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Specific changes in VLF signals induced by astrophysical and geophysical phenomena: possibility of applying machine learning in statistical analyses

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Abstract

In this paper, we present examples of changes in VLF signals used to monitor the lower ionosphere. The mentioned changes in signal characteristics are caused by astro- and geo-phenomena. We indicate the possibility of applying machine learning in statistical analysis of these changes, which is the basis of the work on the Serbian Slovak bilateral project Detection of astrophysical and geophysical phenomena from VLF radio measurements using machine learning methods.

Introduction

Spatio-temporal variations in the Earth's ionosphere are the result of the influence of numerous phenomena in space and different areas of our planet. Changes in ionospheric parameters, and, consequently, signal parameters used for its monitoring, can be specific characteristics for one phenomenon. These specificities enable the detection of phenomena indirectly, based on analyses of ionospheric disturbances and relevant electromagnetic signals, among which are very low frequency (VLF) radio signals.

Statistical analysis of changes in certain characteristics requires the application of machine learning, especially neural networks/deep learning methods. It represents one of the examples of the necessity of cooperation of scientists in different specific fields with scientists in the field of data science. One such collaboration related to the monitoring of the low ionosphere with VLF signals was established between scientists from the Institute of Physics Belgrade, University of Belgrade and the Astronomical Observatory in Belgrade, Serbia and the Technical University of Košice (Faculty of Electrical Engineering and Informatics, Department of Cybernetics and Artifical Intelligence) in Košice, Slovakia. This cooperation is implemented within the Serbian Slovak bilateral project Detection of astrophysical and geophysical phenomena from VLF radio measurements using machine learning methods.

In this paper, we present the phenomena that give specific changes in VLF signals that meet the conditions to be analysed in this project. We will pay special attention to the changes in the intensity of the solar hydrogen Lyα line radiation that arrives in the observed part of the ionospheric D-region (extends in the domain of heights from 50 km to 90 km above the Earth's surface) and sudden emissions of X-radiation during solar X-ray flares.

Observations

In this paper, we present characteristic changes in the amplitude of NAA signal emitted in Cutler (USA) and recorded in Belgrade (Serbia) caused by variations in incoming Lyα radiation to the ionospheric D-region during 16 February 2011 when 15 flares were recorded by the GOES-15 satellite (see Table 1).

Table 1. The times of begins (t_{begin}), flux maxima (t_{max}), and ends (t_{end}) of solar X-ray flares recorded by the GOES-15 satellite on 16 February 2011.

No	t_{begin} (UT)	t_{max} (UT)	t_{end} (UT)	Class
1	00:58	01:05	01:10	C2.0
2	01:32	01:39	01:46	M1.0
3	01:56	02:00	02:05	C2.2
4	05:40	05:45	05:55	C5.9
5	06:18	06:22	06:29	C2.2
6	07:35	07:44	07:55	M1.1
7	09:02	09:11	09:19	C9.9
8	10:25	10:32	10:39	C3.2
9	11:58	12:02	12:05	C1.0
10	14:19	14:25	14:29	M1.6
11	15:27	15:32	15:37	C7.7
12	19:29	19:36	19:43	C1.3
13	20:11	20:15	20:19	C1.1
14	21:06	21:11	21:14	C4.2
15	23:02	00:25	01:07	C2.8

Phenomena that cause specific changes

These phenomena can be divided according to the place of their origin into astro- and geo-phenomena. The most significant influence from the first group is solar radiation, while changes in the atmosphere and lithosphere belong to the second group.

- Astro-phenomena: changes in the arrival of the radiation intensity of the hydrogen Lyα line due to the rotation and revolution of the Earth and solar cycle (Gupta, 1998; Correia et al. (2011); Thomson & Clilverd, 2000, Nina et al. 2021), solar X-ray flare (Nina 2022), solar eclipse (Ilić et al., 2017), gamma ray bursts (Inan et al., 2007, Nina et al., 2015).
- Geo-phenomena: lightning (Inan et al. 2010), lightning induced electron precipitation (Kolarski et al., 2022).

In addition to these cases for which previous studies have clearly confirmed the connection of phenomena with relevant changes, there are also changes for which the considered connections are still being determined. Among them are mentions in the characteristics of VLF signals before earthquakes (Biagi et al., 2011; Nina 2024) and tropical cyclones (Nina et al., 2017).

Results

In this paper, we present characteristic changes in the amplitude of NAA signal emitted in Cutler (USA) and recorded in Belgrade (Serbia) caused by variations in incoming Lyα radiation to the ionospheric D-region during 16 February 2011 when 15 flares were recorded by the GOES-15 satellite.

The daily variations of the X-ray flux recorded by the GOES-15 satellite, and the considered signal are shown in Fig. 2 (upper and bottom panels, respectively). The propagation path of this signal can be completely during the daytime (white area) or nighttime (gray areas) period, but also partially in sunlit side (during the transition from night to day and day to night; hatched areas).

Typical changes in signal amplitude during the day and under the influence of increased solar K radiation can be seen in Fig. 2. These regularities, on the basis of which further statistical studies can be carried out using machine learning, can be described as follows:

- The signal has the highest amplitude values when the path is completely nocturnal,
- The beginning of the decrease of the amplitude indicates the beginning of the insolation of the observed signal path. During the period of partial insolation of the path, the amplitude of the signal varies with pronounced minima.
- During a fully sunlit path, the amplitude first tends to increase and then decrease.

- The beginning of amplitude value variations indicates the beginning of the period of partial sunshine of the path, which ends by reaching higher values typical for the night path of the observed signal.

These changes are visible throughout the year, but the duration of the marked periods as well as the amplitude values change (Nina et al., 2017).

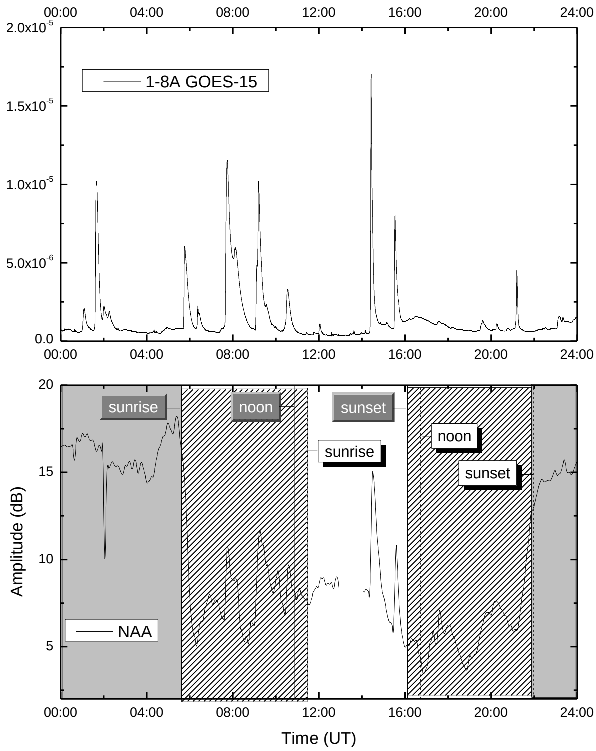

Fig. 2. Upper panel: X-ray flux recorded by the GOES-15 satellite. Bottom panel: VLF signal emitted by NAA transmitter located in the USA, and registered in Belgrade by AbsPAL receiver on 16 February 2011.

A comparison of the displayed panels shows that the amplitude of the signal changes due to the influence of the radiation emitted by solar X-ray flares during the daytime and partially sunlit path. These changes occur a few tens of seconds after the start of the increase in X radiation on the satellite and their characteristics can also be analysed using machine learning in statistical analyses.

For the machine learning part, we will follow the methodology known as CRISP-DM - Cross-industry standard process for data mining (Wirth et al., 2000). This methodology consists of problem and data understanding, data preparation, modelling (phase where machine learning models are created), and validation phases.

The machine learning project has four phases:

- **Problem identification and analysis** – this phase focused on analysis of interesting types of events (astrophysical and geophysical phenomena) for detection based on machine learning. Selected events were described in previous sections of this paper.
- **Data preparation** – in this phase, which is currently running, we focus on preparation of datasets for the machine learning process. Identified phenomena for detection were analysed in detail for ML purposes. The main aim is to prepare training, validation and testing datasets for the machine learning modelling step. It also includes selection of types of models, any data augmentation techniques, annotation of part of data, etc.
- **Building of machine learning models** – during this phase we will focus on the modelling step, i.e., creation and validation of machine learning models based on datasets prepared in the previous phase.
- **Evaluation of machine learning models** – during this step, created models will be more deeply analysed according to their effectiveness in detection of selected phenomena.

The main candidates for family of machine learning models, which we will analyze, design and test during the third phase, will be methods used for analysis of time series based on neural networks techniques, mainly from the area of deep learning models (Goodfellow et al., 2016), especially for models oriented on time series forecasting (Benidis et. al. 2023). Most popular methods in this area include recurrent deep learning architectures (Salem 2022), e.g., LSTM (Long Short-Term Memory), Conv1D (Convolution 1D neural network), and transformer-based architectures, or their different combinations (hybrid architectures). The design of architectures of models will also follow simple adaptation methodology, from analysis of data and preparation of sampling for training datasets when necessary (e.g., over-sampling, under-sampling, augmentations, etc.), preparation of evaluation criteria, selection of starting architectures (usually re-use of existing ones), their adaptation and optimization, training and testing of final models.

From a technological point of view, cloud-based environment called DATALAB (managed by the Technical University in Kosice, Slovakia) will be used for all data processing. It provides a web-based Jupyter Lab interface and processing power with several hundreds of CPUs, GPU-cards for effective training, and data storage (NAS), all used preferably with python, sci-kit, tensorflow/keras, pytorch, and many other packages used for data analysis and machine learning.

Summary

In this paper, the possibility of applying machine learning in statistical analyses of changes in VLF signals caused by various astro- and geo-phenomena is pointed out. This possibility is based on the specific characteristics of the mentioned changes. In this study, the changes occurred on 16 February 2011 are shown as examples that meet the conditions to be analysed in the Serbian Slovak bilateral project Detection of astrophysical and geophysical phenomena from VLF radio measurements using machine learning methods.

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