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Prediction of Space Weather by Adaptive Information Processing

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Abstract: Space weather can be predicted using data from satellites. For example, condition of high-energy electron is vital in providing warnings to spacecraft operations. We investigate an adaptive predictor based on intelligent information processing. Adaptive and learning performances have been focused in the investigation. The predictor can forecast the conditions of high-energy electrons. The predictor was tested with the normal and abnormal test data. Our model succeeded in forecasting the high-energy electron flux 24 hours ahead.

Keywords: sensor network, adaptive information processing, space weather, dynamic relational network.

I. Introduction

Satellites are important social infrastructures. There are high-energy electrons at Geostationary Earth Orbit (GEO). High-energy electrons penetrate circuits and cables deeply and cause deep dielectric charging. There are reports that the spacecrafts anomalies at GEO are associated with enhancement in high-energy electron fluxes. For example, the Intelsat K spacecraft at GEO lost altitude control due to the failure of the momentum wheel control circuitry on January 20, 1994. The analysis of specialists revealed that the spacecraft anomaly occurred due to dielectric charging by the high-intensity and long-duration enhancement of high-energy electrons [1].

The enhancement of high-energy electron fluxes is known to be correlated with solar activities such as Coronal Mass Ejection (CME) (Fig.1) and coronal hole. Fig.2 shows that variation of electron flux in association with solar wind speed (V) and north-south component of interplanetary magnetic filed (B_z). The electron fluxes vary in two phases: initial-to-main phase and recovery phase of geomagnetic storms. During the initial-to-main phase, high-energy electron fluxes rapidly decrease; and after this phase, the fluxes increase significantly. The problem is that higher level of fluxes causes the irreparable damage to the instruments on satellites in the recovery phase of geomagnetic storms.

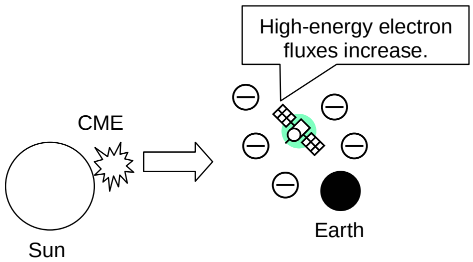

Fig.1 Schematic illustration of relationship between CME and spacecraft.

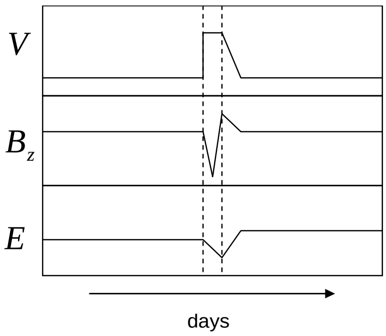

Fig.2 Schematic plot of parameters correlated with CME. The V, Bz and E are corresponded to the solar wind speed, the south-north component of interplanetary magnetic field and high-energy electron fluxes.

The dynamics on variations of high-energy electrons are under investigation [2]. Many studies have reported that the enhancement of high-energy electron is correlated with the high-speed solar wind [3]. Furthermore, the north-south component of the interplanetary magnetic field (IMF) is also known to be another important parameter of the flux enhancement.

Many predictors for high-energy electron fluxes at GEO have been proposed [5, 6]. Those studies have developed predictors that could forecast the predicted the fluxes real. The motivation for developing the predictor is to protect spacecrafts from the deep dielectric charging.

Earlier studies have tried to involve the relationships between high-energy electrons and solar wind parameters to the predictors. In space weather, the huge data for several or decades years are used for forecasting the space environment. The forecast could be done based on profiles of observed data. This paper tries to construct and evaluate a dynamic relational network [7] for anomaly prediction of high-energy electron fluxes. The network could predict whether high-energy electron fluxes attain to the alert level after 24 hours.

II. Profiling of Space Environment Data

2.1 Profiling High-energy Electron Fluxes and Solar Wind Data

We focus on profiling on the activities of high-energy electrons and solar wind. Profiling can be used to extract features of the sensor data [6]. We make the profiles of the relationships among the observed data. Those data involves normal and abnormal data. We define that normal and abnormal data of high-energy electrons are corresponded to the alert and quiet level flux respectively. In this paper, the alert level follows criteria of alerts of Space Weather Prediction Center (NOAA) [9]. The normal data is determined using the solar wind speed and north-south component of IMF when the high-energy electron fluxes are quiet level. In other cases, those data are defined as abnormal. We create the profiles of the normal data from only daily variations of high-energy electron fluxes that not involve coronal hole and CME event data.

2.2 Profiling Time Series Data by Vector Autoregressive Models

The satellites observe the space environment using their sensors. The data are sent to ground station and then stored into databases. The high-energy electron fluxes and the solar wind data are represented in a style with physical values. We can obtain them as time series data from the databases.

We create the profiles from the observed data with a statistical method. As the model for the time series analysis, we use the vector autoregressive models. In the VAR model, not only its own past values but also those of related variables are involved. Let $x(t)$ and $y(t)$ be explained variables; $x(t-1)$,…, $x(t-m)$; $y(t-1)$,…, $y(t-m)$ be explaining variables; and a_1 ,…, a_m ; b_1 ,…, b_m ; c_1 , …, c_m ; d_1, …, d_m be autoregressive coefficients. The VAR model of order m is expressed as follows:

$$x(t) = \underline{\sum_{i=1}^{m} a_i x(t-m) + \sum_{i=1}^{m} b_i y(t-m)} + \varepsilon_x$$

$$y(t) = \underline{\sum_{i=1}^{m} c_i x(t-m) + \sum_{i=1}^{m} d_i y(t-m)} + \varepsilon_y$$

The underlined parts $(x'(t), y'(t))$ represent predicted values while are the residual errors. In offline training, we estimate the autoregressive coefficients by the Levinson's algorithm. The profile is created by estimating the coefficients from couple of observed data. The order of the VAR model is determined by using the values of AIC (Akaike Information Criterion) of the models. We determine the order of the model from the models that the AIC value is the highest.

III. Dynamic Relational Network for Anomaly Prediction of High-energy Electron Fluxes

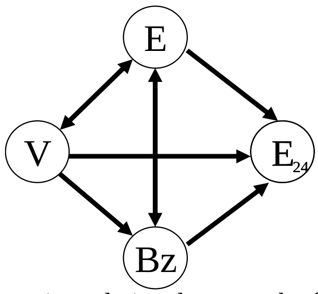

Fig.3 Dynamic relational network for anomaly prediction on high-energy electron fluxes.

This paper tries to predict the alert level flux of high-energy electrons using dynamic relational network. The dynamic relational network is consisted of sensors and arcs. The sensors of the network diagnose each other by evaluating target's sensor data. The credibility of sensors will change dynamically as the diagnosis proceeds, and then the network will adapt to the changes of the environment.

We build the dynamic relational network as black and white model [7] using real three sensors and one virtual sensor (Fig.3). The real sensors are the high-energy electron fluxes (E), the solar wind speed (V) and the north-south component of IMF (B_z). The virtual sensor is high-energy electron fluxes 24 hours ahead (E_{24}). The virtual sensor will be diagnosed from other sensors. The network will detect anomaly when the credibility of the electrons flux after 24 hours is less than the alarm threshold. For estimating the electron fluxes, we regard the current flux data as the future flux data because we cannot obtain them.

The arcs are corresponded to the profiles. The diagnosis of each sensor is done by calculating error $p(t)$ between the actual value and predicted value. The sensor diagnose the target sensor as abnormal when $p(t)$ deviates the threshold θ. The threshold θ is defined as $\theta = n\delta$ where the n and δ are the deviation coefficient and standard deviation of observed data respectively.

IV. Tests and Evaluations

4.1 Data source

We use one hour averaged data of the solar-wind and the high-energy electron flux at GEO. The solar wind data observed by the Advanced Composition Explorer (ACE) satellite are obtained from the OMNI-2 database [8] in the National Space Science Data Center (NSSDC), the National Aeronautics and Space Administration/Goddard Space Flight Center.

The electron flux data observed by the GOES satellite are obtained from the National Geophysical Data Center (NGDC), and the National Oceanic and Atmospheric Administration (NOAA). We obtain both data during the period from January 1, 1998 to December 31, 2006, thus eight years in total.

4.2 Data Handling

The data observed by the satellites could include the missing data due to the instruments troubles by the space weather events and/or various reasons for the operations. We regard the data as missing where the interval of the missing exceeds two hours. The missing data are interpolated if the observation down time is less than three hours. We exclude the missing data in training and simulations.

4.3 Methods and Evaluations

We evaluate the dynamic relational network based on the test results. The network is tested by inputting the test data. The test data are consisted of normal and abnormal data. The normal test data only involves the data where high-energy electron fluxes are the alert level. On the other hand, the abnormal test data involves the data where the flux is the quiet level. The abnormal test data contain the data on coronal hole and CME events. We prepare 20 test cases as normal test data and 7 test cases on coronal hole and CME events (14 cases in total) as abnormal test data. For the abnormal test cases, we choose the test cases from the event list [3]. The period of the test data is about 5 days. The period of the test data is different due to the conditions of the space environment. The performance of anomaly prediction is evaluated by calculating false-alarm rate and missed-alarm rate. We evaluate the test result in each step whether the anomaly prediction succeeds.

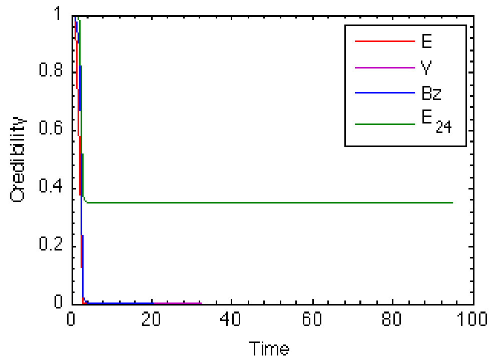

Fig.4 Time evolution of credibility when dynamic relational network tests abnormal data involving CME event. The deviation coefficient is 0.06. The threshold of anomaly detection is 0.5.

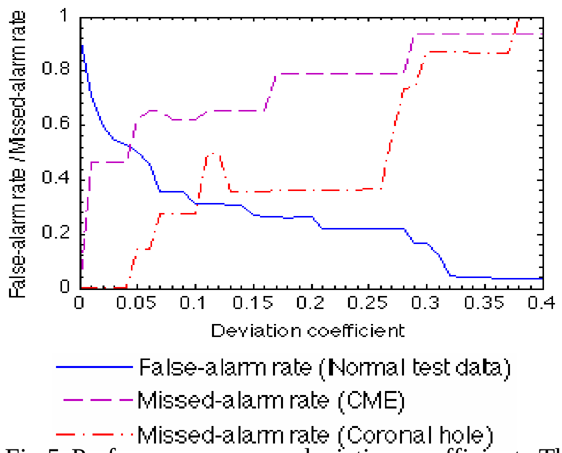

Fig.5 Performance versus deviation coefficient. The deviation coefficient varies from 0 to 0.4. The threshold is 0.5 in this test. The threshold of anomaly detection is 0.5.

4.4 Test Results

Fig.4 shows a diagnosis result of the dynamic relational network for the abnormal data involving CME event.

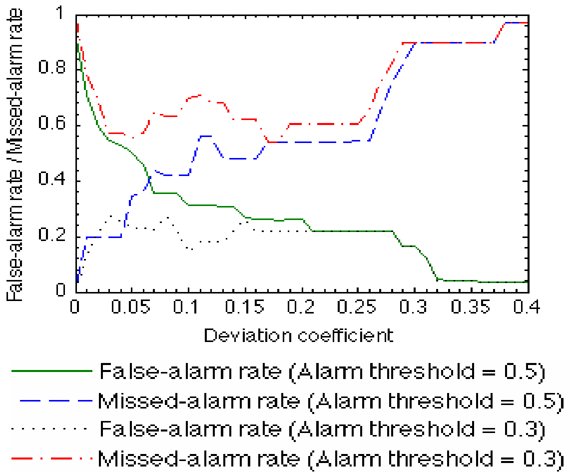

Fig.6 Performance versus deviation coefficient when the alarm threshold is compared with 0.3 and 0.5. The deviation coefficient varies from 0 to 0.4.

The CME happens when the test starts in this test case. The credibility of high-energy electron flux 24 hours ahead is diagnosed as anomaly. The anomaly prediction is successful in this test case.

Fig.5 shows the performance trade-off when the deviation coefficient varies. The false-alarm decreases as the deviation coefficient increases while the missed-alarm rate rises. The performance of the dynamic relational network shows the trade-off on the deviation coefficient.

Fig.6 shows the performance when the alarm threshold is changed. The missed-alarm rate increases when the deviation coefficient is 0.3. On the other hand, the false-alarm rate is kept low level. The dynamic relational network would predict successfully if both parameters are adjusted appropriately.

V. Discussions

We have investigated the performance of the dynamic relational network for the anomaly prediction on high-energy electron fluxes. The diagnosis of the network is done in online and therefore the credibility will change dynamically [6]. Our model differs from the neural network predictors [4, 5] in that it could adapt to the dynamic environment. However, the adaptation of the network is influenced by the tuning parameters [6]. For the tests, the deviation coefficient and the alarm threshold are used as tuning parameters of the network.

The performance of the network changes according to the deviation coefficient. The performances also changes according to the alarm threshold. Each parameter of the networks should be controlled appropriately to achieve the performance requirement in order to protect the satellites from dielectric charging. For future works, we need to evaluate the network using the profiles created from only abnormal data.

VI. Conclusions

We constructed a dynamic relational network for anomaly prediction on high-energy electron fluxes. The network could predict the alert level flux. Furthermore, we investigated the trade-off of the performances in order to manage the performance.

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