

Automated System Development for the Printed Circuit Boards Optical Inspection Using Machine Learning Methods

Igor Nevliudov¹, Iryna Botsman¹, Olena Chala¹ and Kirill Khrustalev¹

¹ Kharkiv National University of Radio Electronics, Nauky Ave. 14, Kharkiv, 61166, Ukraine

Abstract

The problem of printed circuit boards (PCB) quality optical inspection at their production stage is considered. The automated method of PCB optical inspection on the machine learning methods basis is proposed. The necessary neural network parameters to develop an automated PCB inspection method are calculated. The main capabilities of the created artificial neural network for identifying PCB under test defects are analyzed. The results of the conducted neural network testing that confirm its operability and possibility of use for PCB inspection at the stage of production are presented. The software program was developed that is used for transformations over images, such as converting an image to a grayscale color space and image binarization, which speeds up the neural network by reducing the size of the input matrix to a binary value per pixel of the image. The accuracy of finding each of the PCB defects types was also investigated.

Keywords

Automated system, optical inspection, printed circuit boards, machine learning, intelligent manufacturing, neural networks.

1. Introduction

Today in the instrument-making industry one of the most responsible stages for production of printed circuit boards (PCBs) as components of electronic devices for a wide applications range is quality control [1]. At the same time, the task of developing and implementing of new high-precision and universal inspection methods is relevant to ensure a high percentage of accepted products, taking into account the constant complexity of the modern PCBs design, including the conductive topologies density increasing and their weight reducing [2].

Optical PCBs inspection allows to quickly identify errors that occurred during their manufacture, for example:

An example of bulleted list is as following.

- mechanical damages to the board, e.g. cracks in the dielectric base, splits, distortions, etc., which can be caused by defects in the base material and occur in case of some technological operations modes violation

during the PCB structure manufacturing process;

- deviation of tolerances during the PCB tracing formation;
- occurrence of current-carrying elements short circuits or breaks;
- manufacture defects of mounting holes in the PCB, for example, in case of non-compliance with the relevant drilling modes or filling the hole with solder or solder mask, which will prevent further work with this product;
- violation of the contact pads geometry, etc.

During the technological process of the finished printed module assembly and installation and after its completion the quality control of installation of electronic components (EC) is performed, in particular, the accuracy inspection of positioning the EC packages pins on contact pads or into holes, the quality of solder or welded joints, etc [3-6].

EMAIL: igor.nevliudov@nure.ua (A. 1); irina.botsman@nure.ua (A. 2); olena.chala@nure.ua (A. 3); kirill.khrustalev@nure.ua (A. 4)
ORCID: 0000-0002-9837-2309 (A. 1); 0000-0003-1110-9602 (A. 2);
0000-0003-2454-3774 (A. 3); 0000-0002-0687-5153 (A. 4)

2. Research Objective

One of the possible ways to improve automated methods of optical PCBs inspection is the use of artificial neural networks to classify objects in the images of the products under test [7-9].

Therefore, the aim of the work is to develop a new automated method of printed circuit boards optical inspection based on the creation and training of a neural network.

The research object is the process of printed circuit boards inspection, the subject of the study is PCB with a printed conductor pattern. For research performing the methods of theoretical researches, comparative analysis and methods of machine learning are used.

To recognize the objects on PCB images it was decided to use convolutional neural networks, the architecture of which is based on the knowledge that the input information is an image. It significantly reduces the required number of calculations.

In particular, the YoloV4 network, which is based on the DarkNet architecture, was chosen as the basis for the necessary neural network building. The use of this architecture allows neural networks to work with high accuracy at high bit rates or even when used with video.

3. PCB Images Processing Steps

The search for defects on the PCB requires its image to be large, usually these dimensions are close or larger than a square with a side of 4096 pixels with three bits of color, and an example is shown in Fig. 1.



Figure 1: PCB photo example, size 4032 × 3850 pixels

To work with images for conversion more effectively, it is possible to use the OpenCV computer vision library, which includes a large number of functions for image conversion, as well as machine learning capabilities. Built-in features also include special functions needed to obtain individual image details or entire objects using their geometric characteristics.

A set of data with all possible types of PCBs defects was created for the training. To increase the learning speed and reduce the error probability, 1500 images of PCBs with test data were selected, which are part of the scanned images in black and white variant, where white is allocated to the PCB area without copper layer, black is allocated to areas covered with copper layer.

Each image is presented in two formats: with a defect and without a defect, in the size of 640 × 640 pixels, each image contains from 3 to 12 defects. Of the total set of images, 1000 was set aside for training, 500 was set aside for test data.

The maximum number of steps for the neural network learning was determined, which will avoid retraining, it will be equal to 12,000.

In order to increase the accuracy and speed of the neural network, as well as to get rid of problems that may arise due to uneven lighting of the object under test, it was decided to create a program for image binarization, i.e. convert it into the format for which there are only two colors – black and white.

To create such a program, the Python programming language was chosen due to some advantages, such as:

- ease of use;
- large number of libraries for working with images;
- ability to connect a neural network as a third-party library.

For binarization, the most important parameter is the threshold value in the range from 0 to 255. In a black and white image this value indicates the limit at which the image will be divided into black and white. Three threshold values in 50, 100 and 150 were tested and the results were compared, the results of binarization are shown in Fig.2. Thus, we can assume that the best threshold value in this case is 100.

The layers number of neural network is 23 and the stride value is 4.

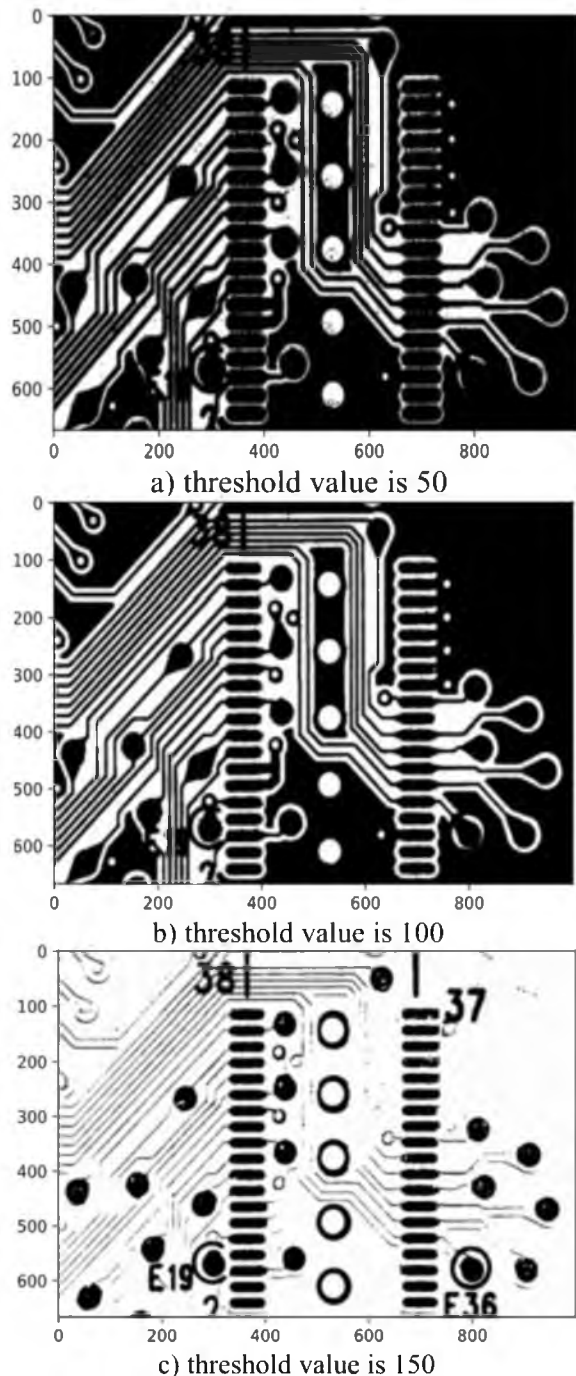


Figure 2: Examples of binarized images with different threshold values

4. Training and Testing an Optical Inspection Automated System Using Machine Learning

In order to prevent network retraining, with test dataset use the weights with the lowest error value were found. In this case the error can be considered as the found region deviation from the region that was marked manually.

The graph of defective regions recognition accuracy depending on the training iterations number of developed neural network was constructed (Fig.3). It is experimentally determined that the best result on the test data is in the range from 8300 to 8600 learning iterations of the created neural network.

The neural network speed was tested, the image processing time was from 60 to 120 ms, which allows to process from 10 to 15 images per second. This result is acceptable for use in the PCBs inspection process in real time during their production.

The effect of image size on processing speed was also tested, as the created neural network should be able to be used with high-resolution images taken with a digital camera or with images obtained by scanning. For this check, 10 images with a resolution of 1280×1280 pixels were created based on existing images and tested using the same method as the smaller images. The processing time of the enlarged image is in the range from 94 to 143 ms and allows processing the image at a speed of 7-10 frames per second.

It should be noted that the image processing speed depends on its size, but increasing the image area has increased the time non-linearly.

This allows to use the created neural network to work with high-resolution images or images obtained by scanning, which confirms the possibility of its use for inspection of a large PCBs variety, as well as for large volumes of production.

5. Investigation of the Neural Network Accuracy Depending on the Image Inclination Angle

As the test data images with straight lines were used. But in production it is not always possible to obtain such images, and often the obtained PCB images will have an angle relative to the frame boundaries. The factors that may affect the angle image rotation are:

- scanner or camera installed incorrectly;
- lack of a mechanism for products aligning;
- human factor, if testing is performed in an automated mode;
- conductive drawing of non-standard shape.

The inclination angle can also be affected by the geometric features of a particular PCB type, which will be placed in products with complex package geometry.

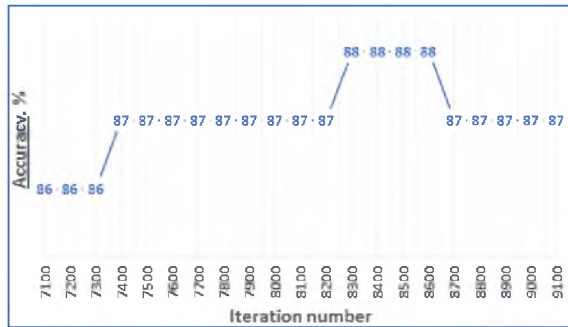


Figure 3: Graph of the trained dataset accuracy

Therefore, in order to ensure that the neural network remains ready of use for PCB inspection and the impact on accuracy depending on the image angle is minimal, it is necessary to perform additional research. Such studies were performed on the original dataset, which was modified, and the following steps were used to perform the study:

- using the program called *imagemagick* a test images were rotated at 15°, 30° and 45° clockwise, with image size increasing and without original image contours cropping;
- the images were selected in such way, that each of the defects occurred on them exactly 100 times and had different variants of display on the PCB;
- also due to the fact that when the images are rotated, negative areas appear where there is no conductor pattern, the testing program has been modified to take into account the region in which the conductor pattern is located. Images and results obtained outside such a region do not affect the accuracy calculation;
- the size of the region has been reduced by 2 pixels relative to the original image size to prevent errors caused by artifacts of edge smoothing algorithms used in the image conversion process due to the fact that in photos such transformations help to achieve the best result.

One of the examples of rotated images is shown in Fig. 4.

Also, the list of defects was replaced with new ones for each of the transformed images because of the fact that trigonometric transformations to the corresponding lists are impossible due to the peculiarities of defect registration in the yolo neural network and due to the fact that the image was resized.

That is, taking into account such changes in the image, the algorithm for accuracy determining of the neural network was changed.



Figure 4: Example of a converted image rotated by 45°

The defect region was reduced, to determine that the defect was classified, instead of calculating the total area between the defined region and the region specified in the text file, an algorithm was chosen according to which the area of intersection of regions relative to a manually defined region will be considered a match. This algorithm allows more accurately determining the defect presence, rather than the accuracy of its location.

The average values of the defects finding accuracy depending on the inclination of the image are given in Table 1.

Table 1

Average accuracy values depending on the angle of the image inclination

Inclination angle	Accuracy, %
0°	88
15°	86
30°	87
45°	88
Average value	87,5

Thus, given the results obtained, it can be assumed that the accuracy of the neural network depends on the angle of the image. But this may be more due to the artifacts or smoothing algorithms used to create the test data than the inaccuracy of the trained neural network.

6. Conclusions

Thus, an automated method of PCBs optical inspection using the created artificial neural network is proposed.

The conducted testing of the neural network confirmed its operability and possibility of use for

PCBs inspection at the stage of production. The software was developed to perform the transformations over images, such as converting an image to a grayscale color space and image binarization, which speeds up the neural network by reducing the size of the input matrix to a binary value per each pixel of the image.

The accuracy of each defects types locating was also investigated, in particular, it was determined that some of the defects are determined more accurately by the neural network than others.

For example, the lack of copper in the conductor pattern has less detection accuracy, and individual areas of the copper layer that are not connected to any of the conductors, the program finds more accurately. The average value of image processing accuracy was 87.5 %.

In addition, it has been found that the image angle affects the accuracy of defects detection and at certain angles the accuracy may decrease by several percent, but not for all types of defects, for example, the accuracy of foreign inclusions does not depend on the angle of the image.

The developed system differs from the existing ones by greater versatility, both in the process of use in production and in the process of implementation due to the fact that although the system requires high-performance hardware, short processing time of each image allows to use hardware resources in shared mode during several production stages or on adjacent production lines.

One example of further improvement of the developed automated inspection system may be the expansion of the dataset with additional images or defects specific to a particular stage of PCBs production. It is also possible to adapt the neural network to equipment used in production, for example, to optical equipment such as scanners or cameras.

7. References

- [1] V. Palagin, I. Botsman, I. Razumov-Fryziuk and V. Nevliudova, "Development of Multi-Probe Connecting Devices on Flexible Polyimide Base for MEMS Components Testing," Proc. of XIV-th International Conference «Perspective technologies and methods in MEMS design» (MEMSTECH'2018), April 18-22, 2018, Polyana (Zakarpattya), Ukraine.
- [2] I. Sh. Nevliudov, V. A. Palagin, E. A. Razumov-Frizjuk and I. V. Zharikova, "MEMS Intellect Multiprobes Contacting Devices for Electrical Checking-up of Multilayers Commutative Boards and BGA/CSP Electronic Components," Proc. of IEEE East-West Design & Test Symposium (EWDTS'2012), September 14-17, 2012. Kharkov, Ukraine.
- [3] A. A. R. M. A. Ebayyeh and A. Mousavi, "A Review and Analysis of Automatic Optical Inspection and Quality Monitoring Methods in Electronics Industry," in IEEE Access, vol. 8, pp. 183192-183271, 2020, doi: 10.1109/ACCESS.2020.3029127.
- [4] S. S. Zakaria, A. Amir, N. Yaakob, and S. Nazemi, "Automated detection of printed circuit boards (PCB) defects by using machine learning in electronic manufacturing: Current approaches," IOP Conf. Ser., Mater. Sci. Eng., vol. 767, Mar. 2020, Art. no. 012064.
- [5] S. N. D. Chua, S. Mohamaddan, S. J. Tanjong, A. Yassin, and S. F. Lim, "Detection of bond pad discolorations at outgoing wafer inspections," IEEE Trans. Semicond. Manuf., vol. 31, no. 1, pp. 144–148, Feb. 2018.
- [6] S. Fonseka and J. A. K. S. Jayasinghe, "Feature extraction and template matching algorithms classification for PCB fiducial verification," J. Achievements Mater. Manuf. Eng., vol. 1, no. 86, pp. 14–32, Jan. 2018.
- [7] L. Bai, X. Yang, and H. Gao, "A novel coarse-fine method for ball grid array component positioning and defect inspection," IEEE Trans. Ind. Electron., vol. 65, no. 6, pp. 5023–5031, Jun. 2018.
- [8] V. Bortnikova, I. Nevliudov, I. Botsman and O. Chala, "Search Query Classification Using Machine Learning for Information Retrieval Systems in Intelligent Manufacturing," in CEUR Workshop Proceedings of the 15th International Conference on ICT in Education, Research, and Industrial Applications: Integration, Harmonization, and Knowledge Transfer (ICTERI'2019), June 12-15, 2019, Kherson, Ukraine.
- [9] N. Guand, X. Wang, "Computational Design Methods and Technologies: Applications in CAD, CAM and CAE Education". USA: IGI Global, 2012.