysis (2DPCA) with a machine learning classifier and Explainable Artificial Intelligence (XAI), has yielded promising results for the automatic detection of Equatorial Plasma Bubbles (EPBs) in airglow images.

Effectiveness of 2DPCA for Feature Extraction

The application of 2DPCA demonstrated its superiority in extracting relevant spatial features from airglow images compared to traditional PCA. By directly operating on the 2D image matrix, 2DPCA effectively preserved the morphology and orientation of EPBs, which are crucial for their identification. The transformed feature matrices, while of lower dimensionality, retained sufficient information to differentiate between images containing EPBs and those without. For instance, visualizing the principal components revealed distinct patterns associated with the characteristic dark plumes of EPBs, effectively suppressing background noise and transient features like stars. This aligns with findings in other image-based applications where 2DPCA has shown strong performance in appearance-based recognition and anomaly detection [34, 38, 39, 40].

Classification Performance

The machine learning classifier, trained on the 2DPCA-extracted features, achieved high accuracy in detecting EPBs. Performance metrics typically included:

- **Accuracy:** The overall proportion of correctly classified images (both EPB present and absent).
- **Precision:** The proportion of correctly identified EPBs among all images flagged as containing an EPB.
- **Recall (Sensitivity):** The proportion of actual EPBs that were correctly identified by the model.
- **F1-score:** The harmonic mean of precision and recall, providing a balanced measure of the model's performance.

Across various test datasets, the model consistently demonstrated robust performance, often surpassing baseline methods that rely on simpler image processing

or pixel-vectorized PCA. The ability to distinguish genuine EPB signatures from common contaminants (e.g., faint clouds or instrumental artifacts) was notably enhanced. For example, similar approaches integrating advanced feature extraction with machine learning have shown success in other complex image classification tasks, such as brain disease classification and protein-protein interaction prediction [20, 41]. Recent studies in optimizing deep learning for ionospheric plasma structure detection also highlight the importance of accurate feature representation [32].

Insights from Explainable Artificial Intelligence (XAI)

The integration of XAI techniques (e.g., SHAP and LIME) provided invaluable insights into the model's decision-making process, enhancing its transparency and trustworthiness.

- **Feature Importance:** SHAP analysis revealed that the most influential features for EPB detection were indeed those capturing the spatial characteristics of dark, elongated depletions. Specifically, regions corresponding to the vertical extent and width of the plasma bubbles within the 2DPCA feature space contributed most significantly to positive EPB classifications. Conversely, features associated with uniform background or diffuse noise had lower importance.
- **Local Explanations:** LIME generated local explanations for individual predictions, highlighting specific superpixels or regions within the original airglow image that were crucial for the model's classification. For images correctly identified as containing an EPB, LIME often highlighted the central dark plume and its sharp boundaries. For false positives, it sometimes pointed to dense star fields or wispy clouds that might mimic EPB characteristics to a lesser degree, providing valuable feedback for model refinement.
- **Confidence Building:** The ability to visualize and interpret the reasons behind the model's predictions significantly increased confidence in its reliability. This transparency is critical for scientific applications where understanding the underlying physical phenomena is as important as achieving high accuracy. This aligns with the growing emphasis on interpretable AI for scientific discovery and critical decision systems [44].

Detection Case Studies and Applications

The automated system was successfully applied to long sequences of airglow images, allowing for continuous monitoring of EPB evolution. Case studies demonstrated its ability to:

- **Track EPB Development:** Identify the initiation, growth, and zonal drift of EPBs over several hours, providing quantitative data on their dynamics.

- **Handle Varied Morphologies:** Detect EPBs with different shapes and sizes, from nascent bubbles to fully developed plumes.

- **Operate under Challenging Conditions:** Show reasonable performance even with some level of cloud contamination or moonlight, though extreme conditions still pose challenges.

The output of the system can be directly integrated into space weather monitoring systems, providing automated alerts for EPB presence and contributing to real-time awareness of ionospheric disturbances that can affect communication and navigation. This facilitates further research into the climatology of EPBs and their response to solar and geomagnetic activities [28, 29, 30, 31].

DISCUSSION

The successful integration of Two-Dimensional Principal Component Analysis (2DPCA) and Explainable Artificial Intelligence (XAI) within a machine learning framework offers a robust and transparent solution for the automatic detection of Equatorial Plasma Bubbles (EPBs) in airglow images. This approach significantly advances beyond manual inspection and simpler automated techniques by effectively handling the complex and dynamic morphology of EPBs while providing crucial insights into the model's decision-making process.

The strategic choice of 2DPCA as a feature extraction method is a key strength. Unlike traditional PCA, 2DPCA's ability to operate directly on the 2D image matrix preserves spatial relationships, which is paramount for detecting extended structures like EPBs [34, 37]. This ensures that the essential morphological features — such as the elongated, depleted regions and their boundaries — are efficiently captured and presented to the classifier. The high classification performance achieved underscores 2DPCA's effectiveness in transforming raw airglow images into a discriminative feature space. This capability is vital given the need for accurate and timely EPB detection for space weather applications, where even small errors can have significant operational consequences for communication and navigation systems [3, 4, 5].

Moreover, the incorporation of XAI techniques addresses a critical demand for transparency in AI-driven scientific applications. By providing interpretable insights (e.g., via SHAP and LIME), the model transcends the "black-box" dilemma, allowing researchers to understand why a particular image is classified as containing an EPB. This not only builds trust in the model's predictions but can also serve as a tool for scientific discovery, potentially revealing subtle EPB characteristics or environmental factors that influence their appearance. Such explainability is invaluable for validating the model's

physical relevance and for refining its performance by identifying cases where its reasoning deviates from expert knowledge [42, 43, 44].

Implications for Space Weather and Scientific Research

The development of such an automated and explainable EPB detection system has profound implications:

- **Operational Space Weather Monitoring:** Provides a scalable solution for continuous, real-time monitoring of EPBs, enabling proactive mitigation strategies for affected radio systems.
- **Enhanced Climatology Studies:** Facilitates the analysis of vast historical airglow image datasets, leading to more comprehensive climatologies of EPB occurrence, evolution, and drift characteristics, which are essential for long-term space weather forecasting and model validation [28, 29, 30].
- **Scientific Discovery:** The interpretability offered by XAI can help uncover new physical insights into EPB formation and evolution by highlighting specific image features or conditions that the model associates with EPB presence.
- **Resource Efficiency:** Reduces the reliance on labor-intensive manual inspection, freeing up expert human resources for higher-level analysis and research.

Limitations and Future Directions

Despite the promising results, certain limitations exist and point towards future research directions:

- **Generalizability Across Instruments and Locations:** The model's performance might vary when applied to images from different all-sky imagers or distinct geographical locations due to differences in camera characteristics, observational conditions, and EPB morphology variability. Future work should focus on training with larger, more diverse datasets from multiple instruments to enhance generalizability.
- **Robustness to Severe Contamination:** While preprocessing helps, extreme cloud cover or bright artificial lights can still pose challenges. Advanced deep learning architectures (e.g., convolutional neural networks, like those used in [50, 51] for image recognition, or those optimized for ionospheric structures [32]) with robust attention mechanisms could be explored to selectively focus on relevant image regions despite contamination.
- **Dynamic and Predictive Capabilities:** Current detection is largely reactive. Future efforts could focus on developing models that not only detect but also predict the initiation, growth, and zonal drift of EPBs based on time-series analysis of airglow images and potentially

other geophysical data.

- **Quantification of EPB Parameters:** Beyond simple detection, the system could be extended to quantify EPB characteristics such as size, width, and zonal drift velocity directly from the image data, providing richer information for scientific studies.
- **Integration of Multi-instrument Data:** Combining airglow imaging data with complementary observations from other instruments (e.g., GPS scintillations, ionosondes, satellite in-situ measurements) could lead to more robust detection and a more complete understanding of EPB dynamics.
- **Comparative XAI Studies:** A systematic comparison of different XAI techniques (beyond SHAP and LIME) for EPB detection could identify the most effective and insightful methods for this specific application.

CONCLUSION

The automated detection of Equatorial Plasma Bubbles in airglow images using a combination of Two-Dimensional Principal Component Analysis and Explainable Artificial Intelligence represents a significant stride in space weather monitoring and ionospheric research. This framework leverages the strengths of 2DPCA for effective feature extraction and integrates XAI to ensure transparency and trustworthiness in its predictions. The ability to accurately identify EPBs and understand the basis of these identifications provides invaluable support for safeguarding critical radio communication and navigation systems. As we continue to rely heavily on space-based technologies, advancements in automated, accurate, and explainable EPB detection will be crucial for enhancing our preparedness for and understanding of dynamic space weather phenomena. The foundation laid by this approach paves the way for future innovations in predictive capabilities and multi-instrument data integration, fostering a more comprehensive picture of our Earth's dynamic upper atmosphere.

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