A improved deep learning algorithm for TEC maps: image completion

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Introduction

A improved deep learning algorithm, R-DCGAN, is proposed for the image completion of TEC maps. The traditional DCGAN (which is a very popular and powerful deep learning algorithm for image completion, such as human face images) needs the training data to be completed observations. Since there is lack of distinct features in the missing data part of the training data that can be utilized by DCGAN to fill these missing values, DCGAN fails to directly learn the observation with data missing. In order to overcome the shortcoming of the original DCGAN method, an improved algorithm, R-DCGAN, is proposed to fulfill missing data completion for the MIT-TEC maps. The R-DCGAN is designed from DCGAN, with an extra discriminator and the reference TECs. The R-DCGAN produces satisfactory ionospheric peak structures at different times and geomagnetic conditions and the results demonstrate that the deep learning algorithm is promising to fill the missing data.

Methods

The DCGAN network parameters can be optimized by solving the following minimization-maximization problem [Goodfellow et al., 2014]:

$$\min_G \max_D V(G,D) = E_{x\sim P_{data}(x)}[\log(D(x))] + E_{Z\sim P_Z(z)}[\log(1-D(G(z)))] \qquad (1)$$

where x is the sample from the data distribution Pdata. The DCGAN has been shown to be more stable to train than GAN and capable of generating good representations of images [Radford et al., 2016]. The applications of using DCGAN for image super-resolution [Ledig et al., 2016] and for image completion or inpanting (i.e. filling the missing data) [Yeh et al., 2017] have shown to be successful when uncorrupted data are available for training.

However, DCGAN may fail to catch the underlying data distribution when the training data always have data missing in certain regions, So we propose a regularized DCGAN (R-DCGAN) by adding an extra discriminator to the original DCGAN, the algorithm parameters can be optimized by solving the following min-max problem:

$$\min_G \max_D V(G,D) = E_{x\sim P_{data}(x)}[\log(D(x))] + \alpha E_{y\sim P_{reference}(y)}[\log(D1(y))] + E_{Z\sim P_Z(z)}[\log(1-D(G(z)))] + \alpha E_{Z\sim P_Z(z)}[\log(1-D1(G(z)))] \qquad (2)$$

Algorithm

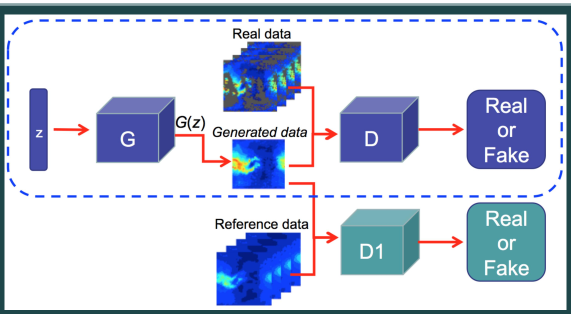

Figure 1. The framework of R-DCGAN. Without the reference data (prior information) and the second discriminator (D1), R-DCGAN collapses into the original DCGAN as shown in the blue dashed box.

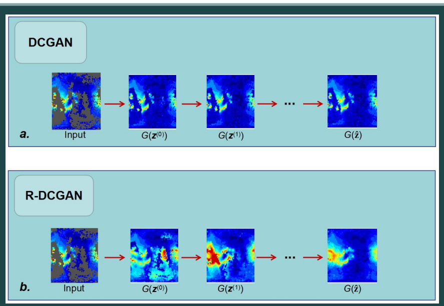

Figure 2.The iterative map completion using two trained models: (a) DCGAN and (b) R-DCGAN

Results

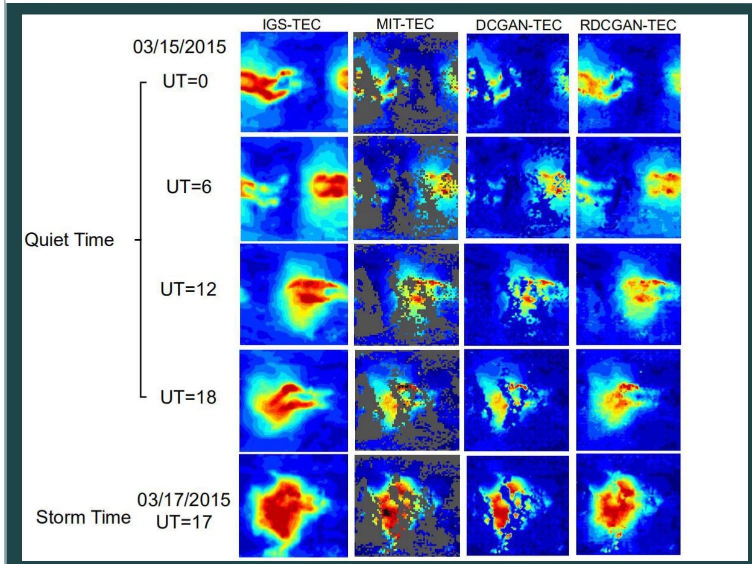

Figure 3. TEC map completion for DCGAN and R-DCGAN at different times and geomagnetic activities. From left to right: the IGS-TEC maps, the MIT-TEC maps, the TEC maps completed by DCGAN, and the TEC maps completed by R-DCGAN.

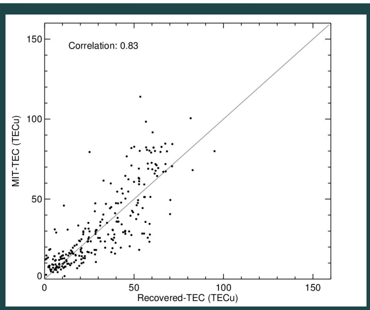

Figure 4. The Y-axis is the original MIT-TEC values at randomly selected locations and the X-axis is the recovered TEC values by R-DCGAN for the corresponding locations with null values.

Summary

1. **Proposing an improved deep learning algorithm to deal with common missing observation data issues.**
2. **The result generated by the algorithm can shows satisfactory ionospheric peak structures at different times and geomagnetic conditions.**
3. **The traditional DCGAN fails to directly learn the observation with data missing, our algorithm overcome this, and have broader application.**