

Application of Hidden Markov Model to Fault Diagnostics of Glass De-chuck System

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1. INTRODUCTION

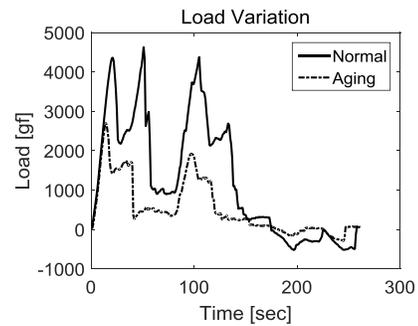
De-chuck operation which attaches object to glues and detaches object from glues has been used in production line to convey materials in vacuum state. The de-chuck operation for glasses or wafers in production line sometimes causes damages on product in detaching it from glues. Since most of failures in de-chuck operation results from abnormal states of glues such as aged states or strong adhesive states, diagnostics of abnormal glues and a timely replacement of glues are the issues of the de-chuck system. In this study, a testbed simulated de-chuck system is devised and a hidden Markov model (HMM) is applied for diagnostics of the problematic glues in de-chuck system of a testbed. As a result, it was measured quantitatively to the rate of accuracy detecting the area of abnormal glues including aged state-glass and strong adhesive state-glass, and the maximum detection accuracy rate was approximately 82%.

aging and crack were assumed to be mostly caused by aged glue and strong adhesive glue, respectively. However, it's difficult to diagnose what area or what point of glue is directly correlated with aging or crack given only the load variation and load center trace data. To detect the problematic glues, the Hidden Markov model (HMM) is used in this study.

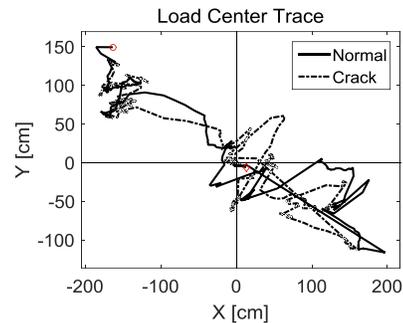
2. RESEARCH AND RESULT

2.1. Simulation of De-chuck Process

The down-sized testbed of de-chuck system for simulating de-chuck operation was manufactured. The testbed consists of four parts: detaching pins, glues, glass, and four load cells. The 39 number of pins are installed in this testbed, and the pins are sorted into 6 groups by height. Also, the 42 number of glues can be classified into 14 groups by the detaching sequence according to movement of the 6 groups of pins. The glass attached on glues is detached as the 6 groups of the pins diagonally ascend in sequence. In this de-chuck simulation, the four load cells measure the load acting on the glass. Through this de-chuck simulation, the load variation over time and the trace of the load center position can be obtained. Given these data as seen in Figure 1. (a) and (b), it is possible not only to classify the system into normal and abnormal state but also to divide the abnormal state into aging and crack. The



(a)



(b)

Figure 1. (a) Load variation and (b) load center trace

2.2. Application of Hidden Markov Model (HMM)

Hidden Markov model (HMM) (Rabiner, 1989), widely used method in pattern recognition, has two discrete variables and two probabilistic parameters: *states*, *observations*, and *transition*, *emission* as illustrated in Figure 2. The *states*, x_i are the elements of cause events set, the *observations*, y_k are the elements of result events set. The *transition*, a_{ij} is a probability to change from a certain state to other state, and the *emission*, b_{ik} is a probability that a certain state appears as a particular observation. The HMM is usually utilized to estimate the posterior (also called Bayesian probabilities or conditional probabilities) which is the probability that the *observation* at the specific time point is resulted from certain *state* given an *observation* sequence, as depicted in Figure 3 and Eq. (1). If the posterior is obtained, the most probable hidden *state* can be estimated by selecting a *state* having a maximum posterior, which is the purpose of the use of the HMM in this study. To calculate the posterior, *transition* and *emission* are required. In practice, it is only known to an *observation* sequence which is the chronological order of the arbitrarily extracted *observations*. Although given only an *observation* sequence, the *transition* and the *emission* can be estimated by using Baum-Welch algorithm, (Durbin, Eddy, Krogh, & Mitchison, 1998) also known as forward-backward algorithm. And then, the most probable hidden *state* can be evaluated by using Viterbi algorithm. (Durbin et al., 1998) These two algorithms are included with the HMM. In order to detect the area of problematic glues by applying the Hidden Markov model (HMM), attached and detached states of glues were defined as the *states*, features extracted from load variation and load center trace were chosen as the *observations* in this study.

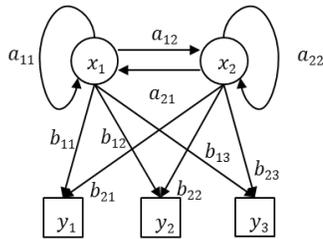


Figure 2. Variables and parameters in HMM

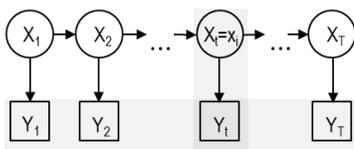


Figure 3. Hidden state and observation sequence

$$p(X_t = x_i | Y_1, Y_2, \dots, Y_T) = \frac{p(X_t = x_i, Y_1, Y_2, \dots, Y_T)}{p(Y_1, Y_2, \dots, Y_T)} \tag{1}$$

2.3. Performance Evaluation of Hidden Markov Model (HMM)

The chronological order of the features from load variation and load center trace was employed to the *observation* sequence. The length of the *observation* sequence was set to 6, 12, 24 and 36, since they were matching with ascent of the 6 groups of pins as referred in section 2.1. The experiment was repeated 100 times for each of aged glue and strong adhesive glue for a total of 200 *observation* sequences. These *observation* sequences were used in training the *emission* and *transition* with the Baum-Welch algorithm, and applied to performance evaluation of HMM with the Viterbi algorithm for the accuracy rate detecting problematic area of glues including aging glues and strong adhesive glues. The result is represented in Table 1.

Table 1. Accuracy rate to detect an area of abnormal glue

Length of an observation sequence	Accuracy rate to detect an area of the aging glues (%)	Accuracy rate to detect an area of the strong adhesive glues (%)
6	44	56
12	57	63
24	61	72
36	70	82

3. CONCLUSION

The maximum value of the accuracy rate is 82% at the case of strong adhesive glue detection when the length of an observation sequence is 36. Based on the result, firstly, the accuracy rate of strong adhesive glue detection is more accurate than that of aging glue detection. It is expected that the features of the load center trace are more strongly correlated with abnormal state than those of the load variation. Features strongly correlated target state enhances estimating the *transition* and *emission* more accurate, which affects the performance of Hidden Markov model (HMM). Secondly, there is a tendency that the longer an *observation* sequence, the higher the accuracy rate of detection. It is supposed that more information can be contained as the length of the observation sequence is longer. It remains to be the future works to extract new features possible to make the length of

the *observation* sequence longer than 36, and to find an optimum length of the *observation* sequence to raise the accuracy rate detecting an area of problematic glues.

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