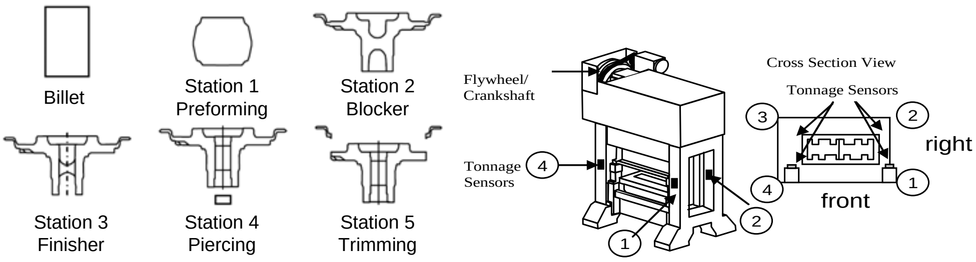
The Second International Conference "Problems of Cybernetics and Informatics"
September 10-12, 2008, Baku, Azerbaijan. Section #3 "Modeling and Identification"
www.pci2008.science.az/3/19.pdf

AUTOMATIC MONITORING OF MULTIPLE OPERATION FORGING PROCESSES

Yong Lei and Jionghua (Judy) Jin
Department of Industrial and Operations Engineering
University of Michigan, Ann Arbor, MI 48109, USA
{*ylei, jhjin*}*@umich.edu*

1. Introduction

With increasing competition in the fast pacing market, multiple-operation forging processes have become popular in practice by considering their high throughput, high precision and high agility. However, monitoring and diagnosis of such processes is still a challenging research issue.



(a) (b)

Fig. 1 (a) A forging process with five operations; (b) sensor mounting on a forging machine

As an example, Fig. 1(a) shows a typical forging process with five operations, and Fig. 1(b) shows four strain gage sensors mounted on four uprights of a forging machine, which measure the aggregated forces exerted on all dies. These tonnage sensors provide rich information about product quality and process conditions. The inherent variation of these tonnage signals reflects the natural process variations, such as randomness of lubrication, die temperature and material uniformity, etc. However, the application of tonnage monitoring in forging processes is still very limited. In most industrial practice, simple statistical process control methods are used for process monitoring. For example, the maximum and the average of a cycle of signals are the most commonly used statistics [1, 2]. A shortcoming of those methods is that a large amount of profile information contained in tonnage signals is not fully utilized. As a result, the monitoring system based on these simple statistics often suffers a high false alarm rate or a high missing detection rate for different faulty conditions. Moreover, most progressive/transfer forging processes usually consist of some operations that generate small tonnage forces hidden in overall aggregated tonnage signal profiles, such as piercing and trimming operations. These weak force operations are usually very difficult to be monitored.

The objective of this paper is to develop an effective monitoring method through automatic feature extraction and sequential classification of continuous production data. The proposed methodology is presented in Section 2 and illustrated by a real world example of a forging process in Section 3. Finally concluding remarks are given in Section 4.

2. Methodology Development

Considering the data complexity of tonnage signals especially those operations generating weak force signals, it is hard to classify different faulty operation conditions through one classifier. In this paper, a new sequential feature selection and classification decision rule is developed to enhance the detection sensitivity and robustness. The proposed analysis procedure is shown in

Fig. 2, where sequential step-by-step classification is used for each working condition classification, that is, only one working condition will be separated from others at one step. α_{π_l} denotes the probability of data in class *l* to be misclassified to all other class *k, (k≠l)* using the selected feature subset by step *j*.

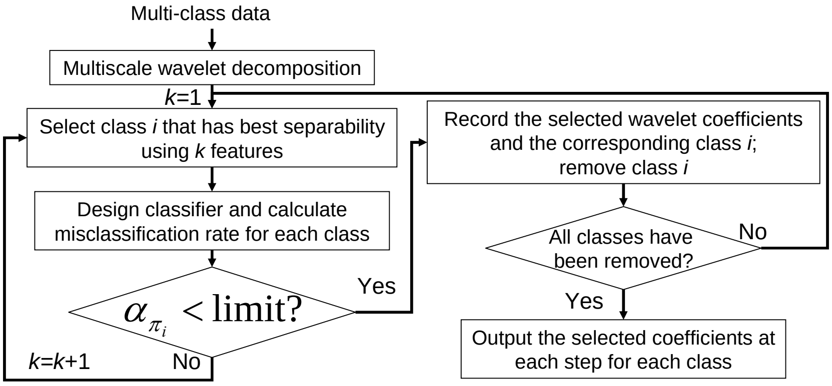


Fig. 2: Framework for sequential feature selection and classification algorithm

2.1 Feature selection and classifier design

Let $f_k(\mathbf{y})$ be the probability density function associated with one of the g group's tonnage data denoted as π_k , $k = 1,\ldots,g$. Here the selected classification features are wavelet coefficients **y**, which can be univariate or multivariate. In this study, discrete wavelet transform is applied to the decomposed individual station signals [3]. DB4 [4] is selected as the wavelet basis and decomposition level of 7 is used. Both detail and approximation coefficients at each level will be evaluated.

Let $P(\pi_k)$ denotes the prior probability of group π_k , $k = 1,\ldots,g$. Under the criterion of the minimum expected misclassification errors [5], **y** is classified as class π_m , if

$$P(\pi_m)f_m(\mathbf{y}) > P(\pi_k)f_k(\mathbf{y}) \text{ for all } k \text{ , } m \neq k \text{ .} \tag{1}$$

Under the normal distribution assumption, we will classify $\mathbf{y}$ as π_m if

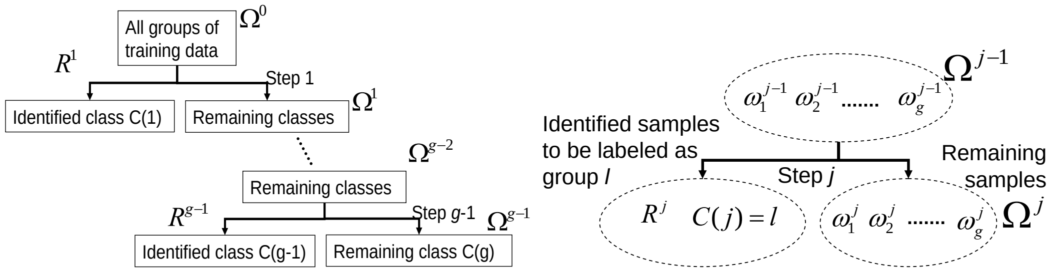
$$\ln P(\pi_m)f_m(\mathbf{y}) = \max_k \ln P(\pi_k)f_k(\mathbf{y}) = \ln P(\pi_m) - \frac{p}{2}\ln(2\pi) - \frac{1}{2}\ln|\mathbf{\Sigma}_m| - \frac{1}{2}(\mathbf{y}-\boldsymbol{\mu}_m)^T \mathbf{\Sigma}_m^{-1}(\mathbf{y}-\boldsymbol{\mu}_m).$$

As shown in

Fig. 2 the classifier is designed with the first effort of using one optimal feature that is selected with the minimal expected classification error. If its classification performance is not satisfied, the feature dimension will be increased until the minimal expected classification error or other stopping criteria is satisfied.

2.2 Analysis of misclassification error

Fig. 3 shows the classification procedures and the resultant sample spaces after classification steps. At the beginning, the whole space consisting of samples under all conditions is denoted as Ω^0 . Assume the data set under working condition *k* is denoted as π_k , $k = 1,\ldots,g$. At each step *j*, $j = 1, 2, ..., g-1$, the group that will be identified is denoted by $C(j)$, e.g. if group *l* is identified at step *j*, we have $C(j) = l$, $j = 1,..., g-1$. For completeness, let $C(g)$ denote the remaining class after *g*-1 steps. Let Ω^j denote the remaining unclassified sample space at step *j*. Considering the possible classification errors, the remaining samples in Ω^j may consist of a small percentage of samples of the previously identified groups, and large percentage of other unidentified group samples. Let ω_i^j denote the samples of π_i left in Ω^j , that is, $\Omega^j = \{\omega_i^j, i = 1,2,\ldots,g\}$. As shown in Fig. 3(b), at step j , Ω^{j-1} will be divided into two subspaces: one is the identified sample space R^j , all of which will be labeled as group *l* at step *j*, the other one is the remaining sample space Ω^j , $R^j \cap \Omega^j = \phi$.



(a) (b)

Fig. 3: (a) Classifier training procedures; (b) resultant sample spaces at step *j*

Furthermore, the classification errors will be analyzed as follows: at the (*j*-1)-th step, the remaining samples of group *i* in Ω^{j-1} will be $\omega_i^{j-1}, i = 1, 2, \ldots, g$. Let P_i^j denote the conditional probability of classifying ω_i^{j-1} to the identified sample space R^j at step *j*, $j = 1, \ldots, g-1$:

$$P_i^j = \Pr\{x \in R^j \mid \omega_i^{j-1}\}, \tag{2}$$

where $i = 1, 2, \ldots, g$. Therefore, a confusion matrix $M \in \Re^{g \times g}$ can be constructed to evaluate the classifier performance after all classification steps. Let M_{kl} denote the probability of samples in class *k* to be classified as class *l*, which is identified at step *j*, i.e. $C(j) = l$. Following the definition, we have

$$M_{kl} = \begin{cases} \Pr\{x \in (R^j \cap \pi_k), C(j) = l\} = P_k^j \prod_{s=1}^{j-1}(1 - P_k^s), & j = 1, 2, \ldots, g-1 \\ \Pr\{x \in (\Omega^{g-1} \cap \pi_k), C(j) = l\} = \prod_{s=1}^{g-1}(1 - P_k^s), & j = g \end{cases}$$

Therefore, the total misclassification probability for $\pi_l, l = 1, \ldots, g$ after all classification steps can be defined as:

$$\alpha_{\pi_l} = \begin{cases} \Pr\{x \notin R^j, C(j) = l \mid \pi_l\} = 1 - M_{ll} = 1 - P_l^j \prod_{s=1}^{j-1}(1 - P_l^s), & j = 1, 2, \ldots, g-1 \\ \Pr\{x \notin \Omega^{g-1}, C(j) = l \mid \pi_l\} = 1 - \prod_{s=1}^{g-1}(1 - P_l^s), & j = g \end{cases} \tag{3}$$

where α_{π_l} is the total probability of the given class *l* to be misclassified into all other classes. From equation (3), we can see that α_{π_l} are affected by the steps up to step *j*, where classification errors are propagated as **chain effect**. In order to obtain optimal classification features for group π_l identification, the smallest misclassification error are used as a criterion for optimal feature selection at each step, which ensures π_l is correctly classified and unidentified group samples are mainly remained in the remaining samples.

3. Case Study

In this paper, the training data set consists of one group of 307 signal samples under the full production condition and 5 groups of signals under the different missing part production, each of which consists of 69 samples. Fig. 4 shows the total tonnage signal profiles under different conditions. In the plot, Group *i* denotes signals with missing part at Station *i*.

The wavelet features selected for all the classification steps and the corresponding misclassification probabilities of the sequential classifier developed previously are shown in Table 1 and Table 2 respectively. From these tables, it is clearly shown that our methodology works well.

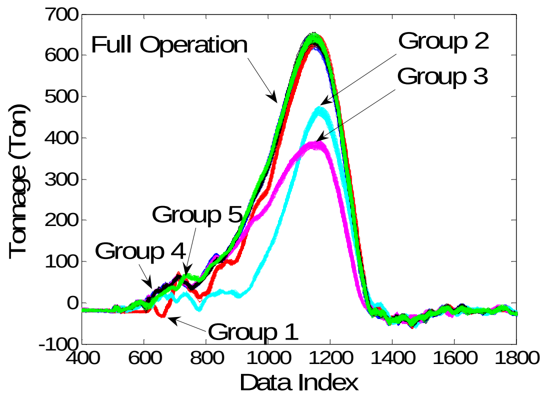


Fig. 4: Tonnage signals under the full operation and five missing part conditions

Table 1: Selected wavelet coefficients at each step (s denotes scale level, d denotes detail level)

Step	Group	1st Coefficient		2nd Coefficient	
		Level	Index	Level	Index
1	2	7(s)	10		
2	3	4(s)	52		
3	1	5(s)	14		
4	5	5(s)	15	4(s)	25
5	4	7(d)	8	6(d)	14

Table 2: Total misclassification probabilities for each group (%)
(group 6 denotes full operation data)

Classified Group (l)	1	2	3	4	5	6
α_{π_l}	0	0	0	0.0084	0	0.0021

(The value less than 0.001 is treated as 0)

4. Conclusion

A new method is developed for monitoring of multiple-operation forging processes. In this paper, wavelets based sequential feature selection and classification procedure is proposed to minimize the misclassification probabilities among different classes. The corresponding classification error assessment method is also derived. A real-world forging process is used to demonstrate the analysis procedures and illustrate the effectiveness of the proposed methodology.

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