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Punching process monitoring using wavelet transform based feature extraction and semi-supervised clustering

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Abstract

Punching is a common sheet metal fabricating process for many industrial applications. On-line health condition monitoring of punching process is becoming more and more important in order to detect and correct process failures in time, and ensure the consistence of the product quality. Effective feature extraction of the process is critical for monitoring the punching process. In this work, piezoelectric strain sensors are used to measure the strain on press column surface which is the response of the press to the stamping force. A feature extraction approach based on the wavelet transform and the energy distribution of the reconstructed wavelet coefficients is proposed. The energy distribution is used as the process feature for similarity distance calculation for the process clustering. Semi-supervised clustering is applied to the process monitoring considering that many normal data sets are available while the failure data is difficult to obtain in practice. The proposed method is applied to the column strain signals from punching process and simulation failure data. The results show that combining the wavelet energy distribution of the strain signal and the semi-supervised clustering is an effective method for health condition monitoring and failure detection in punching processes.

Keywords: Punching process; on-line monitoring; failure detection; wavelet transform; machine learning; semi-supervised clustering

1. Introduction

Sheet metal punching is one of the most common manufacturing operations in modern industries. Various failures such as tool wear, broken tool, slug jamming and tool misalignment may occur in the punching processes. These failures can deteriorate the quality of the holes or interrupt the production. On-

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line monitoring of the punching process is becoming more and more important in order to detect and correct the punching failures in time, ensure the consistence of the product quality, and protect the tools from damage. Sheet metal punching is a highly transient process that usually lasts only a dozen milliseconds or even shorter time period. How to effectively collect process data and extract the features that well characterize the punching process is critical to the process health monitoring.

In stamping or metal forming processes, the stamping force is one of the most important process variables. Monitoring the stamping force is the most direct and effective method for process monitoring and control [1]. However, measuring the stamping or metal forming force directly in metal working process is expensive in terms of both the sensor cost and the installation cost. In practical process monitoring and research work, column strain, acoustic emission, vibration, audio signals and even displacement are also used in addition to the direct force measurement [2-15]. Koh et al [2] used strain gages to measure the tonnage signals from a sheet metal drawing process and applied Haar transform to the segmented tonnage signals for detecting the multiple process failures. Mahayotsanun et al. [3] investigated tooling-integrated complementary sensing system, namely, mutual inductance-based displacement measurement for sheet draw-in and distributed contact pressure measurement at the tool–workpiece interface for stamping process monitoring in laboratory. Kim [4, 5] investigated punching process monitoring with acoustic emission (AE). The AE signal emitted during punching was found to consist of three components: initial impact, shear fracture and rupture. Good correlations were found between the process variables and the AE signals. Klingenberg and Singh [6] proposed the utilization of the force-displacement graphs created by sensor data from a load cell and a displacement transducer for monitoring the progressive tool wear during sheet metal punching. Their work shows that the development of punch wear can be recognized from the shape change of the force-displacement graphs. Zhang et al. [7-8] investigated stamping process monitoring for a blanking process using vibration-based measurements and analysis. Time-frequency distribution [7] and bispectral analysis [8] were used to extract process features; and the typical blanking failures such as misfeed and slug were successfully detected. Wu et al. [9] studied punch failure monitoring in micro-piecing process using vibration measurement and logistic regression model. The logistic regression model is used to estimate the tool condition and detect punch breakage. The authors claimed that using logistic regression model with selected features the prediction accuracy can be up to 99%. Sari et al. [10] conducted experimental work using vibration measurement and the observation of the tool condition and the burr formation of punching process. Their results show that there is a correlation between the tool condition and the vibration signal. Ubhayaratne et al. [11] investigated the monitoring of the tool wear progression of stamping process using audio signal and blind signal separation model; and the authors claimed that the spectral analysis results of the raw and the extracted signals demonstrated a significant qualitative relationship between wear progression and the emitted sound signature. Ge et al. [12-13] used strain sensor to measure strain signals from press column of stamping process and applied wavelet packets and support vector machine (SVM) for signal feature extraction and successfully detected failures in a blanking process. In another work, Ge et al. [14] also studied stamping process monitoring using autoregressive (AR) model for process feature extraction and hidden Markov model (HMM) for failure classification and achieved success rate of 80%-90%. Lee et al. [15] proposed an automatic supervisory system for monitoring blanking punch wear under various die wear conditions using autoregressive (AR) model and linear discriminant function (LDF) classification. Their approach was successfully demonstrated using a series of blanking experiments.

Most of the available research work was conducted in laboratory and some work used complicated or expensive sensing systems like tooling-integrated sensing system or AE sensor. AE signal is of very high frequency and usually the data length for one stamping cycle is very large considering that the high sampling frequency (typically 250 kHz ~ 250 MHz). This requires expensive high frequency data acquisition system and high computational resource. While audio signal is usually of low signal-to-noise ratio with the noise contamination from nearby machines and it needs complex source separate algorithm to extract useful information for process condition monitoring. In real-world condition monitoring applications, sensor cost, installation cost, computational cost, etc. must be taken into account.

In this work, piezoelectric strain sensors are used to measure the strain on press column surface as a process variable considering that the fair sensor cost, low installation cost and short data length for processing. The bandwidth of 1 kHz for the column strain signal is usually sufficient for monitoring the most of the sheet metal working process. The strain signal measured from the press column contains not only the information of the metal deformation during the punching, but also the information of the press structural vibration after the punching. Wavelet transform is used to decompose the column strain signal. Then the energy of the reconstructed wavelet coefficients is calculated. Thus an energy distribution is obtained for a strain signal. The energy distributions are used as features for similarity distance calculation and process clustering. Semi-supervised clustering is applied to process monitoring considering that many normal data sets are available and failure data is difficult to obtain in practice. The proposed method is demonstrated using real-world strain signals measured from a punching press column and simulated failure data. The results show that combining the wavelet decomposition energy distribution of the press column strain signal and semi-supervised clustering is an effective approach for punching process monitoring and failure detection.

2. Punching process and the strain signature measured from the press column

2.1. Punching process and punching force

Punching operation removes a scrap slug from the metal workpiece each time when a punch enters the punching die. This process leaves a hole in the metal workpiece. The sectional dimension and shape of the punch determine the size and the shape of the hole created in the workpiece. The slug from the hole falls through the die into some sort of container to either dispose of the slug or recycle it. When the punch travels upward again, it can happen that it pulls the sheet along. In that case, the stripper releases the sheet from the punch. The higher the fraction of cut on the sheet edge, the better the edge quality. When the punch wears, the frequency of the slug or sheet pulling will be higher, and the quality of the hole also becomes worse.

Blanking is a process similar to the punching, during which a metal workpiece is removed from the primary metal strip or sheet when it is punched. The removed material is the new metal workpiece or blank. Blanking and punching are the same from the metal forming stand point. The tooling and processes are the same for the two operations, the only difference is that in blanking the punched out piece is used as part and in punching the punched out piece is scrap or slug.

The punching process causes sudden changes in press force due to the rapid nature of material breakthrough when the shear strength of the material is exceeded. Fig. 1 shows a typical force-time (or force-displacement) curve in sheet metal blanking process [16]. It is seen that there is a sudden drop when the scrap is separated from the metal sheet, and then a vibration decal follows. This is the feature of the force in sheet metal blanking and punching process. For many of the cases, the product from the blanking is larger than the scrap from the punching, so the metal forming period in punching is usually shorter than that in the blanking. Any change in the force curve indicates the change in the process. And the vibration decay is a result of the punching and it also contains information of the potential process change.

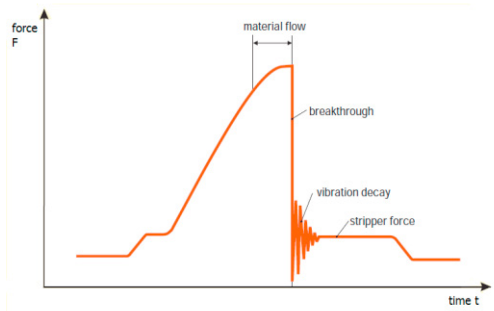


Fig. 1. Force-time curve for sheet metal blanking and punching.

2.2. Strain signature measured from the press column

In this work, piezoelectric strain sensor is used to measure the strain on the press column surface as a process variable that will be used to monitor the punching process. Fig. 2 shows the punching press from which the process data is collected and the sensor mounting location (two strain sensors are mounted on left and right columns and only the strain sensor on one side is shown in the figure). It is a CNC turret punching press (Verona 1225, 30 ton).

Fig. 3 shows typical strain signals measured from the punching press column. Fig. 3 (a) is the column strain signal for a larger hole and Fig. 3 (b) is the column strain signal for a smaller hole. The corresponding holes are shown in Fig. 4. Hole 1 is larger and Hole 2 is smaller.

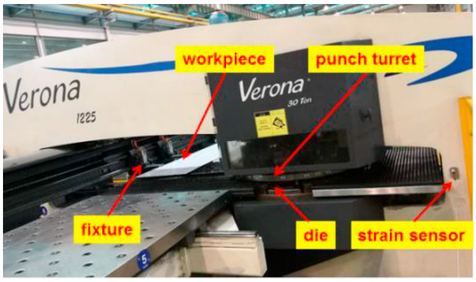


Fig. 2. Punching machine and the sensor location.

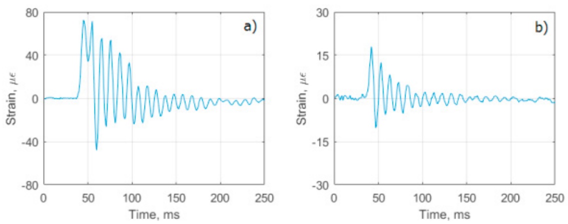


Fig. 3. Strain signals from the press column surface: (a) larger hole; (b) smaller hole.

Fig. 4. Punched holes (larger one and smaller one).

Comparing the strain signals shown in Fig. 3 with the force-time curve shown in Fig. 1, it can be observed that the column strain signal is not that clean as the force curve. The strain signal contains not only the metal forming part, but also the structural vibration part. There is not a clear boundary between the metal forming period and the vibration decay period in the strain signals. The press column strain signal is a superposition of the effects of the punching force and structural vibration. Another thing that can be observed from the strain signal is that the metal forming time period for the hole punching is very short and it usually lasts a few milliseconds to one or two dozen milliseconds. For the strain signals shown in Fig. 3, the metal forming time period for the larger hole (a) lasts less than 20 milliseconds and the metal forming time period for the smaller hole (b) lasts only a few milliseconds.

3. Method for punching process monitoring

As described in the previous section, the strain signal measured from the punching press column surface contains rich process information. It must be preprocessed to extract the features that well characterize the punching process for the purpose of condition monitoring and failure detection. In this section, feature extraction based on energy distribution of the wavelet decomposition on the column strain signal and process failure detection using semi-supervised clustering will be described.

3.1. Wavelet transform

In the past over twenty years, wavelet transform (WT) has attracted lots of attention in a wide variety of fields from seismic data analysis to mechanical fault diagnosis, mainly due to its advantages over Fourier transform in terms of its strong capability for localization in both time and frequency domains. The basic principle of the wavelet transform will be briefly introduced in the following.

Wavelets can be considered as a family of functions constructed from translations and dilations of a single function called the "mother wavelet" $\psi(t)$ [17]. They are defined by the following equation.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \qquad a,b \in R, a \neq 0 \qquad (1)$$

The parameter a is the scaling parameter or scale, and it measures the degree of compression. The parameter b is the translation parameter which determines the time location of the wavelet. From the construction of the wavelets it is seen that the wavelets have time-widths adapted to their frequencies. This is the main reason for the success of the wavelet transform in signal processing and time-frequency analysis.

For a signal $s(t)$, its wavelet transform at scale a, position b is defined as an inner product:

$$W_s(b,a)=\int_{-\infty}^{+\infty} s(t)\frac{1}{\sqrt{|a|}}\psi^*\left(\frac{t-b}{a}\right)dt \qquad (2)$$

WT can be implemented in either continuous or discrete form. Discrete wavelet transform (DWT) is the most widely used one in applications in different fields. DWT is an adaptive decomposition which decomposes a signal with high- and low-pass filters and increases the frequency resolution in lower frequency band. A 3-level discrete wavelet transform (decomposition and reconstruction) is depicted in Fig. 5. The reconstruction coefficients are shown in the frequency or scale domain.

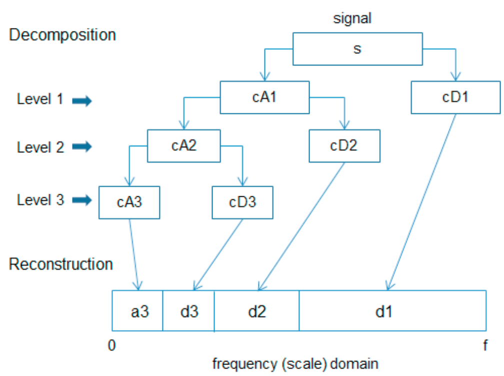


Fig. 5. Depiction of a 3-level wavelet decomposition and reconstruction.

3.2. Feature extraction based on wavelet transform

In order to extract the features of the punching process from the column strain signal, DWT is applied to the decomposition and reconstruction of the strain signals. Fig. 6 shows original waveform and reconstructed coefficients of a 4-level wavelet decomposition on a strain signal (shown in Fig. 3 (a)). Fig. 6 (a) shows the original strain signal. Fig. 6 (b), (c), (d) and (e) show the reconstructed detail coefficients at level 1, level 2, level 3 and level 4 respectively. And Fig. 6 (f) shows the reconstructed approximation coefficients at level 4.

Fig. 7 shows the reconstructed wavelet approximation and the detail coefficients from the 4-level *db4* wavelet transform on a strain signal. The blue curve is the reconstructed approximation coefficients; and the red curve is the total reconstructed detail coefficients. Roughly, the reconstructed approximation part reflects the deformation of the press structure under the punching force. And the total reconstructed detail part is shown in red curve reflects the vibration effects on the press structure.

After the decomposition and the reconstruction, the RMS (root mean square) values, i.e., the signal energy, of the reconstructed coefficients of the wavelet transform are calculated. Thus an energy distribution is obtained for each strain signal. The energy distribution is used as feature for further process classification and failure detection. The energy distribution for the decomposition shown in Fig. 6 is shown in Fig. 8.

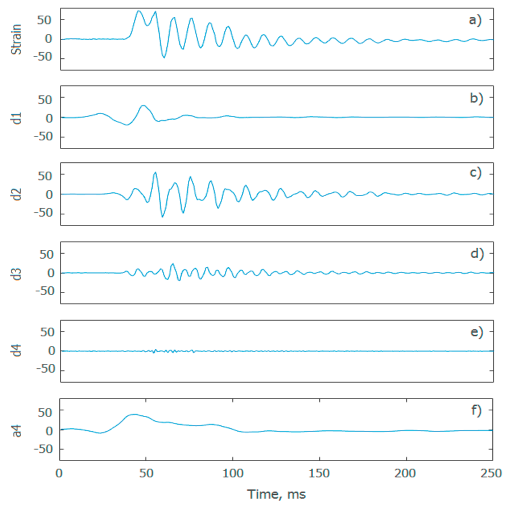


Fig. 6. (a) Original strain signal; (b)-(e) Reconstructed detail coefficients at level 1 (b), level 2 (c), level 3 (d), level 4 (e); (f) Reconstructed approximation coefficients at level 4.

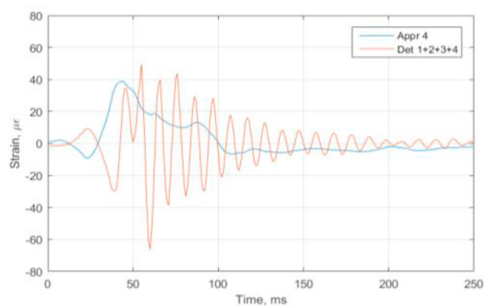


Fig. 7. Reconstructed wavelet coefficients: blue curve is the approximation coefficients at level 4; red curve is the summation of the detail coefficients from level 1 to level 4.

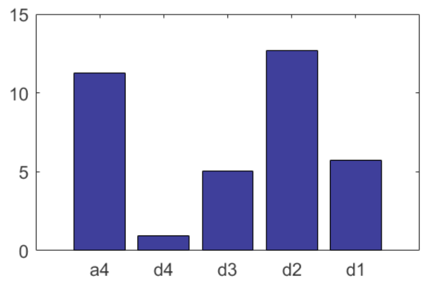


Fig. 8. Energy distribution for a 4-level wavelet decomposition.

3.3. Anomaly detection using semi-supervised clustering

Clustering is a class of unsupervised machine learning algorithms. In clustering, data is grouped according to their similarities. Data distribution of clusters is very important for anomaly detection. Due to the rarity of anomalous data they will be considered as outliers.

One of the popular clustering algorithms is the k-means algorithm. It is intended for situations in which all variables are of the quantitative type.

For a data sample $D = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_m\}$, k-means minimize the squared error for k clusters $C = \{C_1, C_2, \cdots, C_k\}$:

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|_2^2, \qquad \mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x \tag{3}$$

where $\mu_i$is the mean vector of cluster C_i [18].

It's a basic algorithm that performs clustering based on the distance between data points. The result of the k-means algorithm is that we get k number of clusters.

In order to develop algorithm for anomaly detection, the cluster boundaries need to be identified. The cluster boundaries are learned by using the known normal data sets. Generally, a percentile distance value point of each cluster from their cluster centers can be used to determine the cluster boundaries. However, as it requires "no false positives" in real production environment and considering that anomalies will be further away from the normal cluster centers than normal data because they deviate from the normal behavior, in this work we multiply the maximum distance of the data sets with a coefficient to generate the boundaries. The coefficient could be different for various cases. The coefficient value used for this specific case is 1.1.

After determining the cluster boundary of each cluster, we can perform predictions for new data. When a new data point comes in, we determine which cluster it should belong to using the production scheduling information and the information from the controller of the punching machine. The production scheduling information is used to determine which product is being made and the information from punching controller is used to determine which hole is being punched. Then the algorithm checks whether the distance of the data set to the cluster centers is greater than the cluster boundary. If it is, it's considered as an anomaly, since it is outside the clusters' boundary. If not, it's considered as a normal data point since it's inside the clusters' boundary.

4. Application to punching process monitoring

The nature of the condition monitoring and fault diagnosis is pattern recognition or classification. In this section, firstly the principal component analysis (PCA) is applied to both the original strain data and the energy distribution feature to demonstrate the effectiveness of the wavelet transform based feature extraction. PCA is only used for demonstration here and is not used in the proposed method for failure detection of the punching process.

Then the proposed method combining wavelet transform energy distribution and semi-supervised clustering is applied to the normal data set measured from shop floor punching process and simulated failure data. The wavelet transform energy distribution for process feature extraction and the semi-supervised clustering is used to determine the cluster boundary. Once the cluster boundary is learned, it can be used for punching process monitoring and failure detection. Real-world strain signals for normal punching process and the simulated strain signals for punch wear are used to validate the algorithm.

4.1. PCA on strain signals and energy distributions

Fig. 9 shows a long strain signal for 23 holes collected from one sheet metal punching (5 holes for type-A, 5 holes for type-B, 6 holes for type-C, 5 holes for type-D and 2 holes for type-E as indicated in the figure). Strain signals are collected from 50 product sheets with 1150 holes in total.

Firstly, one strain signal for each hole is extracted and thus 1150 strain waveforms are obtained from totally 50 metal sheets. Then, four-level wavelet decomposition is applied to the strain waveforms. Thirdly, RMS values are calculated from the reconstructed wavelet coefficients, and thus an energy distribution is obtained for each hole.

In order to explore the separability of the five types of holes; principal component analysis is applied to both the original strain waveforms and the extracted energy distribution features. Fig 10 (a) shows the PCA results on the original strain signal (only the first two principal components PC1, PC2 are used). It is seen that Hole A and Hole E are easily separated from the other three holes. However, Hole B, Hole C and Hole D are very close in PCA space (PC1-PC2). Hole C and Hole D are even overlapped. Fig 10 (b) shows the PCA results on the wavelet energy distributions of the strain signals. It can be seen that the separability of hole B, hole C and hole D is much better than that shown in Fig 10 (a).

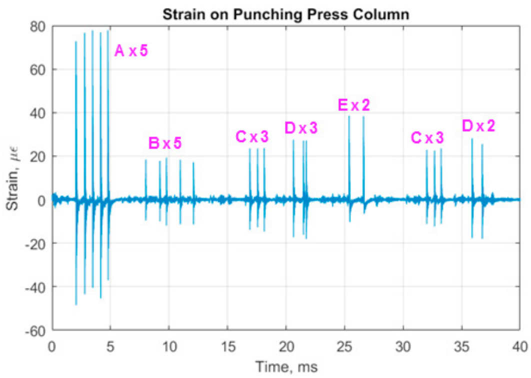
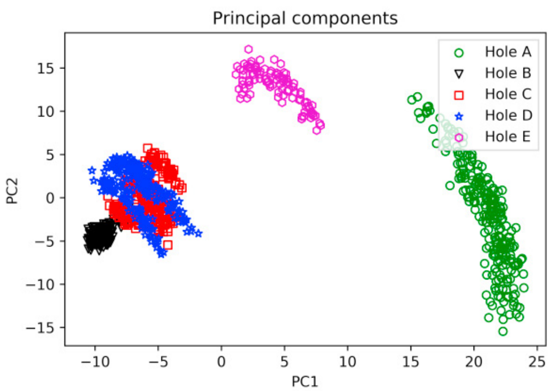
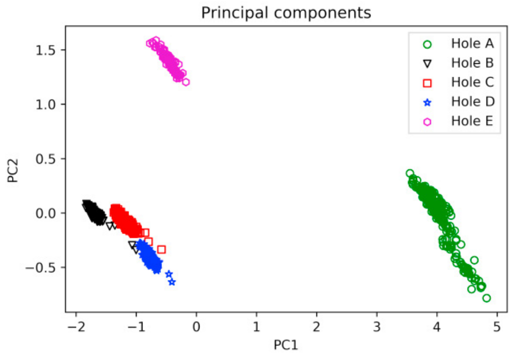


Fig. 9. Strain signal for a product with 23 holes (5 types).



(a) PCA on the original strain signals



(b) PCA on the wavelet energy distributions

Fig 10. Principal component analysis (PCA) for the strain signals and the energy distribution features.

4.2. Failure detection using semi-supervised clustering technique

Most machine learning algorithms train the model using the available data sets with labels. So, in order to achieve better accuracy rates these algorithms need a large amount of labeled data to train and build the models. In real-world process monitoring, we always have many data sets for normal condition. However, it is difficult to obtain sufficient abnormal data sets to train the classification model. Although the normal data sets are similar for a certain process (e.g., punching of the same hole), the anomalous data could be dissimilar. So we need semi-supervised clustering for identifying the centers of the normal clusters and the distance boundary. When a new data set comes, the distance (similarity measure) between the data sets and the cluster center is calculated. If it beyond the identified boundary then is it considered as an anomaly or a process failure.

For the punching process, one of the popular failures is the punching tool wear. When the punching tool wears, the tool becomes blunt and the friction between the punch and the sheet metal also becomes larger. In this case, there could be slug pulling, or even sheet metal pulling when the punch leaves the sheet metal workpiece. Based on the physical understanding of the punching process, we create digital simulation for punching wear with different severity. The actual cases could be even worse than the simulated signals when there is punch failure. In order to create the simulation signals for punch wear, we make assumption that the normal punching process has two phases: a) metal forming;

b) structure free vibration. Then we can assume that the punching process with tool wear has three phases: a) metal forming; b) sheet metal stuck to the punch with a bigger friction when the punch moves back; c) free vibration of the press structure after the punch separates from the sheet metal. Based on this assumption, simulation strain signals for two failure cases were created. Fig. 11 (a) shows a measure column strain signal for Hole A (the larger hole, see Fig. 3 (a)). Fig. 11 (b) shows a simulated signal for a light punch wear case (modified from Fig. 11 (a)). Fig. 11 (c) shows a simulated signal for a severer punch wear. These signals are used for demonstrate the performance of the proposed methods.

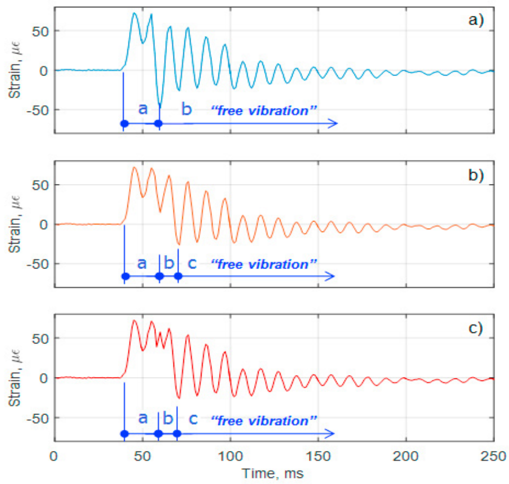


Fig. 11. (a) Normal strain signal; (b) Simulated strain signal: light punch wear; (c) Simulated strain signal: severe punch wear.

Fig. 12 (a) shows the distribution of the normalized Euclidean distances and the learned cluster boundary for the normal punching conditions using the energy distributions of the reconstructed wavelet coefficients. Totally 250 normal data sets from punching of Hole A are used to learn the cluster boundary and the cluster center. It is seen that when there is wear in the punch, the distance to the cluster center becomes significantly larger than that of the normal data sets. In the figure, Failure 1 is light punch wear and Failure 2 is severer punch wear, and their normalized distances to the cluster center are 0.7413 and 1.0 respectively. The normalized distance from the learned boundary to the cluster center is 0.1860. And the distances of Failure 1 point and Failure 2 point to the boundary are $\Delta_1 = 0.5552$ and $\Delta_2 = 0.8140$ respectively. For comparison, Fig. 12 (b) shows clustering results using the original strain signals (without preprocessing). In this case, the normalized distance from the learned boundary to the cluster center is 0.7069. And the distances from Failure 1 point and Failure 2 point to the boundary are $\Delta_1 = -0.0534$ and $\Delta_2 = 0.2931$ respectively. The Failure 1 (light punch wear) is classified as normal and cannot be detected.

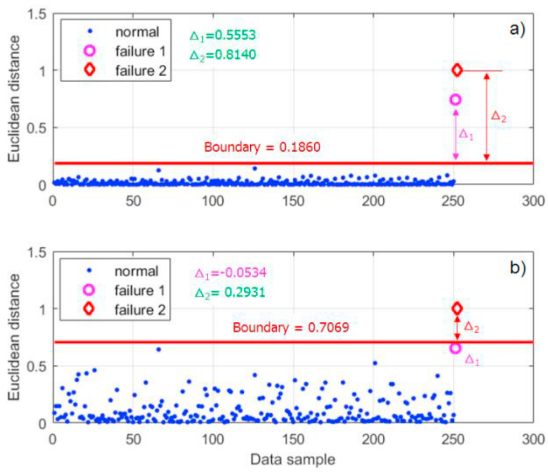


Fig. 12. Normal cluster boundary and the failure detection: (a) Normalized distance to the cluster center based energy distribution of the wavelet reconstruction coefficients; (b) Normalized distance to the cluster center using the original strain signals.

4.3. Discussion

Comparing to other sheet metal working processes such as deep drawing and bending, the punching process is a more highly transient process. This brings challenge to the process feature extraction and the health condition monitoring. Currently, no mature cost-effective method is available for punching process monitoring. The strain sensor measuring system works well for tonnage monitoring for drawing process [2]. In this work, it is demonstrated that by using appropriate data preprocessing approach the column strain signal can also be used for punching process monitoring. The punching processes used in this work only last about 10-20 milliseconds (this is the time period that the punch is in touch with the sheet metal). The one cycle of the sampled strain signal including the structure vibration part for each punching process is about 200 milliseconds. This means that only about one-tenth of the whole sampled punching cycle is corresponding to the metal forming process and the rest of the data results from the structure vibration. In addition to the metal forming part, the structure vibration part also contains rich information of the punching process. This work focuses on feature extraction from the strain signals, and the results show that the wavelet-based energy distribution characterizes the punching process feature well. The semi-supervised clustering is used for achieving automatic process monitoring and failure detection.

5. Conclusion

In this work, strain signal measured on press column surface is used to monitor the sheet metal punching process. The strain signal contains rich information of the punching process including the information from both the metal forming and the structure vibration following the metal forming process. In order to extract the features that well characterize the health condition of the punching process from the strain signal, a 4-level wavelet decomposition is applied to the strain signal. Approximation coefficients at level 4 and detail coefficients from level 1 to level 4 are obtained. The energy distribution of the reconstructed wavelet coefficients is a distribution on the multi-resolution frequency bands; and it is used as the process feature for failure detection using the semi-supervised clustering algorithm. The failure detection results using normal data set measured from the shop floor punching process and the simulated failure data sets show that the proposed approach combining the wavelet energy distribution of the column strain signal and semi-supervised clustering is effective for punching process monitoring.

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