Fault diagnosis of nuclear facilities based on hidden Markov model

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Abstract

Due to the complex structure of nuclear facilities in a high irradiation environment, people are hard to approach it, In view of these situation a fault diagnosis method based on HMM (Hidden Markov Model) of capturing the audio signal while facilities are operating is proposed. With the strong modelling ability, HMM can be applied to analysing such as audio signal non-stationary time signal. By using this method, the original mechanical structures of nuclear facilities are not destroyed. The proposed sensors were needed as few as possible by the whole diagnosis system and which has a simple structure, low cost structure, the fault diagnosis rate is high and so on. State monitoring and fault diagnosis system of complex nuclear power equipment can timely and effective to provide running status and potential failure information for operating personnel, which has a vital significance for the safe and reliable operation of nuclear power equipment.

Keywords: nuclear facilities, Hidden Markov Model (HMM), fault diagnosis

1 Introduction

In March 2011, the nuclear leakage of the Fukushima nuclear power plant was caused by magnitude 9.0 earthquake, which was a major nuclear accident since the nuclear accident of US Three Island nuclear power station and the Chernobyl accident of the former Soviet Union happened in April 1986. The nuclear accident of the Fukushima as the major nuclear accident in the process of the peaceful use of nuclear power, had caused all countries to re-evaluate nuclear power development plan, what's more, human beings had put forward new reflection on nuclear safety, economy and society effect.

Due to the complex structure of nuclear facilities, strong continuity in production, high security requirements, under high temperature and irradiation environment, so the nuclear accident would cause severe economic losses and serious social consequence no matter which fault caused the nuclear accident [1]. Monitoring running condition and fault diagnosis of complex nuclear power equipment would be usually use traditional threshold method: mainly through preset threshold of monitoring parameters, the system send out alarm signal or take protective action when the monitored amount was more than the prescribed threshold, while the fault may not be able to curb [2, 3]. Therefore, research a fault diagnosis based on HMM of capturing the audio signal and fault diagnosis system had great significance for improving the safety and reliability of the nuclear energy development and utilization.

2 Basic theory and algorithm of the HMM

Baum and Peterie put forward the HMM in 1966, Baker and Jelinek had achieved great success in applying speech recognition. In recent years, more and more attention was paying on the HMM, which had been successfully used in speech recognition, molecular biology, image segmentation, fault diagnosis and many other fields [4, 5].

2.1 BASIC CONCEPT OF THE HMM

The HMM is a double stochastic process. It is using the Markov Chain Model to describe changes of the statistical characteristics of the signal. While these changes are indirectly describe by the observed sequence, it can be divided into two-layer structure - hidden state layer and observed layer, Markov Chain lays in hidden state layer, while the observed layer is the output of the hidden state layer [6, 7].

HMM could be short for $\lambda = (\pi, A, B)$, among them:

1) π stand for initial state probability vector;

2) A is state transition probability matrix, each element a_{ij} of A represents the probability of the HMM transfer from state θ_i to state θ_j .

3) B is confusion matrix, each element b_{jk} of B represents the probability of the HMM appears the observed value V_k as its state is θ_j at t time.

The HMM describe the stochastic process through different distribution of π, A and B. Each probability of state transition matrix and confusion matrix is not related

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to the time, so these matrix don't change over time when the system is evaluating.

2.2 TRAINING ALGORITHM OF THE HMM

2.2.1 Forward-Backward algorithm

The main idea of Forward-Backward algorithm is through the Forward and Backward iterative process to calculate two instrumental variable, which is the value of the Forward and Backward variables. In a given observed sequence $O=\{o_1,o_2,...,o_T\}$ and mode λ. It is effective to use Forward-Backward algorithm to calculate and observe probability $P=(O/\lambda)$ of variable sequence O under given model.

2.2.2 The Viterbi algorithm

The Viterbi algorithm provides an effective method to analyse the observed sequence of the HMM and capture the most likely sequence of hidden state. This algorithm use recursion to reduce amount of calculation and use the whole sequence to do judgment, thus to make good analysis of sequence that contains interference. We need to define the instrumental variables $\psi_t(i)$ and $\delta_t(i)$ for Viterbi algorithm, among them:

$$\delta_t(i)=\max_{q_1,...,q_{t-1}} P\left(q_1,...,q_t,q_t=\theta_i,o_1,...,o_t/\lambda\right). \tag{1}$$

The basic process of algorithm is as follows:
(i) initialization:

$$\delta_1(i)=\pi_i b_i(o_1),1\le i\le N, \tag{2}$$

$$\psi_1(i)=0,1\le i\le N. \tag{3}$$

(ii) iterations:

$$\delta_t(i)=\max_{1\le i\le N}\left[\delta_{t-1}(i)a_{ij}\right]b_j(o_t),2\le t\le T,1\le j\le N, \tag{4}$$

$$\psi_t(j)=\arg\max_{1\le i\le N}\left[\delta_{t-1}(i)a_{ij}\right],1\le t\le T,1\le j\le N. \tag{5}$$

(iii) termination:

$$P^*=\max_{1\le i\le N}\left[\delta_T(i)\right], \tag{6}$$

$$q_T^*=\arg\max_{1\le i\le N}\left[\delta_T(i)\right]. \tag{7}$$

(iv) finding the optimal:

$$q_t^*=\psi_{t+1}\left(q_{t+1}^*\right),t=T-1,\mathrm{T}-2,...,1. \tag{8}$$

2.2.3 Baum-Welch algorithm

Baum-Welch algorithm that use maximum likelihood criterion is currently the main training methods used for the HMM. Its concrete ideas is to estimate one of the most appropriate HMM based on an observed sequence and a set of hidden state, therefore, it is to determine the most appropriate description of a triple (π, A, B) for a known sequence.

To define $\xi_t(i,j)$ for a given training sequence (observation sequence) O and model λ, its probability of Markov Chain in the state θ_i at time t and in the state θ_j at time $t+1$, namely:

$$\xi_t(i,j)=p(q_t=\theta_t,q_{t+1}=\theta_j|O,\lambda)= \\ \{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)\}/p\{O|\lambda\}, \tag{9}$$

where $\alpha_t(i)$ is the forward variable and $\beta_t(i)$ is the backward variable. Then, to define probability of Markov Chain in the state θ_i at time t under the given model $\gamma_t(i)$ is:

$$\gamma_t(i)=p(q_t=\theta_i\,|\,O,\lambda)=\sum_{j=1}^{N}\xi_t(i,j)=\alpha_t(i)\beta_t(i)/P(O\,|\,\lambda). \tag{10}$$

Then we can get revaluation formula of the HMM is:

$$\bar{\pi}_i=\gamma_1(i), \tag{11}$$

$$\bar{a}_{ij}=\sum_{t=1}^{T-1}\xi_t(i,j)\Big/\sum_{t=1}^{T-1}\gamma_t(i), \tag{12}$$

$$\bar{b}_{ij}=\sum_{t=1,O_t=v_k}^{T}\gamma_t(j)\Big/\sum_{t=1}^{T}\gamma_t(i). \tag{13}$$

3 State monitoring and fault diagnosis of complex nuclear power equipment

State monitoring and fault diagnosis system collect related characteristics of monitoring device by sensors, then transmitted to the host computer after appropriate processing, it provided on-line state analysis and fault diagnosis by using computer of high-speed data processing. State monitoring and fault diagnosis system of complex nuclear equipment could timely and effectively provide information of running state and potential failure to operating personnel, which had a vital significance for the safe and reliable operation of complex nuclear equipment.

3.1 RESEARCH OF FAULT DIAGNOSIS TECHNOLOGY OF COMPLEX NUCLEAR POWER EQUIPMENT

At present, all countries have done a lot of research on technology of state monitoring and fault diagnosis of nuclear station, also have obtained certain achievement. The United States, Japan, France, Germany and other developed countries had reached a leading position in the research of state monitoring and fault diagnosis. Japan Atomic Energy institute developed DISKET, which was a typical expert system based on knowledge base, the system had passed experiment verification on the pressurized water rector. France took six years to develop a SINDBAD system after the accident of US Three Island nuclear power station, the system was mainly used to do some common fault forecast and diagnosis of the plant by using pattern recognition of process and expert system. Norwegian Fantoni Paolo F and Mazzola Alesandro realized to confirm multiple failure signal of boiling water reactor by using autocorrelation neural network. Canadian Lege RP and Garland Wm J used the cumulative total control graph and neural network for fault detection and diagnosis of heat transport system of CANDU reactor. The Peach Bottom plant of America adopt “advanced real-time state monitoring system” for on-line monitoring, which greatly improved the monitoring crack of circulated pump shaft, it was helpful for fault diagnosis through correlation analysis of vibration, pressure, temperature and other parameters [1, 8, 9].

Some domestic Institute also had done a lot of research work on condition monitoring and fault diagnosis of nuclear power plants. The Tsinghua university developed a fault diagnosis expert system of secondary circuit is relative mature, the system had passed the simulator verification. Harbin Institute of Technology carried out a research of intelligent technology on fault diagnosis of nuclear power plant, which was based on neural network; the safety supervision plate system used by Daya Bay nuclear power plant, with fault identification, actuator supervision, selection of accident regulation, condition monitoring of power station and other functions.

3.2 ANTI-RADIATION SENSOR TEST

The fault diagnosis system need to collect vibration, noise, temperature of the system under test by sensors, while there are not mature products to work in high radiation environment for long term operation, sensors need to adopt high resistance strengthening technique, which limited the sort of monitoring information. Therefore, it was completely different between signal monitoring in high radiation environment and regular environment, because the monitoring information of high radiation environment is greatly reduced. Research results of this project group show that the sound detection method could get more operation information of equipment’s, and anti-radiation properties of acoustic sensor was very excellent.

CMOS (Complementary Metal-Oxide Semiconductor) image sensor is highly integrated, the pixel array, the timing control circuit, the ADC, the signal processing circuit camera system required for the various functional modules are integrated into a single chip, such as seen in Figure 1 [10].

Common camera with CMOS image sensor, which would completely fail under an environment of ^{60}Co as radiation source and dose rate is 15GY/h for seven minutes. Because gamma rays, the image would randomly appear a lot of flake when the camera expose to the radiation environment, the number of flake gradually increased over time. The whole image was full of “snow” after 30 seconds’ exposure. As gamma rays could cause an irreversible destruction to the CMOS image sensors, the camera was unable to work when the radiation time reaches 7 minutes. The total dose of the whole process was 1.75GY.

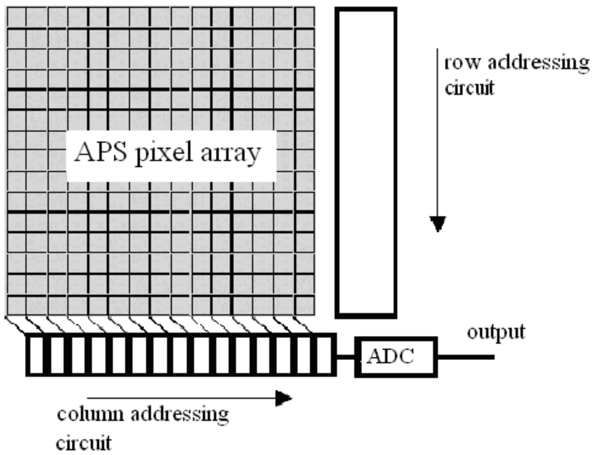

FIGURE 1 CMOS image sensor

FIGURE 2 Not exposed to radiation

Radiation effects lead to performance degradation of CMOS image sensors, mainly due to radiation were trapped charge and interface state generation. The interaction of γ rays and the silicon material to produce secondary electrons by Compton scattering and electron traps and hole traps in the CMOS image sensor. SiO_2 layer of oxide trapped charge (fixed positive charge), the Si-SiO_2 interface at some interface traps. These traps to the Si-SiO_2 interface potential change, resulting in a MOS structure threshold voltage V_{TH} or flat-band voltage V_{FB} move along the voltage axis. The V_{TH} drift and bias voltage is related to positive bias gate voltage CMOS image sensor, the fixed positive charge and interface trap formation becomes faster, the photodiode of the N+ region to capture the fixed positive charge, and V_{TH} decreases. This had led to the depletion region thickness decreases, the more electrons were able to enter the potential well of the photodiode, the density of the dark current or leakage current of the diode increases, the irradiation induced electron - hole pair concentration with the increase in gamma-ray fluence, leading to the dark current increases with the fluence. The white spots appeared in Figure 3 were caused by the increase in dark current.

FIGURE 3 30 seconds after exposure

Maximum direct output voltage signal peak of dynamic sound sensor can reach 300mV. If signal preamplifier circuit is installed in the irradiation room to enlarge the signal, which is then passed through the cable back to the computer, complexity of experiment will increase. And the more, when the signal changes, there is no way to tell it is the result of sensor failure or preamplifier circuit failure. Taking these factors into account, this experiment chooses to transfer coil sound sensor output signal directly through a 40m cable to the PC outside of the irradiation room, which is read by the sound card and the experimental data is also recorded by the sound card. The experiment used a double-shielded cable, making the space electromagnetic interference to reduce the impact. The experiment was performed at Hunan Academy of Agricultural Sciences Radiation Center, ^{60}Co was used as the radiation source.

Anti-radiation properties of the acoustic sensor were several magnitudes higher than the CMOS image sensor. Selecting silicon micro-acoustic sensor SPM0204 under the environment of the radiation source ^{60}Co and dose rate of 1.5KGY/h, the sensor would fail in 90 minutes of exposure with the total dose rate of 2250GY. Figures 4 and 6 show the time domain waveform, Figures 5 and 7 show the frequency domain wave, the incentive source was common ringer. The failure mechanism of sensors remain to be further study, we preliminary estimated that the amplifying circuit of the silicon micro-acoustic sensor and the quiescent point were damaged by the irradiation.

Dynamic acoustic sensors for mechanical structure. According to the relevant literature, the permanent magnet is able to tolerate the radiation dose of 100000 GY with no significant changes in its magnetic properties. There are no electronic components, which is not resistant to irradiation within the sensor and the sensor can still work properly under high doses of radiation.

If we correctly select anti-radiation sensor it should provide powerful hardware support for fault diagnosis. It is very common to use HMM for voice signal analysis and fault diagnosis.

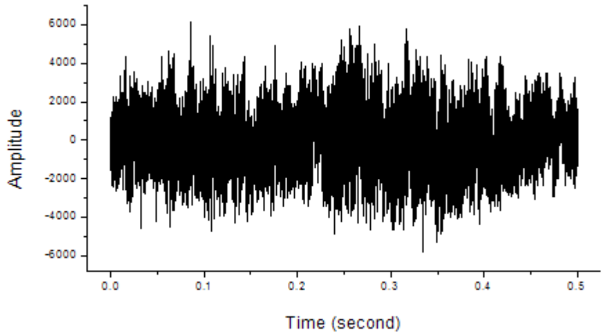

FIGURE 4 time domain waveform (Not exposed to radiation).

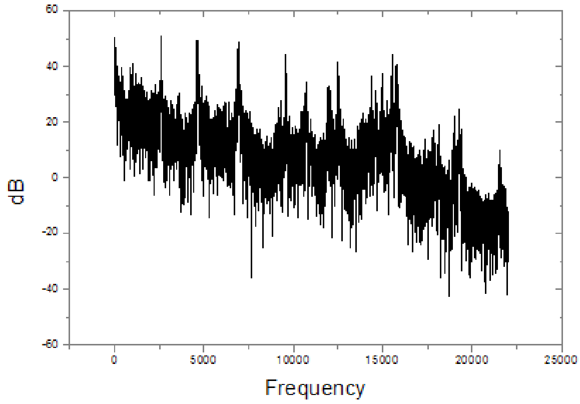

FIGURE 5 frequency domain wave (Not exposed to radiation).

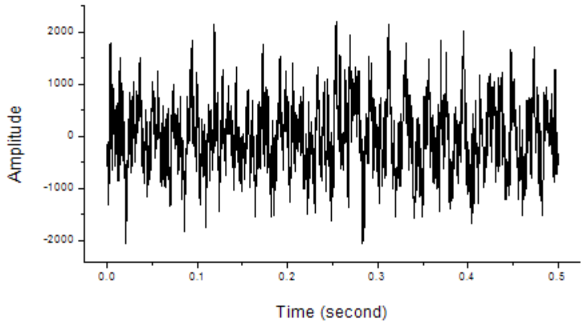

FIGURE 6 Time domain waveform (90 minutes after exposure)

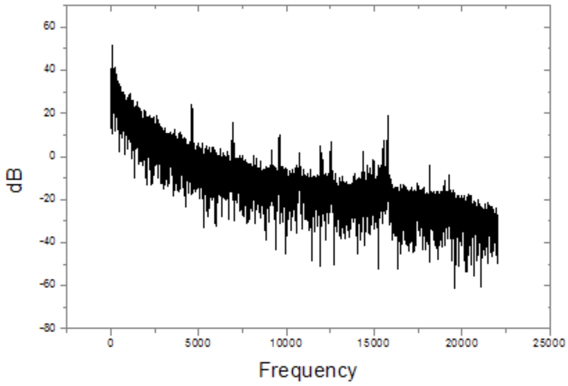

FIGURE 7 frequency domain wave (90 minutes after exposure)

3.3 APPLICATION OF THE HMM IN FAULT DIAGNOSIS OF COMPLEX NUCLEAR POWER EQUIPMENT

The HMM is suitable for the dynamic process modelling of time series, which can solve problem of random uncertainty, especially for analysis of non-stationary and poor repeated sequence. At the same time, it can handle sequence of arbitrary length in theory. These characteristics have a strong pertinence for state monitoring and fault diagnosis of complex nuclear power equipment with characteristics of reliability requirements, informative, non-stationary and poor repeated reproducibility.

A fault diagnosis method based on HMM of capturing the audio signal while the nuclear facilities are operating, which just need to choose a place with a small dose rate but can clearly collect voice signal while the device are operating to place sensors around the nuclear power equipment. To extend the working life of sensors by shielding device.

The audio signal will transmit to the host computer for fourier transform after AD transform, to analyse frequency domain and extract the characteristic of audio signals. Extracting various fault of equipment and establishing fault database, the sound signals of operating equipment will match the information in the database, if it can match, then the device may appear the corresponding fault. Fault diagnosis technology is shown in Figure 8.

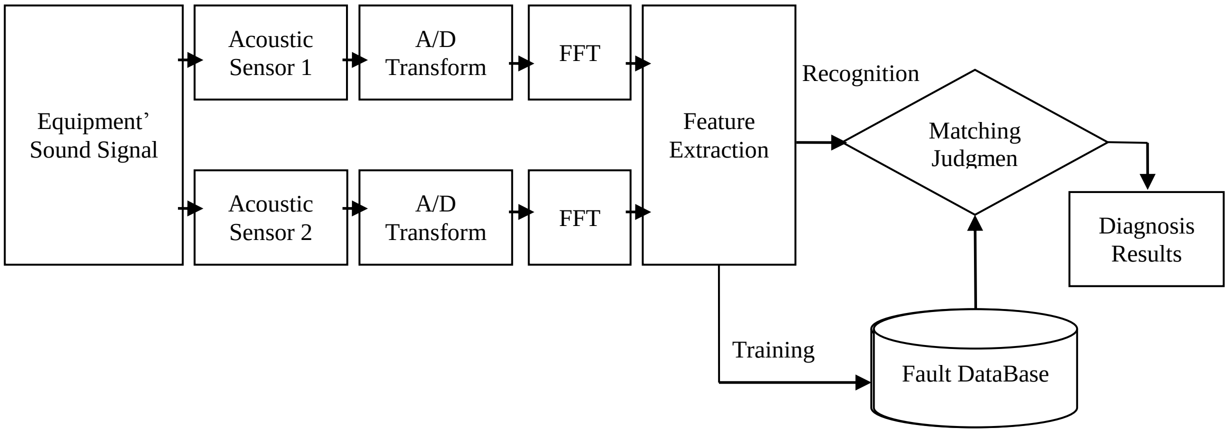

FIGURE 8 System Block Diagram of Fault Diagnosis Technology

4 Conclusion

A fault diagnosis method based on HMM of capturing the audio signal while the nuclear facilities are operating is proposed. Resistance to radiation in the CMOS image sensor in the high radiation environment and moving-coil sound sensor performance study and experimental validation of the mechanical structure of a moving coil sound sensor resistance to radiation performance than the highly integrated semiconductor devices. The advantage of real-time monitoring of voice signal compared with real-time monitoring of video signal lay in anti-radiation of acoustic sensor is obviously stronger than CMOS image sensor. Adopt the method of fault diagnosis of nuclear power equipment with the characteristics of less sensors, high fault diagnosis.

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