Application of Machine Learning to Printed Circuit Board External Inspection

Ken Shioiri, Shoji Hamao

[Summary] External inspection of solder joints. etc., at parts mounting on printed-circuit boards is a key part of assuring reliability. Visual inspection by eye is a fundamental inspection method, but it is difficult to secure well-trained people who can do the easy work, but which requires some training before becoming proficient board inspectors. In addition, the aging population in Japan is experiencing loss of veterans to train new younger staff. At external inspection, automation is combined with image processing, but mistakes are common and final visual confirmation by eye is often required. Improved inspection performance is anticipated following recent advances in image-technologies using machine learning[1), 2), 3), 4)]. This article introduces automation of external inspection using machine learning.

1 Introduction

External inspection of products during manufacturing processes involves visual inspection by people as well as automatic inspection using image processing. Since visual inspection by people relies upon pass/fail judgements using human senses, inspectors can easily make human errors due to randomness in the evaluation criteria. In addition, inspection results can be impacted by the inspection environment, such as illumination levels at the inspection site. Psychological and physical factors can also create differences in work accuracy and speed. Further, parts are becoming smaller and higher density with rising parts quality requirements. Moreover, small-lot production to meet customers' diversifying needs is also increasing and product life-cycles are becoming shorter as customers' requirements change more frequently. These are increasing the work burden on quality assurance management.

Consequently, the current focus is on automation of external inspection using cameras. If camera-based inspection processes can be automated, problems with human errors, randomness in inspection criteria, worker recruitment, training, and labor costs can be eliminated. In addition, automation can increase in-line inspection speeds to improve mass production efficiency while assuring product quality.

There are two methods for automating inspection—using evaluation criteria determined either by people, or by machine learning. The former method is becoming more complex due to the diversification of part types requiring more evaluation criteria, which are difficult to manage and keep corrected. The latter machine-learning method is expected to yield high evaluation performance with sufficient numbers of sample images and correct label information (indicating whether product image is pass or fail, and solving questions, such as whether part position in image is bad, etc.). External inspection using images is becoming increasingly mainstream with the development of machine-learning technologies, and we expect more cases for development of inspection algorithms for imaging solving mass-production line problems.

This article outlines printed circuit board (PC board) manufacturing processes in section 2, typical solder faults in section 3, issues in AOI external inspection of PC boards in section 4, PC board inspection using machine learning in section 5, and evaluation of PC board inspection results using machine learning in section 6.

2 Outline of PC Board Manufacturing

At manufacturing of general-purpose surface-mount PC boards, solder paste[Note 1] is applied to the PC board using a liquid presoldering method. As shown in Figure 1, using the pre-soldering method, first, solder paste is painted onto the board surface through a stencil-like metal mask[Note 2] (Solder Paste Printing). This is followed by application of an adhesive to prevent parts falling off during mounting and then by mounting of parts on the board surface. Next, the pasted board populated with parts passes through the reflow process to melt and solidify the solder paste and secure the

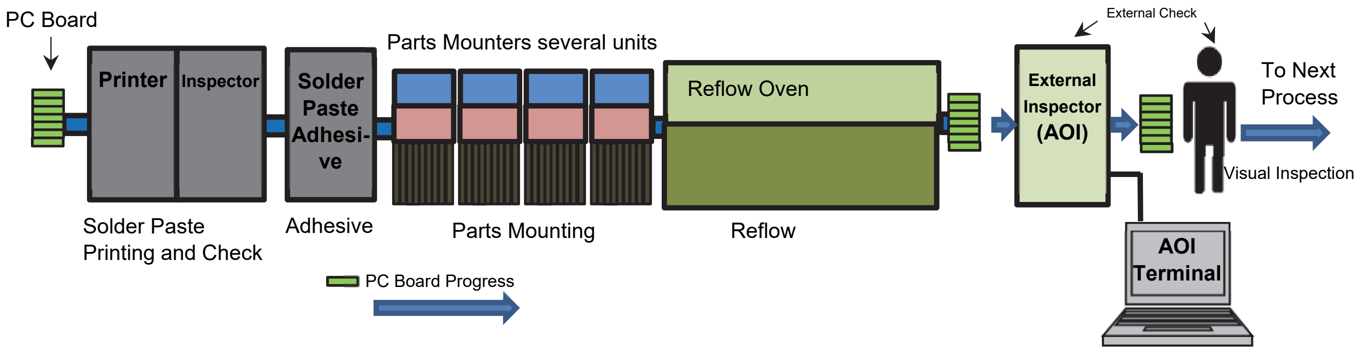


Figure 1 Example of SMT Line

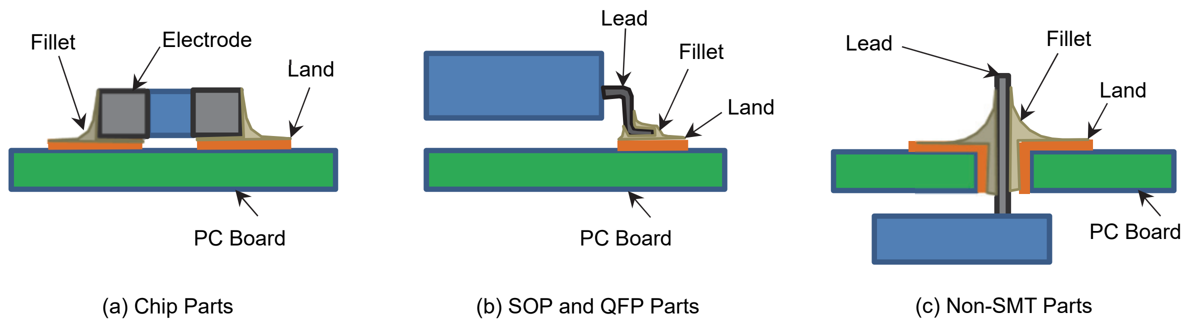


Figure 2 Examples of Normal Fillet Shapes

parts to the board in a single automated process. Generally, technology for producing a PC board with surface-mounted parts is called Surface Mount Technology (SMT). As the PC boards emerge from the reflow oven, the external inspection check is performed to make sure there are no problems with the alignment and soldering of parts on boards. This external inspection check can be performed by either people using the naked eye or a microscope, or by Automated Optical Inspection (AOI) using optical imaging.

At inspection by AOI, an image of the PC board is captured from a fixed reference position and the solder condition of each part is assessed from the image; the presence or absence of parts, their angles, and the part number (printed on part), etc., are checked to evaluate whether the PC board is pass or fail. An error report listing the nature of the faulty part and faulty board is output for failing boards and these boards are finally checked visually by people to confirm the fault evaluation.

Since the AOI camera shot is taken from a fixed reference position, sometimes it may be difficult to visualize the part leads and electrodes, making it difficult to accurately assess the part solder conditions. Consequently, PC boards with parts that cannot be inspected by AOI must depend on inspection by human eye.

Recently, chip mounting densities are increasing using many parts as small as 1.0 × 0.5 mm and 0.6 × 0.3 mm, requiring even more accurate and faster processing using AOI.

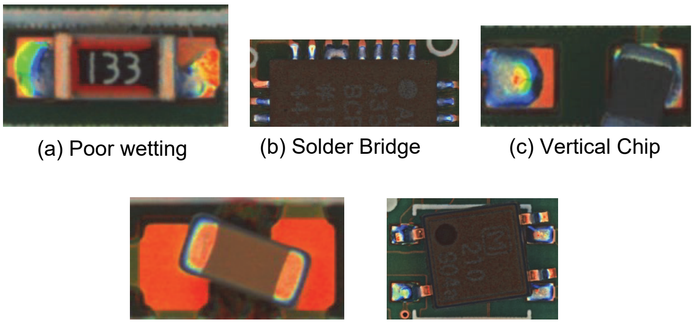
Note 1: Solder paste is a high-viscosity mixture of flux and solder balls with diameters of 20 to 30 μm. It is called solder cream.

Note 2: A solder mask is a stainless-steel stencil sheet that is overlaid on the PC board; the required amount of solder paste is painted accurately at required positions on the PC board through holes cut in the mask.

3 Typical Solder Errors

When parts are mounted correctly, the part lead or electrode is soldered cleanly to the land on the PC board[Note 3] and the external appearance of the joint is a smoothly curved meniscus. This is described as a fillet. In addition, the joint surface is "flowing" and "wets" the connected elements. Figure 2 shows some examples of correct fillet shapes for solder joints.

If there are any problems with applied solder paste amount or position, position of mounted parts, or with the reflow temperature management, the fillet shape may be deformed, resulting in a poor solder joint between the part and board. See reference 5 for details of the causes of various types of poor SMT joints. Some typical examples are listed below and shown in Figure 3.



(a) Poor wetting (b) Solder Bridge (c) Vertical Chip

(d) Missing Solder (e) Rotated Part

Figure 3 Examples of SMT Mounting Faults

(1) Poor wetting

The solder is not spread evenly in the correct amount over the part leads and electrodes and the fillet form does not appear wetted. The causes are insufficient solder, leads or electrodes not in contact with land, and insufficient heat at reflow.

(2) Solder bridging (shorts)

This problem tends to occur when using very small SOP and QFP ICs with sizes of 0.5 mm and 0.4 mm[Note 4] or when the correct amount of solder is not applied to adjacent leads. The causes are poor solder printing, bent solder leads, and poor parts mounting.

(3) Vertical chip (gravestone and Manhattan)

This problem occurs when both electrodes of a part are not soldered simultaneously and surface tension at the end wetted first causes the chip to stand vertically on one soldered electrode.

The countermeasures are improving the land dimensions and mounting accuracy, and preheating to reduce the solder melt time difference.

(4) Non-contact, missing solder

This is caused by the solder paste not melting during reflow and remaining in a paste state. The causes are old solder paste or poor reflow oven temperature control.

Missing solder is caused by lack of solder at the part and is caused by poor solder paste printing.

(5) Rotated and slipped parts

Rotated or slipped parts are the result of part leads or electrodes projecting outside the land or from poor positioning by the parts mounter. Vibration at mounting other parts or at conveying/transport between processes can result in surface tension issues causing displacement as in vertical chip faults.

Note 3: The land is a part where the copper forming the PC board traces is exposed for soldering to the part leads and electrodes. Sometimes the land surface is gold-plated.

Note 4: SOP and QFP describe IC packages. A SOP (Small Outline Package) has L-shaped legs from two sides of the rectangular package connecting to lands. A QFP (Quad Flat Package) has multiple leads on all four sides of the package connecting to lands.

4 AOI PC Board External Inspection Issues

AOI inspection sets strict evaluation criteria using multiple parameters so as to not allow fail products to pass inspection. As a result, so-called "excess watching" is a common problem. Excess watching is a phenomenon where products passing at the visual-inspection level are evaluated as fail by the AOI inspection system. If there is too much excess watching, visual confirmation after automatic inspection is increased.

To proactively suppress excess watching, the soldered part digital evaluation criteria are readjusted repeatedly over but there can be a problem where excess watching does not decrease because fine-adjustment cannot be completed due to momentary changes in the processing conditions caused by PC board condition and parts mounting randomness.

5 PC Board External Inspection using Machine Learning

Applying machine learning to the visual confirmation work following AOI inspection has helped with excess watching inspection efficiency.

5.1 Leaned Image Data Acquisition

Collecting and annotating (labeling) images used for machine learning is a key process in applying machine learning. Consequently, we configured a system (Figure 4) to capture AOI inspection image data for use as learning images.

Generally, dedicated terminals are required to capture AOI inspection results and inspection image data. In this development, we obtained the terminal interface specifications from the AOI maker and developed software to directly capture inspection results and learning images (inspection images) at a connected personal computer (PC).

This software was run on one Image Training PC on the AOI LAN (Figure 4).

AOI-related PCs are connected over a dedicated AOI local area network (LAN) from the viewpoint of higher security and to prevent non-factory network problems affecting plant mass-production.

To assure the independence of the AOI LAN, the machine-learning environment (③ and ④ in Figure 4) was configured on the in-company LAN via a separate independent LAN (c. Independent LAN in Figure 4) and multiport Network Attached Storage (NAS) (② in Figure 4).

Required data is shared via files on the NAS and the PC for capturing learning images is programed to send images and evaluation data stored on the AOI-DB server periodically to the machine-learning PC.

Generally, at machine learning, only images of pass products are required, but not images of faulty products. However, due to disk-space limitations at the AOI-DB server, there were problems with inability to save images for products evaluated as pass. Consequently, the focus of attention was only on trouble locations such as electrodes and leads for images of parts evaluated as fail and machine learning was used to capture images of fillets of electrodes and leads of pass parts from within images of fail parts.

When introducing machine evaluation to external inspection, the learning model obtained from the Machine-Learning PC was transferred to the Machine Evaluation PC and the result for the evaluated image was saved in the AOI-DB server as the visual evaluation result that the Image Training PC input to the AOI terminal. If images evaluated by AIO as fail were evaluated by machine learning as pass, the operator in charge of visual evaluation handled the image as if it had already been visually evaluated.

Reduction of visual inspection and confirmation by eye is expected with introduction of machine learning because only parts evaluated as fail by both AOI and machine learning are inspected.

5.2 Machine Learning Discriminator

Machine learning is a method for allowing a computer to learn human-like recognition and evaluation. It is performed using the following two processes: Learning, and Evaluation[1), 2), 3)].

(1) Learning Process

Even the best machine-learning algorithm is worthless without a learning process which must be performed first using learning data. Learning is repeated over until the accuracy (learning mistakes) reach the required accuracy and the learning model is completed.

(2) Evaluation Process

The discriminator (model with completed learning) evaluates whether input image data are pass or fail. For example, a discriminator that has learned labelled (named) product images can accurately evaluate the names of products for unknown images that have not been learned.

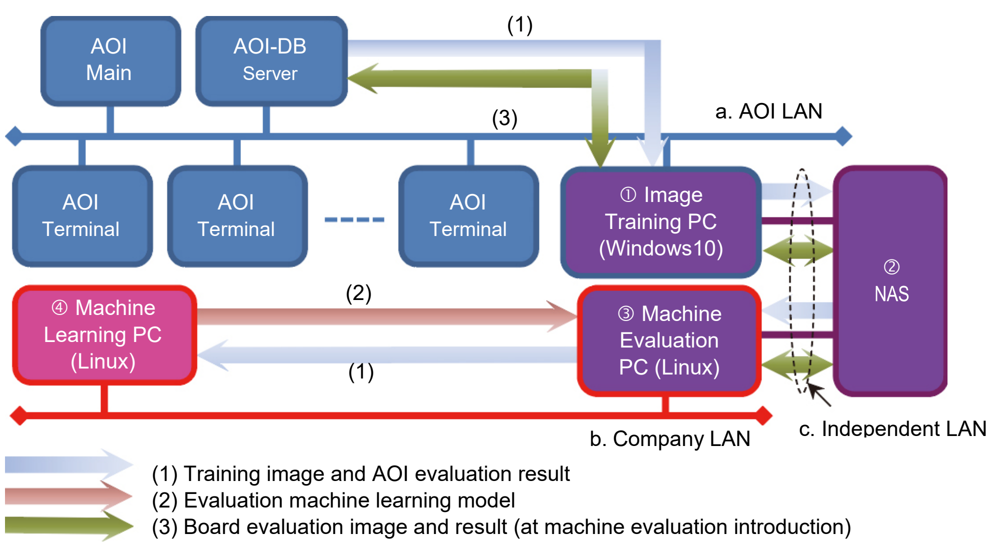


Figure 4 Image Acquisition System Configuration

(3) Discrimination Procedure

We used a convolutional neural network with excellent image-recognition performance as the machine-learning discriminator. A convolutional neural network is configured from a pile of levels, such as convolution layers and pooling layers with various special functions to form a number of deep levels. The convolutional neural netwok used in this study had 10 levels composed of convoluted layers with coefficients of 3 × 3 and 3 × 1 (height × width).

Figure 5 illustrates the discrimination procedure. First, pre-processing loads the image to be inspected and identifies the solder locations. The solder locations identified by the discriminator are output as numeric discrimination results in the range of 0.0 to 1.0 indicating the normality distribution of the solder locations, with a value of 1.0 being maximum normality. The normality threshold value determines whether the solder joint condition is pass or fail.

As shown in Figure 6, this inspection uses multiple discriminators and evaluation is performed using the model average, which averages the output of each discriminator. Better performance can be expected[1), 2)] with suppressed randomness, etc., by changing the learning parameter default values and combining multiple discriminators than when using a single discriminator.

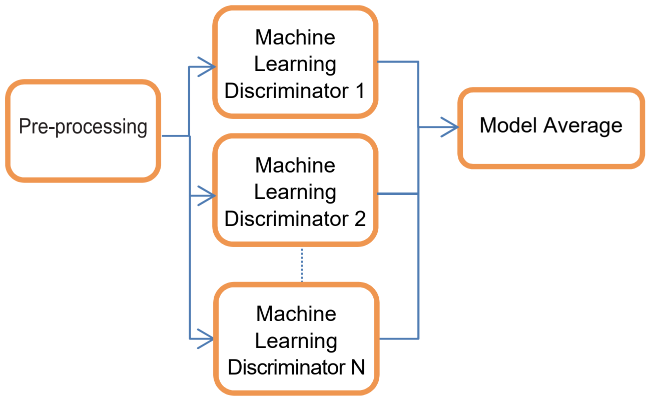


Figure 6 Model Averaging

6 Evaluating Results of PC Board External Inspection using Machine Learning

6.1 Detection Performance

The performance of the algorithm proposed in this article was evaluated using the model averaging technique applied to 560 inspection images of pre-specified parts (60 pass parts and 500 fail parts). The images used for evaluation were not used for learning.

The results are shown in Table 1; eight learning models were provided. As shown in Table 1, model averaging was performed without making a specific evaluation to suppress randomness in the detection performance for each learning model.

Figure 7 shows the cumulative distribution confirming the normality distribution. The red line is the cumulative distribution of normality for fail parts (493 locations) and the blue line is the cumulative distribution of normality for pass parts (65,168 locations). The fail parts cumulative distribution origin is 1.0, but is best if distributed in the lower half with the origin at less than 0.5. In addition, the pass parts cumulative distribution is the distribution with 0.0 as the origin, but is best if distributed in the upper half with the origin at more than 0.5. Since the cumulative distributions for the pass and fail locations intersect, evaluation mistakes occur when evaluating using a threshold.

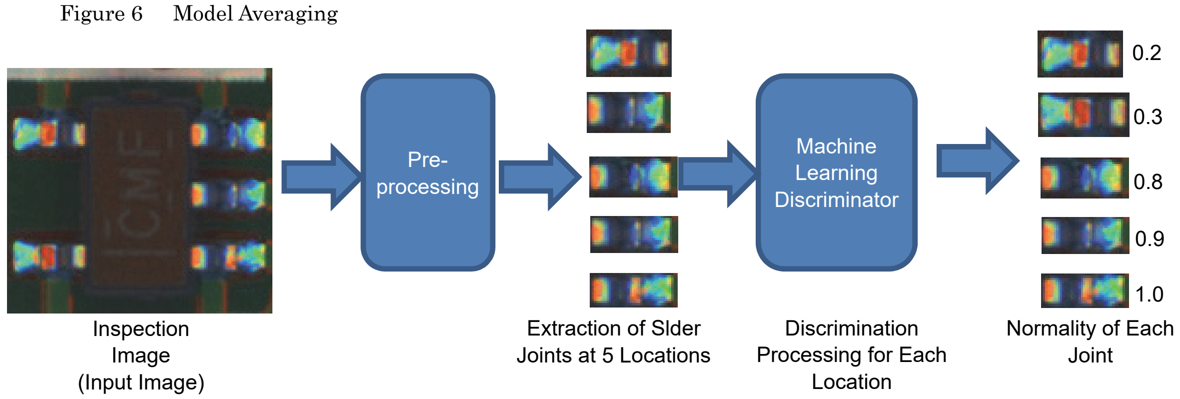


Figure 5 Discrimination Procedure using Machine Learning

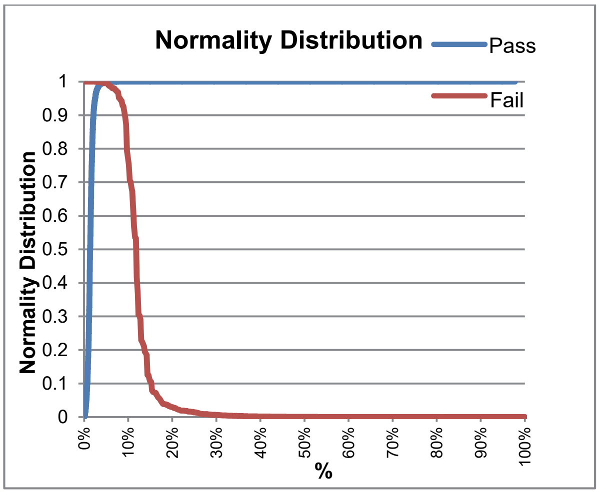


Figure 7 Normal Board Distribution

Figure 8 shows a comparison of the normality for the model average and single model results. The value for pass locations increases by using the model average compared to not using it, and the normality improves because the value for fail locations decreases. However, evaluation mistakes occur when using the evaluation threshold due to the distribution intersection.

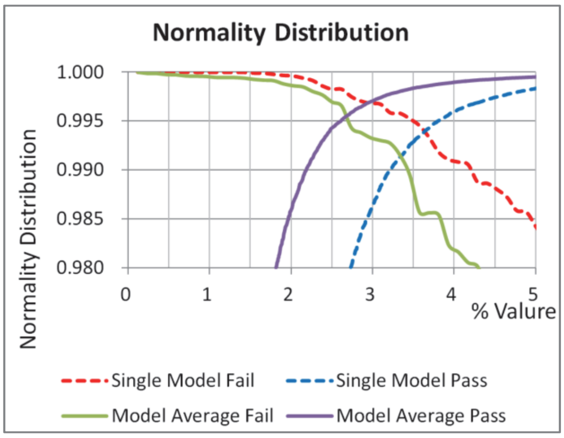


Figure 8 Comparison of Model Average and Single Model Normal Board Distribution

6.2 Distribution of Board Image Evaluation Mistakes

To confirm the mis-detection phenomenon, actual images were checked. Figures 9 to 11 show examples of fail results using machine learning. For AOI-evaluated fault locations, on-site visual inspections were performed by a specialist and the results were compared with the machine-learning results. In these figures, locations evaluated as pass by AOI are enclosed in a blue frame, while those evaluated by AOI as fail are enclosed in an orange frame; locations evaluated as fail by both AOI and visual inspection are enclosed in a pink frame. The numerical values in Figures 10 and 11 indicate the normality output by machine learning. The orange-frame locations in Figure 10 were evaluated as fail by AOI but pass by visual inspection. We clearly see the high numeric value of the results assigned by machine learning to these orange locations. Additionally, the pink frames in Figure 11 which were evaluated as fail locations by both AOI and visual inspection, were assigned low numeric values by machine learning. The machine-learning normality output is extremely close to the results of visual evaluation by a specialist.

Frame Color	AOI Evaluation	Visual Evaluation
	Pass	—
	Fail	Pass
	Fail	Fail

Figure 9 Classification Method

Table 1 Detection Performance

Training Model	500 Images (Failure)					60 Images (Pass)	
	Failure	Pass	Number of Miss-Fail Detection	Detection Ratio	Miss-Detection	Number of Fail-Detection at Excess Watching	Reduction Ratio of Fail Detection
1	545	495	50	0.91	28	0	0.00
2	545	504	41	0.92	25	0	0.00
3	545	478	67	0.88	11	0	0.00
4	545	497	48	0.91	17	3	0.04
5	545	496	49	0.91	20	0	0.00
6	545	495	50	0.91	10	4	0.06
7	545	489	56	0.90	21	0	0.00
8	545	501	44	0.92	26	3	0.04
Model Average	545	495	50	0.91	12	0	0.00

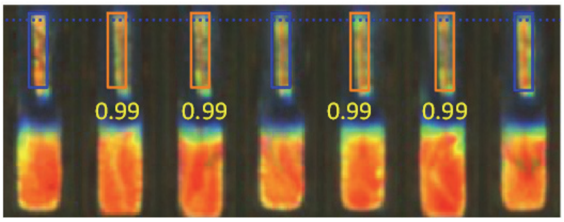


Figure 10 Example of Correct Answer
(Fail Detection at Excess Watching)

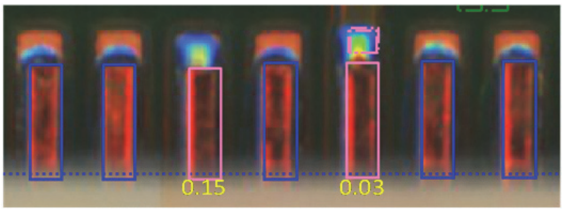


Figure 11 Example of Correct Answer (Fail Detection)

Figure 12 shows examples of images where the machine-learning evaluation results was incorrect (fail location evaluated by machine learning as pass). In these cases, fail locations (in pink frame) were assigned a high normality value by machine learning. It seems it is difficult to detect some fails just from the image since the image color distribution is not unlike a pass location. Additional information from an inspector seems to enable better evaluation.

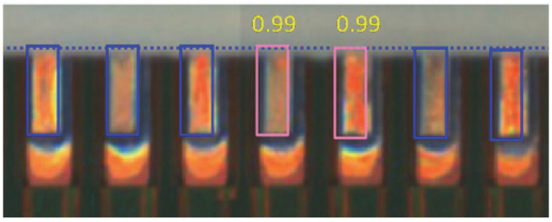


Figure 12 Example of Mis-detection (Missed Fail Location)

When applying the machine-learning method, only the normality parameter requires adjustment, so we may expect a reduction in on-site adjustment procedures. However, it was not possible to reduce evaluation mistakes (excess watching) to zero. It seems necessary to tune the learning model by analyzing differences in the output distribution of each layer of the convolutional neural network using correct- and incorrect-evaluation images to analyze the learning process model.

7 Conclusions

This article introduces automation of PC board external inspection using machine learning. Tests focused on several out of many part types and specifications to detect solder joint fail locations. Future work on analysis of mis-detected images is ongoing in our work to fine-tune learning models.

References

1) T. Hastie, R. Tibshirani, J. Friedman, The Elements of Statistical Learning, Springer (2015), Japanese translation by Sugiyama.

2) C. Bishop, Pattern Recognition and Machine Learning, Springer (2015)

3) T. Okaya, Deep Learning Trends in Image Recognition, Artificial Intelligence, Vol. 31, No. 2, pp. 169-179 (2016) (In Japanese)

4) T. Okaya, Deep Learning, Robotics Society of Japan, Vol. 33, No. 2, pp. 92-96 (2015)

5) Japan Welding Engineering Society, Microsoldering Working Group, Standards Microsoldering Technology, Third Edition, Nikkan Kogyo Shimbun (2012) (in Japanese)

Authors

Ken Shioiri
Advanced Technology Development Center
Technical Headquates

Shoji Hamao
Tohoku Anritsu Corp.