Multi-objective Ensemble of Regression Chains Prediction Algorithm for Pose Correction Errors of Precise Vision-based Printing Equipment

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Abstract. To accurately know the working condition of the Precise Vision-based Printing Equipment (PVPE) and improve its printing accuracy and stability, this paper proposes a multi-objective ensemble of regression chains algorithm to predict the pose correction (position and orientation) errors of PVPE’s alignment platform. Since this algorithm uses XGBoost as a base learner, it’s called XGBoost Ensemble of Regressor Chain (XGB-ERC) prediction algorithm. The algorithm is verified by a test set, which is constructed based on experimental data of PVPE. The experimental result shows that the Mean Absolute Percent Error (MAPE) of this algorithm for pose correction errors \( x \), \( y \) and \( \theta \) is 6.868\%, 6.495\% and 5.342\%, which is 25.1\%, 27.6\% and 16.8\% higher than that of the traditional XGBoost single-objective prediction algorithm. The predicted result of the proposed algorithm can be used to compensate the correction errors of the alignment platform, which will help improve the printing accuracy and stability of PVPE, and promote the development of the field of Surface Mount Technology (SMT).

1. Introduction
Precise Vision-based Printing Equipment (PVPE) is one of the key equipment of Surface Mount Technology (SMT) production line, and its printing accuracy is the main factor affecting the product quality of SMT production line. Zhang[1] pointed out about 70\% of the circuit board defects can be traced back to poor solder paste printing. With the continuous progress of science and technology, electronic products have been developing towards miniaturization, high density and zero defect. Therefore, the requirements for solder paste printing equipment' precision and stability are becoming higher and higher.

PVPE mainly consists of visual alignment system (including visual measurement module, correction motion mechanism) and printing system. Zhan et al[2] proposed that PVPE has mechanism’s motion errors, visual measurement errors and other systematic errors caused by manufacturing and assembly tolerances, hinge clearance, etc., greatly restricting the improvement of its printing accuracy. Mo et al[3] conducted Kinematic calibration of the correction platform through the PVPE vision-based alignment system, and compensated the pose correction error of the platform with the result of calibration, effectively improving the alignment accuracy of the correction platform. Based on precise visual measurement, Liang et al[4] evaluated the repeated positioning accuracy of the parallel mechanism platform and designed a test scheme including step-by-step error measurement,
parameter identification and error compensation, which significantly improved the positioning accuracy of the parallel mechanism platform. Li et al.[5] introduced a degenerated perspective n-points algorithm based on normal equations to fast and accurately calculate the pose of a 3-degree of freedom (DOFs) mechanism. Factors that cause measuring error in this algorithm are identified and analyzed in detail to improve the measuring accuracy.

The pose correction errors of the printing equipment directly affect its process flow. In addition, these errors continue to accumulate in the process flow, and ultimately lead to serious problems with the printing accuracy and stability of the equipment. In industrial applications, in order to achieve higher accuracy, some basic error parameters of the equipment will be identified and corrected, while other difficult-to-identify errors will be integrated into system errors for error compensate. However, with the long-term operation of the equipment, there are factors such as component wear, reference position shift, and other environmental disturbances, which cause the working condition of the equipment to change. In this case, the effect of previous correction parameters and system error compensation will not meet the current accuracy requirement. Therefore, to further improve the correction accuracy of the motion mechanism of the vision-based alignment system, it is necessary to monitor the working condition during its work.

The aim of this paper is to find a better way to predict the pose correction errors of PVPE after a long-term operation. In the current research of the related field, machine learning is widely used. For example, Shi et al.[6] pointed out a feature learning approach based on XGBoost for driving assessment and risk prediction. Feng et al.[7] proposed a weighted combination approach based on XGBoost and LSTM in his sales prediction. Xu et al.[8] applied XGBoost in predicting the risk of 90-day readmissions in patients with ischaemic stroke. Xie et al.[8] used XGBoost to predict monthly housing rents. Son et al.[9] introduced XGBoost to the prediction of Bitcon price. XGBoost is widely used in prediction scenarios such as classification and regression, but it is limited to single-objective prediction, while the correction poses is multi-objective. Read et al.[11] proposed an integrated classifier chain scheme for multi-classification problems, and Zhang[12] proposed a multi-objective ensemble regression chains algorithm by referring to Read’s ideas. The last input sample and the objective value in the predicted regression chain are used as the input to predict the next objective value of the chain, which ignores the the prediction effect of the model mentioned before. Based on this algorithm in this paper, the residual error of the prediction objective value is introduced, and an algorithm (XGBoost Ensemble of Regressor Chains, XGB-ERC) of multi-objective ensemble of regression chains based on XGBoost is proposed. The predicted result of the proposed algorithm can be used to compensate the correction errors of the alignment platform, which will help improve the printing accuracy and stability of PVPE, and promote the development of the field of SMT.

2. Vision-based Alignment System of PVPE
The vision-based alignment system is an important part of PVPE, whose main function is realizing PCB and template alignment, and the alignment precision directly affects the product printing quality. The PVPE vision-based alignment system model studied in this paper is shown in figure 1. The vision-based alignment system of PEVP is composed of a vision-based motion subsystem, motion system of correction platform and CCD industrial camera. The work flow of the alignment system correction is
shown in figure 2. The correction process is as follows: the vision-based motion system drives the CCD industrial camera to the specified position and simultaneously takes the image of the template and PCB. The collected image is filtered, enhanced and benchmark recognized, getting the template and PCB benchmark’s distance to the image center. Then it is converted into a template and PCB benchmark coordinate. Next, through the alignment correction algorithm, the motion amount of displacement and rotation needed by the correction of the circuit board is calculated. Finally, the correction mechanism is driven to complete the correction.

2.1 Principle of PVPE alignment correction algorithm

The simplified model of PVPE correction platform is shown in figure 3. The coordinate system $O-XY$ of correction platform is established, and points $A$, $B$ and $C$ are the hinge centre poses of correcting drive motors $X_1$, $Y_1$ and $Y_2$ at zero, respectively. $S_1(X_{s1}, Y_{s1})$ and $S_2(X_{s2}, Y_{s2})$ are the two Mark points of the template, while $P_1(X_{p1}, Y_{p1})$ and $P_2(X_{p2}, Y_{p2})$ are the two Mark points of PCB. The alignment system needs to drive the correction drive motors $X_1$, $Y_1$ and $Y_2$ to align the PCB with the template. The alignment system is parallel, and its inverse kinematic solution is multiple [13], respectively representing different working modes. In order to facilitate the operation of the mechanism, the mechanism is generally only allowed to work in one working mode. Therefore, to make the solution of the correcting poses unique, the $Y_1$ and $Y_2$ correction motors are defined to move in the opposite direction with the same displacement to achieve the uniqueness of angle correcting. In practice, PCB and template alignment can be realized by obtaining the Mark point position of PCB and template, and using the transformation relationship between PCB correction poses and coordinates. Its geometric relationship [14] is as follows:

$$x = \left[ (X_{s1} + X_{s2}) \cos^2 \theta - (Y_{p1} + Y_{p2}) \cos \theta - (Y_{s1} + Y_{s2}) \sin \theta \cos \theta \right] / 2$$  \hspace{1cm} (1)

$$y = \left[ (Y_{s1} + Y_{s2}) \cos^2 \theta - (Y_{p1} + Y_{p2}) \cos \theta - (X_{s1} + X_{s2}) \sin \theta \cos \theta \right] / 2$$  \hspace{1cm} (2)

$$\theta = \arctan \left( \frac{X_{p1} - X_{p2}}{X_{s1} - X_{s2}} \right) - \arctan \left( \frac{Y_{p1} - Y_{p2}}{Y_{s1} - Y_{s2}} \right)$$  \hspace{1cm} (3)

$$\begin{align*}
X_1 &= x \\
Y_1 &= y - BC \times \tan \Delta \theta \\
Y_2 &= y + BC \times \tan \Delta \theta
\end{align*}$$  \hspace{1cm} (4)

Where $x$ is the transverse relative pose between PCB and template; $y$ is the longitudinal relative pose between PCB and template; $\theta$ is the angle relative pose between PCB and template. The theoretical motor input can be obtained from the correction poses as in equation (4).
3. Prediction Model of PVPE Correction Poses

3.1. Single-objective prediction model of PVPE correction poses

PVPE correction poses prediction can be regarded as the prediction of regression. XGBoost [15] is an improved ensemble learning algorithm based on a gradient-enhancing decision tree algorithm. XGBoost continuously iterates to generate a new tree to fit the residual of the previous tree. As the number of iterations increases, the accuracy continues to increase. Therefore, XGBoost can predict the PVPE correction pose.

| Table 1. XGB-ERC Single-chain Algorithm |
|----------------------------------------|
| **Algorithm:** Single Chain XGB-ERC    |
| **Input:** X, Feature of Sample        |
| **Input:** Y, Multi-object \( Y_1, Y_2, \ldots, Y_n \) |
| **Input:** C, Order of Multi-objective Prediction, \([0, 3, \cdots, m, \cdots, 4]\) |
| **Input:** m, Dimension of Y            |
| Randomly split X into m Portions, \( x_1, x_2, \cdots, x_m \) |
| for \( i = 1 \) to m do                 |
|   if \( i = 1 \) do                     |
|     \( x \leftarrow x_i \)             |
|   else do                              |
|     for \( k = 1 \) to \( i - 1 \) do   |
|       if \( k = 1 \) do                 |
|         \( \text{tmp}_x \leftarrow x, \) |
|         \( \text{tmp}_y \leftarrow 0 \) |
|       else do                          |
|         \( \hat{y}_{c3} \leftarrow f_{c3}.predict(\text{tmp}_x) \) |
|         \( \text{tmp}_x \leftarrow \text{tmp}_x + y_{c3} + y_{c3} - \hat{y}_{c3} \) |
|         \( \text{tmp}_y \leftarrow \text{tmp}_y + y_{c3} + y_{c3} - \hat{y}_{c3} \) |
|     end                                 |
|     \( x \leftarrow x_i + \text{tmp}_y \) |
| end                                    |
| \( f_{c3} \leftarrow \text{XGBoost.fit}(x, y_{c3}) \) |

3.2. Multi-objective prediction model of PVPE correction poses

On the one hand, during the positioning and correcting of PVPE, the correction poses \( x, y \) and \( \theta \) relative to the template can be gotten; then PVPE’s correction mechanism makes the PCB overlap with the template. So the correction poses are multi-objective. On the other hand, XGBoost is a single-objective prediction algorithm that requires modeling of the poses \( x, y \) and \( \theta \), respectively, and the correction mechanism is parallel, thus, XGBoost for PVPE correction poses prediction ignores the correlation among correction poses. That is why XGB-ERC is proposed in this paper. The specific processes are as follows:
3.2.1 Multi-objective single-chain prediction model

Based on XGB-ERC, a single-chain algorithm, a multi-objective regression chain with its own order needs to be determined first; the detail is as follows: assume a default regression chain \( C = \{Y_1, Y_2, \cdots, Y_m\} \), where \( C \) represents the set of regression chain order, \( Y(Y_1, Y_2, \cdots, Y_m) \) represents the prediction objective. Next, the training set is divided into \( m \) parts of \( D(x_1, x_2, \cdots, x_n) \) according to the number of prediction objectives. Finally, when some objective in the chain is predicted, all objective values before the objective and their prediction residual values are introduced to establish the objective prediction model.

\[
\begin{align*}
\text{tmp}_{-} x &= 0 \\
\text{tmp}_{-} x &= x_1 + \text{tmp}_{-} x \\
y &= Y_1 \\
f_{C_1} &= \text{XGBoost.fit}(x, y) \\
\text{tmp}_{-} x &= \bigcup_{i=1}^{j-1} (Y_{i-1} - f_{C_{i-1}}(\text{predict}(x_j))) \bigcup_{i=1}^{j-1} Y_i, \\
x &= x_1 + \text{tmp}_{-} x \\
y &= Y_{C_j} \\
f_{C_j} &= \text{XGBoost.fit}(x, y)
\end{align*}
\]  

(5)

Where \( \text{tmp}_{-} x \) is the objective values and their prediction residual values of the base model established by the regression chain according to the training sample; \( x \) is the input; \( y \) is objective value of the training model; \( Y_{C_j} \) is the objective value of the \( j \)-th model trained in the regression chain; \( f_{C_j} \) is the XGBoost model with \( Y_{C_j} \) as output according to the order of regression chain. According to the order of the selected regression chain \( C \), the multi-objective model is established, respectively. The algorithm code is shown in table 1.

3.2.2 Multi-objective prediction model of the ensemble regression chains

The prediction process above is a multi-objective prediction process of the single regression chain \( C \). The multi-objective prediction is sequential and sensitive to the selected chain \( C \), which has the following problems: 1). The objective before the sequence of the regression chain cannot make use of the subsequent objectives and their prediction residuals; 2). When new test samples are predicted, the prediction error will continue to be amplified and propagated along with the regression prediction chain. In order to reduce the impact of these problems, this paper introduces ensemble of regression chains to solve it. \( K \) kinds of different prediction chains are used, and the output is the average value of the multi-objective prediction values of the \( K \) regression chains. The well-segmented data set is adopted to establish the model according to the sequence of the regression chain. By doing so, the problem of incomplete use of sample data caused by the random sampling method on the training set can be avoided, and random \( K \) in different regression chain also increased the randomness in the process of training, improving the generalization ability of the model. This algorithm is XGB-ERC, which regards XGBoost as the base learner.

4. Experimental Analysis

4.1. Experimental environment and data collection

The configuration of the computer used in the experiment is as follows: the CPU is Intel i7-8750 (2.2 GHz, ROM 8GB); operating system is Windows 10 (64-bit). Programming is Python3.6; the
The integrated development environment is Pycharm Community Edition 2019. The data under study was collected from a PVPE produced by Tron Wintech company in China, which is shown in figure 4. The data set contains 30,000 training samples and 200 test samples. The repeated posing coordinates of the visual system measured by the visual alignment system of PVPE, the deviation value of the Mark point, the correction poses calculated theoretically, the input value of the motor, and the accuracy of PCB and template serve as the input, and post-correction poses \( x \), \( y \) and \( \theta \) serve as the objective values.

![PVPE Used in the Experiment](image)

**Figure 4. PVPE Used in the Experiment**

### 4.2. Experimental results

\[
E_{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|
\]

\[
E_{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|
\]

\[
E_{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}
\]

In this paper, to compare the prediction effects of PVPE correction poses, XGB-ERC and XGBoost are used. In order to better evaluate the prediction effects of the two algorithms on the data set, the model performance evaluation index is selected with Mean Absolute Percent Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), as in equation (7), where: \( y_i \) is the actual value of the correction poses, and \( \hat{y}_i \) is the predicted value of the model of correction poses, and \( n \) is the sample number. It should be emphasized that compared with RMSE and MAE, MAPE is equivalent to normalizing the error of each point, reducing the impact of the absolute error brought by individual outliers, and the results are more representative. Therefore, MAPE is selected as main indicators, others as auxiliary indicators.

XGBoost, single-objective prediction algorithm, is compared with XGB-ERC, multi-objective prediction algorithm, in this paper. The results are as follows: as shown in figure 5, figure 6 and figure 7, both XGBoost and XGB-ERC have a good prediction effect on the correction poses of PVPE, and both can be used for the prediction of correction poses. As can be seen from Table 2, compared with XGBoost for the correction poses \( x \), \( y \) and \( \theta \) of PVPE, XGB-ERC increased the accuracy of MAE by 25.3%, 27.7% and 15.8%, the accuracy of RMSE by 27.4%, 29.5% and 17.6%, and the accuracy of MAPE by 25.1%, 27.6% and 16.8%, respectively. Under the working condition of PVPE, its printing accuracy and angle accuracy are within the range of \( \pm 5 \mu m \) and \( \pm 0.003^\circ \) respectively, so the value of MAE, RMSE and MAPE are relatively low. According to the above analysis, compared with XGBoost, the prediction effect of XGB-ERC in the correction poses \( \theta \) is not significantly improved.
compared with that of correction poses $x$ and $y$. This is because that pose value $\theta$ is low compared with that of $x$ and $y$, so the evaluation index of poses $\theta$ does not decrease significantly. The above analysis shows that compared with XGBoost, XGB-ERC is more effective in predicting the correction poses of PVPE.

Figure 5. Deviation of Correction Poses $x$ on XGB-ERC and XGBoost

Figure 6. Deviation of Correction Poses $y$ on XGB-ERC and XGBoost

Figure 7. Deviation of Correction Poses $\theta$ on XGB-ERC and XGBoost

Table 2. Prediction Effect of XGBoost and XGB-ERC for the PVPE Correction Poses

| Algorithm | Correction poses | $E_{\text{MAE}}$ ($\mu m$) | $E_{\text{RMSE}}$ ($\mu m$) | $E_{\text{MAPE}}$(%) |
|-----------|------------------|----------------------------|----------------------------|---------------------|
|           |                  | Train | Test | Train | Test | Train | Test |
| XGBoost   | $x$              | 0.275 | 0.328 | 0.376 | 0.383 | 8.623 | 9.171 |
|           | $y$              | 0.286 | 0.314 | 0.327 | 0.343 | 8.514 | 8.966 |
|           | $\theta$         | 0.176‰ | 0.183‰ | 0.187‰ | 0.193‰ | 5.376 | 6.424 |
| XGB-ERC   | $x$              | 0.239 | 0.245 | 0.264 | 0.278 | 6.587 | 6.868 |
|           | $y$              | 0.214 | 0.227 | 0.237 | 0.242 | 6.104 | 6.495 |
|           | $\theta$         | 0.139‰ | 0.144‰ | 0.144‰ | 0.149‰ | 4.235 | 5.042 |

5. Conclusion

In this paper, XGB-ERC is proposed to predict the correction pose errors of PVPE’s alignment platform. This algorithm uses XGBoost as a base learner. In multi-objective prediction, other objective values and corresponding base learners are added to the regression chain to predict residuals. The proposed algorithm is verified by a test set, which is constructed based on experimental data of PVPE. The results show that the MAPE of XGB-ERC is 6.868%, 6.495% and 5.342%, which is 25.1%, 27.6% and 16.8% higher than that of the traditional XGBoost single-objective prediction algorithm.
The reason is that the addition of other objective values and the prediction residuals of the corresponding base learners in the XGB-ERC algorithm can introduce the correlation among multiple objectives. The predicted result of the proposed algorithm can be used to compensate the correction errors of the alignment platform, which will help improve the printing accuracy and stability of PVPE, and promote the development of the field of SMT.

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