PRECURSOR SIGNAL ESTIMATION USING ELF BAND OBSERVATIONS FOR PREDICTING EARTHQUAKES USING MONTE CARLO FILTER

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ABSTRACT

The tectonic activities that precede significant earthquakes release electromagnetic (EM) waves that can be used as earthquake precursors. We have been observing EM radiation in the ELF (extremely low frequency) band at about 40 observation stations in Japan for predicting significant earthquakes. The recorded signals contain, however, several noise components generated from the ionosphere, human activity, and so on. Most of the background noise in the captured signals is attributed to lightning in the tropics. In this paper, we introduce a self-tuned state space model and a Monte Carlo filter to reduce the noise. The good performance of the proposed method is confirmed.

1. INTRODUCTION

It is well known that EM (electromagnetic) waves are radiated from the earth's surface before earthquakes[2],[3]. This data can be processed in several ways to predict earthquakes [4]–[7]. Given the importance of this subject, we have been observing EM radiation in the ELF (extremely low frequency) band at over forty sites in Japan. Our goal is to be able to use EM precursor signals to predict earthquakes accurately. The ELF band is suitable for detecting the precursor signals, which are extremely weak.

The main source of prediction uncertainty is inaccurate determination of the origin of a signal. This is because the observed signals are contaminated with several noise components such as lightning radiation, man-made noise, and so on. Existing models, however, fail to adequately handle these noises which yields observation errors. What is needed is a model that can isolate the essential information from these noises. Linear state space modeling and Kalman filtering have been used in state estimation[8]. Earthquake prediction, however, demands the application of nonlinear non-Gaussian state space modeling because the observed signals are nonlinear and non-Gaussian.

This paper proposes new models to extract earthquake precursors from ELF data. Generalized state space modeling, which includes linear state space modeling as a particular case, and Monte Carlo filter (MCF) are used to our proposed model.

2. OBSERVING ELECTROMAGNETIC RADIATION

2.1 Observation System

This section describes the current observation system. It is important to remove as many noise components as possible when initially collecting the data. For this purpose, the observation window is restricted to the Extremely Low Frequency (ELF) band. Wide band observation might, in general, prove to be more accurate. However, since many noise components lie outside the ELF band, this restriction is reasonable and provides relatively high signal-to-noise ratios.

Given that commercial power supply systems in Japan use either 50 Hz or 60 Hz, we tuned to 223 Hz (a prime number) with 1 Hz bandwidth. We used about 40 observation stations installed throughout Japan. Each observation station has three axial loop antennas with east - west, north - south and vertical orientations. The three antennas observe the variation in magnetic flux densities. The collecting circuits average the received signals over 6 second periods.

2.2 Observed Signal's Feature

Even though the observation stage eliminates many noise sources, the signal still contains several noise components. The dominant background noise is the radiation from tropical lightning, which is reflected between the ionized layer and the surface of the earth. Therefore, all data sets show a strong correlation and a daily variation. As lightning events are common in the tropics, the background noise is assumed to a Gaussian random noise with normal distribution (statistically). There are seasonal trends; about 1 to $2pT/\sqrt{\text{Hz}}$ in the summer, and 0.3 to $1pT/\sqrt{\text{Hz}}$ in the winter (Northern Hemisphere).

3. STATE SPACE MODELING AND MONTE CARLO FILTER

3.1 State space modeling

To extract new knowledge from observed time-series data it is critical that the model matches the target's features. This paper uses an unified solution method based on a state space model. If y_n is a time series of d_y dimensions, the state space model of the linear model is

$$\boldsymbol{x}_n = \boldsymbol{F}_n\boldsymbol{x}_{n-1} + \boldsymbol{G}_n\boldsymbol{v}_n \quad (1)$$

$$\boldsymbol{y}_n = \boldsymbol{H}_n\boldsymbol{x}_n + w_n, \quad (2)$$

where n is time and $\boldsymbol{x}_n$ is a time series of d_x dimensions. $\boldsymbol{v}_n$ and w_n are, respectively, d_v and d_w dimensional white Gaussian noise (WGN) with variance-covariance matrix $\boldsymbol{Q}_n$ and $\boldsymbol{R}_n$. In addition, $\boldsymbol{F}_n$, $\boldsymbol{G}_n$ and $\boldsymbol{H}_n$ are $d_x \times d_x$, $d_x \times d_v$ and $d_y \times d_x$ dimensional matrices respectively. This model can represent various time series models. Furthermore, the state of the model can be estimated by Kalman filtering.

If $\boldsymbol{v}_n$ and $\boldsymbol{w}_n$ follow arbitrary probability distributions, state space modeling would be nonlinear and non-Gaussian and be represented as follows:

$$\boldsymbol{x}_n = F(\boldsymbol{x}_{n-1}, \boldsymbol{v}_n) \tag{3}$$
$$y_n = H(\boldsymbol{x}_n, w_n) \tag{4}$$

where $\boldsymbol{v}_n$ and $\boldsymbol{w}_n$ are WGN according to probability density function $q(v)$ and $r(w)$, respectively. In general, F and H are nonlinear functions. It is known that the probability distribution of the state $p(\boldsymbol{x}_n|\boldsymbol{Y}_j)$ can be estimated recursively as follows:

[one-step-ahead prediction]

$$p(\boldsymbol{x}_n|\boldsymbol{Y}_{n-1}) = \int_{-\infty}^{\infty} q(\boldsymbol{x}_n|\boldsymbol{x}_{n-1}) p(\boldsymbol{x}_n|\boldsymbol{Y}_{n-1}) dx_{n-1} \tag{5}$$

[filter]

$$p(\boldsymbol{x}_n|\boldsymbol{Y}_n) = \frac{r(y_n|\boldsymbol{x}_n) p(\boldsymbol{x}_{n-1}|\boldsymbol{Y}_{n-1})}{p(y_n|\boldsymbol{Y}_{n-1})} \tag{6}$$

[fixed interval smoothing]

$$p(\boldsymbol{x}_n|\boldsymbol{Y}_N) = p(\boldsymbol{x}_n|\boldsymbol{Y}_n) \times \int_{-\infty}^{\infty} \frac{p(\boldsymbol{x}_{n+1}|\boldsymbol{Y}_N) q(\boldsymbol{x}_{n+1}|\boldsymbol{x}_n)}{p(\boldsymbol{x}_{n+1}|\boldsymbol{Y}_n)} dx_{n+1}. \tag{7}$$

where $\boldsymbol{Y}_j$ represents measurement data up to time j:

$$\boldsymbol{Y}_j = \left\{ y_1, y_2, \cdots, y_j \right\}. \tag{8}$$

3.2 Monte Carlo Filter

The MCF was proposed for nonlinear/non-Gaussian models[1]. In the MCF, probability distributions used in state estimation are approximated by m particles as follows:

- prediction
  $\left\{\boldsymbol{p}_n^{(1)}, \cdots, \boldsymbol{p}_n^{(m)}\right\} \sim p\left(\boldsymbol{x}_n|\boldsymbol{Y}_{n-1}\right)$
- filter
  $\left\{\boldsymbol{f}_n^{(1)}, \cdots, \boldsymbol{f}_n^{(m)}\right\} \sim p\left(\boldsymbol{x}_n|\boldsymbol{Y}_n\right)$
- system noise
  $\left\{\boldsymbol{v}_n^{(1)}, \cdots, \boldsymbol{v}_n^{(m)}\right\} \sim q\left(\boldsymbol{v}_n\right)$.

It is not necessary to approximate a distribution of the observation model by particles, because approximate quantities are calculated by substituting observed data and particles into the system model. State estimation is carried out by repeating the following one-step-ahead prediction and filter process:

[one-step-ahead prediction]

Calculate particles $\{\boldsymbol{p}_n^{(1)}, \cdots, \boldsymbol{p}_n^{(m)}\}$ representing the prediction distribution $p(\boldsymbol{x}_n|\boldsymbol{Y}_{n-1})$ using $\{\boldsymbol{f}_{n-1}^{(1)}, \cdots, \boldsymbol{f}_{n-1}^{(m)}\}$ and $\{\boldsymbol{v}_n^{(1)}, \cdots, \boldsymbol{v}_n^{(m)}\}$ as follows:

$$\boldsymbol{p}_n^{(i)} = F\left(\boldsymbol{f}_{n-1}^{(i)}, \boldsymbol{v}_n^{(i)}\right). \tag{9}$$

[filter]

Calculate the likelihood $\alpha_n^{(i)}$ of particle $\boldsymbol{p}_n^{(i)}$ using observation data y_n and observation noise distribution as follows:

$$\alpha_n^{(i)} = p\left(y_n|\boldsymbol{p}_n^{(i)}\right) = r\left(h^{-1}\left(y_n, \boldsymbol{p}_n^{(i)}\right)\right) \tag{10}$$

Calculate particles $\boldsymbol{f}_n^{(i)}$ of filter distribution by resampling particles $\boldsymbol{p}_n^{(i)}$ in accordance with the following probabilities:

$$Pr\left(\boldsymbol{f}_n^{(i)} = \boldsymbol{p}_n^{(i)}\right) = \frac{\alpha_n^{(i)}}{\alpha_n^{(1)} + \cdots + \alpha_n^{(m)}}, i = 1, \cdots, m \tag{11}$$

$p(\boldsymbol{x}_n|\boldsymbol{Y}_{n-1})$ and $p(\boldsymbol{x}_n|\boldsymbol{Y}_n)$ at all time $n = 1, \cdots, N$ can be estimated by calculating, from the initial condition, $p(\boldsymbol{x}_0|\boldsymbol{Y}_0)$, and by repeating the one-step-ahead prediction and filter process.

In addition, MCF can be extended to smoothing in principle. Let $(\boldsymbol{s}_{1|n}^{(i)}, \cdots, \boldsymbol{s}_{n|n}^{(i)})^T$ be instances of the i-th of simultaneous distribution $p(\boldsymbol{x}_1, \cdots, \boldsymbol{x}_n|\boldsymbol{Y}_n)$, smoothing can be realized by resampling all particles of the past $\{(\boldsymbol{s}_{1|n-1}^{(i)}, \cdots, \boldsymbol{s}_{n-1|n-1}^{(i)}, \boldsymbol{p}_n^{(i)})^T, i = 1, \cdots, m\}$ by the same weight used in the case of filtering, where ^{T} represents transposition.

4. THE MODEL OF OBSERVED DATA

4.1 Time-varying variance model

Fig.1 shows the level of EM radiation captured over a 10 day period up to February 19th in 2001, at Nannoh station in Gifu. The horizontal axis represents days, and the vertical axis is the level of EM radiation. An earthquake of magnitude Mj 5.3 occurred on the 23rd of February 2001 at latitude 34.8 north and longitude 137.5 east. A precursor signal was observed between 16th and 19th.

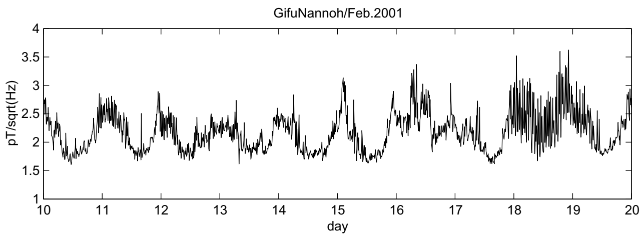

Figure 1: Raw data captured at Nannoh station in Gifu.

The observed data contains some extemporaneous noises, most of which are due to human activities or the observation system. The one-dimensional random walk model used to reduce these outliers is given by

$$t_n = t_{n-1} + v_n \tag{12}$$
$$y_n = t_n + w_n \tag{13}$$

. The Cauchy distribution, which is a heavy-tailed distribution, is selected for observation noise:

$$r(w) = \frac{\tau}{\pi(w^2 + \tau^2)} \tag{14}$$

where τ is a scale parameter. In addition, the distribution of the system noise is also assumed to follow a Cauchy distribution because the observed signal jumps when the precursor occurred. Thus the state space model can be represented as a linear Gaussian state space model:

$$\boldsymbol{x}_n = \boldsymbol{F}\boldsymbol{x}_{n-1} + \boldsymbol{G}\boldsymbol{v}_n \tag{15}$$
$$y_n = \boldsymbol{H}\boldsymbol{x}_n + w_n \tag{16}$$

where $\boldsymbol{x}_n = t_n$, $\boldsymbol{F} = \boldsymbol{G} = \boldsymbol{H} = 1$, $\boldsymbol{v}_n = v_n$.

Furthermore, the variance of the observed signal clearly increases after the 17th in Fig.1. Therefore, time-varying variance modeling based on the self-tuned state space model is used to deal with the change in the variance.

In the self-tuned state space model, unknown parameters, which are contained within the state vector, can be estimated as well as the state. To be more precise, the parameter vector $\theta_n = [\,\log\tau_n^2 \;\; \log\sigma 2_n\,]^T$ is added to state vector $\boldsymbol{x}_n$ as follows:

$$z_n = [\; \boldsymbol{x}_n^T \;\; \theta_n^T \;]^T. \tag{17}$$

This allows state estimation to become possible by changing the transition matrices in accordance with new state vector z_n as follows:

$$\boldsymbol{F} = \left[\begin{array}{c|cc} 1 & 0 & 0 \\ \hline 0 & 1 & 0 \\ 0 & 0 & 1 \end{array}\right], \boldsymbol{G} = \left[\begin{array}{c|cc} 1 & 0 & 0 \\ \hline 0 & 1 & 0 \\ 0 & 0 & 1 \end{array}\right], \tag{18}$$

$$\boldsymbol{H} = [\; 1 \;|\; 0 \;\; 0 \;], \boldsymbol{v}_n = \left[\; v_n \;\; v_{\tau^2} \;\; v_{\sigma^2} \;\right]. \tag{19}$$

By using the self-tuned state space model, parameter estimation requires only one filtering and smoothing step.

In addition, a part of the self-tuned state space model is a stochastic difference model:

$$\theta_n = \theta_{n-1} + \boldsymbol{u} \tag{20}$$

where $\boldsymbol{u} = [\; v_{\tau^2} \;\; v_{\sigma^2} \;]^T$. Therefore, this model can estimate the variation even when parameter θ changes with time.

The trend of the observed signal, given by the self-tuned state space model, is shown in Fig.2. Additionally, estimated observation noise is shown in Fig.3.

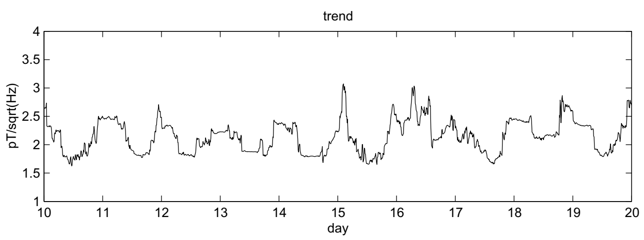

Figure 2: Smoothed results of self-tuned state space model.

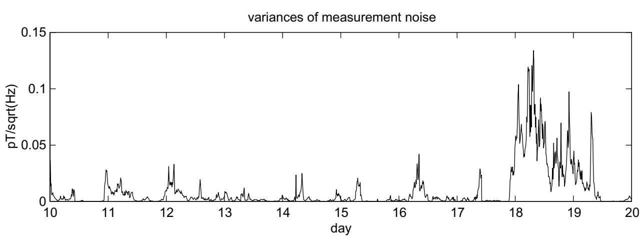

Figure 3: The variance of the observation noise.

Note that the variance surges at the beginning of the 18th and is large until the middle of the 19th. On the other hand, the trend in Fig.2 changes widely independent of the variance.

4.2 Daily variation removal

Trend estimation based on the self-tuned state space model was described in the above section. However, the observed signal still contains undesired signals. One of them, called global noise, is due to lightning in the equatorial region. This noise shows a daily variation due to ionospheric fluctuation. To express this noise, a term representing ionospheric effectI_n is added to equation(13) as follows:

$$\begin{aligned} y_n &= t_n + I_n + w_n & (21)\\ t_n &= t_{n-1} + v_{n1} & (22)\\ I_n &= ai_n + b & (23) \end{aligned}$$

where i_n represents the ionosphere's height. This height is calculated using IRI(International Reference Ionosphere).

This extended model is described as the following state space model:

$$\boldsymbol{x}_n = [\, t_n \;\; a \;\; b \,]^T, \;\; \boldsymbol{H}_n = [\, 1 \;\; i_n \;\; 1 \,], \tag{24}$$

$$\boldsymbol{F} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \;\; \boldsymbol{G} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{25}$$

The corresponding self-tuned state space model is

$$\begin{aligned} \begin{bmatrix} \boldsymbol{x}_n \\ \log\tau_n^2 \\ \log\sigma_n^2 \end{bmatrix} &= \begin{bmatrix} \boldsymbol{F} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_{n-1} \\ \log\tau_{n-1}^2 \\ \log\sigma_{n-1}^2 \end{bmatrix} \\ &\quad + \begin{bmatrix} \boldsymbol{G} \\ 0 \\ 0 \end{bmatrix} \boldsymbol{v}_n, & (26) \\ y_n &= [\; \boldsymbol{H}_n \;\; 0 \;\; 0 \;] \begin{bmatrix} \boldsymbol{x}_n \\ \log\tau_n^2 \\ \log\sigma_n^2 \end{bmatrix} + w_n. & (27) \end{aligned}$$

Fig.4 shows the trend as determined by this model and the observed signal. Note that the daily variation disappeared, especially at midday on the 18th. In addition, the leading edge of the precursor signal, which was observed to commence on the 18th, is precisely extracted.

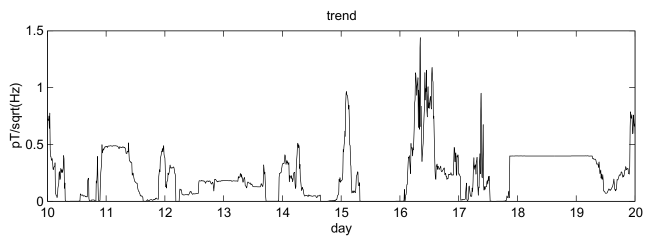

Figure 4: Trend component estimated by proposed model.

5. CONCLUDING REMARKS

A stochastic model for extracting earthquake precursor signals has been proposed. Automatic outlier removal and identification of trend swings were made possible by using a self-tuned state space model and MCF (Monte Carlo Filter).

In addition, a term representing the ionospheric effect was added to the random walk model. This term depends on the ionosphere's height, which can be obtained from IRI. Smoothed results verified the usefulness of this proposed model.

One remaining problem is to remove the ionospheric effect (global noise) more completely.

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