
Use partly hidden Markov model to evaluate a future failure

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Abstract: The diagnosis of failures, if done properly and enabling early degradation detection, represents a means to optimise the production unit and to reduce the costs by avoiding failures. This challenge can be addressed through hidden Markov models (HMMs) that can estimate the probability of a future failure based on observation system. However, sudden changes in system behaviour due to either system malfunction or one of its components will affect the operation process. Thus, previous errors have an impact on the current system state and a regular HMM does not meet this requirement unlike partly hidden Markov models (PHMMs), which combines the power of conditioning the state transition probability to the previous observation. In this paper and for the first time, we propose to use PHMM as a mechanism to identify a future failure of industrial furnace. The obtained results prove that using PHMM seems to be particularly effective, efficient and outperforms the HMM.

Keywords: failure; HMM; hidden Markov model; PHMM; partly hidden Markov model; industrial furnace; thermal signature.

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1 Introduction

Any organised system is fallible, and will therefore fail certainly at some time (*"Anything that can go wrong, will go wrong"* Murphy's Law). The best-intentioned quality controller, working conscientiously with the right tools, will meet a failure that he should detect.

To ensure the system dependability, different means exist: Fault removal, Fault prevention and Fault forecasting. Since it is impossible to build perfect systems because of their increasing complexity, the solution is to use the *fault tolerance*. This technique aims to ensure the continuity of the systems operations in the presence of faults; it employs a strategy of two-steps: Error Detection and Recovery

System (Avizienis et al., 2004). However, conventional mechanisms of fault tolerance: majority voting, watchdog, rollback, etc., consume resources and time. Moreover, the systems complexity increases and they are crucial means to maintain system safety and reliability (Wang et al., 2013). Therefore, employing a method for early detection of failure state before it manifests, to eliminate or minimise the risks, is a potential solution (Salfner et al., 2010; Strangas et al., 2013). This approach is an active research area, well-supported by many works as Chen et al. (2012) and Shin et al. (2013).

The idea is to calculate a probability of possible degradation using logical reasoning based on observation system. This approach has many advantages: it saves time,

is less costly (in terms of resource) and leads to auto-improvement over time through learning from observed data system.

Hidden Markov models (from now on HMM) are the most probabilistic models effective for sequences representation (Rabiner, 1989). They require rather knowledge provided that they get enough data for training. To solve complex problems such as facial expression recognition (Wen and Zhan, 2010) and intelligent video surveillance in pervasive computing (Xiao and Guo, 2010), HMMs have been successfully used in modelling. The model comprises a double stochastic processes, the first is *hidden* and can be *observed* through the second stochastic process; the system state cannot be measured but it can be observed through generated values and this what corresponds to HMM's description. Many HMM-based researches for predicting anomalies have been made: in industrial machine (Wang and Wang, 2012), communication network (Baldoni et al., 2012) and genetic sequence analysis applications (Dhilon et al., 2013).

However, HMM overlooks observation dynamic features: as we know it considers that the output probability in each state is unique which means HMM deals with only piecewise stationary process (Camci and Chinnam, 2010). Moreover, there are systems that are decomposed into components, once one is damaged, observation changes and this will affect the health-state of this component or another, and since it is defective another error will be produced. After a while, the same happens to a third component and so one (Mohamed and Zulkermine, 2010). Thus, the parameter of the observations and state transitions depends on previous observation; and partly hidden Markov model (PHMM) is the suitable tool to ensure the conditioning between current state and previous observation.

Glass industry is a highly concentrated heavy industry that faces a growing demand. Thus, the furnace¹ must ensure a high dependability. Since there is not a perfect system, the furnace could fail (the most efficient furnace tendency is 6–7 years) and repair could take up to five years, and so the glass factory must design its oven integrating methods enabling it to optimise its economic performance. Therefore, it is suitable that the factory can forecast a future failure based on furnace observation.

The paper is organised as follows: Section 2 gives a brief background on HMM with related works, discusses their limits to solve the issue discussed in the beginning of this section and offers a detailed presentation of PHMM. Section 3 presents the oven architecture and details of the collected data for machine learning and obtained results. We conclude in Section 4.

2 Background

Failure is detected when an unexpected event occurs leading to an incorrect service. The deviation is an *error* which is often caused by *fault*. As known, the HMM are called 'hidden' since it is assumed that only the generated symbols can be 'observed' and that the state of the

stochastic process is *hidden* from the observer (Salfner and Malek, 2007). Moreover, thermal signals in a way show furnace behaviour in any time scale. These two points match with dependability threats: *Faults* are unobserved and *Errors* (derived from faults) represent *observation*.

2.1 Related work

Salfner and Malek (2007) use hidden semi-Markov model (HSMM) to anticipate failure on a commercial telecommunication system based on error logs. Along with sequence clustering and noise filtering, their approach achieved a failure prediction *F*-measure of 66%. Zhao et al. (2010) explore further this prediction approach by combining HMM to HSMM. They treat self-monitoring and reporting technology (SMART) data as time series to classify 'failed disks' and 'good disks'. Using the best single attribute, the proposed prediction models achieved a detection rate of 46% and 52% at 0% false alarm for single and multiple-attributes. On the same data type (SMART data), Teoh et al. (2012) modified the structure of regular HMM that is specifically designed for the low false-alarm case. They have selected 24 attributes and obtain accuracy of about 90%.

On the other hand, Camci and Chinnam (2010) implemented hierarchical HMM (HHMM) as dynamic Bayesian networks (DBNs) for health-state and remaining-useful-life (RUL) estimation. The proposed method was implemented for monitoring drill-bits on a CNC machine. HHMM represent all health-states and offer several advantages over pools of standard HMM, such as better diagnostic accuracy and ease of implementation and training.

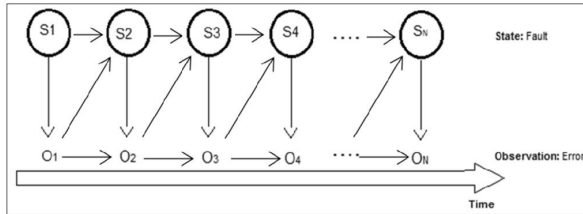
However, HMM, HHMM and HSMM disregard dynamic features of state: an industrial furnace is a complex installation assuming a high-level functional goal, decomposed into components providing one or more well-defined functions. Once one component is damaged, the temperature changes and affects the health-state of this component or another component that depends on it. Since it is defective, another error will be produced. Shortly afterwards, the same happens to a third component (Change of its health-state) and so on. This problem is defined as follow: *generated error has an impact on the current state*. However, regular HMM tend to be limited in their ability to solve this complexity but PHMM can deal with it (see Figure 1). PHMM was proposed by Kobayashi and Haruyama (1997), which combines the power of explicit conditioning on past observations and the power of using hidden states where the output probability is represented by second order model (Kobayashi and Haruyama, 1997):

$$P(O_t | O_{t-k} O_{t-k+1} \dots O_{t-1}) = P(O_t | S_t, O_{t-1}). \quad (1)$$

This pattern matching method was applied to gesture recognition (Kobayashi and Haruyama, 1997), where PHMM improved the player-closed score by 73%, compared with HMM. In speech recognition (Kobayashi et al., 1999), it improved error rate by 39%. These results

show the PHMM's potential, since it performed with high likelihood rate, we expect that it will be efficient for forecasting failure.

Figure 1 Faults and errors according to partly hidden Markov model



2.2 Partly hidden Markov model

PHMM is defined by a structure composed of a set of N states: $S = \{S_1, S_2, \dots, S_N\}$ and M Observations: $V = \{V_1, V_2, \dots, V_M\}$. A time t the generated observation is denoted as O_t . Since the output probability of O_t is conditioned by O_{t-1} (see Figure 1), the model is presented by three other parameters then the regular HMM:

$c_{ij}(O_{t-1})$: The probability that the last output is O_{t-1} in case that the current state is S_i and the next state is S_j .

$d_i(O_t, O_{t-1})$: The probability that the current output is O_t and the last output is O_{t-1} in case that the current state is S_i .

$e_i(O_1)$: The probability that the first output is O_1 and the initial state is S_i (Kobayashi and Haruyama, 1997).

PHMM is used to model observation sequences of discrete and continuous nature, as the temperature signal is a set of real number then b_i, c_{ij}, d_i are represented by Gaussian Distributions (Rabiner, 1989):

$$f_i(O_t) = \sum_{w=1}^W c_{iw} \mathcal{N}(O_t; \mu_{iw}, \sigma_{iw}), \tag{2}$$

where c_{iw} is the weighting coefficients, $\sum_{w=1}^W c_{iw} = 1$, μ_{iw} is mean vectors, σ_{iw} is covariance matrices, W is total number of weighted probability distribution.

An observation depends on two conditions: the current hidden state and the previous observation so the probability of transit from state S_i to state S_j is defined as

$$A_{ij} = P(q_t = S_j | q_{t-1} = S_i, O_{t-2} = x) = \frac{a_{ij} c_{ij}(x)}{b_i(x)}. \tag{3}$$

The probability to observe the symbol x in state S_i is defined as

$$B_j(x) = \frac{P(O_t = x, O_{t-1} = y | q_t = S_j)}{P(O_{t-1} = y | q_t = S_j)} = \frac{d_j(x, y)}{b_j(x)}. \tag{4}$$

We refer the reader to Kobayashi and Haruyama (1997) and Kobayashi et al. (1999) for more details of the main properties of the PHMM.

3 The experiment

PHMM, as machine learning, is based on observations for classification. These observations represent characteristics or signatures associated with indicative symptoms of failures (Salfner, 2008). There are several types of signatures, depending on the type of system: vibration signatures (Wang and Wang, 2012), acoustic signatures, magnetic signatures, thermal signatures, radiographic signatures and electrical signatures (Rabiner, 1989).

The industry ovens represent an important tool for glass industry, where the quality of produced glass is highly dependent on the accuracy of temperature and any unexpected thermal change generates flaws in the structure of the glass (seeds, stones, cords and surface discontinuities) (Beerckens et al., 2002). The work presented in this paper is based on thermal signature. Therefore, using equipment to monitor it, becomes a necessity to prevent electrical and mechanical faults.

3.1 Data monitoring

The furnace is directly connected to a computer with a system of monitoring. A large amount of temperature measurements was collected each hour over a period of 333 days (see Table 1), taken from four different sensors: Zone1 and Zone2 in fusion bath and top and low point in labour basin as shown in Figure 2.

The factory applies the 3 × 8 h shift work and production quality is measured at the service end of each team. Therefore, we obtained for each day, three matrices with 8 rows and 5 columns corresponding to temperatures taken during the service at each sensor (see Figure 2), where each matrix is associated with one value of quality production.

Table 1 Example of sensors temperature data logged during this experiment

Hour	BF.1	BF.2	BT.G	BT.D
08h00	1501.958	1538.958	1128.250	1501.958
09h00	1499.917	1525.875	1132.250	1499.917
10h00	1499.435	1529.261	1133.609	1499.435
11h00	1499.792	1528.958	1137.083	1499.792

3.2 Data classification

Failures are classified according to their impact on staff and equipment. We distinguish two types of failures that affect a system, depending on the level of severity or frequency of their appearances which make it unable to perform the function it was designed for (Avizienis et al., 2004). However, the estimation of failure frequency is not easy, we can rely on statistics (must have a large history) or on information provided by a supplier, so we have decided to classify the failures according to their severity as shown in Table 2.

Unfortunately, it is impossible to measure the failure level. However, if the oven wears out, this will impact on quality production thus, the failure is more serious and the consequences will be more disastrous on glass production. Thus, the severity level of failure will be measured in terms of bad production rate as shown in Figure 3.

For classification, we need a set of vectors. We decided to reduce the size of each matrix and a simple average may distort treatment.

The solution is the concatenation of the rows of each matrix (rows side by side). This does not lead to a loss of information. We decided to remove the Hour attribute because it will have no effect on the production quality. Thus each matrix of 8 lines and 5 columns becomes an array 32 values ($8 \times (5 - 1) = 32$).

3.3 WEKA input parameters

We performed our experiment under the Weka software (version 3.7.7). It is an open source software tool for data mining, implemented by the Machine Learning Group at University of Waikato (Hall et al., 2009), Weka implements different classification, regression and clustering techniques algorithms that could be easily applied to large sets of raw data (datasets). It provides too a number of visualisation tools. Currently, it is considered a powerful and adequate environment for data mining tasks.

We succeeded to modify the source code of HMMWeka package. The purpose is to observe the performance of PHMM relative to regular HMM.

Figure 2 On left: Oven Design: Four sensors for capturing thermal signal; Top right: Data acquisition; Bottom right: Reviews of data monitored (see online version for colours)

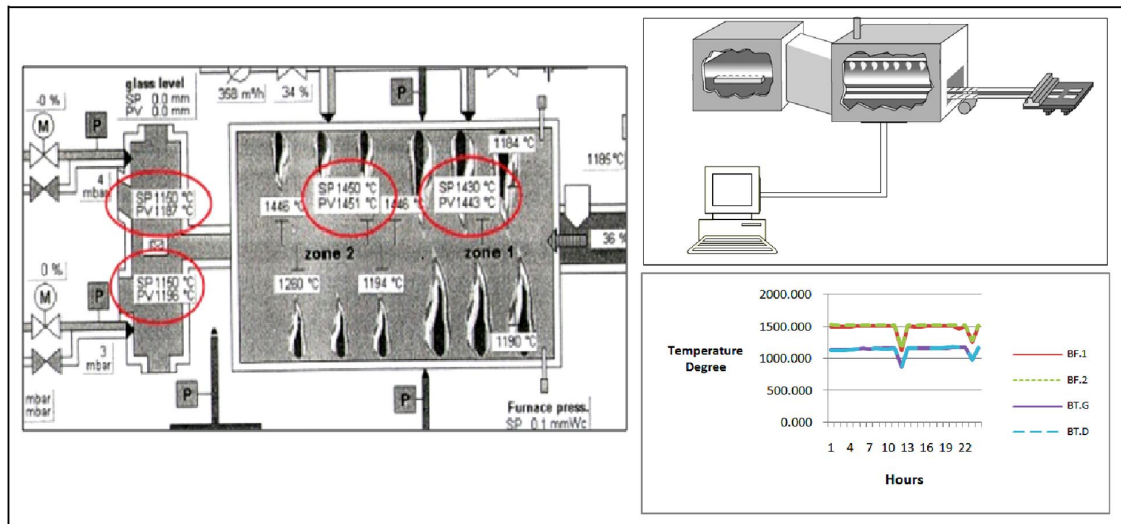


Table 2 Classification of failures

Severity level	Impact on equipment
Minor	Hardware intact
Average	Quickly repairable equipment
Major	Repair long
Catastrophic	Significant property damage, the environment around the machine is affected
Unacceptable	Destruction of production tool, requiring replacement and accident involving personal safety

3.3.1 State transition

The future occurrence of failures can be identified by evaluating log-likelihood value $P(O|\lambda)$:

$$P(O|\lambda) = \sum_Q P(O|Q, \lambda) \cdot P(Q|\lambda) \tag{5}$$

Figure 3 Failure type according to bad production rate (see online version for colours)



However, direct assessment is an exponential complexity, there is another solution: the Forward-Backward (FB) algorithm and the probability is calculated according to two variables α and β (Forward and Backward, respectively):

$$P(O|\lambda) = \sum_{i=1}^N \alpha_i(i) \cdot \beta_i(i). \quad (6)$$

In case of default, state of oven may get worse or stay the same, but cannot get better as time progresses (until repair), so we select the 'left-to-right' option, i.e., only forward transition:

$$P(O|\lambda) = \sum_{i=1}^N \alpha_i(i). \quad (7)$$

3.3.2 Test option

There are 999 instances with 33 attributes (32 temperature values + failure class) in dataset that must be divided into two classes (one for training data and the other for the test data). As we know, in Weka framework there are four different Test options. The high classification accuracy was performed with 10-fold Cross Validation (for both models), i.e., it produces 10 equal sized sets. Each set is divided into two groups: 900 instances are used for training and 99 instances data are used for testing.

3.3.3 Number of states

The number of states is determined by an automatic selection process, in which the PHMM and HMM were trained with number of states varying from 6 to 30 and finally, we choose 10 states that maximise the correctly classified Instances rate.

3.4 Results and discussion

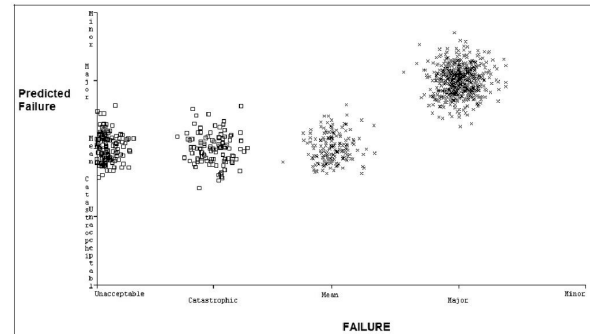
It has been observed that the detection rates obtained by the HMM are low compared with PHMM, we report a rate of 74.57% and 25.43% at Correctly Classified Instances and Incorrectly Classified Instances for PHMM, respectively, while HMM reported a rate of 56.66% and 43.34%. PHMM does not outperform HMM, as much, at mean absolute error (0.246 for HMM and 0.1134 for PHMM), possible reasons for this observation is that PHMMs require more data to be evaluated.

Note that the crosses in Figure 4 represent correctly classified instances, and squares show incorrectly classified instances. We notice a density of Correctly Classification Rate at the Major class because common instances are Major type which mean that more monitoring data are required to make PHMM identify all cases (failure types).

We note also that the performance of PHMM: 67.1% for $F_measure$, 64.1% for $Precision$ and 74.6% for $Recall$, is different from HMM: 41.0% for $F_measure$, 32.1% for $Precision$ and 56.7% for $Recall$, still, we distinguish a large difference with other metrics in which PHMM achieves a True Positive Rate and False Positive Rate of 74.6% and 5.8%, respectively.

By and large, PHMM offers results are rather different from HMM. However, using more data might improve the performance of PHMMs and we will surely explore more options in the future, i.e. these obtained results are so promising that we may proceed to the second phase of our approach.

Figure 4 Classify error graph



4 Conclusions and outlook

It is very important to predict system behaviours. For example, in some systems such as nuclear power stations and rocket control loops (Zhou et al., 2010) that have high requirements for safety, it is necessary to predict the system behaviours that may lead to major faults. Many works were realised to detect failures based on thermal signal, such as (Deng et al., 2012).

In this paper, we propose to use PHMM as a machine learning method. The model proved remarkably effective for the classification process compared with HMM on one side and on the other it justifies and promotes continuity of the proposed approach. Since not all collected data reflect all possible cases, more temperature data will be monitored for offline learning of PHMM and calculating the probability of a future failure in real time.

For instance, our case study has shown that PHMM can start to provide an acceptable failure prediction service after only 47 weeks of training phase. We conclude that this machine learning is a potential tool that can effectively learn and predict furnace failure.

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Note

¹For more details about industrial furnaces, please visit: <http://www.falorniglass.com/>