Analysis of Individual Die Tonnage Using Multiple Tonnage Sensors for Multiple Operation Forging Processes

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Project summary: Four tonnage sensors are generally installed on four columns of a forging press, by which the mixed aggregated sensor signals are used to measure the embedded multiple independent or dependent dies' operation forces. In this research, a new method is developed to estimate these independent or dependent die source signals from the linear mixed tonnage sensor signals by combining the Independent Component Analysis, the Sparse Component Analysis, and the engineering knowledge. Furthermore, two statistical rules are developed to check the sparse property and to monitor the individual operations based on the estimated source signals, respectively. Different from the existing tonnage signal analysis method using the sum of four sensor measurements, this research is at the first time to fully utilize the extra information from individual four sensor signals. A case study at a real world forging process is conducted, which demonstrates the effectiveness of the proposed methods in abnormality detection of individual operations.

1. Introduction

In general, a complex forging process consists of multiple either independent or dependent operation dies, where it is impossible or unaffordable to directly measure all individual die forces separately. The available tonnage sensor measurements (called mixed sensor signals) are usually obtained by four sensors installed on four press columns, which can be obtained as the linearly combined tonnage responses of multiple die operations (called source signals), which cause a high dimensional functional data structure and complex nonstationary characteristics in both the time and frequency domains. As a result, although system monitoring methods based on mixed sensor signals can be used to detect the abnormalities of a system, it is generally difficult to find out which die has a problem. Direct monitoring of individual die forces instead of mixed sensor signals, on the country, can provide explicit diagnostic information of individual die conditions. Thus, there is a substantial need for research on estimating individual die forces based on the press tonnage sensor measurements.

For the purpose of estimating individual source signals from the mixed sensor signals when their linear relationship is unknown**,** Independent Component Analysis (ICA) [1-2] and Sparse Component Analysis (SCA) [3-5] are two general methods studied in the literature. The ICA method is effectively used for separating the mixed sensor signals into individual source signals with the assumption that the source signals are statistically independent and non-Gaussian. Differently, the SCA method can be used to separate the dominant source signals from the mixed sensor signals no matter whether they are dependent or not. A source signal is justified as a dominant signal if this source signal can provide a dominant contribution to the mixed sensor signals at a specific time period or a frequency range.

Significant successes have been achieved in either the ICA or SCA field. However, the application of ICA and SCA method to the forging process monitoring is still limited because such a complex process usually contains some die force signals which cannot be fully represented by a single category of either independent components or dominant components. Therefore, this research is intended to develop a new estimation method under a more general case in which the die forces are assumed to be either independent signals or dependent signals that have some dominant components in the time or frequency domain. Different from the existing tonnage signal analysis method using the sum of four sensor measurements, this research will use individual four sensor signals. The method includes two steps: first, ICA method is first applied to estimate independent die signals, whose contributions on the mixed sensor signal are then eliminated; second, by using the remaining sensor signals, dependent die signals are estimated based on the SCA method in the time and frequency domain, respectively. Furthermore, based on the estimated die signals, a statistical rule is developed to detect abnormality of individual operations.

2. Mathematical Model

The relationship between the die signals and the mixed sensor signals can be generally defined as (1).

$$\mathbf{X}(t) = [\mathbf{A}^I, \mathbf{A}^D] \times [\mathbf{S}^I(t), \mathbf{S}^D(t)]^T + \boldsymbol{\varepsilon}(t) \tag{1}$$

where t denotes the discrete sampling time index, t=1,2,…,N, and N is the number of data points sampled within a sample of signals. $\mathbf{S}^I(t) \equiv [S^{I_1}(t)\ S^{I_2}(t)\ \cdots\ S^{I_p}(t)]^T \in \Re^{p\times N}$ represents p independent die source signals that are statistically independent with other source signals. $\mathbf{S}^D(t) \equiv [S^{D_1}(t)\ S^{D_2}(t)\ \cdots\ S^{D_q}(t)]^T \in \Re^{q\times N}$ represents q die dependent source signals that are statistically dependent because these corresponding operations may share some common physical factors. $\mathbf{X} \equiv [X^1(t)\quad X^2(t)\quad \ldots\quad X^n(t)]^T \in \Re^{n\times N}$ represents n ($n \ge p+q$) mixed sensor signals; $\mathbf{A}^I \in \Re^{n\times p}$ and $\mathbf{A}^D \in \Re^{n\times q}$ are unknown constant mixing matrices, representing the linear relationship between the mixed sensor signals and the independent/dependent die source signals, respectively; and $\boldsymbol{\varepsilon}(t) \equiv [\varepsilon^1(t)\quad \varepsilon^2(t)\quad \ldots\quad \varepsilon^n(t)]^T \in \Re^{n\times N}$ represents n sensor noises.

The dependent source signals, $\mathbf{S}^D(t)$, is assumed to be a linear combination of r ($r \le q$) independent die signals ,denoted as $\mathbf{V}(t)$**,** which represent the common physical factors shared by dependent die source signals, i.e.

$$\mathbf{S}^D(t) = \mathbf{D}\mathbf{V}(t) \tag{2}$$

where $\mathbf{D} \in \Re^{q\times r}$ is an unknown constant matrix; and $\mathbf{V}(t) \equiv [V^1(t)\ V^2(t)\ \cdots\ V^r(t)]^T \in \Re^{r\times N}$, called common factor signals.

Substituting (2) into (1), then

$$\mathbf{X}(t) = [\mathbf{A}^I, \mathbf{A}^D] \times [\mathbf{S}^I(t), \mathbf{D}\mathbf{V}(t)]^T + \boldsymbol{\varepsilon}(t) \tag{3}$$

3. Estimation of Source Signals from Mixed Sensing Signals

3.1 Estimation of Independent Source Signals

The ICA method is first applied on the mixed sensor signals $\mathbf{X}(t)$ to obtain estimated independent die source signals, denoted as $\hat{\mathbf{S}}^I(t) \in \Re^{p\times N}$. The ICA method is to find an constant unmixing matrix $\mathbf{W} \in \Re^{(p+q)\times n}$ such that $\mathbf{Y}(t) = \mathbf{W}\mathbf{X}(t)$, $\mathbf{Y}(t) \in \Re^{(p+q)\times N}$ estimates die source signals by maximizing the "independence" of the estimated signals. Based on equation (2), the estimated independent die signals of ICA result, $\mathbf{Y}(t)$, should include $\hat{\mathbf{S}}^I(t)$ and $\hat{\mathbf{V}}(t)$, where the estimator of independent common factor signals $\hat{\mathbf{V}}(t)$ is obtained instead of estimator of the interested dependent source signals $\mathbf{S}^D(t)$, denoted as $\hat{\mathbf{S}}^D(t) \in \Re^{q\times N}$.

Although $\hat{\mathbf{V}}(t)$ is estimated by the ICA method, the estimated dependent die source signals, $\hat{\mathbf{S}}^D(t)$, cannot be obtained because the constant matrix $\mathbf{D}$ in (2) is unknown. To estimate $\mathbf{S}^D(t)$, the impact of the independent die source signals are first eliminated from the mixed sensor signals. The remaining sensor energy, called reduced mixed sensor signals and denoted by $\tilde{\mathbf{X}}(t) \in \Re^{n\times N}$, will be used to estimate $\mathbf{S}^D(t)$ in the next subsection. $\tilde{\mathbf{X}}(t)$ can be estimated as follows:

$$\tilde{X}^i(t) = \sum_j R_i^j Y^j(t) \quad \text{where } j \notin P \tag{4}$$

where $P = \{i \mid Y^i(t) \in \hat{\mathbf{S}}^I(t)\}$ **;** $\tilde{X}^i(t)$ is the i^{th} element of $\tilde{\mathbf{X}}(t)$,i=1,2,…,n, estimating the i^{th} reduced mixed sensor signal; $Y^i(t)$ is the i^{th} element of $\mathbf{Y}(t)$ **;** and R_i^j is the element of $\mathbf{R} \in \Re^{n\times(p+q)}$ at the i^{th} row and the j^{th} column, and

$\mathbf{R} = (\mathbf{W}^T \mathbf{W})^{-1} \mathbf{W}^T$. Due to the sensor noise and the estimation error, $\tilde{X}^i(t)$, t=1,2,…,N, can be treated as a random variable, i.e.,

$$\tilde{X}^i(t) = \sum_{k=1}^{q} A_i^{D_k} S^{D_k}(t) + \tau^i(t), \ i=1,\ldots,n \tag{5}$$

Where $A_i^{D_k}$ is the element of $\mathbf{A}^D$ at the i^{th} row and the k^{th} column, i=1,2,…,n, and k=1,2,…,q; and $\tau^i(t)$ is the random noise.

3.2 Estimation of Dependent Source Signals

After $\tilde{\mathbf{X}}(t)$ is obtained, $\hat{\mathbf{S}}^D(t)$ are obtained in this subsection by using the SCA method in the time domain and the frequency domain, respectively. The basic idea of SCA method is to first estimate $\mathbf{A}^D$, based on which statistical methods, e.g., the least squares method, can be straightforwardly applied to obtain $\hat{\mathbf{S}}^D$ based on (5). Specifically, the SCA method is used to estimate the k^{th} column of $\mathbf{A}^D$, based on a time window $t \in [t_{k,a}\ t_{k,b}]$ where only the k^{th} dependent source signal $S^{D_k}(t)$ dominant. For the derivation of $[t_{k,a}\ t_{k,b}]$ and $\hat{\mathbf{A}}^D$, please refer to [3,4]. .

In the SCA literature [3], "a source signal $S^{D_k}(t)$ is "dominant" in the time or time/frequency window", is defined as $S^{D_k}(t) >> S^{D_i}(t)$, i=1,2,…,q and $i \neq k$. This definition, however, does not define the sparse property quantitatively, and thus is difficult to be justified in practice. In this paper, the sparse property is tested by rule I based on the statistical t-test.

Rule I: A source die signal $S^{D_k}(t)$ is justified as dominant for $t \in [t_{k,a}\ \ t_{k,b}]$, if the following condition is hold:

$$\frac{\left|\hat{\mu}_{Z_i^k(t)} - \hat{\mu}_{\tilde{X}^i(t)}\right|}{\sqrt{\dfrac{\hat{\sigma}^2_{Z_i^k(t)} + \hat{\sigma}^2_{\tilde{X}^i(t)}}{K}}} < t_{\alpha/2,\nu}, \text{ for } i=1,2,\ldots,n \tag{6}$$

Statistical rule I is formed to test the equivalence of two means: the mean of the reduced mixed sensor signals $\tilde{X}^i(t)$, i.e., $\mu_{\tilde{X}^i(t)}$, and the mean of $A_i^{D_k} S^{D_k}(t)$, representing the impact of the k^{th} sensor on the reduced mixed sensor signals, at each $t \in [t_{k,a}\ \ t_{k,b}]$. Because both $A_i^{D_k}$ and $S^{D_k}(t)$ are unknown, the mean of $\hat{A}_i^{D_k} \hat{S}^{D_k}(t)$, denoted as $\mu_{Z_i^k(t)}$, is used instead of the mean of $A_i^{D_l} S^{D_l}(t)$. The sample means and sample variances of $\tilde{X}^i(t)$ and $\hat{A}_i^{D_k} \hat{S}^{D_k}(t)$, i.e., $\hat{\mu}_{Z_i^k(t)}, \hat{\mu}_{\tilde{X}^i(t)}, \hat{\sigma}^2_{Z_i^k(t)}$, and $\hat{\sigma}^2_{\tilde{X}^i(t)}$, can be estimated based on K samples of signals collected under the normal condition. $t_{\alpha/2,\nu}$ is the upper $\alpha/2$ percentage point of a t distribution with ν degrees of freedom, and $\nu = (K+1)\left(\hat{\sigma}^2_{Z_i^k(t)} + \hat{\sigma}^2_{\tilde{X}^i(t)}\right)^2 \Big/ \left(\hat{\sigma}^4_{Z_i^k(t)} + \hat{\sigma}^4_{\tilde{X}^i(t)}\right) - 2$ [7].

Under most situations, the source signals are overlapping in the time domain and the sparse property of each dependent source signals cannot be satisfied in the time domain. A transformation of the dependent source signals to a new domain, e.g., frequency domain, results in the satisfaction of the sparse property. Suppose $\mathbf{\Phi} \in \Re^{N \times L}$ is a known constant matrix which transforms signals from the time domain to a new domain. Base on (5),

$$\tilde{X}^i(t)\mathbf{\Phi} = \sum_{k=1}^{q} A_i^{D_k} S^{D_k}(t)\mathbf{\Phi} + \tau^i(t)\mathbf{\Phi} \tag{7}$$

Let $\tilde{F}^i(\theta) = \tilde{X}^i(t)\mathbf{\Phi}$, θ=1,2,…,L, i=1,2,…,p+q, and $F^k(\theta) = S^{D_k}(t)\mathbf{\Phi}$, θ=1,2,…,L, j=1,2,…,q, indicating vectors of coefficients in the transformed domain for reduced mixed sensor signals and dependent source signals, respectively. If there exist a time/frequency window, the coefficients of the k^{th} dependent source signal, i.e., $F^k(\theta)$, dominant, the k^{th} column of $\mathbf{A}^D$ can be similarly estimated based on $F^k(\theta)$ instead of $S^{D_k}(t)$ [4]. Furthermore, rule I can be similarly performed to test the sparse property in the transformed domain based on $\tilde{F}^i(\theta)$ and $F^k(\theta)$, instead of $\tilde{X}^i(t)$ and $S^{D_k}(t)$, respectively.

4. Monitoring of Individual Operations Based on Estimated Source Signals

Based on the estimation of the independent/dependent source signals, control charts are established to monitor the individual operations. Due to the sensor noise and the estimation error, each estimated die source signal $\hat{S}^i(t), \hat{S}^i(t) \in \{\hat{\mathbf{S}}^I(t), \hat{\mathbf{S}}^D(t)\}$, i=1,…,p+q, can be assumed to be a vector of random variable, i.e.,

$$\hat{S}^i(t) = \mu_{\hat{S}^i}(t) + e^i(t) \tag{8}$$

where i=1,2,…,p+q; $\mu_{\hat{S}^i(t)}$ is the mean of the random vector. $\hat{S}^i(t)$.

At phase I of the monitoring chart construction, M (M>N) samples of mixed sensor signals, with each sample containing n mixed sensor signals, are collected under the normal working condition. For the j^{th} sample, the estimated source signal, denoted as $\hat{S}^i_j(t)$, are obtained based on the method introduced in Section 3. $\mu_{\hat{S}_i(t)_i}$ and $\sigma^2_{\hat{\mathbf{S}}^i}$ can then be estimated based on $\hat{S}^i_j(t)$. At the phase II stage, when a new sample of estimated source signal, denoted as $\hat{S}^i_0(t)$, is obtained, $\hat{S}^i_0(t)$ need to be firstly calibrated to $\mu_{\hat{S}_i(t)}$ due to the scale ambiguity of both SCA and ICA method, i.e., both ICA method and SCA method cannot determine the magnitude of the estimated signals, because any scalar multiple in one of the sources signals can always be cancelled by dividing the corresponding column in mixing matrices , $\mathbf{A}^I$ or $\mathbf{A}^D$, since both source signals and mixing matrices are unknown. Thus, an optimal scale variable k_0 need to obtained to minimize the difference between $k_0\hat{\mathbf{S}}^i_0$ and $\boldsymbol{\mu}_{\hat{\mathbf{S}}^i}$ for the purpose of , which can be formulized as the following optimization problem:

$$\text{Objection function: } \underset{k_0}{Min} \sum_{i=1}^{M}\sum_{t=1}^{n}(k_0\hat{S}^i_0(t) - \mu_{\hat{S}^i(t)})^T(k_0\hat{S}^i_0(t) - \mu_{\hat{S}^i(t)}) \tag{9}$$

The optimization problem in (9) can be solved by Levenberg-Marquardt method [8] or Gauss-Newton method [9] that are studied in the literature. After obtaining the optimal scale variable k_0, statistical rule II can be used to detect the abnormality of individual operations.

Statistical rule II: An abnormality happens on the i^{th} source signal if the following condition is hold:

$$\frac{(M^2-1)\sum_{t=1}^{n}(k_0\hat{S}^i_0(t) - \mu_{\hat{S}^i(t)})^T(k_0\hat{S}^i_0(t) - \mu_{\hat{S}^i(t)})}{M(M-N)\hat{\sigma}^2_{\hat{S}^i(t)}} > F_{N,M-N}(\alpha) \tag{10}$$

where the sample mean and sample variance, i.e., $\mu_{\hat{S}^i(t)}$ and $\hat{\sigma}^2_{\hat{S}^i(t)}$ can be estimated an phase I, and $F_{N,M-N}(\alpha)$ is α percentage point of a F distribution with N and M-N degrees of freedom.

5. Case Study

The developed methods are applied to a multiple operation forging process illustrated in Fig. 1, where a part is produced after five sequential operations: performing, blocker, finisher, piercing, and trimming. At each press stroke, five operations are performed by five embedded dies with each die striking on the different intermediate part at each station. Fig. 2 shows the source signals generated by these five die operations. Based on the engineering design, it is known that the source signals include two independent source signals generated by station 4 (piercing) and station 5 (trimming) respectively, and three dependent source signals generated by stations 1~3. From Fig. 2, it can be seen that the magnitudes of the independent source signals of stations 4 and 5 are much smaller than those of the dependent source signals from stations 1~3. Therefore, either single ICA method or the SCA method cannot be used to fully separating the source signals from mixed sensing signals.

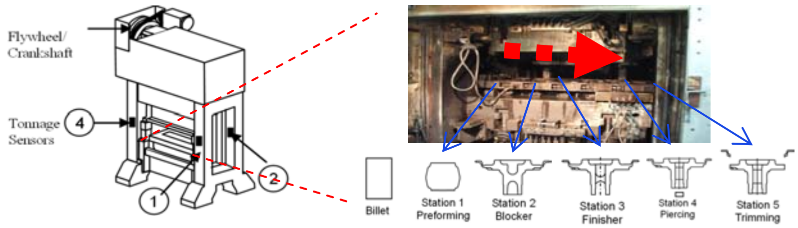


Figure 1: A multiple operation forging process with five operations

During continuous production, strain gage sensors are usually installed on the linkages or columns of the forging press to measure the press tonnage forces. The force measurements from the gage sensors can be reasonably considered as a linear combination of the die forces of all embedded individual operations. In this case study, in order to fully separate five die forces, five sensor signals must be installed, otherwise only four die forces can be separated. In order to demonstrate the proposed methodology, we generated two arbitrary sensor mixture matrix $\mathbf{A}^I$ and $\mathbf{A}^D$ for five sensors, which is used to demonstrate the generality of the proposed method applicable to an arbitrary sensing system independent of sensor locations. The sensor noise $\boldsymbol{\varepsilon}$ is assumed to be $MN(0,\mathbf{I})$, $\mathbf{I}$ is an $N \times N$ identity matrix. Fig. 3 illustrates the simulated mixed sensor signals $\mathbf{X}(t)$.

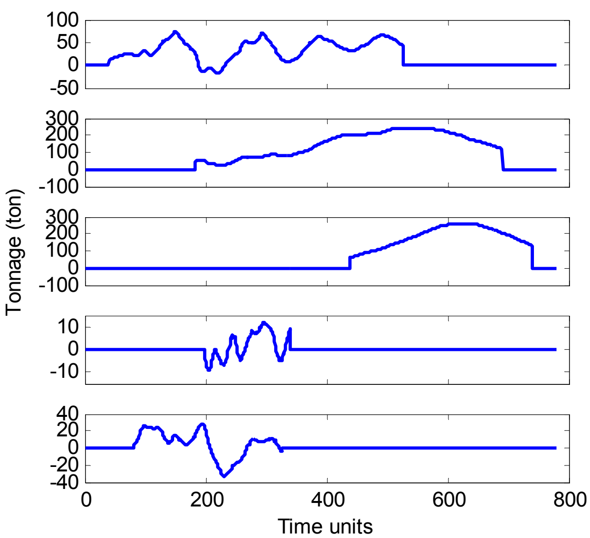


Figure 2: Source signals generated by five die operations

$$\mathbf{A}^I = \begin{bmatrix} .66 & .58 \\ .36 & .94 \\ .85 & .39 \\ .93 & .66 \\ .68 & .97 \end{bmatrix}, \ \mathbf{A}^D = \begin{bmatrix} .40 & .26 & .14 \\ .28 & .17 & .92 \\ .55 & .96 & .32 \\ .26 & .49 & .79 \\ .46 & .70 & .36 \end{bmatrix}$$

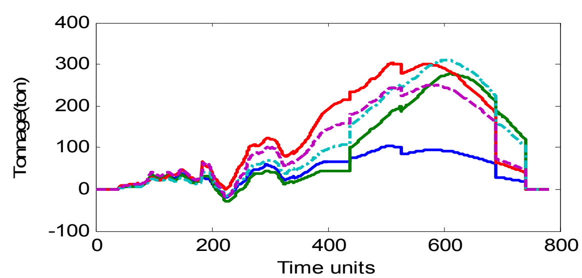
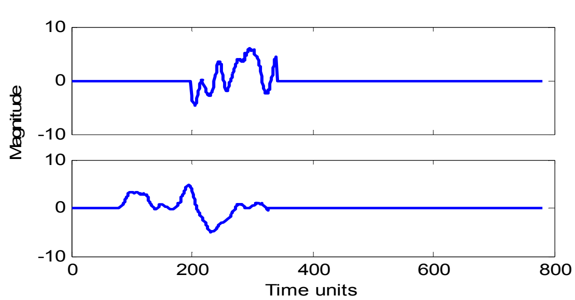


Figure 3: Simulated mixed sensor signals

5.1 Estimation of Independent/Dependent Source Signals

After applying the method in section 3 on $\mathbf{X}(t)$, both independent source signals and dependent source signals can be successfully estimated, which are illustrated in Fig.4(a) and Fig.4(b), respectively.



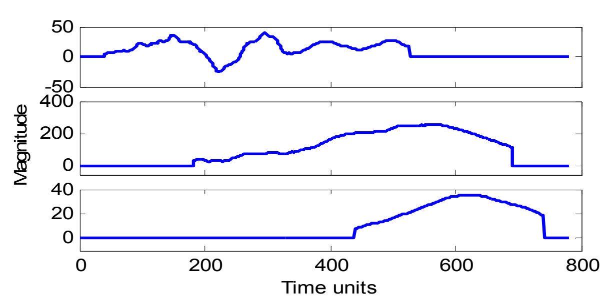


Figure 4(a): Estimated independent source signals (b): Estimated dependent source signals

5.2 Monitoring of Individual Operations Based on Estimated Source Signals.
Suppose abnormality happened on the first and the fourth dies and the corresponding faulty die signal are illustrated in Fig. 5. The estimated independent and dependent die signals are illustrated in Fig. 6. It can be seen that both the independent faulty die signal and the dependent fault die signals are successfully estimated. Rule II is further performed based on the estimated source signals, and the results show that the abnormalities of the first and the fourth operations are detected.

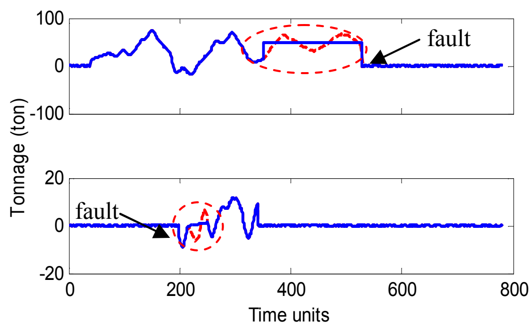


Figure 5: Fault source signals

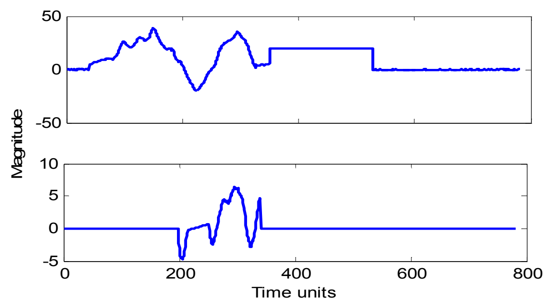


Figure 6: Estimated fault source signals

7. Conclusion

This research proposed a new method for estimating the individual die signals from the multiple tonnage sensor signals by combining the Independent Component Analysis (ICA) method, the Sparse Component Analysis (SCA) method, and the engineering knowledge. The newly developed method consists of two major steps: first, the ICA method is applied on multiple tonnage sensor signals. The impacts of the independent die signals on the measured sensor signals are then eliminated. The reduced sensor signals are separated using SPC method in the time and frequency, respectively. Furthermore, two statistical rules are developed to check the sparse property and to monitor the individual operations based on the estimated source signals, respectively. A case study on a forging process is conducted to demonstrate the developed methods. The case study showed that the independent/dependent die signals can be successfully estimated by the proposed estimation method, while neither the ICA method nor the SCA method can deliver satisfactory results. The estimation of the source signals offers efficient monitoring and quality assessment of the individual die operations, thus enhances the diagnosability of the tonnage monitoring system.

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