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Removing Train Noise from Telluric Current Data by Neural Networks for Automatic Short-term Earthquake Prediction in Japan

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Abstract

The goal of this research is to obtain a practicable and reliable method for short-term earthquake prediction to detect seismic electric signals in telluric current data, which is used for the VAN method, by computers automatically. In this paper we perform experiments to know if neural networks can be applied to the reduction of train noise from telluric current data, which is considered as the main problem for the effective use of the VAN method in Japan and describe the experimental results.

短期地震予知のためのニューラルネットを用いた地電流データからの電車ノイズ除去

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概要

我々は，VAN 法を用いて観測される地電流データから，地震前兆シグナルを計算機により自動的に検出し，より実用的かつ信頼性の高い短期地震予知を行う研究に着手している．本稿では，地震前兆シグナルを検出する際に問題となる電車ノイズの除去が，ニューラルネットを用いることによって，可能かどうかの実験を行い，その結果について報告する．

1 Introduction

Since the great Hanshin earthquake in 1995, short-term earthquake predictions have been investigated as an emergent and eager research topic. Although some statistic methods are used for long-term earthquake predictions in conventional seismology, it is obviously difficult to apply the same statistic methods to the short-term earthquake predictions. The VAN method [1][2] is known to be an effective method for the short-term earthquake predictions, and has been investigated to be used in Japan. For recent several years, telluric current data (TCD), which is weak electric current flowing within the surface layer of the earth, has been observed for the application of the VAN method in Japan as a research topic of Information Frontier Program on Earthquake Research(RIKEN IFPER) [3]. In TCD observed by the VAN method, seismic electric signals (SESs) are often detected before the occurence of great earthquakes. Although experts of the VAN method can recognize the SESs with a careful glance, they are not mathematically modeled as time series data. The amount of TCD observed in Japan for recent four years becomes too huge (several Tera bytes) to be analyzed by hand. In addition, since 90 percents of TCD in Japan are affected by train noise, detecting SESs in TCD itself is considered as an extremely arduous job.

On the other hand, detecting SESs in TCD containing train noise, namely, recognizing a specific pattern, which can be distinguished by human experts, out of huge data with lots of noise is equivalent to a pattern recognition technology. So a recognition system by neural networks, which attract notice recently as new pattern recognition methods, may perform such complicated detection.

Considering this background, we started a research project of automatic detection of SESs in TCD as a pattern recognition research.

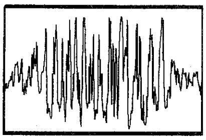

Figure 1: train noise

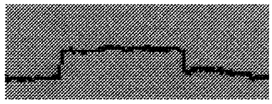

Figure 2: SES

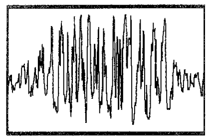

Figure 3: train noise with SES

In this paper, as the first step of automatic detection of SESs in TCD, we propose the way of a noise reduction filter by neural networks. We explain the design, implementation and evaluation results of a neural network which removes just the train noise from TCD with a SES and train noise.

In section 2, we explain the characteristic of TCD. In section 3, we show the basic idea of detecting SESs by neural networks, and describe the design, implementation and evaluation result of the train noise reduction filter.

2 Telluric Current Data (TCD)

2.1 Train noise

TCD are measured as electric potential difference between electrodes at different sites. TCD are sampled at 10 sec interval at 42 observation points in mainly Tokai and Hokuriku area since 1997. Each observation point has 8 or 16 channels in different directions.

We chose TCD of Matsushiro observation point in Nagano prefecture, where train noises appear very clearly, observed on the 20th of August 1999. Using the time series data and the train timetable at Nagano railway Matsushiro station, we find train noises in the TCD [4]. The wave pattern represents the train noise of the first 6:31 train (see Fig.1). The number of train noises frames is about 120 to 250; about 20 to 50 minutes.

2.2 Seismic electric signals

It is known in laboratory experiments that electric current is generated before fracture in rocks under load. Earthquakes are also a kind of rocks fracture phenomena, so it is considered that electric currents flow in the earth before great earthquakes. We call such irregular change of electric currents as seismic electric signals (SESs). Observing TCD by the VAN method, it becomes easier that SESs are detected. Typical SESs are observed in TCD before the occurence of great earthquakes several days to several weeks in advance (see Fig.2).

An example of short-term earthquake prediction by the VAN method is a great earthquake at Pirgos city in Greece on March 1993. Before the earthquake, SESs were observed in TCD. As the result to obey the earthquake prediction, although a half of buildings in the city were completely or partially destroyed, there were no casualties. Therefore the VAN method is available for short-term earthquake prediction.

2.3 The problem of the use of the VAN method in Japan

In Japan, train noises described in 2.1 occupy 90% of TCD. In the case that an SES is observed outside of train noises, VAN method experts can find the SES. However, in the case that an SES overlaps with a train noise, detecting the SES is exteremely difficult even for VAN method experts. The noise represents as Fig.3. Comparing Fig.3 with Fig.1, these noises seem to be nearly same. Therefore, the application of the VAN method for short-term earthquake prediction in Japan is quite difficult.

We performed some experiments to recognize train noises in TCD by neural networks, and confirmed that neural networks can be recognized train noises [4]. The experiments indicate that SESs may be distiguished from train noises by the use of neural networks. So we believe automatic short-term earthquake prediction in Japan by computers are possible.

3 Train Noise Reduction Filter for TCD by a Neural Network

3.1 The method of detecting SESs

In this paper, we do not adopt the direct detection of SESs, but a structured detection method. The structured detection method is obtained by the two levels of hierarchical neural networks: 1) the lower level neural network which removes train noises from TCD, and 2) the higher level neural network which detects SESs in the TCD without train noises. At this point, the neural networks need not to receive the 8,640 time series data as inputs but receive just a part of the data with appropriate length (a window of several hundreds time series data). The learning and recognition of the neural networks are performed with scanning the window on the 8,640 time series data for each day. Therefore in this paper, we construct a train noise reduction filter for TCD by a neural network.

3.2 Overview of train noise reduction filter

In this subsection, we describe the design, implementation and evaluation result of the neural network that works as a train noise reduction filter with the below requirements.

1. Receive time series data that contains specific train noises and an SES, and generate the time series data by removing just the train noises.
2. The time series data has reasonable fixed length so that typical train noises and the SES are included within the data.
3. The train noise reduction is valid regardless of the places where the train noises and the SES are located.
4. A pair of TCD from two orthogonal channels is used for inputs to the neural network.

Although the requirement 1 is the kernel of the train noise reduction filter, there is a problem of unavailability of training samples as described below. The requirement 2 is for decreasing the calculation of learning instead of using the 8,640 time series data for inputs as explained in section 3.1. The requirement 3 makes the neural network more flexible as also described in section 3.1. Since trains move, the train noises, which are observed on different channels, have directionality. On the other hand, SESs do not have such directionality because the source of SESs does not move in general. Thus the requirement 4 makes the learning of the neural network much easier.

3.3 Artificial generation of training and supervising samples

To construct a neural network for the train noise reduction filter, we found an essential problem of unavailability of training and supervising samples. Although we have a large amount of TCD, the TCD with train noises and SESs are very limited. Actually we could find only several tens cases from 42 observation points for past four years. What we need is the TCD with the same SESs and without the train noises, and it is impossible to find such cases.

Hence, we investigated a model of TCD for the train noise reduction filter. Using the model, we generated training and supervising samples artificially for the neural network [5].

3.4 Construction and experiments

We implemented a feed-forward 3 layered neural network, which works as a train noise reduction filter, with 600 input layer cells, 300 hidden layer cells, and 600 output layer cells. According to the steps described in 3.3, we generated 1,320 training and supervising samples for the neural network from the TCD of channel 2 and 7 of Matsushiro observation point in Nagano prefecture on the 20th of August 1999 and an SES (see Fig.2) that was observed in the same channels of the same observation point on the 17th of January 1999.

After the enough learning, we performed experiments to validate that neural networks can remove just train noises from TCD. We used four sets of TCD described below.

1. A 300-frame of TCD which are generated artificially by adding a train noise and an SES (Fig.4).
2. TCD of the 20th of August 1999, which are used to generate the training samples, with train noises but SESs (every 300-frame is scanned from TCD) (Fig.5).
3. TCD of the 20th of August 1999, which are used to generate the training samples, with train noises and several SES that is generated and added randomly (every 300-frame is scanned from TCD) (Fig.6).
4. TCD of the 23rd of August 1999, which are unknown data to the neural network, with train noises and several SES that is generated and added randomly (every 300-frame is scanned from TCD) (Fig.7).

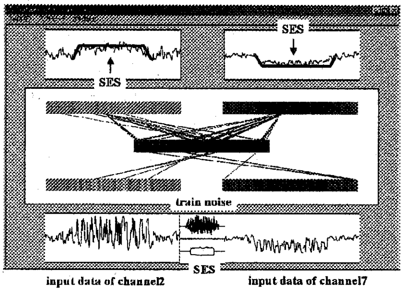

Figure 4: artificial generation of TCD

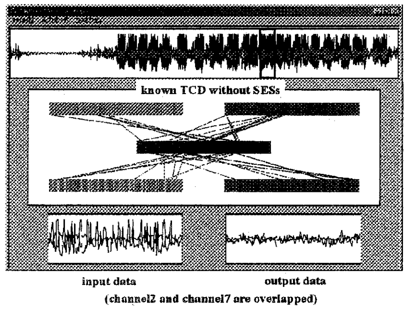

Figure 5: filtering known TCD without SESs

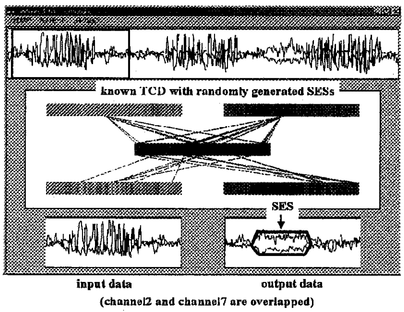

Figure 6: filtering known TCD with randomly generated SESs

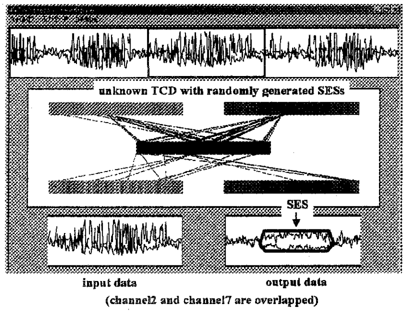

Figure 7: filtering unknown TCD with randomly generated SESs

Applying the train noise reduction filter to these four sets of TCD, just the train noise was removed with keeping SESs, although the train noises are unknown samples to the neural network as Fig.7. Therefore, we succeeded to construct a train noise reduction filter by neural networks.

4 Conclusions

We performed experiments of and validated the application of neural networks to the reduction of train noises from TCD, which is considered as the main problem for the effective use of the VAN method in Japan. As the result, it turned out that the application of neural networks to analyze TCD was more promising than we had expected, and the reduction of train noises from TCD was possible. Therefore, we succeeded to construct a train noise reduction filter by neural networks. We believe this is a big progress toward the structured detection of SESs in TCD for automatic short-term earthquake predictions in Japan.

Constructing larger neural networks, the filter should be applied to any railway train noise at the same observation point. Furthermore, it may be possible for a huge neural network to remove any railway train noise at any observation point.

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