Detection of Magnetic Dipole Target Signals by Using Convolution Neural Network

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***Abstract*—An intelligent method for detection of magnetic dipole target signals (MDTS) by using the convolution neural network (CNN) is proposed. First, the contaminated MDTS are intercepted and converted into 2D images through the Wigner-Ville time-frequency transforms. Then, a set of images are selected for training of the CNN until a satisfying level. Last, all images are tested to identify which images contain MDTS. Both simulation and experiment results show that the proposed method possess very high detection possibility, which, under the same signal-noise rate (SNR), outperform the conventional signal energy-based constant false alarm rate (CRAR) algorithm.**

***Index Terms*—convolution neural network, intelligent detection, magnetic dipole target signals.**

I. Introduction

Magnetic anomaly detection (MAD) has wide applications in unexploded ordnance search, mineral reconnaissance, and anti-submarine warfare [1]. A magnetic object at a distance farther than several times of its dimension may be taken as a magnetic dipole target. Most locating methods for magnetic dipole targets are based on uses of three-component vector magnetometer data [2]-[3]. Unfortunately, common tri-axial fluxgate sensors are unstable in diverse environments and have low sensitivity. Scalar magnetometers, such as many optical-pumping atomic magnetometers, are very stable and immune to environmental temperature, and have very high precision. Some detection methods for scalar magnetic dipole target signals (MDTS) was reported, among which the orthonormal basis functions (OBF) decomposition scheme has drawn much attention [4]-[5]. The method can extract the signal energy by expressing the MDTS as a superposition of three characteristic functions. Constant false alarm rate (CRAR) detection method is employed to judge whether a target exists based on an adaptive energy threshold value. This approach uses the signal energy as the unique feature, which seems to be an obvious weak point. In fact, this approach suffers from very high false rate under low signal-noise-rate (SNR). Seeking for robust detection schemes for MTDS is highly expected, and AI-based method should be hopeful, which motivates the present study.

II. Method

In this Section, the characteristics of MDTS and ambient geomagnetic noise are described first. Then the convolution neural network (CNN) method for detection of the MDTS is outlined.

A. Magnetic Dipole Target Signal and Geomagnetic Noise

Refer to Fig. 1. A magnetic dipole target with magnetic moment $\mathbf{M}$ is situated at $\mathbf{r}_0$. A moving scalar magnetometer measures the MDTS along a line, which makes angle φ_P with the local magnetic north pole. The MDTS measured by the sensor is

$$B(t) = \frac{\mu_0}{4\pi}\hat{\mathbf{F}}_0 \cdot \left(\frac{3\mathbf{R}\mathbf{R}}{R^5} - \frac{\bar{\mathbf{I}}}{R^3}\right)\cdot \mathbf{M} \tag{1}$$

where $\hat{\mathbf{F}}_0 = [\cos\psi\cos\varphi_P, -\cos\psi\sin\varphi_P, \sin\psi]$ is the local Earth magnetic direction, with ψ being the magnetic dip angle, and $\bar{\mathbf{I}}$ being the unitary dyadic. It is obvious that characteristics of measured MDTS are varying with (i) the sensor moving direction φ_P, (ii) the orientation of the magnetic dipole target $\mathbf{M}$, (iii) the local geomagnetic direction $\hat{\mathbf{F}}_0$, and (iv) the closest proximity approach (CPA) $\mathbf{R}_0$. The first three factors determines the shape of the signal, while the last factor determines the stretching of the signal. Some typical MDTSs by changing the first three factors are shown in Fig. 2.

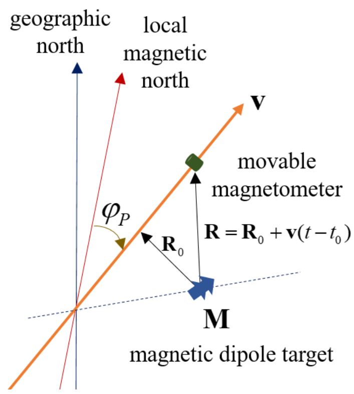

Fig. 1. Configuration of magnetic dipole target detection.

In real applications, the ambient geomagnetic field is mainly constituted by two parts: the geological magnetic noise due to inhomogeneity of the Earth and the aerial magnetic noise originated from the disturbance of free electron density in the ionosphere. In general, the ionospheric magnetic noise is more untraceable, which produces spurious target signal and thus increases the false alarm rate in the detection of MDTS. Some typical sequences of geomagnetic fields measured on ground at a fixed place (without moving the magnetometer) are shown in Fig. 3. It is seen that the geomagnetic noise is hard to predict and to remove from the measured mixed signals that may contain true target signal.

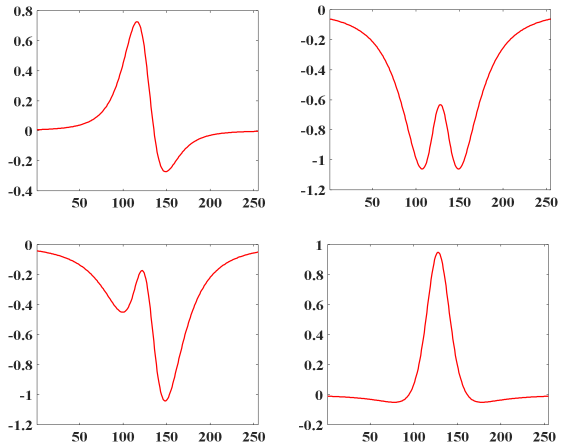

Fig. 2. Some typical magnetic dipole target signals (MDTSs). The vertical axis gives magnetic field in nT, and the horizontal axis shows time in second.

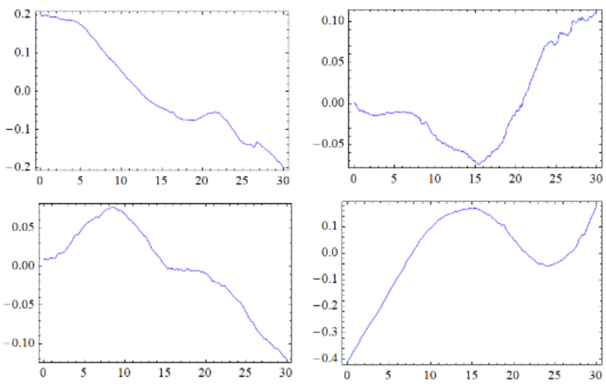

Fig. 3. Some typical sequences of geomagnetic fields measured at a fixed site in Beijing outskirts. The vertical axis gives magnetic field in nT with averaged value subtracted, and the horizontal axis shows time in second.

B. Time-Frequency Analysis

What measured by a scalar magnetometer is the addition of the MDTS and the background magnetic field. We hope to convert the 1D mixed signal into 2D image and use intelligent image detection methods to identify whether a MDTS is contained in the mixed signal. To this end, the Wigner-Ville time-frequency transform [6] is adopted, which is found particularly suitable for MDTS compared with other time-frequency analyses, such as the Gabor transform and the Margeneu-Hill transform. For simulation purpose, the four typical MDTS shown in Fig. 2 are added randomly to measured geomagnetic field, and then converted into 2D time-frequency images. Some representative 2D images are shown in Fig. 4. Note that some images contain MDTS but some images are completely ambient magnetic field. A total of 5000 images are obtained. Half of the images are used for training of CNN, while the other half of the images are used for testing to estimate the recognition rate.

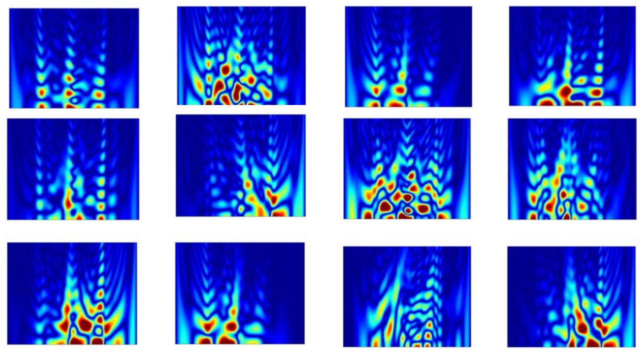

Fig. 4. Some representative 2D time-frequency images.

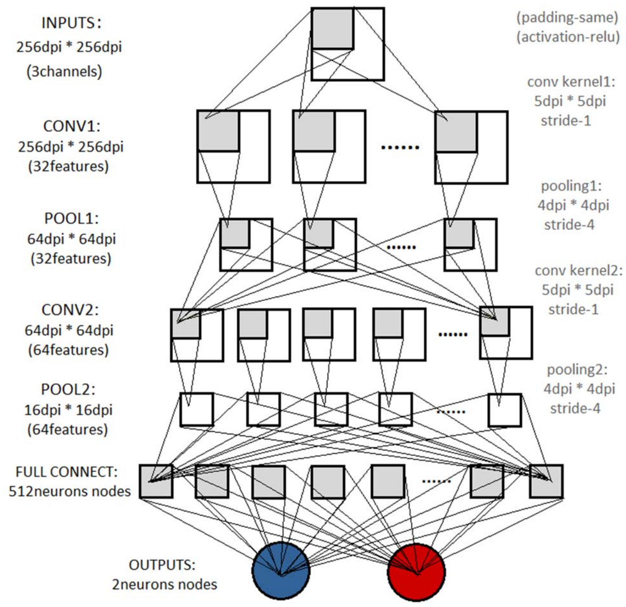

Fig. 5. The structure of a convolution neural network used in this paper.

C. Convolution Neural Network for Detection of MDTS

Convolutional neural network (CNN) is an efficient and appealing recognition method developed in recent years [7]. It is mainly used to identify displacement, scaling, and other forms of distortion-invariant two-dimensional images. It is insensitive to the location of the target. The basic structure of the CNN model is shown in Fig. 5. It contains one input layer, two convolutional layers, two pooled layers, one hidden fully connected layer and one output layer. The original images are in the RGB color space, and the input image sizes are 256×256. The first convolution layer uses 32 convolution kernels whose size is 5×5, to obtain a feature map of size 256×256×32 through the convolution operation, and then obtaining a feature map whose size is 64×64×32 through down sampling using a 4×4 pooled kernel in the first pooling layer. The second convolution layer takes the output of the first pooling layer as input, and uses 64 convolution kernels with 5×5 to obtain a feature map of size 64×64×64 through the convolution operation, and then down sampling to obtain a 16×16×32 feature map using a 4×4 pooled kernel in the second pooling layer. After that, the result is transformed into a one-dimensional vector and is used as the input of a fully connected layer with 512 neurons. Finally, classify through the output layer with two neurons to identify whether the input image contains a MDTS.

III. DEMONSTRATION

A. Training and Testing of CNN

As mentioned above, 5,000 image samples are generated, among which 2,500 contain MDTS. The 5,000 samples are divided randomly into training set and testing set, each with 2,500 samples. Then the samples are input into the CNN model, and the training and testing results are shown in Fig. 6. It is seen from the learning curves that recognition rate of the testing set starts to decline when the model is trained to about 320 rounds, which means that the model tends to overfitting and should stop training here. The final recognition rate of the model testing set is 96.94%. Please note that the SNR has been set to be 1, which is defined as the peak-peak value of the MDTS compared with the local peak-peak value within the same interval of the background magnetic field after de-trending. If we use the conventional energy-based detection method, a recognition rate greater than 70% is almost impossible at SNR of 1, which illustrates the superiority of the proposed method.

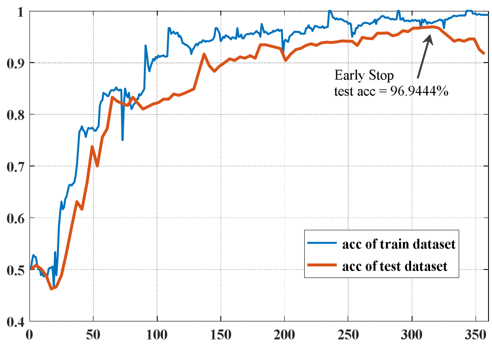

Fig. 6. The training and testing results of the image samples.

B. Detection of MDTS for Sequence Data

In real applications, we are faced with sequence data. A sliding window with a width of 400 data is used to cut out a piece of data from the sequence at a step of 145 data. The width of a MDTS is 255, so that not a MDTS will be missed. Fig. 7 shows a part of a measured sequence, in which four MDTS are mixed with the background magnetic field. Using the sliding window, a total of 32 samples are intercepted and converted into 2D images. Then the 32 images are input into the trained CNN to calculate the possibility to contain a MDTS, and the results are shown in Fig. 8. It is seen that the recognition rate is 100% if a possibility greater than 0.5 is judged to contain a MDTS and two neighbored MDTS is taken as the same target. This simulation experiment has been conducted repeatedly, and the overall recognition rate is nearly 100%, which indicates that the proposed method is viable to sequence data.

VI. CONCLUSION

A viable procedure for detection of MDTS using CNN is proposed in this work. The measured sequence data are first intercepted at a step using a sliding window, and then converted

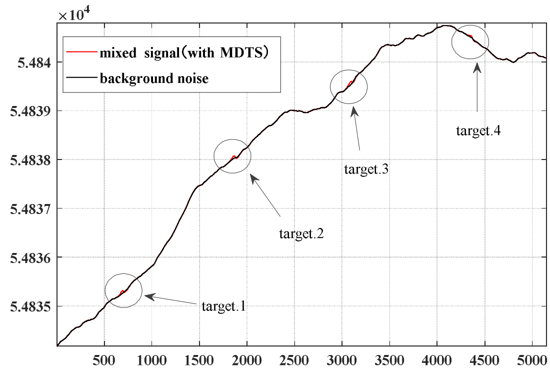

Fig. 7. A measured sequence containing four MDTS.

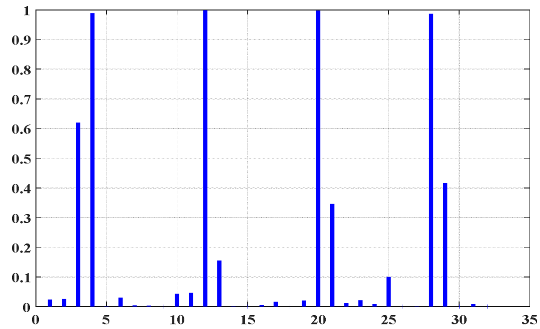

Fig. 8. The possibility to contain a MDTS of the 32 intercepted samples.

into 2D images through Wigner-Ville transform. When the 2D images are input into a trained CNN, very high possibility to identify whether an image contains a MDTS can be achieved at a SNR of 1, which much outperforms the conventional energy-based detection algorithm. Training of the CNN can be implemented by using simulated MDTS and real background magnetic field data, because the simulated MDTS can be the same as real MDTS.

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