Comparison of Algorithm and Kernel Accuracy in Defect Detection Using Pressure in Sleeve Soldering Equipment

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Abstract—As the degree of device integration increases, detecting soldering defects on electronic boards becomes more complex, and the need for automatic inspection increases. In this study, we propose a method for distinguishing the quality of soldering for sleeve-soldering equipment. The object to be soldered is covered with a heated sleeve, and the solder pieces dropped in the sleeve are melted for soldering. Nitrogen gas is injected into the sleeve, and the pressure inside the sleeve changes as the solder pieces melt and flow into the through-hole. The proposed method identifies the quality of the solder using the features extracted from the pressure change. We compare the prediction accuracy when applying multiple kernels to the support vector machine (SVM) and relevance vector machine (RVM). The experimental results show that the Polynomial kernel of the SVM exhibits the best performance with an average accuracy of 100% and average False Negative of 0%.

Index Terms—soldering, prediction, SVM, RVM

I. Introduction

The quality of soldering that joins a printed wired board (PWB) and a device affects the strength of the joint, which has considerable impact on reliability of a device in environments with vibrations, such as electric vehicles. Therefore, soldering defects must be detected. A major inspection method is a worker visually confirming whether the through-hole is filled with enough solder; however, this method depends on the experience and ability of the worker. In addition, owing to the miniaturization of devices, the degree of device integration has increased, making visual inspection difficult. Therefore, methods for automatically inspecting solder joints are being researched.

The sleeve-soldering device is one of the devices used for soldering. The device covers the through-hole with a heated ceramic cylinder (sleeve) and melts the solder by dropping the solder pieces into the sleeve. As the solder is melted inside the sleeve, scattering of the ball solder is prevented, and a constant amount of solder can be supplied to the joint; this has the advantage of stabilizing the quality of the solder. Also the device fills the sleeve with nitrogen gas prevents the solder from oxidizing, enabling the melted solder to flow into the through-holes, thus preventing the formation of the cold solder joint. As a constant amount of nitrogen gas is continuously supplied from the top of the sleeve, the pressure inside the sleeve changes from variations in gas outflow due to the melting of solder pieces and contact between the sleeve and the PWB.

In a previous study, the quality of soldering was evaluated by using the Random Forest and support vector machine (SVM) against pressure changes during soldering with a sleeve-soldering machine, and an accuracy of 95.5% was obtained with the SVM [1]. In this study, to improve the classification accuracy, we compare the prediction accuracy of the SVM and its advanced method, the relevance vector machine (RVM). In addition, we compare multiple kernel functions and identify combinations with high classification accuracy.

II. Related research

A typical method for identifying the quality of soldering is to extract feature values from images of soldered boards. Wu [2] employed machine learning to extract image features after locating solder joints from board images. The accuracy of five machine-learning methods (decision tree, k-neighborhood method, SVM, neural network, and Random forest) were compared, and the Random forest was able to predict five types of defective solder with 100% accuracy. Dai et al. [3] used YOLO, an object detection method, to classify the types of defective solder by utilizing the features of the solder joints localized from the board image; the annotation error rate was less than 1.5% for all datasets. In the research using board images, inspection is performed after all soldering on one board is completed. By contrast, in the proposed method using the pressure change in the sleeve-soldering device, the soldering can be inspected immediately after it is completed in each through-hole without interruptions; this enables real-time defect detection. In addition, the pressure waveform of the sleeve-soldering device is considered to reflect the differences in the operations of the soldering device in each process of soldering. Therefore, the cause of a defect in each process can be identified from the pressure waveform.

Kernel methods in machine learning are used in various research fields. As the performance of kernel methods is affected by the selection of a kernel function suitable for the data distribution, comparing different kernel functions is necessary when the characteristics of the data are unclear. SVMs and RVMs are often used in classification for detection, prediction, etc. [4] [5] [6] [7] [8] [9], and are compared for classification accuracy [10] [11]. Classification accuracy with different kernel is also major topic in research field [12] [13] [14]. Xiang-min et al. [11] compared performances on the Heart_scale, Breast_cancer, Boston, and Wdbc datasets, and the results showed that the RVM was equivalent to the SVM in terms of learning efficiency and classification accuracy and superior in terms of sparsity characteristics, generalization ability, and decision speed. Karal [13] conducted an experiment to confirm the effectiveness of kernel functions and k-point cross-validation in the SVM and showed a maximum change of 17.4% for each kernel function and 16.7% for k-point cross-validation. Wijayanti et al. [14] used four kernels to analyze bullying on twitter by employing the SVM and compared the classification accuracy; their results showed that the sigmoid kernel achieved the highest accuracy of 83.6%.

In this study, we compare the accuracy of different kernel functions when using the SVM and RVM in determining the quality of solder. The pressure change in the sleeve-soldering device, which is the subject of this study, overlapping the data of correct solder and incorrect solder is highly probable. Therefore, in addition to evaluating the SVM, which exhibited the highest accuracy in a previous study [1], we compare the accuracy of multiple kernel functions when using the RVM, which is more resistant to data overlap and outliers than the SVM. Thus, we determine the combination with the highest accuracy.

III. Inspection method for sleeve-soldering

Current point soldering includes iron soldering and laser soldering. Iron soldering is a method in which solder is melted with a heated iron tip and supplied to the joint between the pin and the PWB. Laser soldering is a method in which a laser irradiates a pin and a PWB to generate heat, raising the temperature of the joint to the melting point of the solder and supplying solder from the device. Sleeve soldering has better wettability (which indicates the spread of solder) than iron soldering, and the tip of the soldering iron need not be replaced to prevent wear. In addition, unlike in laser soldering, in sleeve soldering, no solder scattering occurs and a fixed amount of solder pieces can be supplied, resulting in stable quality. Moreover, nitrogen gas prevents oxidation of the solder surface by blocking oxygen.

Fig. 1 shows the state and pressure change inside the sleeve during soldering. Figs. (a)–(c) depict the contact between the sleeve and the board, the falling solder pieces, and the solder pieces melting, respectively. Fig. (d) displays the rise of the sleeve with correct solder, and Fig. (d') shows the rise of the sleeve with incorrect solder. Let t = 0 s be the time when the solder piece is cut at the top of the sleeve. (a) At t = −0.57 s, the sleeve and the board come into contact with each other, narrowing the flow path of the nitrogen gas and increasing the pressure. (b) At t = 0 s, the solder pieces are introduced into the sleeve, further narrowing the flow path and increasing the pressure. (c) When the solder piece melts at t = 1.2 s, it closes the through-hole and rises to the maximum pressure. (d), (d') At t = 2.5 s, the sleeve starts to rise and the pressure drops. (d) In the case of good solder, the solder solidifies into a volcano shape near the through-hole; thus, nitrogen gas flows out as soon as the sleeve rises, and the pressure drops. (d') In the case of cold solder, the solder stays on the top of the pin and solidifies into a spherical shape at a position farther from the board than good solder. Therefore, even if the sleeve rises, the gas flow path cannot be formed immediately, and a considerable amount of time is required for the pressure to decrease.

In a previous study, a method for distinguishing correct/incorrect solder was proposed, focusing on the difference in the timing of pressure changes [1]. The state of the solder was classified by applying machine learning using eleven features, such as the time when the pressure starts to drop from the maximum value and the rate of drop. The Random forest and SVM were used as machine-learning algorithms, and the accuracy in classifying three patterns, namely ”solder on component land side,” ”solder in through-hole,” and ”no solder in through-hole,” was 82.7% for the Random forest and 87.1% for the SVM. In addition, the accuracy in classifying two patterns, namely ”solder in through-hole” and ”no solder in through-hole,” was 94.5% for the Random forest and 95.5% for the SVM. The accuracy in classifying “solder on component land side” and ”solder in through-hole + no solder in through-hole” was 89.9% for the Random forest and 93.3% for the SVM. In this study, we distinguish between two patterns: ”solder in through-hole” and ”no solder in through-hole.” We compare the accuracy when using multiple kernel functions for the SVM and RVM to determine the combination with the highest accuracy.

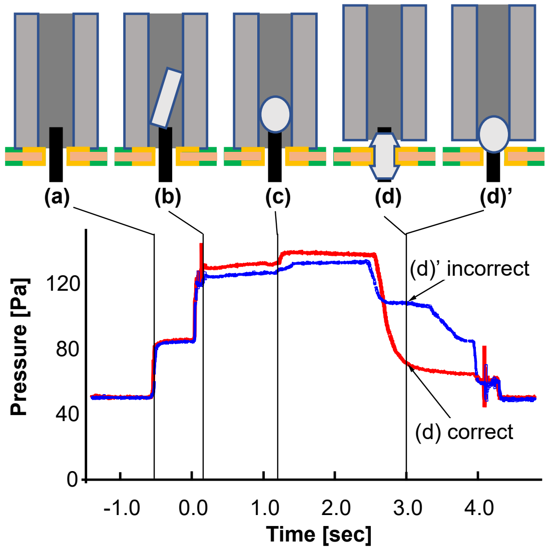


Fig. 1: Pressure change during soldering

IV. Experiment

A. Dataset

The pressure change during soldering is measured using Smart Shot, a sleeve-soldering device manufactured by And Co., Ltd. The pressure inside the sleeve is measured at 500 Hz during soldering. A universal board with 320 (20 × 16) through-holes is used for soldering.

The practical settings of the sleeve-soldering device rarely occur defective soldering, hence obtaining a sufficient number of data for learning is difficult [1]. In this study, we focus on insufficient preheating, which is a cause of defects even in actual environments. Preheating refers to heating the PWB in advance by lowering the sleeve and bringing it into contact with the board. The suitable preheating time and temperature for correct soldering depend on the size and type of the board to be soldered. For example, a new design board such as a multi-layered board has a higher possibility to incorrect soldering caused by insufficient preheating. In the experiment, the board is cooled by blowing air from an air pump, and the time interval between soldering is changed from less than 1 s to 30 s to create an environment in which the preheating during the previous soldering is cooled.

One of the soldering device developers scores each soldering result within the range of 0–9 points. A score of 0–2 indicates incorrect solder with no solder in the through-hole, and a score of 4–9 indicates correct solder with solder in the through-hole. The score 3 was not selected in this experiment. Table I shows the number of obtained correct/incorrect solder. TH_{NG} indicates incorrect solder, TH_{OK} indicates correct solder, and the higher the score, the better is the soldering. Incorrect solders are labeled as × for solder without back fillet, and △ for solder without back fillet. These labels are not used for learning. The total number of incorrect solder is 440,

TABLE I: Number of data in the experiment

Correct/Incorrect	Label	Score	# Data	# Extract
TH_{NG}	×	0	3	3
		1	390	390
		2	47	47
TH_{OK}	△	4	989	75
		5	546	75
		6	482	75
		7	172	75
	○	8	163	75
		9	334	75
Total			3,126	890

whereas the total number of correct solder is 2,686, which is considerably greater than 440. We equalize the number of correct/incorrect data by random sampling to prevent biased learning from the imbalanced data. From 3,126 data acquired in the experiment, all the incorrect solder and 890 correct solders (with 75 points from each score) are randomly extracted to create a dataset. The same operation is repeated 100 times to create 100 datasets. In the RVM, the score is used as the prediction label. In the SVM, correct/incorrect labels are used as the prediction label.

B. Feature extraction

The characteristics of correct/incorrect solder are reflected in the pressure during processes (a)–(d'). If the board is not preheated enough, the heat will not be transferred to the solder pieces sufficiently, delaying the start of melting. The timing of the sleeve rises during soldering is the same in every case. Hence when the sleeve rises before the melted solder flows into the through-hole, causing the solder to solidify in the middle of the pin, i.e. incorrect solder. The solder in the middle of the pin blocks the gas flow path in the sleeve; hence, the pressure drop is slower than correct solder. Therefore, quality can be classified by pressure dropping time from the maximum pressure.

We use three types of features to identify the quality of solder: the kurtosis of the pressure waveform, peak length, and time required for pressure drop. Kurtosis is a value that expresses the sharpness of the distribution, and the sharper the waveform, the larger is the value. Therefore, it is considered to be useful as a feature quantity that expresses the difference in the melting speed of solder pieces. The peak length is the length of time that the maximum pressure value is maintained after pressure reaches the maximum. The maximum pressure is the state in which the melted solder blocks the through-holes. Here, the starting point is the point where "maximum pressure * 0.9" is first reached from the start of soldering, and the end point is the point where the pressure is less than the "maximum pressure * 0.9." Pressure drop time is defined as the time required for the pressure to drop from the maximum pressure (100%) to a specified percentage. The minimum pressure (0%) is defined as the average value of the pressures measured at 0.02 to 0.04 s of each soldering. When the soldering is completed, the sleeve separated from the board and the pressure drops from the maximum to the minimum; the slope is expected to be gentle if the through-hole is not filled because the incorrect solder in the middle of the pin hinders the pressure drops. In this study, the time ($T_{90\%}, T_{80\%}, ..., T_{10\%}, T_{5\%}$) that the time to reach the specified pressure (90%, 80%,...,10%, 5%) is used as a feature that expresses the pressure drop.

C. Classification

Classification is performed on 100 datasets using the feature values described in Section IV-B. We compare the combination of two learning algorithms (SVM and RVM) and three kernels (RBF, Polynomial, and Linear.) We perform 10-fold cross-validation 10 times while changing the combination of hyperparameters for each of the 100 datasets. For tuning the hyperparameters, the training function[1] of the classification and regression training (caret) package, which is an R language package, is used.

Accuracy is determined by distinguishing between correct and incorrect solder for each combination of the algorithms and kernels with tuned hyperparameters. We tune hyperparameters with TuneLength = 100 for the RBF kernel of the SVM and three kernels of the RVM. TuneLength is not used for the Polynomial kernel of the SVM. For the linear kernel of the SVM, the range of 15 values of C is searched in increments of 0.001.

V. Results and discussion

A. Comparison between SVM and RVM

Table II shows the classification accuracy for each kernel when using the SVM. We show the highest, lowest, and average accuracies when making predictions on 100 datasets. In addition, the average of False Negative (FN), which indicates an instance of erroneously predicting incorrect solder as correct solder, is shown. The highest accuracy is 100.0% for all kernels, and the average accuracy is 100.0% and average FN is 0.0% for the Polynomial and Linear kernels. The largest value of the lowest accuracy is 99.9% with the Polynomial kernel, which exhibits the highest values across all indices. By contrast, the RBF kernel achieves the worst values in terms of the lowest and average accuracies and average FN, and the lowest accuracy is 1.7% lower than that of the Polynomial kernel.

Table III shows the classification accuracy for each kernel when using the RVM. The RBF kernel has the highest values for all indices and identifies correct or incorrect solder with an average accuracy of 98.6%. By contrast, the Linear kernel exhibits the lowest values for all indices, with an average accuracy of 93.1%, a difference of 5.5% compared with the RBF kernel.

[1] https://www.rdocumentation.org/packages/caret/versions/6.0-92/topics/train

TABLE II: Prediction accuracy at SVM

Kernel	Accuracy			FN
	Maximum	Minimum	Average	Average
RBF	100.0%	98.2%	99.7%	0.3%
Polynomial	100.0%	99.9%	100.0%	0.0%
Linear	100.0%	99.1%	100.0%	0.0%

TABLE III: Prediction accuracy at RVM

Kernel	Accuracy			FN
	Maximum	Minimum	Average	Average
RBF	99.6%	97.5%	98.6%	0.8%
Polynomial	94.3%	92.5%	93.5%	5.9%
Linear	93.7%	92.2%	93.1%	6.3%

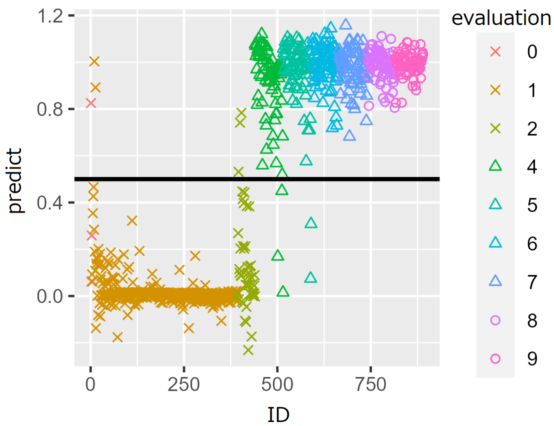
Fig. 2 shows the prediction results on the 100th dataset for the RBF, Polynomial, and Linear kernels when using the RVM. The vertical axis shows the predicted score for each solder, the higher value means the predicted as correct soldering. The horizontal black line indicates the threshold of 0.5. Incorrect solder with a score of 0–2 is indicated by $\times$, correct solder with a score of 4–7 (without back fillet) is indicated by $\triangle$, and correct solder with a score of 8 or 9 (with back fillet) is indicated by $\circ$. For all kernels, the number of solders classified as incorrect decreases as the score increases, and all good solder with an 8 or 9 (with back fillets) are classified as correct. However, the prediction results for solder with a 4 (correct solder) and 2 (incorrect solder), corresponding to the boundary between correct solder and incorrect solder, are widely distributed vertically. Solders with a 0 or 1 (both incorrect) is incorrectly classified as correct because the predicted scores are high for some data.

A comparison between kernels in RVM reveals that the RBF kernel has the highest accuracy, its average accuracy being 5% higher than those of the other kernels. The results presented in Fig. 2 show that the Polynomial and Linear kernels classify incorrect solder with a score of 1 or 2 as correct solder more frequently than the RBF kernel does, and the cause of this misclassification should be determined by analyzing the pressure waveform of the soldering where the misclassification occurred.

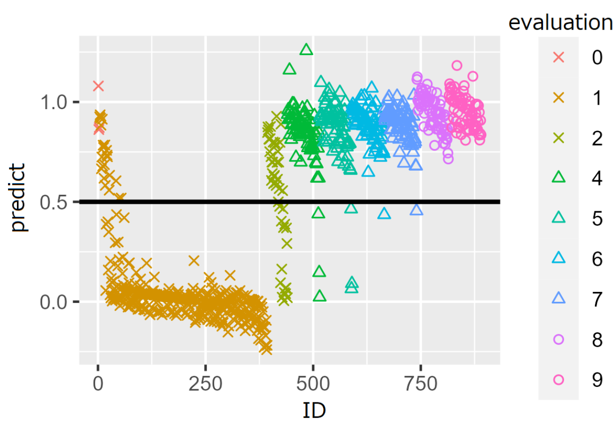
A comparison between the combinations of algorithms and kernels reveals that the Polynomial kernel of the SVM has the highest accuracy. In addition, the SVM is more accurate than the RVM regardless of the kernel being used. The reason behind the low precision of the RVM needs to be investigated in the future.

B. Hyperparameters and overfitting

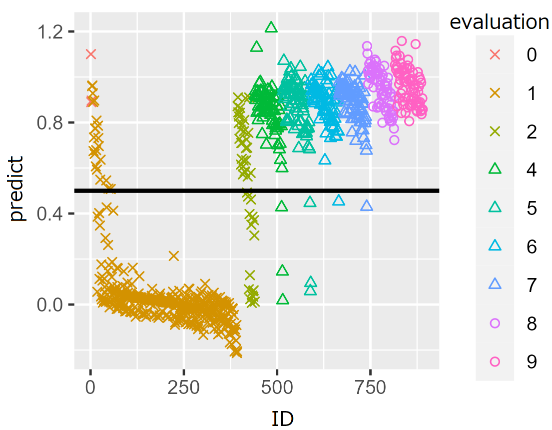
Here, we consider whether a risk of overfitting exists in the results of this study. Overfitting is a state in which a constructed prediction model is excessively optimized for the data used for training, and the model with overfitting has lower prediction accuracy for other data. In this study, 10-fold cross-validation and hyperparameter tuning are



(a) RBF kernel



(b) Polynomial kernel



(c) Linear kernel

Fig. 2: RVM prediction results

used to prevent overfitting, but the following two points need further verification.

- Lack of tuning
  In the training function of the caret package used in the experiment, only three values are tested for each of the three parameters; thus, a possibility of insufficient tuning exists.
- Insufficient number of data on incorrect solder
  In this study, to equalize the numbers of correct solder and incorrect solder, 100 datasets are created by randomly sampling correct solder and used for evaluation. However, as the number of incorrect solder is small, the data of incorrect solder are the same in all datasets, and this may cause overfitting. We implement countermeasures by using cross-validation for each dataset; however, in the future, performing random sampling and evaluating incorrect solder will be necessary.

TABLE IV: Prediction accuracy for All data

		Sampling + 10-fold	All data
# training data		801	890
# prediction data		89	2236
Accuracy	Maximum	100.0%	100.0%
	Minimum	99.9%	97.9%
	Average	100.0%	99.4%

C. Prediction result for all data

Here, we examine the classification result with all correct/incorrect soldering data. In this experiment, training is performed on each of the 100 datasets created in section V-C, which means all incorrect soldering (440) and sampled correct soldering (450) are used to train a model. The classification target is 2236 correct soldering, which is not sampled for training data. We select the SVM with Polynomial kernel combination, the best performance in Section . Hyperparameters are tuned for each dataset, and other settings are the same as in section V.

The results are shown in Table IV. FN is not used in this analysis because defective solder is not included in the prediction target. The left column (sampling + 10-fold) shows the same result as Table II for comparison. The prediction result with all data shows the average and minimum accuracies decreased by 0.6% and 2.0%, respectively. The result indicates that some datasets used for training do not contain every feature of correct soldering; correct soldering that has unlearned features may not be properly classified. The result also shows the highest Accuracy was 100%, hence some training data may contained all correct soldering features. In our sampling experiment (see section V-C), half of the prediction target is correct solderings, hence lack of some correct soldering features in training data has a limited affect to the accuracy. On the other hand, most soldering in practical setting is corecct soldering, so training all various correct soldering features is essential.

VI. Conclusion

In this study, we focused on a sleeve-soldering device, extracted features from pressure changes in the sleeve, and distinguish between correct and incorrect solder by applying machine learning. We used the SVM and RVM algorithms and compared the classification accuracy combining three types of kernels: RBF, Polynomial, and Linear. The experiment results revealed that the SVM with Polynomial kernel shows average accuracy was 100.0%, and average FN was 0.0%.

In future work, classification accuracy at the boundary between correct/incorrect solders (score 4 and 2) should be improved. The prediction results of scores 4, 2, and 1 in RVM were widely distributed for correct and incorrect. The result indicates a new feature is necessary to classify these soldering. In addition, the presence or absence of overfitting should be examined, and the effects should be clarified by analyzing changes in the prediction model owing to random sampling. In the experiments, a universal board was used as the soldering target; however, the size of the board to be soldered and the number of elements affect the time required for preheating. Therefore, evaluating PWB, which has different characteristics, and clarifying the generalization performance of the proposed method is an interesting future work. Oversampling the incorrect solder data is a way to use all the correct solder data while maintaining balance. In the experiment, correct solderings were sampled to equalize the number of correct/incorrect solders, hence some feature in correct soldering is not trained. Further improvement of accuracy through training all correct solderings may expected by balancing correct/incorrect soldering by oversampling.

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