Automated process adjustments of chip cutting operations using neural network and statistical approaches

Hong-Dar Lin\textsuperscript{1*} and Wan-Ting Lin\textsuperscript{2}

\textsuperscript{1*}Department of Industrial Engineering and Management, Chaoyang University of Technology, 168 Jifong E. Rd., Wufong Township, Taichung County, 41349, Taiwan TEL: 886-4-2332-3000 Ext.4258; FAX: 886-4-2374-2327
e-mail: hdlin@cyut.edu.tw

\textsuperscript{2}College of Business, University of Missouri-Columbia, 213 Cornell Hall, Columbia, MO 65211, USA

Abstract

This research explores the automated process adjustments of chip cutting operations by using neural network and statistical approaches in a computer-aided vision system. Multi-layer ceramic capacitors (MLCC), owing to their excellent electronic characteristics, are applied in the design of high-density PC boards. The excellences of MLCCs are accomplished through rigorous controlling of every production step, especially the accuracy-demanding chip cutting operation. This research applies computer vision techniques to find mass centers of chips, locate cutting lines and calculate cutting distances for the automated, precise, and high-speed cutting of MLCCs. The statistical bounded adjustment method with response surface methodology and the radial basis function network model are proposed to solve the cutting deviation problems and to timely and quantitatively adjust the process towards the target values. Two common kinds of process deviations, shift and trend deviations, are explored in this research. Experimental results show that the statistical bounded adjustment and the radial basis function network, respectively, increase the effective adjustment rates of cutting deviations by 35% and 60% more than the current cutting method.

Keywords: Automated process adjustments, Chip cutting, Computer-aided vision system, Neural network approach, Statistical method.
1. Introduction

With the miniaturization of electronic products, chip-type components have been gaining their popularity and replacing traditional components. Multi-layer ceramic capacitors (MLCCs), owing to their excellent electronic characteristics, are widely applied in the high-density design of products such as PC boards, digital cameras, mobile phones, etc. The excellent electronic properties of high capacity, high stability and no positive or negative electrode are achieved through elaborate planning and rigorous controlling of every production step, especially the accuracy-demanding chip cutting operation which greatly impacts the electronic properties of ceramic capacitors.

Cutting alignment refers to positioning the MLCC substrate so the blade cuts at the intended position. Manual alignment requires the operator to align the MLCC substrate using a microscope. Automated alignment utilizes a vision system to recognize the target on the MLCC substrate and has the machine adjust the blade and the substrate position automatically. Automated alignment is capable of continuously adjusting the cutting positions to minimize process variations, while manual alignment has no such capability. The key of automatic alignment lies in successfully recognizing the target, which is easy for targets with fine patterns but difficult for MLCCs with poorly defined edges.

In Figure 1, about twenty five thousand chips are printed in the essence part of a work-in-process capacitor. Along the R (row) axis, cutting marks are printed in the center of the interval between two adjacent chips, and the ideal length between two contiguous cutting marks is 0.97mm. Along the C (column) axis, one block is actually composed of two chips, so cutting marks are located either in the middle of a block or in the center of the interval between two adjacent blocks, and the ideal length between two contiguous cutting marks is 1.89mm. As the width (0.02mm) of the cutting blade is thinner than that (0.1mm) of the cutting mark, existing capacitor cutting practices further identify the midpoint of a cutting
mark and then involve human judgment to decide an adequate cutting position. As chips are often tightly packed in a capacitor to maximize productivity, how to cut the crowded, tiny chips in an automated, precise, and high-speed manner presents a great challenge for MLCC manufacturers (Lieberenz, & Sigmund, 2003).

Cutting marks are easily distorted into irregular shapes because: (1) the marks are not properly printed in the first place, (2) the cutter exerts too much pressure on the capacitor, or (3) spaces among chips diminish and chips push one another during the cutting process. As cutting operations are conducted continuously, tension among chips accumulates and deviation errors occur. The cumulative deviation errors do hurt the cutting accuracy but interrupting the operation to make cutter adjustment decreases manufacturing speed and productivity.

To raise reliability and stability in chip cutting processes, comprehensive monitoring and diagnosis aimed at cutting variation problems become increasingly important. Sequential tolerance control, which is predicated on the ability to measure the output of prior operations, has been developed to compensate for the effect of random variation in process outputs (Fraticelli et al., 1997). However, random variation is not the only disturbance that affects a process. Cutting tools wear with time creating a gradual loss of cutting tool material that introduces a systematic variation in the output of the machining operation. Fraticelli et al. (1999) presented a method for using the techniques of sequential tolerance control to address the problem of tool-wear correction. Existing tool wear control methods are based on off-line prediction of tool wear, on regular measurement of the tool wear length or shape, or on a combination of both. Bleys et al. (2004) developed a new wear compensation method, incorporating real-time wear sensing based on discharge pulse
evaluation. Tool wear is continuously evaluated during machining, and the actual wear compensation is adapted on the basis of this real-time wear evaluation.


This research aims to improve the performance of existing MLCC cutting practices. We first utilize machine vision techniques that calculate chip mass centers on work-in-process MLCC images to find proper cutting distances. Then, we propose the bounded adjustment method integrating statistical process control (SPC) and engineering process control (EPC) techniques and the radial basis function (RBF) network to rectify cutting deviations caused by the cumulative push among chips during the cutting operations. Suitable process control models are applied to detect and rectify deviations that exceed the allowed limits. The cutting operation is continuously monitored to timely adjust the cutting position. Finally, experiments on real work-in-process MLCCs are implemented to evaluate the performance of the proposed system and the current cutting practices.
2. Proposed Methods

2.1. Computer-aided vision system

Cutting marks, because of their distorted shape problems, are not proper references for the cutting operation. Contrarily, work-in-process capacitor chips have no deformation problem and their image features are good bases for determining cutting positions. By using a charge-coupled device (CCD) camera and an electronic control X-Y table, the sample images of a work-in-process capacitor chip can be sequentially captured.

The proposed method applies computer vision techniques to find the mass center of each chip and locates a virtual cutting line at the midpoint of two adjacent mass centers. The virtual cutting line serves as a guiding line and need not be printed like the cutting marks of existing practices. The proposed method needs the position marks only at the four corners of a work-in-process MLCC for specifying the whole scope of the printed chips, which greatly saves the printing costs. As shown in Figure 2, the cutting distance is defined as the length between two adjacent cutting lines by the proposed method and as the length between two adjacent cutting marks by the existing cutting method.

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Figure 2 should be here

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Before chips are cut, some pre-processing tasks such as image segmentation, noise reduction and morphology must be done to the images captured by the CCD camera to precisely locate the mass centers of ceramic chips. Figure 3 presents an example of a chip image pre-processed by computer vision techniques. The coordinates of the mass centers of two adjacent chips are first obtained; then by averaging the coordinates of the two mass centers the location of the cutting line can be identified. The difference between two
adjacent cutting lines is called the cutting distance, which plays an important role in this research. The cutting process is controlled by minimizing the difference between the actual cutting distance and the ideal cutting distance. Timely, quantitative adjustments are made to keep the real cutting distance close to the target value.

2.2. **Statistical bounded adjustment method**

Bounded feedback control is based on integral control, which conducts a series of regular adjustments on a manipulatable variable to keep the process output close to the desired target. By combining integral control and the concept of statistical process control, Box and Luceno (1997) build a bounded feedback control model that monitors predicted values of disturbances. If the disturbance exceeds the control bounds, an adjustment message is generated. The objective of integral control is to timely adjust the process and avoid over control.

Process deviation derives from the disturbance of assignable causes in the manufacturing process, so constructing a proper model for the disturbance is needed. Based on Montgomery and Mastrangelo’s (1991) findings, when the process is disturbed at
time \((t+1)\), the predicted value \(\hat{N}_{t+1}\) of the disturbance can be modelled by using the exponentially weighted moving average (EWMA) prediction method:

\[
\hat{N}_{t+1} = \hat{N}_t + \lambda \left( N_t - \hat{N}_t \right) = \hat{N}_t + \lambda \varepsilon_t
\]

(1)

where \(\varepsilon_t = N_t - \hat{N}_t\) is the prediction error at time period \(t\) and \(0 < \lambda \leq 1\) is the weighting factor for the EWMA. The difference between the two EWMA predictions \((\hat{N}_{t+1} - \hat{N}_t)\) can be rewritten as:

\[
\hat{N}_{t+1} - \hat{N}_t = \lambda \varepsilon_t = \lambda (y_t - T)
\]

(2)

where \(y_t\), the process output characteristic of interest at time period \(t\), should be kept as close as possible to the target \(T\). This process involves a manipulatable variable \(x\), the cutting distance. A change in the cutting distance will exert all its effect on \(y\) within one period. That is, \(y_{t+1} - T = g x_t\). Furthermore, since the actual error at time \(t\), \(\varepsilon_t\), is simply the difference between the output and the target, an adjustment should cancel out the disturbance. In period \(t+1\), the output deviation from target should be \(y_{t+1} - T = \varepsilon_{t+1}\), where \(\varepsilon_{t+1}\) is the prediction error in period \(t\). That is, \(\varepsilon_{t+1} = N_{t+1} - \hat{N}_{t+1}\). The actual adjustment to the manipulatable variable made at time \(t\) is:

\[
x_t - x_{t-1} = -\frac{1}{g} \left( \hat{N}_{t+1} - \hat{N}_t \right)
\]

(3)

where \(g\) is a constant usually called the process gain. The gain is like a regression coefficient, in that it relates the magnitude of a change in \(x_t\) to a change in \(y_t\). Therefore, combining Eqs. (2) and (3), the adjustment to be made to the manipulatable variable at time period \(t\) becomes:

\[
x_t - x_{t-1} = -\frac{\lambda}{g} (y_t - T) = -\frac{\lambda}{g} \varepsilon_t
\]

(4)

The actual setpoint for the manipulatable variable at the end of period \(t\) is simply the sum of all the adjustments through time \(t\), or:
The adjustment procedures require that an adjustment be made to the process after each observation. However, situations can arise in which the cost or convenience of making an adjustment is a concern. For example, in discrete parts manufacturing it may be necessary to actually stop the process to make an adjustment. The bounded adjustment is a modification to the feedback control procedure so that less frequent adjustments are required. The bounded adjustment is made only when the EWMA forecast exceeds the bounds $\pm L$. The boundary value $L$ is usually determined from engineering adjustment, after the costs of being off target are weighed against the costs of making the adjustment (Montgomery, 2005).

Many researchers focus on the parameter studies of the EWMA feedback control model. Box and Kramer (1992) build up an integrated moving average (IMA) model and study its variograms at different $\lambda$ values. Luceno (1995) proposes a dynamic choice of $\lambda$ values for process variation in an environment that applies EPC. The parameter relationship gets complicated when the feedback control belongs to the bounded adjustment type. Ruhhal et al. (2000) try to find suitable $\lambda$ and $L$ values of the EWMA feedback control model for different process deviation levels to achieve the minimum mean square errors. This research refers the work of Ruhhal et al. (2000) to further explore the EWMA weight parameter $\lambda$ and process gain parameter $g$, two important parameters related to adjustment effect. The combinations of the two parameters generate different process adjustment results under distinct process deviation situations. The response surface methodology (RSM) (Montgomery, 2000; Myers, & Montgomery, 2002) is used to determine the optimum parameter combination for obtaining the best process adjustment effect.

$$x_t = \sum_{j=1}^{t} (x_j - x_{j-1}) = -\frac{\lambda}{g} \sum_{j=1}^{t} E_j$$ (5)
2.3. Neural network approach

RBF network predicts and controls the output of a correlated process by conducting network training (West et al., 1999). Drawing on the knowledge of biological receptive fields, Moody and Darken (1989) propose the RBF network structure that employs local receptive fields to perform function mappings. The RBF network structure has three layers: input, hidden, and output layers. Unsupervised learning is conducted between the input and hidden layers, while supervised learning is done between the hidden and output layers.

In the unsupervised learning of the first stage, K-means clustering algorithm divides the training input \( \tau \), a multidimensional input vector, into \( J \) clusters. The hidden layers thus contain \( J \) receptive field units, for each of which the network calculates and records its mean and variance. The communication between hidden layers and output layers depends on activation levels of the receptive field units. The basic activation level is based on Euclidean distance and the equation can be written as:

\[
A_i = R_i(\tau) = R_i\left(\|\tau - u_i\|/\sigma_i\right), \quad i = 1, 2, ..., J
\]  

(6)

where \( \tau \) is a multidimensional training input vector, \( J \) is the number of receptive field units, \( u_i \) is the objective vector for the \( i \)-th receptive field unit with the same dimension as \( \tau \), \( \sigma_i \) is a smoothing parameter greater than zero, and \( R_i(\cdot) \) is the \( i \)-th radial basis function for the \( i \)-th receptive field unit. Typically, \( R_i(\cdot) \) is a Gaussian function (Jang, & Sun, 1993):

\[
R_i(\tau) = \exp\left(-\frac{|\tau - u_i|^2}{2\sigma_i^2}\right)
\]  

(7)

Hence, the activation level of the radial basis function \( A_i \) computed by the \( i \)-th hidden unit is maximized when the input vector \( \tau \) is at the center \( u_i \) of that unit.

When the activation levels of all receptive field units are calculated in the hidden layer, the supervised learning of the back-propagation network is used in the second stage of the
RBF network. This supervised learning will adjust the connection weights between the hidden layer and the output layer. The output of an RBF network can be computed in two ways. In the simpler way, the final output is the weighted sum of the output value associated with each receptive field unit (Jang et al., 1997):

$$d(\tau) = \sum_{i=1}^{J} w_i A_i = \sum_{i=1}^{J} w_i R_i(\tau)$$

where $w_i$, the output value associated with the $i$-th receptive field, can also be viewed as the connection weight between the $i$-th receptive field and the output unit. A more complicated method for calculating the overall output is to take the weighted average of the output associated with each receptive field:

$$d(\tau) = \frac{\sum_{i=1}^{J} w_i A_i}{\sum_{i=1}^{J} A_i} = \frac{\sum_{i=1}^{J} w_i R_i(\tau)}{\sum_{i=1}^{J} R_i(\tau)}$$

Moody and Darken (1989) suggest that the RBF network, owing to its local-turned property, has a faster learning speed than the back-propagation network. The local-turned property clusters the input vectors before supervised learning is conducted, which reduces learning units and computer processing time. Besides, the combined learning property can be expressed as the combination of linear equations. Compared with non-linear equations of other common neural networks, linear equations achieve the converge effect faster and are thus more suitable for the approximation of adaptive control.

3. Experiments and analyses

To verify the feasibility of the proposed approach, we build up a machine vision system and use a CCD camera to capture pictures of real chip cutting operations in a production environment. Separating all the rectangular chips in a square work-in-process MLCC requires 114 cuttings in the C axis and 227 cuttings in the R axis. To prepare samples for experiments, we use seven pieces of the work-in-process MLCCs, which include 798 data
sets in the C axis and 1589 data sets in the R axis. The bounded adjustment and RBF
network methods are both implemented and evaluated.

3.1. Adjustment evaluation of statistical method

As shown in Figure 1, a work-in-process MLCC has two R axes (R1 and R2) and two C
axes (C1 and C2). The average of the cutting distances in R1 and R2, and the average of
the cutting distances in C1 and C2 form the adjusted values of the bounded adjustment
method. The cutting distances are determined based on the chip mass centers of the
proposed method. The bounded adjustment is applied to adjust the deviation from the
target cutting distance. Since small deviations occur in the course of printing capacitor
chips, the values of the target cutting distance vary with time. To avoid confusion, we use
the real cutting distance minus its corresponding target value to obtain the difference \( \Delta d \).
After the subtraction, the new process target value becomes zero. These difference values
\( \Delta d \) are the data that will be adjusted to keep the process close to the new target value zero.
When the values \( \Delta d \) deviate from zero, the deviated situations can be classified into shift
or trend deviations. Shift deviations, characterized by the sudden increase of the output
deviation, may result from machine breakdown or process operators’ errors. Trend
deviations, characterized by the gradual increase of the output deviation, may result from
machine wear or operators’ weariness (Huang, & Lin, 2002). If the magnitudes of the shift
or trend deviations are less than one standard deviation, the process is considered normal
and no adjustment is needed. Otherwise, the process will be adjusted based on the bounded
adjustment models of shift or trend deviations. Table 1 presents a bounded adjustment
example.

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In Table 1, the new process target value is zero for every observation. The process difference $\Delta d$, equal to the original process output minus the original target, is used as the disturbance to construct an EWMA prediction model for obtaining the time of process adjustments under the given conditions. The related parameter settings of the bounded adjustment method in this example are $\lambda = 0.25$, $g = 1.25$, and $L = \pm 9.015$. For instance, the disturbance of the EWMA prediction at Observation 3 is $-10.830$, which exceeds the lower control limit $-9.015$ and thus must be adjusted at the magnitude of $7.679$ by the bounded feedback control. The adjustment is executed at Observation 4, whose process difference $\Delta d$ is $3.015$. After the bounded adjustment, the adjusted process output at Observation 4 becomes $10.695$.

When the process is adjusted at Observation 4, the disturbance of the EWMA model needs to be re-calculated and then the other disturbances must be monitored to find the time of the next adjustment. Before the next adjustment is determined (Observation 11, in this example), the cumulative adjustment of the system remains at $7.679$. The final process output will be different from the original process output if the bounded adjustment is executed. The next adjustment is detected after the time of Observation 11 and the amount of cumulative adjustment is $13.639$ (i.e. $7.679 + 5.959$). Similarly, the second adjustment is executed at Observation 12. Following the same procedure, the adjusted process output at Observation $t$ after the bounded adjustment can be written as: Adjusted process output ($t$) = Process output difference ($t$) + Cumulative adjustment ($t$-$I$). The final process output at Observation $t$ after the bounded adjustment can be written as: Final process output ($t$) = Adjusted process output ($t$) + Original target ($t$).

Figure 4 shows the adjustment chart of the disturbance model using EWMA prediction for monitoring the sample data of the capacitor chip cutting operation. It is clear to see
which Observation is beyond the control limits. Exceeding the control limits implies that the process needs to be adjusted. Therefore, how many bounded adjustments (6 times, in this case) have been executed during the process can be known from checking the adjustment chart. Owing to the high accuracy request of the capacitor chip cutting process, this research focuses on adjusting the process to achieve maximum improved effect. That is, getting the process output as close as possible to the desired target after the bounded adjustment.

To present the effect of the process after the bounded adjustments, the mean square errors ($MSE$) with the target values of the process before ($MSE_{\text{before}}$) and after ($MSE_{\text{adjusted}}$) the bounded adjustments need to be calculated. A performance evaluation index called the effective adjustment rate is defined as:

$$
\text{Effective adjustment rate} = \frac{MSE_{\text{before}} - MSE_{\text{adjusted}}}{MSE_{\text{before}}} \times 100\% 
$$

The effective adjustment rate increases when the mean square error of the process outputs with desired target decreases after the bounded adjustments. Therefore, the final effective adjustment rate can represent how close the process output is to the desired target after the bounded adjustments. The higher the effective adjustment rate, the closer the process output is to the desired target.

If the effective adjustment rate is used as an evaluation index, we study the influenced effect of the parameter settings for $\lambda$ and $g$ on the effective adjustment rate. Response surface methodology is applied to find the parameter combination of $\lambda$ and $g$ that help achieve the best effective adjustment rate. As suggested in the EWMA model of
Montgomery (2005), the $\lambda$ value is set at three factor levels: 0.1, 0.25 and 0.4. The $g$ value is set at 0.5, 1.25 and 2, according to our repeated experimental results.

The deviations of the cutting operation can be classified into shift and trend deviations, for both of which bounded adjustments are conducted and related data are recorded. Tables 2 and 3 display the effective adjustment rates of shift and trend deviations in the two axes. The higher the effective adjustment rate, the closer the process output is to the target. In Table 3, most of the effective adjustment rates are above 20% for the trend deviations. The bounded adjustment excels in bringing the process output close to the desired target.

In Table 2, the C axis obtains higher effective adjustment rates for shift deviations of more than one standard deviation, while the R axis has lower ones for shift deviations of less than one standard deviation. This illustrates that the bounded adjustment exerts no significant effects on process shift of less than one standard deviation. Actually, forcing bounded adjustment on a process of little deviation may sometimes increase the mean square errors of the process outputs. In such a case, making no adjustment is suggested for it saves the costs of unnecessary adjustments and the negative impact of over-adjustment.

RSM is capable of selecting the best parameter setting for the feedback control of the chip cutting operation. The optimum search procedure of RSM applies the Steepest Ascent technique by moving sequentially along the path of steepest ascent in the direction of the maximum increase in the response. When the response variable has no significant change under different factor levels, the RSM finds the optimum of the response variable and determines the best parameter combination of the factor levels (Myers, & Montgomery,
Tables 4 and 5 are the parameter settings for obtaining maximum effective adjustment rates of shift and trend deviations in the R and C axes. Since the shift deviations in the R axis are less than one standard deviation, they are regarded as normal and need no adjustment.

As shown in Tables 4 and 5, the suggested parameter combinations \( \lambda \) and \( g \) of factor levels from RSM are input into the testing cutting process to conduct the bounded adjustments. Two performance evaluation indices of the bounded adjustment, average of MSE and effective adjustment rate are calculated and presented in Tables 6 and 7. When the bounded adjustment model adopts the suggested parameter settings, its average MSE is significantly smaller than that of the current cutting operation. The average of the effective adjustment rates is 34%. This implies that the outputs of the bounded adjustment method are closer to the desired targets than those of the current cutting operation.

3.2. Adjustment evaluation of neural network approach

The RBF network structure applied in this research has one hidden layer, and the numbers of operators in the input, hidden, and output layers are 2, 2, and 1, respectively. The cutting distances of C1 and C2 or those of R1 and R2 form the inputs of the network. The C axis uses its first 570 data sets as the training patterns and the subsequent 228 data sets as the testing patterns. The R axis uses its first 1135 data sets as the training patterns and the subsequent 454 data sets as the testing patterns. Figure 5 shows the architecture of
the RBF neural network applied to the chip cutting operation. The sample sets of the cutting distances with less deviation from target values are selected as the training samples to ensure network training accuracy. In the first learning stage, Gaussian function serves as the activation function of the unsupervised learning. In the second learning stage, the back-propagation learning obtains a learning rate of 0.1 for the supervised learning. To avoid network divergence, the momentum coefficient is set at 0.8 to stabilize the adjustments of weights between the hidden and output layers. This research adopts a specified number of learning times as the stop condition for the network learning under various considerations of learning accuracy, learning speed, and sample size. After the network learning is conducted for 100,000 iterations, the final root mean square error can converge to 0.0988 in our experiments.

After the training stage, the cutting distances of the testing samples can be input into the network, which at the same time produces predictive values by using the network re-call ability. These values are the outputs of the adjusted process if we compare with the adjustment procedure of feedback control. Tables 8 and 9 present the output results of adjusting shift and trend deviations in the R and C axes by the RBF network and the current cutting methods. Both tables indicate that the RBF network, with a significantly reduced overall mean square error, achieves a much better effective adjustment rate than does the current cutting method.
3.3. Summarized analyses

This research proposes two techniques to solve the deviation problems in the capacitor chip cutting operation. The first method uses the RSM to find the best parameter combination and then applies the parameters to the bounded adjustment model. The second method applies the RBF network to predict inference values of the cutting distances by using network learning and recall ability. Tables 10 and 11 compare the sample statistics and adjustment performance of shift and trend deviations in the R and C axes by the three methods.

Table 10 & Table 11 should be here

Results in Tables 10 and 11 lead to the following conclusions: (1) the two proposed methods excel the current cutting method in all of the performance indices. (2) The RBF network can keep the process mean close to the desired target and substantially decrease the variability. The bounded adjustment can also decrease the deviation of the process mean from the target but have a larger variance than the RBF network. (3) Generally speaking, the RBF network has the smallest MSE and the bounded adjustment has the second least MSE. The RBF network shares similar effects with the bounded adjustment. Actually, their averages of MSE are the same when the process incurs trend deviations. The two proposed methods have the same adjustment effects on trend deviations when central tendency is the major concern. The RBF network excels when the focus is on reducing spread tendency. (4) The bounded adjustment makes no adjustment when regulating shift deviations of less than one standard deviation in the R axis. Our experimental results show that the MSE of the adjusted process is almost the same as that
of the current cutting operation. Thus, adjustment costs can be saved when the bounded adjustment is applied to regulate process shifts of less than one standard deviation.

From the above analysis, both of the two proposed methods provide better cutting effects than the current cutting operation. However, some differences exist between the two proposed methods. When the effective adjustment rate is selected as the evaluation index, the RBF network can provide better predictions of cutting distances for the chip cutting operation. Figure 6 compares how the RBF network method and the bounded adjustment method adjust the process towards the targets.

Owing to its excellent feedback adjustment ability, the RBF network obtains better effective adjustment rates than does the bounded adjustment, when regulating shift deviations in the R and C axes, and trend deviations in the R axis. Though the RBF network excels in detecting and feeding back small process shifts of less than one standard deviation in the R axis, the adjustment costs can be saved by applying the bounded adjustment to regulate process shifts of less than one standard deviation. Figure 9 indicates that the RBF network and the bounded adjustment achieve similar effects when regulating trend deviations in the C axis.

4. Conclusion

This research applies computer vision techniques to find mass centers of chips, locate cutting lines and calculate cutting distances for the automated, precise, and high-speed cutting of MLCCs. The statistical bounded adjustment method and the RBF network model are proposed to solve the cutting deviation problems and to timely and quantitatively adjust
the process towards the target values. Two common kinds of process deviations, shift and trend deviations, are explored in this research. The bounded adjustment method timely adjusts the process by using RSM to determine the parameter combination that obtains the maximum effective adjustment rate. The RBF network method makes better predictions of the cutting distances through the recall ability of the trained network.

Experimental results show that the statistical bounded adjustment and the RBF network, respectively, increase the effective adjustment rates of cutting deviations by 35% and 60% more than the current cutting method. The two proposed methods both surpass existing chip cutting practices. While the RBF network achieves significantly improved effects and minimum process variability, the bounded adjustment can be applied to regulate process shifts of less than one standard deviation to save adjustment costs. As to potential future applications of this research, the proposed process control systems can be integrated with chip cutting machines to conduct surveillance and feedback control functions.

Acknowledgements

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References:


Fig. 1. Cutting marks along the two axes of a work-in-process MLCC

Fig. 2. The cutting distance diagrams of the two methods

Fig. 3. Application results of computer vision techniques to a work-in-process MLCC
Fig. 4. The adjustment chart of a disturbance model using EWMA prediction for chip cutting operation

Fig. 5. The architecture of RBF neural network applied to MLCC cutting operation

Fig. 6. Effective adjustment rates of the RBF network and the bounded adjustment method
Table 1. Data sets of feedback control by the bounded adjustment method (Unit: \( \mu m \))

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<td>13.639</td>
<td>1891.098</td>
<td>1883.323</td>
</tr>
</tbody>
</table>

Table 2. The effective adjustment rates of shift deviations in the two axes

<table>
<thead>
<tr>
<th>Shift deviations in C axis</th>
<th>( \lambda ) values</th>
<th>Shift deviations in R axis</th>
<th>( \lambda ) values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g ) values</td>
<td>0.1       0.25 0.4</td>
<td>( g ) values</td>
<td>0.1       0.25 0.4</td>
</tr>
<tr>
<td>0.5</td>
<td>32.83     31.92 8.34</td>
<td>0.5</td>
<td>1.37      0      0</td>
</tr>
<tr>
<td>1.25</td>
<td>29.62     33.29 30.45</td>
<td>1.25</td>
<td>1.63      0.72   0</td>
</tr>
<tr>
<td>2.0</td>
<td>25.24     33.75 32.90</td>
<td>2.0</td>
<td>2.25      1.67   0</td>
</tr>
</tbody>
</table>

Unit: percentage

Table 3. The effective adjustment rates of trend deviations in the two axes

<table>
<thead>
<tr>
<th>Trend deviations in C axis</th>
<th>( \lambda ) values</th>
<th>Trend deviations in R axis</th>
<th>( \lambda ) values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g ) values</td>
<td>0.1       0.25 0.4</td>
<td>( g ) values</td>
<td>0.1       0.25 0.4</td>
</tr>
<tr>
<td>0.5</td>
<td>24.35     25.65 10.94</td>
<td>0.5</td>
<td>24.91     14.33 0.32</td>
</tr>
<tr>
<td>1.25</td>
<td>11.07     27.17 29.26</td>
<td>1.25</td>
<td>32.00     35.21 31.49</td>
</tr>
<tr>
<td>2.0</td>
<td>4.26      21.74 30.03</td>
<td>2.0</td>
<td>27.53     36.64 32.57</td>
</tr>
</tbody>
</table>

Unit: percentage

Table 4. Parameter settings for shift deviation adjustment by RSM

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameters for shift deviations in C axis</th>
<th>Parameters for shift deviations in R axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main factors</td>
<td>( \lambda ) value</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>( g ) value</td>
<td>2.00</td>
</tr>
<tr>
<td>Response variable</td>
<td>Effective adjustment rate</td>
<td>25.680%</td>
</tr>
</tbody>
</table>

Table 5. Parameter settings for trend deviation adjustment by RSM
Table 6. Output results of shift deviation adjustment by the bounded adjustment and the current cutting methods

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameters for trend deviations in C axis</th>
<th>Parameters for trend deviations in R axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>λ value</td>
<td>0.40</td>
<td>0.23</td>
</tr>
<tr>
<td>g value</td>
<td>2.00</td>
<td>1.48</td>
</tr>
<tr>
<td>Response variable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effective adjustment rate</td>
<td>31.532 %</td>
<td>37.191 %</td>
</tr>
</tbody>
</table>

Table 7. Output results of trend deviation adjustment by the bounded adjustment and the current cutting methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Average of MSE for shift deviations in C axis</th>
<th>Average of MSE for shift deviations in R axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current cutting method</td>
<td>198.438</td>
<td>Since the deviations are less than one standard deviation, no adjustment is needed.</td>
</tr>
<tr>
<td>Bounded adjustment method</td>
<td>126.169</td>
<td></td>
</tr>
<tr>
<td>Effective adjustment rate</td>
<td>36.418 %</td>
<td></td>
</tr>
</tbody>
</table>

Table 8. Output results of shift deviation adjustment by the RBF network or the current cutting method

<table>
<thead>
<tr>
<th>Methods</th>
<th>Average of MSE for shift deviations in C axis</th>
<th>Average of MSE for shift deviations in R axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current cutting method</td>
<td>198.438</td>
<td>51.717</td>
</tr>
<tr>
<td>RBF network</td>
<td>51.323</td>
<td>7.974</td>
</tr>
<tr>
<td>Effective adjustment rate</td>
<td>74.137 %</td>
<td>84.581 %</td>
</tr>
</tbody>
</table>

Table 9. Output results of trend deviation adjustment by the RBF network or the current cutting method
### Table 10. Sample statistics of shift deviation adjustment by the three methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Average of MSE for trend deviations in C axis</th>
<th>Average of MSE for trend deviations in R axis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current cutting method</td>
<td>259.394</td>
<td>91.224</td>
</tr>
<tr>
<td>RBF network</td>
<td>182.308</td>
<td>47.168</td>
</tr>
<tr>
<td>Effective adjustment rate</td>
<td>29.718%</td>
<td>48.294%</td>
</tr>
</tbody>
</table>

### Table 11. Sample statistics of trend deviation adjustment by the three methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>C axis</th>
<th>R axis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std Dev</td>
</tr>
<tr>
<td>Target values</td>
<td>1879.992</td>
<td>7.266</td>
</tr>
<tr>
<td>Inference values (RBF Network)</td>
<td>1878.232</td>
<td>1.502</td>
</tr>
<tr>
<td>Adjusted values (Bounded adjustment)</td>
<td>1877.121</td>
<td>8.855</td>
</tr>
<tr>
<td>Actual values (Current cutting method)</td>
<td>1870.536</td>
<td>8.576</td>
</tr>
</tbody>
</table>

Unit: μm