Recognition of unnatural variation patterns in metal-stamping process using artificial neural network and statistical features

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Abstract. Unnatural process variation (UPV) is vital in quality problem of a metal-stamping process. It is a major contributor to a poor quality product. The sources of UPV usually found from special causes. Recently, there is still debated among researchers in finding an effective technique for on-line monitoring-diagnosis the sources of UPV. Control charts pattern recognition (CCPR) is the most investigated technique. The existing CCPR schemes were mainly developed using raw data-based artificial neural network (ANN) recognizer, whereby the process samples were mainly generated artificially using mathematical equations. This is because the real process samples were commonly confidential or not economically available. In this research, the statistical features - ANN recognizer was utilized as the control chart pattern recognizer, whereby process sample was taken directly from an actual manufacturing process. Based on dynamic data training, the proposed recognizer has resulted in better monitoring-diagnosis performance (Normal = 100%, Unnatural = 100%) compared to the raw data-ANN (Normal = 66.67%, Unnatural = 26.97%).

1. Introduction

In manufacturing industry such as metal-stamping, production of the precision stamping parts requires for a proper scheme of quality control (QC). In order to avoid a bad quality production, the industrial practitioners such as QC inspectors and production operators are also well trained in identifying the unnatural variation (UV) during metal-stamping process based on control chart patterns (CCP). A proper monitoring and diagnosis of CCP will efficiently trigger against the defective or bad quality production. Nowadays, the UV is able to be monitored-diagnosed automatically using control chart pattern recognition (CCPR) technique. In-line with the development of machine learning technology such as an artificial neural network (ANN), various CCPR schemes have been proposed in many reported researches [1-4]. These schemes were applied in QC for automatically recognizing CCP towards improving ability in monitoring-diagnosis. In monitoring aspect, the CCPR scheme is theoretically designed to rapidly identify the UV or out-of-control process condition with minimum false alarm. In diagnosis aspect, the CCPR scheme is theoretically designed to accurately classify the
sources of UV or out-of-control condition. Based on the specific CCP, an effective identification for the sources of UV will significantly speed up the corrective action efforts.

When discussing on the ANN-based CCPR schemes, an ANN model is utilized as a pattern recognizer to identify the CCP through supervised training using a sufficient amount of samples (data streams) of CCP. The advantage of an ANN recognizer is the ability to recall the learned patterns of noisy samples [4]. In the related study, features-based ANN recognizers have been reported as provided a significant contribution to the recognition result. Theoretically, the features properties are extracted and selected from the original samples to be an input representation into an ANN recognizer to reduce neural network size of architecture and processing time. If the extracted features represent the characteristics of CCP explicitly and their components are reproducible with the process conditions, the recognition accuracy will be significantly increased [5]. The extracted features have been investigated in several forms, including shape features [6 – 7], multi-resolution wavelet analysis [8 – 9], and statistical features [10]. In the existing researches, most of the samples are computerized generated using an established mathematical model since the real samples from manufacturing process environment are not economically available [10]. In this research, samples of CCP for supervised ANN training were taken directly from real manufacturing process, i.e., metal-stamping. Besides that, a new and simple set of statistical features was investigated as input representation for an ANN recognizer.

2. Research Methodology
The development of CCPR scheme has underlying three (3) main phases. Phase 1 involves the efforts for identification of quality defects, Phase 2 focuses on pattern recognizer design, and Phase 3 dealing with training-testing of the scheme.

2.1 Phase 1: Identification of quality defect
In metal-stamping industry, the stamp terminology denotes all press-work processes such as blanking, punching, bending, coining, and other shaping operations. Figure 1 shows an illustration of blanking process. In practice, the stamping process will be influenced by UV when it was running in an out-of-control condition. In such undesired bad condition, defected parts produced will downgrade the quality and the productivity, which cause losses to the manufacturer.

![Figure 1. Blanking process.](image)

In this research, the types of defects can be classified as follows:
Static defects: non related process such as surface imprints that is caused by contaminated die or tooling surface. This defect can be overcome by cleaning the die or tooling surface before starting the stamping process.

Dynamic defect: process related that is caused by stamping operation. For example, cracking and necking are commonly occurred when formability of the deformed sheet materials is limited. Table 1 summarizes the other process related issues in the metal-stamping process as found in production line.

| Stamping Process | Type of Defects | Source of Defects |
|------------------|-----------------|-------------------|
| Blanking         | - Dimension out | - Uneven clearance between punch & die |
|                  | - High burr     | - Tooling wear & tear |
|                  |                 | - Material thickness out of spec. |
| Piercing / Punching | - Hole undersize / oversize | - Tooling wear & tear |
|                  | - High burr     | - Reverse punch |
|                  |                 | - Punch not guided in stripper plate |
| Bending          | - Spring back   | - Die-height out setting |
|                  | - Cracking      | - Tooling wear & tear |

Recognition on CCP was focused on normal pattern and four (4) types of dynamic defects such as dimension out, high burr, double punch, and rivet slanting. These CCP can be presented graphically as shown in Figure 2.

2.2 Phase 2: Pattern recognizer design

Based on an ANN model, the multilayer perceptrons (MLP) with three (3) layer network architecture as shown in Figure 3 was selected as the CCP recognizer. Size of input representation determines the number of neuron in input layer. Output layer contains five (5) neurons, which was determined according to the number of pattern categories. Number of hidden layer neurons was determined empirically. Investigation involves two (2) network architectures as follows: (i) Raw data-based ANN model (3 x 29 x 5), and (ii) Statistical features-ANN model (10 x 33 x 5).

Proper selection of input representation will influence the performance of CCP recognizer. Based on window size or pattern length equal to 10, the raw data input representation consists of ten (10) values of original samples of each CCP, whereas the statistical features input representation consists of three (3) values of extracted features: average, maximum, and minimum.

2.3 Phase 3: Training – testing the pattern recognizer design

The Levenberg-Marquart (LM) algorithm was selected in training and testing the CCP recognizer. Based on numerical experiment, this algorithm provided rapid training time and suited for small amount of training data. Each CCP category consists of 100 patterns. These patterns were divided to training (60%), testing (20%), and validation (20%).
| Statistical Features | Raw Data |
|----------------------|----------|
| Normal               | ![Normal](image1.png) | ![Normal](image2.png) |
| Dim. Out             | ![Dim. Out](image3.png) | ![Dim. Out](image4.png) |
| Double Punch         | ![Double Punch](image5.png) | ![Double Punch](image6.png) |
| High Burr            | ![High Burr](image7.png) | ![High Burr](image8.png) |
| Rivet Slanting       | ![Rivet Slanting](image9.png) | ![Rivet Slanting](image10.png) |

**Figure 2.** Type of defects
3. Results and Discussion

Table 2 summarizes the training-testing results that considered a thorough analysis for number of hidden layer neuron between 10 and 35. The Statistical Features-ANN gave an efficient recognition accuracy (Normal = 100%, Shifts = 100%) at hidden layer neuron 29. Thus, the network architecture (3 x 29 x 5) was selected as an optimum recognizer. In comparison, the Raw Data – ANN recognizer gave an inefficient recognition accuracy (Normal = 66.7%, Shifts = 26.9%) at hidden layer neuron 33, with network architecture (10 x 33 x 5).

In terms of network size, the Statistical Features-ANN represents a smaller network architecture to reduce computational effort. Based on input representation (IR) approach, the selection of a suitable IR will promote efficient recognition accuracy. In this research, the utilization of statistical features IR as described in Section 2.2 has proven efficient for training-testing using dynamics samples of CCP as compared to the utilization of raw data IR. Based on graphical representation of CCP as shown Figure 1, the statistical features IR indicated a clear representation and identification for each type of defects (UV), whereby it can be discriminated numerically. Inversely, the raw data IR indicated that each type of defects (UV) has the similar trend, which is difficult to be distinguished.

4. Conclusion

In the metal-stamping industries, the statistical features-ANN recognizer has been proven effective in monitoring-diagnosis the UV. Using the CCPR approach, the statistical features-ANN recognizer gave an efficient recognition accuracy (Normal = 100%, Shifts = 100%) as compared to the raw data – ANN recognizer (Normal = 66.67%, Shifts = 26.92%). This result can be supported graphically using IR plots, whereby the statistical features IR indicated a clear identification for each type of defects (UV) as compared to the raw data IR. This research will be useful for industrial practitioners whose dealing with the related manufacturing process.

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### Table 2. Training-testing results

| Hidden Layer Neuron | Statistical Features - ANN | Raw data – ANN |
|---------------------|--------------------------|----------------|
|                     | Recognition Accuracy (%) | MSE x10^3 | Epoch | Time (s) | Recognition Accuracy (%) | MSE x10^3 | Epoch | Time (s) |
|                     | Normal | Shifts | 18.1 | 41 | 4 | 15 | 5 |
| 10                  | 84.2   | 81.3   | 46.7 | 58.3 | 98.2 | 15 | 5 |
| 11                  | 92.1   | 90.0   | 60.0 | 57.1 | 97.8 | 12 | 5 |
| 12                  | 92.1   | 97.5   | 56.7 | 70.8 | 97.2 | 11 | 3 |
| 13                  | 92.1   | 89.7   | 43.3 | 54.2 | 92.6 | 17 | 7 |
| 14                  | 86.8   | 83.3   | 53.3 | 56.0 | 64.2 | 15 | 3 |
| 15                  | 79.0   | 72.4   | 63.3 | 82.6 | 82.5 | 11 | 3 |
| 16                  | 86.8   | 81.5   | 46.7 | 66.7 | 170.3 | 13 | 4 |
| 17                  | 86.8   | 82.8   | 46.7 | 66.7 | 73.3 | 11 | 3 |
| 18                  | 97.4   | 97.0   | 63.3 | 76.0 | 101.5 | 9 | 3 |
| 19                  | 89.5   | 85.2   | 50.0 | 52.0 | 78.2 | 12 | 4 |
| 20                  | 92.1   | 88.9   | 50.0 | 56.0 | 89.7 | 10 | 3 |
| 21                  | 89.5   | 86.9   | 46.7 | 41.7 | 122.1 | 11 | 4 |
| 22                  | 86.8   | 84.5   | 50.0 | 47.8 | 63.8 | 13 | 4 |
| 23                  | 94.7   | 92.3   | 53.3 | 56.0 | 77.7 | 10 | 4 |
| 24                  | 84.2   | 81.3   | 50.0 | 54.6 | 86.0 | 14 | 5 |
| 25                  | 94.7   | 92.6   | 50.0 | 62.5 | 81.2 | 16 | 6 |
| 26                  | 97.4   | 96.2   | 60.0 | 59.1 | 74.4 | 12 | 7 |
| 27                  | 94.7   | 93.1   | 53.3 | 50.0 | 101.8 | 13 | 6 |
| 28                  | 97.4   | 96.4   | 53.3 | 69.6 | 64.9 | 12 | 6 |
| 29                  | 100    | 100    | 53.3 | 56.0 | 115.6 | 15 | 7 |
| 30                  | 86.8   | 84.4   | 63.3 | 59.3 | 66.7 | 11 | 9 |
| 31                  | 89.5   | 85.7   | 50.0 | 60.0 | 93.2 | 15 | 7 |
| 32                  | 92.1   | 88.9   | 46.7 | 52.4 | 88.4 | 10 | 6 |
| 33                  | 92.1   | 88.9   | 66.7 | 26.9 | 67.7 | 20 | 10 |
| 34                  | 94.7   | 93.1   | 50.0 | 52.2 | 78.9 | 13 | 7 |
| 35                  | 92.1   | 88.9   | 40.0 | 52.4 | 82.0 | 10 | 7 |
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