A Frequent Pattern Mining Based Shape Defect Diagnosis Method for Cold Rolled Strip Products*

Xinhang Li, Ningyun Lu, Bin Jiang, Huiping Zhao

Abstract—Flatness is one of the most important specifications for strip products in cold rolling processes. Shape control of cold rolled product is often characterized as a complex process with multiple operation conditions, multi-variables, time-varying parameters, strong coupling and nonlinearity. Accurate online shape defect diagnosis is still a difficult task. This paper proposed a frequent pattern mining algorithm based shape defect diagnosis method, aiming to solve a bottleneck problem associated with the Apriori algorithm when applied for defect diagnosis in complex industrial processes. An improved Apriori algorithm is presented, which maps the defect data into a 0-1 matrix and then calculates the unique frequent itemssets for different defect data via pruning and processing of matrix and mining of correlation between different shape defects and operation conditions. The obtained shape defect diagnosis results can be supportive to improve product quality management in the rolling processes. Case study based on the data collected from Baosteel 2030 cold rolling product line can show the validity of the proposed method.

Key words: Frequent pattern mining; Apriori algorithm; defect recognition; cold rolling process

I. INTRODUCTION

With the remarkable technology advancements and intense market competition in the iron and steel industry, user's demand for higher strip product quality is increasing constantly [1-2]. Flatness is one of the most important specifications for strip products in a cold rolling process. Shape control of cold rolled product is often characterized as a complex process with multiple operation conditions, multi-variables, time-varying parameters, strong coupling and nonlinearity. Accurate online shape defect diagnosis is still a difficult task [3].

Due to frequent switchover of raw materials and market demands, rolling process often works at time-varying operation conditions. Different operation conditions usually have similar process mechanisms but quite different data features [4]. A general data-driven shape defect identification and reason diagnosis is an urgent need in the iron and steel industry. The existing methods can be roughly grouped into three categories: statistical analysis based techniques, signal analysis based techniques and quantitative knowledge based techniques [5-6]. For example, GA-Hopfield NN is developed for flatness pattern recognition, where the feedback network that has strong computing ability is applied for real time information processing [7]. Wavelet transform has also been applied for defect recognition in rolling processes, which can identify complex defects such as quarter waves and compound waves [8]. Nowadays, data mining techniques become popular, such as fuzzy neural model, least squares support vector regression, clustering algorithm, and so on, which have been investigated for flatness pattern prediction and recognition [9-11].

In this paper, a frequent pattern mining based shape defect diagnosis method is proposed for the first time, which can deal with the large amount of industrial data and be applicable for the processes with frequent changing of the operation condition. Apriori algorithm is the most widely used frequent pattern mining technique, but it can’t be directly applied to the case concerned in this paper. An improved Apriori algorithm is developed, which maps the data of defect products into 0-1 matrix and then calculates the unique frequent itemssets for different defect data via pruning and processing of matrix and mining of correlation between different shape defects and operation conditions. The obtained shape defect recognition results can be supportive to improve product quality management in a rolling process. Case study based on the data collected from Baosteel 2030 cold rolling product line can show the validity of the proposed method.

II. DSR SHAPE CONTROL SYSTEM OF BAosteel 2030 COLD ROLLING PROCESS

Dynamic Shape Roller (DSR) is adopted in the Baosteel 2030mm five-stand cold rolling mill for flatness control [12]. Fig.1 shows the structure of the five-stand tandem rolling and the location of DSR system. DSR is an advanced technology used for flatness control. The basic structure of a DSR roll is shown in Fig.2. There are in total seven pressure pads in DSR shape roller, each pad is actuated by a hydraulic roll load cylinder which allows the pressure to be individually adjusted at each pad location. This ensures the control of sleeve deformation and of load distribution across the product width in the roll gap to revise all kinds of flatness defects. Generally, there are several basic types of flatness defect: left waves, right waves, center waves, doubleedge waves, quarter waves and edge-center waves.

Although DSR was introduced aiming to improve the shape quality, which indeed had achieved satisfactory outcomes in the past, it brought challenges for defect recognition and trouble-shooting because of its complex structure and complex control strategy. Since DSR has seven pads, in DSR control system, strips are divided into ten grades.
according to their widths, as shown in Table I. It has advantages for fine shape control, especially for continuous rolling of strip products with different grades, but at the same time, it requires a general defect recognition method that can be applicable for strip products with different grades. It is not an easy task for data-driven methods, because the process data show significant differences among different grade of products [13-14]. Pattern mining method is a good alternative, as it is inherent to be able to different kinds of objects.

Process variables are listed in Table II, including 21 variables from the fifth stand such as the rolling speed, force, tension and so on. 670 batches during four months are collected. After screening, 130 batches that cover nine product grades (w02-w10) and contain both normal shapes and various defect shapes are used for frequent pattern mining and method validation.

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**Fig.1 Illustration of the baosteel 2030 five-stand tandem rolling line**

**Fig.2 The basic constitution of the DSR roll**

**TABLE I. PRODUCT GRADES WITH DIFFERENT STRIP WIDTH**

<table>
<thead>
<tr>
<th>Grades</th>
<th>W10</th>
<th>W09</th>
<th>W08</th>
<th>W07</th>
<th>W06</th>
</tr>
</thead>
<tbody>
<tr>
<td>Width (mm)</td>
<td>850-949</td>
<td>950-1049</td>
<td>1050-1149</td>
<td>1150-1249</td>
<td>1250-1349</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Grades</th>
<th>W05</th>
<th>W04</th>
<th>W03</th>
<th>W02</th>
<th>W01</th>
</tr>
</thead>
<tbody>
<tr>
<td>Width (mm)</td>
<td>1350-1449</td>
<td>1450-1549</td>
<td>1550-1649</td>
<td>1650-1749</td>
<td>1750-2030</td>
</tr>
</tbody>
</table>

**TABLE II. SELECTED PROCESS VARIABLES FOR FLATNESS PREDICTION**

<table>
<thead>
<tr>
<th>Measured variables</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 G5 rolling speed</td>
<td>mpm</td>
</tr>
<tr>
<td>2 G5 rolling force</td>
<td>T</td>
</tr>
<tr>
<td>3 G5 exit tension</td>
<td>KN</td>
</tr>
<tr>
<td>4 Errors</td>
<td>um</td>
</tr>
<tr>
<td>5 Errors</td>
<td>um</td>
</tr>
<tr>
<td>6-12 Pressures</td>
<td>T</td>
</tr>
<tr>
<td>13 Position</td>
<td>um</td>
</tr>
<tr>
<td>14 Position</td>
<td>um</td>
</tr>
<tr>
<td>15-21 Temperatures</td>
<td>°C</td>
</tr>
</tbody>
</table>

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III. DEFECT DIAGNOSIS BASED ON FREQUENT PATTERN MINING

A. Variable Contribution Plot
The first step is to identify process variables that can reflect the shape defects. Contribution plot will be adopted, which is obtained after performing principal component analysis (PCA) \[15\] on the defect data. PCA is conducted on the normal process data collected from the batches with good shape quality.

Process data form a two-dimensional data matrix \(X(n \times m)\), where \(n\) is the number of data samples, and \(m\) is the number of process variables. By using PCA, \(X\) is decomposed into \(m\) subspaces, i.e.

\[
X = TP^T = \sum_{j=1}^{m} t_j p_j^T = t_1 p_1^T + t_2 p_2^T + \cdots \tag{1}
\]

where \(t_j \in \mathbb{R}^{n\times1}\) is a score vector, \(p_j \in \mathbb{R}^{m\times1}\) is the corresponding load vector, \(T\) and \(P\) are the principal component score matrix and load matrix, respectively\[16\] . For data compression purpose, only the first \(4\) subspaces are retained, which contain most of the variance information in \(X\), then the PCA model can be described in a reconstruction form as,

\[
\hat{X} = \sum_{j=1}^{4} t_j p_j^T = \bar{T}\bar{P}^T = X\bar{P}'\bar{P}' \tag{2}
\]

The residual can be summarized by SPE \[17\]. For a new sample, \(\hat{x}_{\text{new}}\), its deviation from the PCA model (i.e. normal data) can be measured by SPE,

\[
SPE = \sum_{j=1}^{m} (x_{\text{new},j} - \hat{x}_{\text{new},j})^2 \tag{3}
\]

\[
\hat{x}_{\text{new}} = x_{\text{new}} - \bar{P}'\bar{P}' \]

Contribution plots can be drawn for each abnormal sample. For example, Fig.3 shows the contributions of all process variables at different sampling points for strip products with different shape defects. By the contribution plot, one can isolate a group of process variables that may cause the shape defects. The next step is to find the frequent patterns for those shape defects.

![Fig.3 Contribution plots for different shape defects](image)

(a) Sample #246 in the coil 12167660; (b) Sample #324 in the coil 12167706; (c) Sample #376 in the coil 12167720

B. An Improved Frequent Pattern Mining Algorithm
The purpose of frequent pattern mining is to discover the common knowledge on the shape defects for different strip products \[19\]. Apriori algorithm, the most popular association rules algorithm, is used in this paper. It searches for all frequent itemsets firstly, and then generates strong association rules from the frequent itemsets.

Apriori algorithm can generate association rules effectively \[20\]. However, it will meet some difficulties when it is used for diagnosing the reasons of various strip shape defects. Firstly, it is inefficient to deal with the mass data generated in the cold rolling process. There will be a large number of candidate frequent itemsets when the Apriori algorithm is in layered iteration. Secondly, it is inefficient to deal with the dynamic dataflow for online application.

In order to overcome the two drawbacks, an improved Apriori algorithm is developed, as detailed below. As shown in Table III, binary variables are used to represent the defect data, where each row represents a group of defect data and its element means the contribution significance of the corresponding process variable. When the contribution of a variable with respect to the SPE is greater than a pre-defined threshold \(\sigma\), it is marked as 1; otherwise, it is marked as 0.

<table>
<thead>
<tr>
<th>Defect data</th>
<th>Process variable 1</th>
<th>Process variable 2</th>
<th>Process variable 3</th>
<th>……</th>
<th>Process variable 20</th>
<th>Process variable 21</th>
</tr>
</thead>
<tbody>
<tr>
<td>Defect data 1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>……</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Defect data 2</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>……</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>……</td>
<td>……</td>
<td>……</td>
<td>……</td>
<td>……</td>
<td>……</td>
<td>……</td>
</tr>
<tr>
<td>Defect data n</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>……</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

TABLE III. TRANSFORMING THE DEFECT DATA INTO 0-1 MATRIX
By doing so, all defect data are represented in a 0-1 matrix, 
\[ D = \{d[i,j]\}, \text{ where } d_{ij} = \begin{cases} 0 & (e_i < \sigma) \\ 1 & (e_i \geq \sigma) \end{cases} \quad i=1,2,\ldots,n; \]
\[ j=1,2,\ldots,21, \quad e_i \text{ represents the contribution of the } i^{th} \text{ process variable to its SPE.} \]

Then, the Apriori algorithm is implemented as follows.

- Each row of the 0-1 matrix \( D \) represents a transaction \( F_i \), each column represents a project \( I_j \).
- The number of items per transaction is the sum of each row; the support of each item is the sum of each column. Augment the matrix \( D \) by adding a new row that is the sum of columns in \( D \) and adding a new column that is the sum of rows in \( D \). Then, rearrange the columns according to the support projects in descending order to obtain a new matrix \( D_{\text{new}} \in R^{(m+1)\times(n+1)} \).
- Determine the minimum support number \( \text{minSupport Count} \). Given a minimum support degree of itemset, \( \text{MinSupport} \) (for example, 50%), calculate the product of \( \text{MinSupport} \) and the number of transactions (i.e., \( n \), the number of rows in \( D \)), \( \text{MinSupport Count} \) is the integer value just greater than or equal to the product \( \text{MinSupport} \times n \).
- Obtain \( N \) frequent itemsets \( L[N] \). Since the vector inner product operation is used for calculating the frequent itemsets support \( N \), only if all items are 1, the result is 1, otherwise 0. So when getting frequent \( N \) items, the row which number less than \( n \) can be removed. Then sum the column again and rearrange it according to the number of support from big to small. The number of support which is less than the minimum number of columns should be detected, then sum the column again, repeatedly to get the candidate \( N \) item set \( C[N] \). After calculation of the number of support itemsets by the vector inner product operation and comparison of the number of \( \text{MinSupport} \), \( N \) frequent itemsets \( L[N] \) is finally got.

### IV. VERIFICATION

Two typical shape defects are studied to show the feasibility of the proposed methodology. The results are well consistent with the experts’ diagnosis results.

#### A. Example 1

Ten sets of left wave samples are selected out including the coils 12167660, 12167770 and 12167720. According to the variable contribution plot, the threshold for determining the variables with significant contribution is \(-0.05 \leq \sigma \leq 0.05 \). Matrix \( D_3 \) is obtained as below.

\[
D_3 = \begin{bmatrix}
0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
\end{bmatrix}
\]

#### B. Example 2

Six sets of left quarter wave sample are selected out including the coil 12169320, 12255710 and 12269630. According to the variable contribution plot, the threshold for determining the variables with significant contribution is \(-0.05 \leq \sigma \leq 0.05 \). Matrix \( D_3 \) is obtained as below.

\[
D_3 = \begin{bmatrix}
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
\end{bmatrix}
\]

Based on the above 0-1 matrix \( D_3 \), the results after performing the Apriori algorithm are shown in Table IV.

<table>
<thead>
<tr>
<th>Order</th>
<th>Frequent items</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>{10'2', 10'20', 10'3', 10'9', 17'20', 17'3', 2'20', 2'3', 2'9', 20'7', 20'9', 3'7', 3'9'}</td>
</tr>
<tr>
<td>3</td>
<td>{10'2'20', 10'2'3', 10'20'3', 10'20'9', 10'3'9', 17'20'3', 2'20'3', 20'3'7', 20'3'9'}</td>
</tr>
<tr>
<td>4</td>
<td>{10'2'20'3', 10'20'3'9'}</td>
</tr>
</tbody>
</table>

From Table IV, the fourth-order frequent itemsets are \{10'2', 20'3'\}, \{10'20'3', 9'\}, and the intersection of the two frequent items is \{10'2', 20'3'\}. This means there is a strong correlation between the left quarter wave product defect and the G5 exit trend (Variable 3), the pressures of Pad 6 (Variable 11) and Pad 7 (Variable 12) in the DSR roller. Since pad pressures are the controlled variable in the DSR control system, the main reason causing a left-wave defect is the unsatisfactory control of G5 tension. The second-order frequent itemsets involve all process variables. The pair of G5 rolling speed (‘1’) and the pressure of pad 6 (‘11’) is the most frequent item. It indicates that the abnormal pressure of Pad 6 is highly related to the abnormal G5 rolling speed. In order to eliminate the product defect, one should adjust the control of G5 rolling speed and G5 exit tension.
wave defect is the unsatisfactory control of G5 tension. The third-order and second-order frequent itemsets involve all process variables. The pair of G5 rolling force (‘2’) and the pressure of pad 5 (‘10’) is the most frequent item. It indicates that the abnormal pressure of Pad 6 is highly related to the abnormal G5 rolling force. In order to eliminate the product defect, one should adjust the control of G5 rolling force and G5 exit tension.

V. CONCLUSION

In this paper, a defect diagnosis method based on frequent pattern mining is proposed, which is capable to deal with the large amount of data and frequent changing of the working condition in rolling process. The paper analyses and diagnoses several typical failure data appeared in the rolling process and presents specific frequent pattern mining results on the left waves and left quarter waves. By comparing the process variables frequent items got by the improved algorithm with the real flatness failure data, it can be found that the frequent items of process variables got by the algorithm consistent with the real flatness fault location, the conclusion also accords with the actual engineering principle. Therefore, it is feasible to apply the data mining technology into cold rolling strip shape control, this method can utilize massive process data effectively, extract the control law, compensate problems for strip shape control model and the accuracy of data collection. Above all, the paper provides a new analysis method for improving the quality of strip shape.

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