Research on Fault Prediction Model and Algorithm of Communication System Based on HMM

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Abstract—The hidden model is a typical state prediction model, which has been widely used in the field of industrial production state monitoring in recent years. This paper analyzes the basic principle of HMM, puts forward three basic algorithms for fault prediction of communication system, analyzes the structural properties of the algorithm, puts forward the application model architecture of HMM, and provides the theoretical basis for constructing the fault prediction system based on HMM model.

Keywords—hidden model; communication system; fault prediction; algorithm

I. INTRODUCTION

As a statistical model of signal dynamic time series, Hidden Model(HMM) is very suitable to deal with continuous dynamic signals, and it has solid theoretical foundation, learning function and adaptive ability, and can acquire knowledge to monitor system state through training. The HMM, proposed by Baum and others in the late 1960s, developed gradually in the mid-1980s and began to be applied to signal processing and so on. In recent years, many scholars devoted to Hidden Model in the industrial field of state monitoring and fault classification, have achieved good results. In view of the similar properties of communication system and industrial state monitoring system, we can try to use HMM in state monitoring and health management of communication system.

II. THE APPLICATION PRINCIPLE OF HMM

HMM is a probabilistic model describing the statistical characteristics of stochastic processes. It is developed from chain. chain is a random process of discrete variables. At different times, the system is only in one state, each state corresponds to an observation value, the transition between States has the corresponding transfer probability, and the state transfer probability only depends on the current state, independent of the past state. Unlike the chain, HMM is a double random process, one is a chain with a finite state, describing the transfer of state, and another describes the statistical correspondence between each state and observed values. Not only is the transfer between states random, but the observation value of each state is also random. You can only see the observation value from the observer's point of view, not directly, but you can perceive the state through a random process

The Hidden Model mainly solves three kinds of problems. One is to assess the problem. Solve the size of the probability of producing a specific observation sequence by a HMM, that is, given the model λ and the observation sequence O , the calculation probability $P(O|\lambda)$ is usually calculated by the forward-backward algorithm. The second problem is decoding. For a given model λ and an observed sequence O , the most likely state sequence Q is usually implemented by Viterbi algorithm. Third is the question of study. Solve the problem of how to learn a parameter of HMM by a set of observation sequences in the maximum likelihood sense, namely the training of model. For a given observation sequence O , learn to get the model $\lambda = (\pi, A, B)$ to $P(O|\lambda)$ the maximum, usually trained by Baum-Welch algorithm.

III. BASIC ALGORITHM OF HMM

The assessment, decoding and learning problems described above can be addressed using forward-backward, Viterbi and Baum-Welch algorithms, respectively.

A. Forward-backward Algorithm

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For a fixed state sequence $Q = \{q_1, q_2, \dots, q_T\}$ could be described as follow:

$$P(O|Q, \lambda) = \prod_{i=1}^T P(o_i | q_i, \lambda) = b_{q_1}(o_1) b_{q_2}(o_2) \cdots b_{q_T}(o_T) \quad (2-5)$$

$$b_{q_t}(o_t) = b_{jk} | q_t = S_j, o_t = V_k \quad 1 \leq t \leq T.$$

For given λ , probability of generating Q could be described as follow:

$$P(Q | \lambda) = \pi_{q_1} a_{q_1 q_2} a_{q_2 q_3} \cdots a_{q_{T-1} q_T}$$

The calculated probability is:

$$\begin{aligned} P(O | \lambda) &= \sum_{i=1}^T P(o_i | Q, \lambda) P(Q | \lambda) \\ &= \sum_{q_1, q_2, \dots, q_T} \pi_{q_1} b_{q_1}(o_1) a_{q_1 q_2} b_{q_2}(o_2) \cdots a_{q_{T-1} q_T} b_{q_T}(o_T) \end{aligned}$$

The calculation of the above equation increases exponentially by an order of $2TN^T$ magnitude. Therefore, this method can not be used to solve the $P(O | \lambda)$, so Baum proposed forward-back algorithm.

1) *Forward algorithm*: The forward variable could be definite as follow:

$$\alpha(i) = P(o_1, o_2, \dots, o_t, q_t = S_i | \lambda) \quad 1 \leq t \leq T$$

This can be done in three procedures:

Firstly is initialization, could be described as follow:

$$\alpha(i) = \pi_i b_i(o_1) \quad 1 \leq i \leq N$$

Secondly is recursive process, could be described as follow:

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^N \alpha_{t(i)} a_{ij} \right] b_j(o_{t+1}) \quad 1 \leq t \leq T-1, 1 \leq j \leq N$$

Thirdly is end, could be described as follow:

$$P(O | \lambda) = \sum_{i=1}^N \alpha_T(i)$$

Then $b_j(o_{t+1}) = b_{jk} \mid o_{t+1} = V_k$

The forward algorithm makes the computation become $N(N+1)(T-1) + N$ submultiplication and $N(N-1)(T-1)$ subaddition, and greatly reduces the computation.

2) *Backward algorithm*: The backward variable could be definite as follow:

$$\beta_t(i) = P(o_{t+1}, o_{t+2}, \dots, o_T \mid q_t = \theta_i, \lambda) \quad 1 \leq t \leq T-1$$

Then $\beta_T(i) = 1$

This also can be done in three procedures:

Firstly is initialization, could be described as follow:

$$\beta_T(i) = 1 \quad 1 \leq i \leq N$$

Secondly is recursive process, could be described as follow:

$$\begin{aligned} \beta_t(i) &= \sum_{j=1}^N a_{ij} b_j(o_{t+1}) \beta_{t+1}(j) \\ t &\leq T-1, T-2, \dots, 1, \quad 1 \leq j \leq N \end{aligned}$$

Thirdly is end, could be described as follow:

$$P(O | \lambda) = \sum_{i=1}^N \beta_1(i)$$

The computation of the backward algorithm is about order of N^2T magnitude.

B. Viterb Algorithm

Set $\delta_t(i)$ to time T along a path $q_1, q_2, \dots, q_t$, and $q_t = \theta_i$, then could generate the maximum probability of $q_1, q_2, \dots, q_t$ is:

$$\delta_t(i) = \max P(q_1, q_2, \dots, q_t, q_t = \theta_i, o_1, o_2, \dots, o_t \mid \lambda)$$

The best state sequence Q^* is obtained by three procedures:

Firstly is initialization, could be described as follow:

$$\begin{cases} \delta_i(i) = \pi_i b_i(O_1) & 1 \leq i \leq N \\ \varphi(i) = 0 & 1 \leq i \leq N \end{cases}$$

Secondly is recursive process, could be described as follow:

$$\begin{cases} \delta_t(j) = \max_{1 \leq i \leq N} [\delta_{t-1}(i) a_{ij} b_j(O_t)] & 2 \leq t \leq T, 1 \leq j \leq N \\ \varphi_t(j) = \arg \max_{1 \leq i \leq N} [\delta_{t-1}(i) a_{ij}] & 2 \leq t \leq T, 1 \leq j \leq N \end{cases}$$

Thirdly is end, could be described as follow:

$$\begin{cases} P^* = \max_{1 \leq i \leq N} [\delta_T(i)] \\ q_T^* = \arg \max_{1 \leq i \leq N} [\delta_T(i)] \end{cases}$$

The order of status obtained is as follows:

$$q_t^* = \varphi_{t+1}(q_{t+1}^*) \quad t = T-1, T-2, \dots, 1$$

The recursion process is the most important part. When the optimal state sequence $q_1, q_2, \dots, q_t$ is given from Observation value set $o_1, o_2, \dots, o_t$, it is used to find the optimal state sequence when the part observation sequence $q_1, q_2, \dots, q_t, q_{t+1}$ adds a moment. As a result, the following approximation $P(Q^* | O, \lambda) \gg \sum_{\forall Q \neq Q^*} P(Q | O, \lambda)$ is established:

$$P^* \approx \sum_{\forall Q} P(Q | O, \lambda)$$

Therefore, the Viterbi algorithm can also approximate calculation $P(O | \lambda)$.

C. Baum-Welch Algorithm

The algorithm mainly solves the training of HMM parameters by observation sequence, making the maximum $P(O | \lambda)$. The idea of Baum-Welch algorithm is to give an initial model λ_0 , could obtain $P(O | \lambda_0)$ by the forward-backward algorithm and the observation sequence O based on λ_0 , then to get the new model λ . If $P(O | \lambda) - P(O | \lambda_0) < \epsilon$, parameters by maximizing the expected value, indicates that the training has achieved the desired effect, the algorithm ends. Otherwise, $\lambda = \lambda_0$, the repetitive training will continue until it converges. The algorithm is described in detail as follows:

Derived from the previously defined forward and backward variables as follow:

$$P(O | \lambda) = \sum_{i=1}^N \sum_{j=1}^N \alpha_i(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j) \quad 1 \leq t \leq T-1$$

Due to the limited training sequence given, the best method for parameter finding can not be obtained. Baum-Welch takes advantage of recursive processes to get bigger $P(O | \lambda)$, and get the best parameters.

Given training O and models λ . The probability that the chain is in a S_i state and is in a state S_j at a time $t+1$, $\xi_t(i, j)$ could be definite as follow:

$$\xi_t(i, j) = P(O, q_t = S_i, q_{t+1} = S_j | \lambda)$$

This leads to:

$$\xi_t(i, j) = [\alpha_i(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)] / P(O | \lambda)$$

Could also leads to:

$$\xi_t(i) = P(O, q_t = S_i | \lambda) = \sum_{j=1}^N \xi_t(i, j) = [\alpha_i(i) \beta_i(i)] / P(O | \lambda)$$

Then the expectation of the number of times the state S_i is

transferred could be described $\sum_{t=1}^{T-1} \xi_t(i)$, and the expectation of the number of times the state is transferred from S_i to S_j , could be described $\sum_{t=1}^{T-1} \xi_t(i, j)$. The Baum-Welch revaluation formula follows:

$$\begin{cases} \hat{a}_{ij} = \sum_{t=1}^{T-1} \xi_t(i, j) / \sum_{t=1}^{T-1} \xi_t(i) \\ \hat{b}_{jk} = \sum_{\substack{t=1 \\ o_t = V_k}}^{T-1} \xi_t(i, j) / \sum_{t=1}^{T-1} \xi_t(j) \\ \hat{\pi}_i = \xi_1(j) \end{cases}$$

Model $\lambda = (\pi, A, B)$ update to $\hat{\lambda} = (\hat{\pi}, \hat{A}, \hat{B})$. Baum proved $P(O | \hat{\lambda}) \geq P(O | \lambda)$ that the revalued parameters can better describe the observation sequence O , from which time to train until the convergence condition is met, the best model parameters of HMM are obtained.

IV. ANALYSIS OF FAULT FORECAST MODEL OF COMMUNICATION SYSTEM BASED ON HMM

In the process of state monitoring and diagnosis of communication system, the state of the system is very difficult to be directly observed. What can be detected is often some signals symptoms corresponding to the state of the communication system.

Usually in the state diagnosis of communication system, the state can be divided into two categories, that is, positive normality and failure state. In fact, the state of most communication systems from normal to fault is a slow process, its health condition is gradually declining. If the change of the fault can be studied in detail and given the corresponding intermediate state, the state of communication systems can be

more truly reflected. So between normal state and fault state, there can also be a breakdown of the intermediate fault state. These intermediate faults can not be directly observed and need to be inferred from the observed symptoms.

The fault degree of the communication system is that the change from normal to fault state is irreversible with the deepening of the time of use. Therefore, HMM of left and right type is used to monitor and diagnose the state of the communication system. The application model could be described as figure1.

FIGURE 1. APPLICATION MODEL STRUCTURE OF COMMUNICATION SYSTEM FAULT PREDICTION

In Figure 1, the state of the communication system is divided into four types: positive normality(0), weak failure(1), intermediate failure(2), and complete failure(3). The intermediate failure state consists of two classes: State 1 and state 2. $a_{ij} (i, j = 0, 1, 2, 3)$ represents a transfer probability value between states, $O_k (k = 0, 1, 2, 3)$ representing the sequence of data observed in various states, that is, a fault symptom.

In most cases the choice is not important, and the B matrix is most important because it is directly related to the output observation symbol. State transfer probability array A can reflect process state sequence correlation information, which is important for some sequence-related modeling problems. In most cases, the initial parameter of A and π is set to uniform distribution or non-zero random number. The communication system is always in normal working condition at the time of initial work or operation. The initial state probability parameter in the model parameter is set to $\pi = [1 \ 0 \ 0 \ 0]$.

Then the state transfer matrix could be described as follow:

$$A = \begin{bmatrix} a_{00} & a_{01} & 0 & 0 \\ 0 & a_{11} & a_{12} & 0 \\ 0 & 0 & a_{22} & a_{23} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

It is shown that the model structure of the left-right HMM can reflect the irreversibility of the fault development and eventually develop into a complete fault.

Usually, the HMM model can be distinguished from the continuous HMM (CHMM) model and the discrete HMM

model(DHMM). In this paper, the discrete hidden Markov model is adopted, in view of the discrete characteristic of the circuit fault signal of the communication system. The biggest difference between DHMM and CHMM is parameter B. The B matrix of DHMM is a probability matrix. The observation data sequence is composed of a series of discrete vectors. For left-right HMM, it is not possible to train the model using a single observation sample sequence because the transient nature of the internal state of the model allows only a few observations for each state. So reliable model parameters need to be trained by multiple observation data sequences. The evaluation formula of Baum-Welch algorithm must be amended when using multiple observation sequences to train HMM. There are K order of observation as follows:

$$O = [O^{(1)}, O^{(2)}, \dots, O^{(K)}]$$

It indicates that $O^{(k)} = [O_1^{(k)}, O_2^{(k)}, \dots, O_{T_k}^{(k)}]$ is the length of the K observation sequence is generally set to equal length observation sequence, that is, all $T_k = T$, and requires that each observation sequence be independent of other observation sequences, and that:

$$P(O | \lambda) = \prod_{k=1}^K P(O^{(k)} | \lambda) = \prod_{k=1}^K P_k$$

The goal of model training is to adjust the parameters of the model λ to maximum $P(O | \lambda)$. The reevaluation formula of multiple observation sequences can be obtained by summing up the probability of each observation sample. When training HMM using L observation sequences, the reevaluation formula is amended to read:

$$\left\{ \begin{array}{l} \bar{\pi}_i = \sum_{l=1}^L \alpha_{1,l}(i) \beta_{1,l}(i) / P(O_l | \lambda) \quad 1 \leq i \leq N \\ \bar{a}_{ij} = \frac{\sum_{l=1}^L \sum_{t=1}^{T_l-1} \alpha_{t,l}(i) a_{ij} b_j(O_{t+1,l}) \beta_{t+1,l}(j) / P(O_l | \lambda)}{\sum_{l=1}^L \sum_{t=1}^{T_l-1} \alpha_{t,l}(i) \beta_{t+1,l}(j) / P(O_l | \lambda)} \quad 1 \leq i \leq N, \quad 1 \leq j \leq N \\ \bar{b}_{ik} = \frac{\sum_{l=1}^L \sum_{t=1 \cap O_t = V_k}^{T_l-1} \alpha_{t,l}(j) \beta_{t+1,l}(j) / P(O_l | \lambda)}{\sum_{l=1}^L \sum_{t=1}^{T_l-1} \alpha_{t,l}(j) \beta_{t+1,l}(j) / P(O_l | \lambda)} \end{array} \right.$$

Among them: α is forward variable, β is backward variable, L is observation sequence number, T_i is each observation sequence length. The above formula is valid for DHMM, could play an important role for fault diagnosis of communication system.

V. CONCLUSION

From the preceding analysis, it can be seen that the HMM model is suitable for the application of communication system fault diagnosis. The three algorithms and fault prediction models presented in this paper are suitable for the communication system with typical electronic system signal characteristics. In order to improve the level of fault diagnosis and health management of communication system, the next step is to forecast the health status of communication system by combining with the life design of communication system.

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