Investigation of the Relation Between Magnetospheric Activity and Solar Wind Parameters Based on Potential Learning

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Abstract

Nowadays, it is so important in saving our economic activity and evading the disasters caused by terrestrial electromagnetic effects to predict both temporal and spatial scales of the geomagnetic disturbances based on in-situ solar wind observations. Recently, Neural Network (NN) is one of the notable techniques for the predictions of the magnetospheric activities. However, NN has a problem referred to as 'black box', which is difficult to extract which solar wind parameters are the most important for prediction. In this study, we examine a significant relationship between Kp index, which represents the magnetospheric activity, and the solar wind conditions based on an interpretable neural network: 'Potential Learning (PL)'. A feature of the PL is to make a network that can understand the input variables by learning the "input potentialities", which are indices calculated using the variances of the solar wind parameters as input variables. In this study, we investigate the magnetospheric activity profile when the Interplanetary Magnetic Field (IMF) oriented southward (Bz $<$ 0). As the input solar wind data, we utilize the two components of the magnetic field (Bx, By) in GSE, and solar wind flow speed, and number density during 20 years between 1999 and 2018. Furthermore, we divide the associated values of Kp into two groups (targets): 'Kp = 6- to 9 (positive target)' and 'Kp = 0 to 1+ (negative target)'. Because the data number of positive target was smaller than that of negative target, the negative target samples are randomly selected so that the data numbers of both targets become equal. Based on the PL neural network, we obtain two important results; 1) the solar wind plasma flow speed might have the most influential in the increase of the Kp index, and 2) as the secondary influential parameter for the Kp increase, the solar wind proton density is considered. In the presentation, we will discuss feasibility of the application to the prediction of the magnetospheric activity based on the solar wind parameters.

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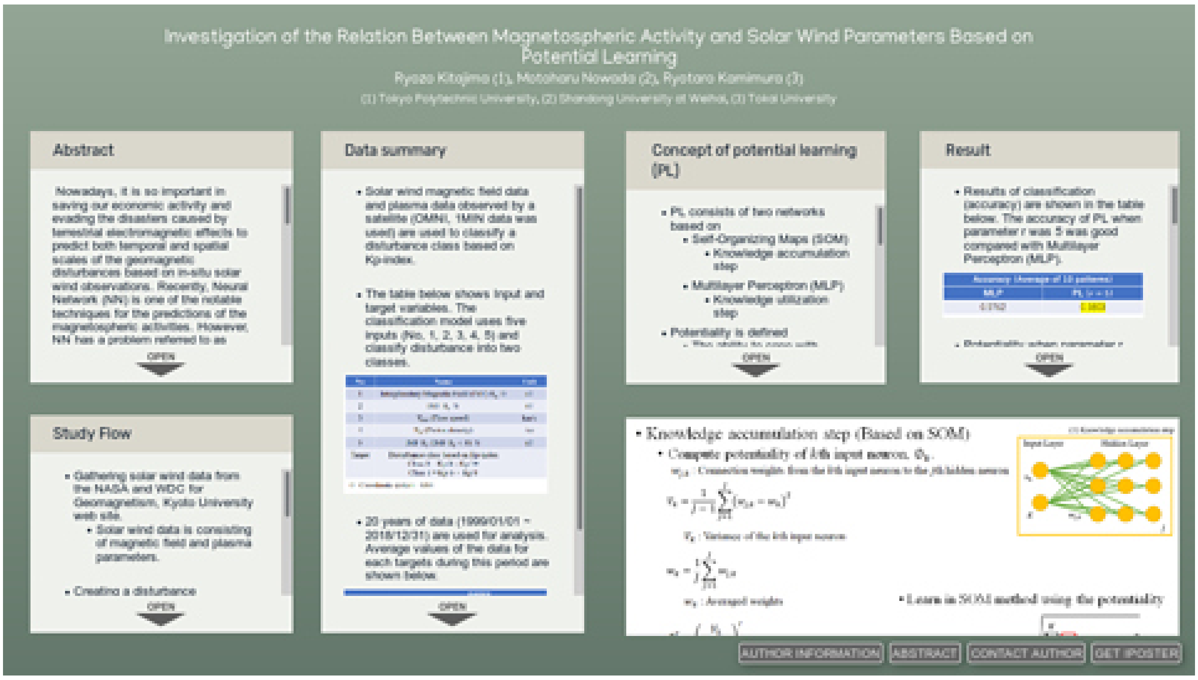

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In this study, we investigate the magnetospheric activity profile when the Interplanetary Magnetic Field (IMF) oriented southward ($Bz < 0$). As the input solar wind data, we utilize the two components of the magnetic field (Bx, By) in GSE, and solar wind flow speed, and number density during 20 years between 1999 and 2018. Furthermore, we divide the associated values of Kp into two groups (targets): ‘Kp = 6- to 9 (positive target)’ and ‘Kp = 0 to 1+ (negative target)’. Because the data number of positive target was smaller than that of negative target, the negative target samples are randomly selected so that the data numbers of both targets become equal. Based on the PL neural network, we obtain two important results; 1) the solar wind plasma flow speed might have the most influential in the increase of the Kp index, and 2) as the secondary influential parameter for the Kp increase, the solar wind proton density is considered. In the presentation, we will discuss feasibility of the application to the prediction of the magnetospheric activity based on the solar wind parameters.

STUDY FLOW

- Gathering solar wind data from the NASA and WDC for Geomagnetism, Kyoto University web site.
  - Solar wind data is consisting of magnetic field and plasma parameters.

- Creating a disturbance classification model (A class based on Kp-index) by “potential learning, PL.”

- Examining the accuracy of the classification.

- Extracting and interpreting variables that affect disturbance.

DATA SUMMARY

- Solar wind magnetic field data and plasma data observed by a satellite (OMNI, 1MIN data was used) are used to classify a disturbance class based on Kp-index.

- The table below shows Input and target variables. The classification model uses five inputs (No, 1, 2, 3, 4, 5) and classify disturbance into two classes.

No	Name	Unit
1	Interplanetary Magnetic Field (IMF) B_x ※	nT
2	IMF B_y ※	nT
3	V_{sw} (Flow speed)	km/s
4	N_p (Proton density)	/cc
5	IMF B_s (IMF $B_z < 0$) ※	nT
Target	Disturbance class based on Kp-index Class 0 = Kp 0 ~ Kp 1+ Class 1 = Kp 6- ~ Kp 9	

※ Coordinate system : GSE

- 20 years of data (1999/01/01 ~ 2018/12/31) are used for analysis. Average values of the data for each targets during this period are shown below.

Variable name	Average	
	Class 0	Class 1
B_x	0.0527	-0.2266
B_y	0.0860	2.0272
B_s	-0.5712	-6.6241
V_{sw}	380.5150	582.8564
N_p	5.2434	9.7649

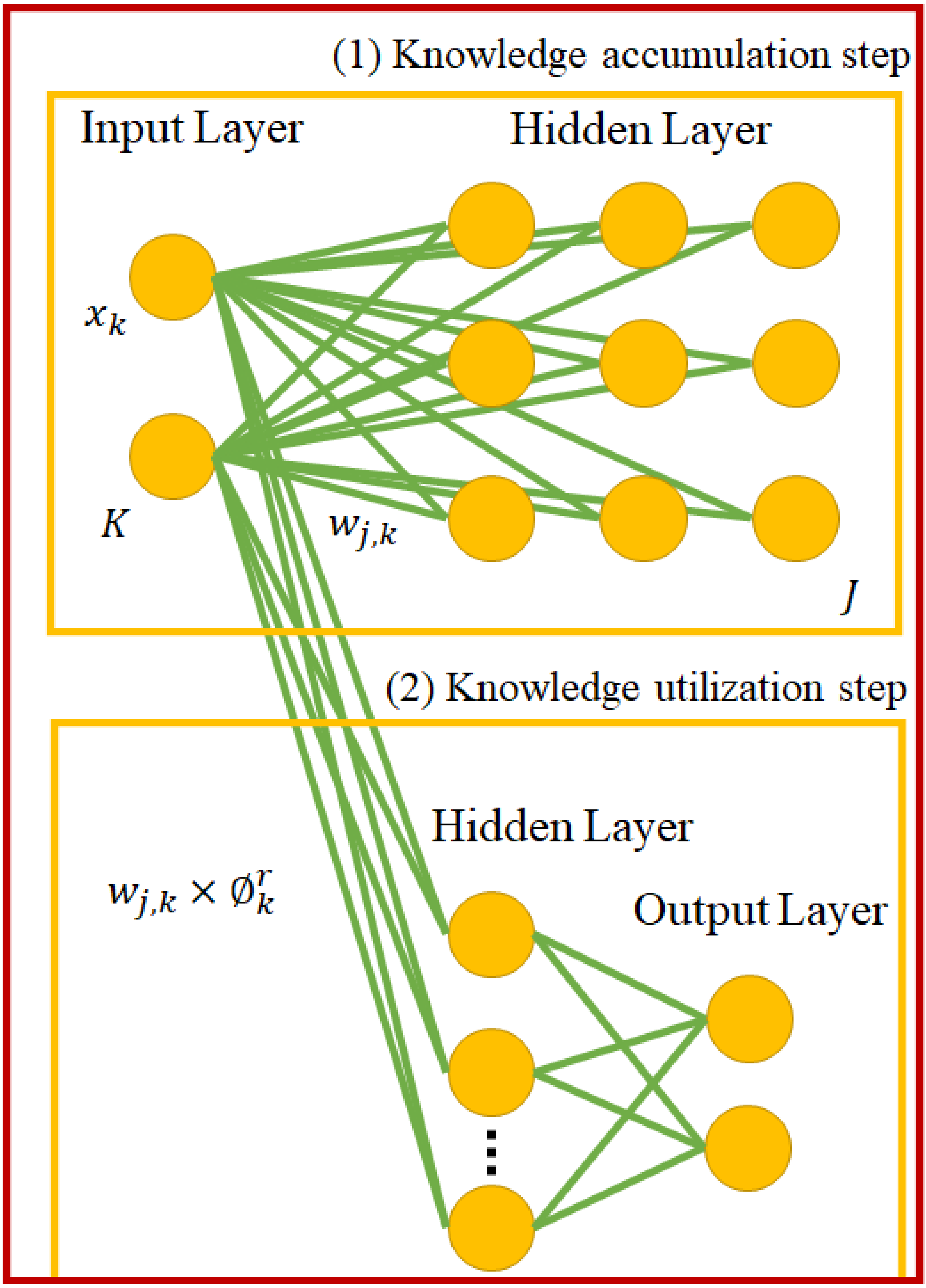
CONCEPT OF POTENTIAL LEARNING (PL)

- PL consists of two networks based on
  - Self-Organizing Maps (SOM)
    - Knowledge accumulation step
  - Multilayer Perceptron (MLP)
    - Knowledge utilization step
- Potentiality is defined
  - The ability to cope with various situations
    - Neurons with high potentiality : Play an important role in learning.

(neurons capable of dealing with

various situations)

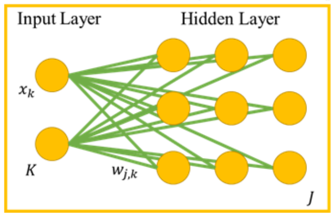
- The figure below shows an overview of PL.



- In knowledge accumulation step (Based on SOM), potentiality of kth input neuron, $\emptyset k$, are computed. This flow is shown in the figure below.

- Knowledge accumulation step (Based on SOM)
  - Compute potentiality of kth input neuron, $\emptyset_k$.

(1) Knowledge accumulation step



$w_{j,k}$: Connection weights from the kth input neuron to the jth hidden neuron

$$V_k = \frac{1}{J-1}\sum_{j=1}^{J}\left(w_{j,k} - w_k\right)^2$$

V_k : Variance of the kth input neuron

$$w_k = \frac{1}{J}\sum_{j=1}^{J} w_{j,k}$$

w_k : Averaged weights

$$\emptyset_k^r = \left(\frac{V_k}{\max V_k}\right)^r$$

r : A parameter that controls the computed potentiality

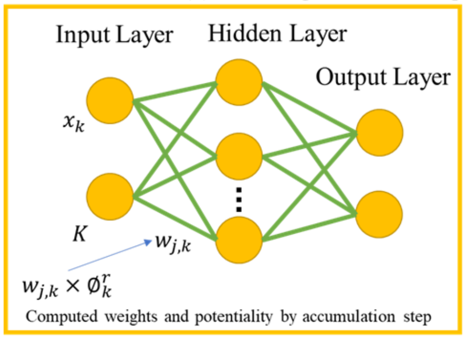
- Learn in SOM method using the potentiality

$$d_j = \sqrt{\sum_{k=1}^{K} \boxed{\emptyset_k^r}\left(x_k - w_{j,k}\right)^2}$$

- In knowledge utilization step (Based on MLP), disturbance is classified into two classes. ∅k computed in knowledge accumulation step are used for initial weights of knowledge utilization step. This is shown in the figure below.

- Knowledge utilization step (Based on MLP)
  - Predict classes
    - Initial weights
      - Are set to the value calculated from weight and potentiality obtained in the knowledge acquisition step
    - Expect classification based on the acquired knowledge

(2) Knowledge utilization step

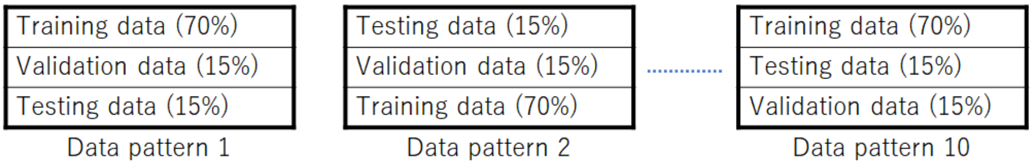


- 20 years of data is used divided into three parts, in this study. Details are shown in the figure below.

Training and Testing data

- Training : 85% of all samples
  - Training : 70%
  - Validation (overfitting prevention) : 15%
- Generalization ability check : 15%

- 10 patterns created
  - 10 models were created.
  - The classification results described in the result part, uses these 10 averages.



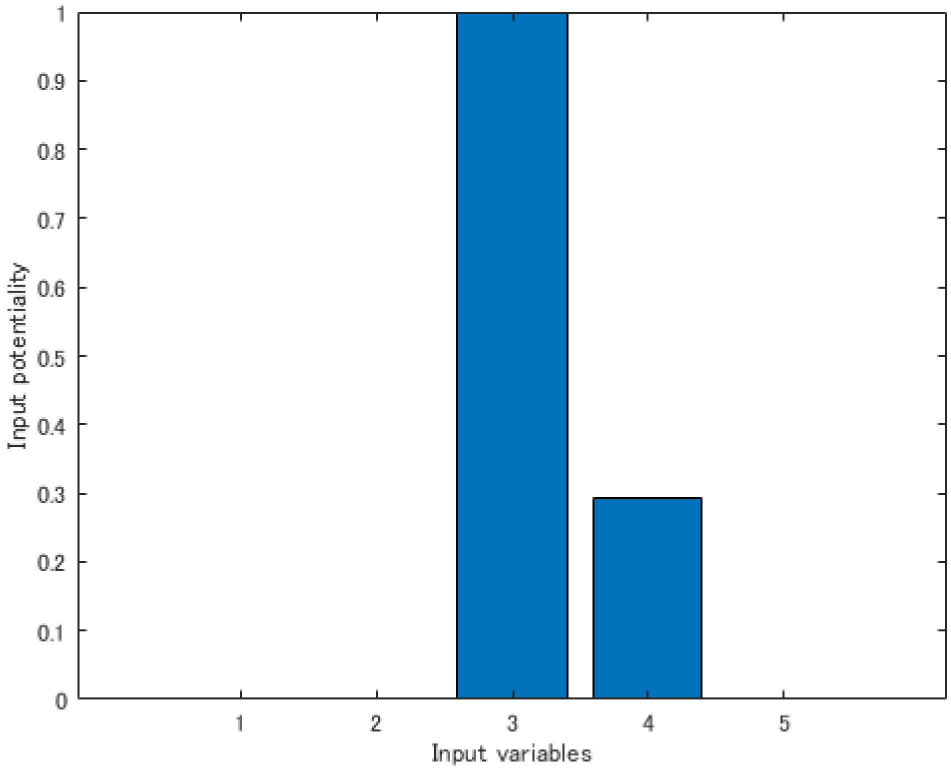
- Parameter r
  - It was changed from 1 to 50 in one step
  - Parameter value with the best performance rate was identified through a search.

RESULT

- Results of classification (accuracy) are shown in the table below. The accuracy of PL when parameter r was 5 was good compared with Multilayer Perceptron (MLP).

Accuracy (Average of 10 patterns)	
MLP	PL ($r = 5$)
0.9762	0.9803

- Potentiality when parameter r was 5 is shown in the figure below. From this figure, we can see that variable No.3 (flow speed) is the most important variable and variable No.4 (proton density) is the next most important variable.



- One may predict that the southward magnetic field component (Bs) should have the highest potentiality. However, note that the Bs did not always have hight potentiality because this analysis is made under the southward conditions (Bs) .

- The Vsw and Np show high potentiality, suggesting that the dynamic pressure (mNpVsw^2) can also be a key parameter to disturb the magnetosphere as well. Thus, we investigate the value of Pdy. Furthermore, we also caluclated and discussed the clock angle to examine that how degree the Bs component is strong, and resultant geomagnetic disturbances become higher.

- The dynamic pressure and clock angle values are displayed at 0~1- and 8+~9 classes. This results is shown in the table below.

		Class 0			Class 1		
		Kp 0	Kp 1-	Kp 1+	Kp 8-	Kp 8+	Kp 9
Average	P_{dyn} ※1	0.9156	1.1876	1.3652	8.1009	13.3333	8.1452
	Clock Angle (Plus) ※2	64.8035	72.5037	71.8126	82.7808	92.5367	114.2281
	Clock Angle (Minus) ※2	-57.6107	-67.0191	-65.9351	-75.8065	-85.3272	-88.8309

※1 $P_{dyn} = mN_P{V_{sw}}^2$
m : proton mass

※2 $\theta_{Clock} = \mathrm{atan}\left(\frac{B_y}{B_z}\right)$

- The results shown above tell us that higher magnetospheric disturbances are brought by stronger Bs component rather than Pdy. This is because the values of clock angle are larger than that of Pdy as Kp index increases.

- Through this study, we conclude that the Potential Learning can use to predict the magnetospheric disturbances under a condition, and extract the most crucial solar wind parameters to cause them.

AUTHOR INFORMATION

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