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Support Vector Machines-Based Abnormality Detection and Prediction in Stencil Printing Process

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Abstract: Surface mounting technology (SMT) is the main manufacturing process used in the electronics assembly industry. It is critical to improve the first-time-yield of printed circuit boards (PCBs) in an SMT assembly to save the manufacturing costs. The stencil printing process (SPP) is one of the main contributors to the SMT soldering defects. This research is motivated by enhancing the SPP from early detection and prediction of unnatural patterns in the deposited solder paste volume. A novel multi-stage predictive abnormality detection framework is proposed for the SPP. At the first stage, a support vector regression (SVR) based exponential weighted moving average (EWMA) control chart is developed to effectively monitor highly autocorrelated SPP system and identify the existing patterns. At the second stage, a support vector machine (SVM) predictive modeling is used to predict the occurrence of abnormal patterns before they arise based on several statistical features extracted from the control chart patterns (CCPs) using a moving window recognition approach. Once abnormal conditions are recognized, appropriate corrective actions can be taken to the SPP. The experimental results confirm the effectiveness of the proposed model architecture in early detection and prediction of the abnormal CCPs to prevent solder paste printing defects and reduce high reworking costs for large scale production.

Keywords: Stencil Printing Process, Support Vector Machines (SVMS), Regression Residual Control Chart, Abnormality Detection, Anomaly Prediction.

1. Introduction

Surface mounting technology (SMT) is a principal technique used in the assembly industry of sophisticated electronics, in which surface mounted components (SMCs) are directly attached to the printed circuit board (PCB) pads. The assembled PCBs go through three subsequent operations including solder paste printing (SPP) process, pick and place (P&P) step, and solder reflow stage. Consequently, the output quality of the first stage significantly affects that of subsequent stages. Therefore, any solder paste printing defect can lead to poor quality in the downstream SMT stages. According to the literature, about 50-70% of the SMT soldering defects are caused by the SPP process (Ma, 2018). Furthermore, defect correction costs usually increase five to tenfold with each preceding step in the SMT assembly line (Amir, 1994). Accordingly, earlier abnormal patterns detection in the SPP process can enhance the first-pass yield of PCBs and consequently, reduce the rework costs.

The SPP is extremely sensitive to the volume of solder paste allocated on the top of each component pad, it acts as a vital response in the SPP. Many studies have utilized the convectional Shewhart control chart, which is one of the most widely statistical process control (SPC) tools adopted in the SMT industry, to recognize abnormal patterns presence within the deposited solder paste volumes by continuously monitoring both outputs mean and variation about the mean. The sample statistics are plotted on a control chart, then if any point exceeded a predefined limit, this indicates that the process is not functioning properly due to the presence of an assignable cause. Therefore, quality experts can search for potential causes and take appropriate corrective actions to return the SPP process into normal conditions. Once detected abnormal patterns are corrected, this can reduce the high reworking cost.

However, utilizing the traditional Shewhart control charts to detect abnormal patterns within the SPP is not very useful to minimize the number of defective parts, since they signal after the product has already failed, then appropriate corrective action can be made. Furthermore, since the solder paste printing quality is significantly influenced by various process factors simultaneously, the outcomes of using these control charts could be biased. Using the traditional Shewhart control charts requires a fundamental assumption, that the process data should not be autocorrelated, which is a predominant problem in SMT data (Gauri, 2009). Instead, the focus of this research is on predicting the abnormal patterns before leading to the production of defective boards. Once an abnormal pattern is predicted, a quality expert can take proper preventive action before a defective part is produced. Therefore, this preventive policy can significantly eliminate solder printing defects, and consequently, improve the entire SMT assembly line productivity and quality, and eliminate the need for board reworking which is associated with high costs. To achieve this defect preventive approach, a novel multi-stage SPP predictive abnormality detection framework is proposed by the integration of SPC and machine learning-based techniques. At the first stage, a kernel support vector regression (SVR) is used to model the nonlinear relationship in the system. The regression residuals from the SVR predictor are utilized to develop an exponential weighted moving average (EWMA) based regression residual control chart to monitor the process when a high autocorrelation problem is predominant. By the adoption of the regression-based control chart, the problem of simultaneous effects and autocorrelation can be solved as proposed by (Hawkins, 1991). At the second stage, abnormal patterns are predicted by applying a kernel support vector machine (SVM) classifier using several statistical features extracted from the control chart patterns (CCPs) using a moving window recognition approach. By the adoption of the proposed prognosis based multi-stage framework into the SPP, early detection and prediction of the abnormal CCPs can be achieved, and therefore, prevent solder paste printing defects and reduce high reworking costs for large scale production.

The rest of the article is organized as follows. Section 2 contains a survey of the related literature. A detailed discussion of the proposed methodology for abnormality detection and prediction in the SPP process is described in Section 3. The experimental results and analysis are shown in Section 4. Finally, concluding remarks and future work are presented in Section 5.

2. Related Literature

In the literature, multiple research papers have addressed the application of classical SPC techniques in the SMT industry. The traditional Shewhart charts have been applied to monitor the process by charting the defects proportion per PCB. If the total number of defects exceeds a predefined threshold, the equipment should be tuned up and returned to normal operating conditions (Goh, 1991). Rowland highlighted the limitations of conventional Shewhart control charts in SMT, because of autocorrelation, high false alarm rate, and inability to efficiently detect when the process deteriorated (Ho, 2003). A modified regression residual control chart is proposed to recognize the unnatural patterns of the deposited solder paste volume in the SPP based on Nelson's run rules. A linear regression function was established to capture the relationship between the deposited solder paste volume and the SPP control factors based on the design of experiments (DOE) and ANOVA analysis (Tsai, 2009). Extensive work in the literature is related to DOE, where planned experiments were conducted to determine the effect of different printing parameters on the solder paste volume during the SSP process (Tsai, 2011).

Several researchers reported on the application of artificial intelligence-based approaches to automatically detect anomalous patterns utilizing features extracted from CCPs as the input vectors. Artificial neural networks (ANNs) have been broadly employed for detecting unnatural CCPs (Pham, 1997). Other CCP recognition algorithms include principal component analysis (PCA), decision trees, and SVMs, based on statistical learning theory, are gaining attention in the pattern recognition area as a result of their excellent generalization capability (Sukchotrat, 2009).

From the above literature surveys discussed, most of the studies have been focused on the detection of abnormal patterns in SMT using traditional Shewhart control charts. However, limited research has been focused on using data mining approaches to prevent defects within the SPP process by automatic prediction of abnormal patterns before leading to defective products. To overcome these challenges, a novel abnormality predictive data mining and machine learning-based approach is proposed focusing on defects prevention rather than only defect detection to eliminate the high reworking costs and enhance the SPP quality and productivity.

3. Methodology

3.1 Support Vector Machines (SVMs)

SVM is a relatively new type of machine learning algorithm that can perform both regression and classification tasks based on the statistical learning theory and the structural risk minimization (Cortes, 1995). Initially, SVM was developed to solve linear separable classification examples, by solving a quadratic optimization problem to find an optimal hyperplane that separates a set of negative instances from a set of positive instances with maximum margin. Later, SVM was extended to solve nonlinear separable cases by the introduction of an inner product space (kernel functions) into the dual problem using the Lagrange multipliers. Suppose D is the set of training examples denoted by $D = (x_i , y_i) : x_i \in \chi^n, yi \in Y, i= 1,\ldots,m$, where χ^n is a *n*-dimensional feature space, $Y = \{-1 , +1 \}$ is the corresponding target output, and *m* represents the training set size. The dual form of a C-SVM model is given by Eqs. (1) - (3).

$$\max_{\alpha} \sum_{i=1}^{m} \alpha_i \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} y_i y_j \alpha_i \alpha_j \kappa(x_i . x_j) \tag{1}$$

$$\text{s.t. } 0 \leq \alpha_i \leq C \; \forall i \tag{2}$$

$$\sum_{i=1}^{m} \alpha_i y_i = 0 \tag{3}$$

where α_i represents Lagrange multipliers, κ denotes kernel function, and C is the regularization term, which is set by the user to tolerate the input noise and control the upper bound on α_i.

3.2 EWMA Control Chart

EWMA control chart was developed to overcome the limitation of Shewhart control charts of their insensitivity to moderate and small shifts in the process mean since they utilize only information from the most recent observation. To detect a small shift, the EWMA chart accumulates information from both the most recent observation and the last observations. It gives the weight of the last observation based on its significance in characterizing the process. The EWMA plotted points are characterized iteratively by the next exponential smoothing operation:

$$Z_i = \lambda R_i + (1-\lambda) Z_{i-1} \; \forall i \tag{4}$$

where λ is the exponential smoothing constant and is determined by the user, where the larger value of λ means the more impact of the last observation, R_i is the i^{th} subgroup means, and k denotes subgroups. The EWMA chart signals if the plotted statistics exceeds a predetermined value of H.

3.3 Two-Stage SPP Abnormality Predictive Framework

Figure 1 shows the general steps of the proposed methodology. At the first stage, a kernel-based SVR model is applied to capture the nonlinear relationships between the control factors (X) and the printed solder paste volume (y). Then, the residuals between actual and predicted values of the response variable (deposited solder paste volume) are calculated based on the developed nonlinear regression model. Hence, the error term is normally and independently distributed with a zero mean and a standard deviation of σ, and thereby the problem of high autocorrelation is solved, and the process can be monitored effectively. The EWMA control chart of regression residuals is then constructed to monitor the process, with a centerline of zero and control limits of $\pm H$. The sample statistics are plotted on the constructed control chart. If the plotted samples are fallen outside the limits, then the process is in out-of-control conditions. However, in many practical cases, even when all samples are within the control limits, the patterns of a control chart usually display nonrandom behavior which gives valuable diagnostic information. The common patterns that may show up on the residual-based control chart are normal and abnormal including cyclic, increasing trend, decreasing trend, upward shift, and downward shift patterns. These anomalous patterns indicate that the process is not working properly, and an adjustment must be made to return the process to normal conditions. Hence, in the real process data, there is no prior knowledge of the unnatural patterns are available. Therefore, to recognize the existing unnatural CCPs, Nelson's run rules are applied (Nelson, 1984).

Secondly, SVM classifier can be implemented for the purpose of CCP prediction, where the class of each data point i (where $i = 5,6,\ldots,n$) is predicted based on the feature extracted from the former observations using a moving average window approach (in this study, its length is set to four observations). As abnormal CCPs start to show up in the data series, the pattern features gradually strengthen as the observing window proceeds forward through the process data series. It is well known that each CCP has different features and properties that distinguish it from other patterns. If some effective features can be extracted from observation data to reflect the different patterns and used as input data, it would be easier for the classifier to predict the existing abnormal patterns efficiently instead of using the raw data. Accordingly, at each point, two statistical features including mean and standard deviation, are extracted from the previous four data points, which can effectively discriminate natural from other CCPs. For example, the mean for unnatural patterns is around zero, while that for other abnormal patterns is different from zero. Finally, a grid search method is used to tune the regularization and kernel function parameters, as SVM performance highly affected by the selected values of those parameters.

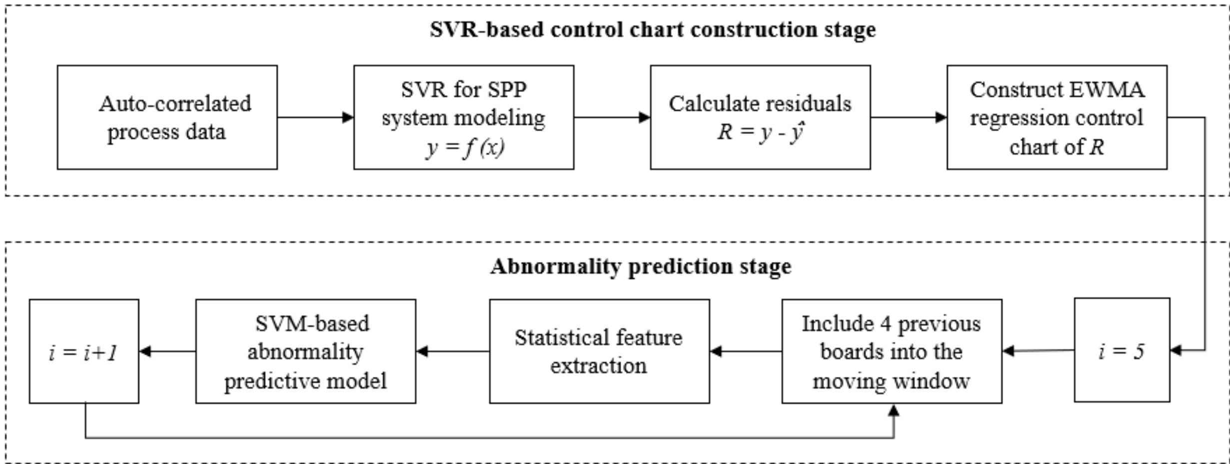

Figure 1. Architecture of the multi-stage abnormality predictive model in auto-correlated processes

4. Experimental Results and Analysis

4.1 Data Description

The data set for this study was obtained from printing 289 PCBs using different printing settings. The printing speed levels were selected as 30, 45, and 60 mm/s, the printing pressure was applied at 40, 60, and 80 N, and the separation speed levels were 1, 3, and 5 mm/s. The data set contains both natural and unnatural patterns. Each PCB consists of different aperture shapes, sizes, and orientations that were printed with one squeegee stroke. In this research, two mainly aperture shapes were printed: rectangular and circular since they are the most commonly used shapes in SMT applications. Aperture size was represented by the area ratio of the stencil aperture, which is the area of aperture opening divided by the area of sidewalls. 17 different area ratios were selected, ranging from 0.59 to 2. For rectangular pads, two orientations were used, either placed horizontally or vertically relative to the printing direction. Cleaning aging was performed every 17 PCBs, which represents how many printing iterations are performed between two machine cleaning steps, is considered one of the key factors that may influence the soldering quality during SPP. After the first printing iteration, changes in quality behavior of the next iterations are expected because of some solder paste remained in the stencil apertures, therefore, the PCB sequence after the cleaning process was considered as a factor with 17 different levels.

To summarize, the important variables impacting the solder paste volume in this research were: printing process-related parameters (printing speed, printing pressure, and separation speed), stencil related factors (aperture shape, aperture size, and orientation), and PCB sequence after the cleaning cycle. It is expected that these variables could explain most of the variability in the solder paste volume which is the major response and control point in the SPP process.

4.2 SVR-EWMA Chart and CCP Recognition

SVR with three different kernel functions (including the Gaussian radial basis function (RBF) kernel, the polynomial kernel, and the linear kernel) was implemented to capture the complex relationship between the solder paste volume and the selected independent variables. The RBF kernel function fitted the data better than the other kernels. Therefore, the residuals of the SVR with RBF kernel prediction model were used to construct the EWMA chart. Hence, if the prediction model is accurate enough, then any shift in the monitored variable of a nonlinear process would affect the distribution of residuals, and consequently, the residual control charts can provide a better understanding of the system behavior over time and efficient detection abilities than observation control charts. Figure 2 shows the residual SVR-EWMA chart. The samples plotted outside the control limits represent out-of-control conditions, which accounted for 16.3% of the total plotted points. By referring to the initial printing setting, most of these samples were printed at a speed of 45 mm/s, printing pressure of 60 N, and separation speed of 3mm/s. Therefore, it can be concluded that this combination of printing setup might not be a good choice for the PCBs configuration printed in this study.

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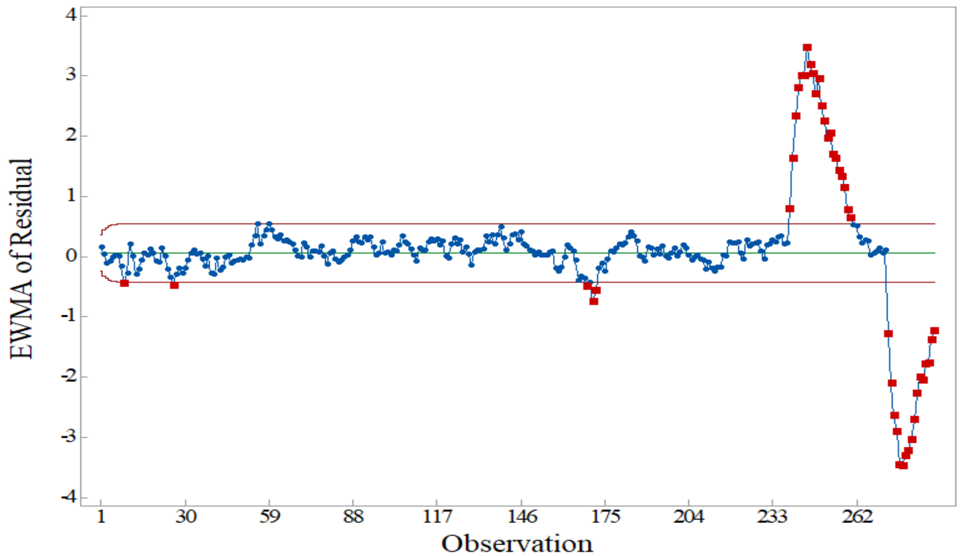

Figure 2. The SVR-EWMA control chart of the regression residuals

4.3 SVM-Based CCP Prediction

To predict the abnormal pattern in the data set, the mean and standard deviation of a moving window of length four points were calculated. In other words, the pattern at each sample was predicted based on the statistical features calculated from the previous four plotted samples, since any pattern would grow gradually in the time series data. Several prediction models were applied, including SVMs with several kernel functions (including RBF, polynomial, and linear kernels), random forest (RF), and logistic regression (LR). Since 16.3% of the data were abnormal, while the remaining were normal, synthetic minority over-sampling technique (SMOTE) was used to train the prediction models to deal with the problem of imbalanced data set.

Table 1. CCP prediction results with different models

Prediction model	Kernel function	Accuracy (%)	AUC (%)	Sensitivity (%)	Specificity (%)
RF		94.18	91.84	**89.00**	97.00
SVM	RBF	**97.67**	**93.79**	**89.00**	**99.00**
	Polynomial	**97.67**	88.88	78.00	**100.00**
	Linear	93.02	86.29	78.00	95.00
LR		94.18	86.94	78.00	96.00

The performance of predictive models was assessed by testing accuracy, the area under the ROC curve (AUC), sensitivity, and specificity. The summary results of the different models are given in Table 1. The most accurate ones are shown in bold. Overall, SVM with RBF kernel outperformed all the other models. The comparison results showed that the SVM model with RBF kernel function obtained the best results in terms of accuracy, AUC, and sensitivity, with values of 97.67%, 93.79%, and 89%, respectively, and the second highest specificity of 99%. Though SVM with polynomial kernel achieved the highest specificity values of 100%, but its sensitivity was much lower than that of SVM with RBF kernel. Generally, the overall performance of the models was good, which confirms the effectiveness of basic extracted statistical features in differentiating the different patterns from each other. The obtained results provide a promising area to prevent the printing defects, and consequently, enhancing the first-pass yield of PCBs and reducing the rework costs significantly.

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5. Conclusion and Future Work

In this research, a novel multi-stage predictive abnormality detection framework is proposed for the SPP, which is the main contributor to SMT soldering defects. An effective way to monitor the SPP stage quality properly was developed using an SVR-based EWMA chart, which can provide more efficient detection abilities than observation control charts. In addition, an accurate predictive model was built to estimate the occurrence of abnormal conditions before the pattern grows catastrophically. The experimental results provided a promising area to prevent the printing defects, and accordingly, enhancing the first-pass yield of PCBs and reducing the rework costs significantly.

In the future, this research can be extended in several aspects. A multi-classes SVM model can be implemented in order to discriminate the six common patterns that might appear in the process: normal, up-trend, down-trend, up-shift, down-shift, and cyclic patterns from each other, and thereby, reduces the possibilities for an out-of-condition assignable cause. Several useful statistical and shape features can be extracted from the CCPs for this purpose. Moreover, a similar system can be proposed to differentiate human errors from those generated by the printer. Therefore, appropriate corrective action can be made efficiently.

6. References

Amir, D. (1994). Expert System for SMT Assembly. *Proceedings of the Surface Mount International Conference and Exposition-Technical Program*, 691-699.

Cortes, C. and Vapnik, V. (1995). Support-Vector Networks. *Machine Learning*, 20(3), 273-297.

Gauri, S.K. and Chakraborty, S. (2009). Recognition of Control Chart Patterns Using Improved Selection of Features. *Computers & Industrial Engineering*, 56(4), 1577-1588.

Goh, T.N. (1991). Statistical Procedure for Defect Control in High Quality Manufacturing. *American Society of Mechanical Engineers, Production Engineering Division (Publication) PED*, 55, 395-401.

Hawkins, D.M. (1991). Multivariate Quality Control Based on Regression-Adjusted Variables. *Technometrics*, 33(1), 61-75.

Ho, S.L., Xie, M. and Goh, T.N. (2003). Process Monitoring Strategies for Surface Mount Manufacturing Processes. *International Journal of Flexible Manufacturing Systems*, 15(2), 95-112.

Nelson, L.S. (1984). The Shewhart Control Chart-Tests for Special Causes. *Journal of Quality Technology*, 16(4), 237-239.

Ma, X., Xu, B., Chen, Y., Cheng, Y., Liu, F., Liang, Z., Chen, B., Li, S., Mo, H., Zhong, Z. and Wang, H. (2018). Flexible IC Interconnection and Electrical Continuity Verification. In *Numerical Modelling in Engineering*, 1-10.

Pham, D.T. and Wani, M.A. (1997). Feature-Based Control Chart Pattern Recognition. *International Journal of Production Research*, 35(7), 1875-1890.

Sukchotrat, T., Kim, S.B. and Tsung, F. (2009). One-Class Classification-Based Control Charts for Multivariate Process Monitoring. *IIE transactions*, 42(2), 107-120.

Tsai, T.N. and Chen, L.H. (2009). Monitoring of the Stencil Printing Process Using a Modified Regression Residual Control Chart: an Empirical Study. *International Journal of Industrial Engineering: Theory, Applications and Practice*, 16(4).

Tsai, T.N. (2011). Improving the Fine-Pitch Stencil Printing Capability Using the Taguchi Method and Taguchi Fuzzy-Based Model. *Robotics and Computer-Integrated Manufacturing*, 27(4), 808-817.