An automatic optical inspection system for the diagnosis of printed circuits based on neural networks

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An Automatic Optical Inspection System for the Diagnosis of Printed Circuits Based on Neural Networks

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Abstract **The aim of this work is to define a procedure to develop diagnostic systems for Printed Circuit Boards, based on Automated Optical Inspection with low cost and easy adaptability to different features. A complete system to detect mounting defects in the circuits is presented in this paper. A low-cost image acquisition system with high accuracy has been designed to fit this application. Afterward, the resulting images are processed using the Wavelet Transform and Neural Networks, for low computational cost and acceptable precision. The wavelet space represents a compact support for efficient feature extraction with the localization property. The proposed solution is demonstrated on several defects in different kind of circuits.**

Keywords: Automated Optical Inspection, Wavelets, Neural Networks, Printed Circuit Boards diagnosis

I. INTRODUCTION

In automatic industrial inspection of Printed Circuit Boards (PCB) we can distinguish two important classes: electrical/contact methods and non-electrical/non-contact methods. Contact methods are characterized by a high cost, low speed and the fact that they can not detect non electrical defects, such as linewidth or spacing reductions. On the other hand non-contact methods can improve the diagnostic capabilities in terms of speed and tasks. Automated Optical Inspection (AOI) plays a very important role in the automatic production process of PCBs. Advances in computers, image processing, pattern recognition, and Artificial Intelligence have led to better and cheaper equipment for industrial visual inspection in the electronics industry, especially in Surface Mounting Technology (SMT). Traditionally, PCB visual inspection is executed by the human operator, but the diagnosis is slow and a steady performance can not be guaranteed. Several authors [1-5] proposed the AOI approach, using different decision makers, such as Fuzzy Systems, Neural Networks or Expert System. Sometimes, these AOI systems are either time consuming or they need complicated illumination sources, such as several lasers, a sophisticated lighting design [2], or many CCD cameras, making the acquisition of good images extremely complicated.

The approach presented in this paper is particularly simple and cheap. In fact, it only needs one CCD camera, and the PCB has not to be placed onto a precision X-Y table. In this way the PCB can be located on an automatic conveyor line, without interrupting the line production. The diagnostic system can be trained by a non expert operator. The system performs the diagnosis on the basis of a database of images of components and defects. The operator stores the images using a graphical procedure, and then the system automatically trains a neural network to recognize such images. The input data for the training are the WaVelet Transform (WVT) coefficients. Indeed, WVT [6-7] has the advantage of decomposing an image into different contributions in several frequency bands and at different scales. Thus, the information of interest can be efficiently accessed in one of those contributions that are the compact space.

II. THE DIAGNOSIS APPROACH

The diagnostic process works as a pattern recognition system where the patterns are the images of the components. Typically, a pattern recognition system is made up of three modules: a transducer which acquires the data on a physical device; a feature extractor which reduces the amount of data and computes some features or properties; a classifier which makes the final decision on the state of the device. In our AOI system the physical device is a PCB, the transducer is a CCD camera, and the classifier is a neural network. The purpose of the diagnostic system is to automatically detect a set of defects, which can be recognized by visual inspection. The architecture

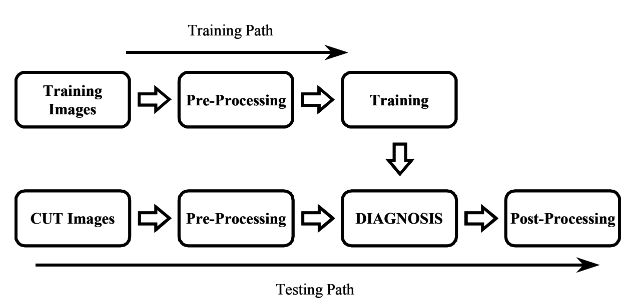


Figure 1 Architecture of the proposed diagnostic system

of the proposed diagnostic system is shown in Fig. 1. The system consists of two procedures, one to train the diagnostic system, the other to diagnose the circuit under test.

A. Training procedure

A set of neural networks are trained to diagnose all the possible components. Each neural network is trained using a set of patterns, corresponding to the defects to be diagnosed on the corresponding component.

B. Testing procedure

Given a board to be diagnosed, a CCD camera acquires a circuit image. This image is pre-processed to extract the significant features, and then it is used as an input to the set of neural networks previously trained to recognize the defects on that circuit. The outputs of the neural networks represent the diagnosis of the system.

The method used to create the training set allows us to set the diagnostic system before implementing the production line. This is very useful, because it reduces the cost of the diagnosis and allows us to start the production line and the diagnostic system simultaneously.

III. The Diagnostic System Architecture

The described logical architecture has been implemented in a prototype. In Fig. 2, the modular diagram and a photo of the diagnostic system are shown. In the following, the main parts of the system are described.

A. The Image Acquisition System

An X-Y positioning system supervises all the displacements of the CCD camera. The dimension of the framed region is controlled by modifying the lens zooming. We chose to move the CCD rather than the PCBs in order to obtain a faster and more flexible system, independent of the production line. In this way the AOI is very useful not only in the electronic industry but also in a wide range of applications. In order to control the illumination conditions, the acquisition system is covered with black screens that avoid external light sources. The circuit under test is illuminated using commercial fluorescence lamps.

B. The Database

A database supports all the tasks performed by the diagnostic system. Such database, developed in SQL language, represents the knowledge of the system. A set of procedures permits to update the database, whether directly using a graphical interface or automatically, in real time, during the system functioning.

The main type of data stored in the database is the images. Given the layout of a new circuit under test, an image without defect (golden board) is built by assembling images of the components stored in the databank. The golden image has no application in the diagnosis process, but it is used as reference image by the operator. The databank stores the images of the components and the images of all the defects to detect. As for the golden board, it is possible to obtain an image of the faulty component, simply by superposing the defect image to the images without defects stored in the database. This procedure is totally automatic. The operator task is just to fix the defects set which the system must diagnose; therefore he only needs information about the process but not about the diagnostic system. Each component or region is associated to a neural network, which is trained to recognize the corresponding defects that can occur. The layouts of the circuits that have been produced in the farm are stored in the database. Each of them has a record, with all the data concerning the production,

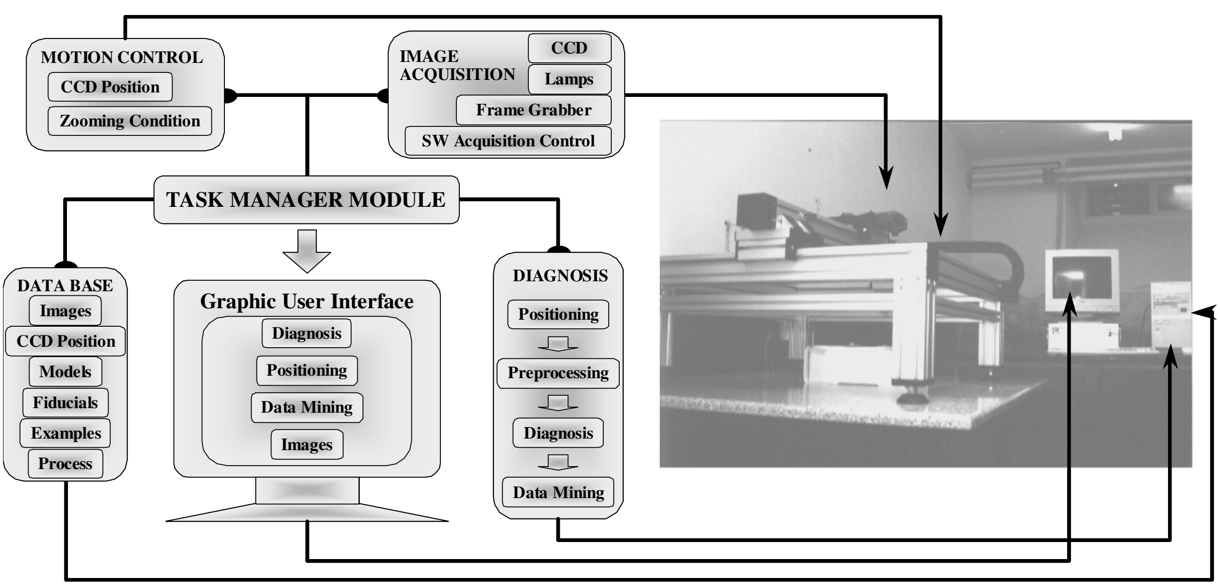


Figure 2 The diagnostic system

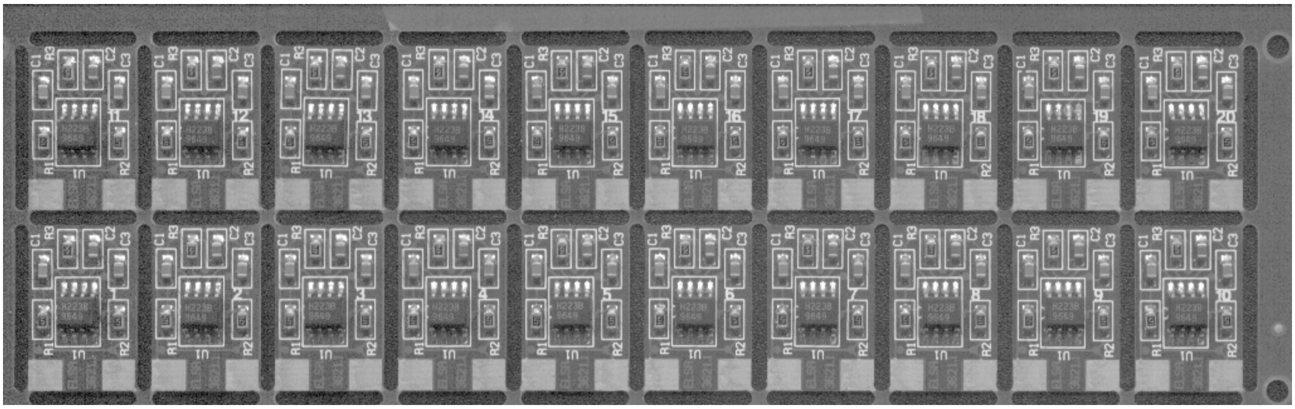


Figure 3 Example of a tested PCB

making them available for successive statistical analysis. Finally, each operator, working on the diagnostic system, is catalogued, with the corresponding grants and password, in order to avoid the knowledge of the system to be corrupted by inadequate skills of the operator.

C. The Procedures

A number of procedures have been implemented in the system for the management of the tasks. The procedures performed by the diagnostic system have been developed in LabView™ environment. The procedures executed with the operator are managed by means of a Graphical User Interface (GUI), implemented in the same environment. In the following the main procedures are briefly described.

a) Template matching, devoted to identify the fiducial points in the CUT. Thanks to this procedure the CCD camera can move on the reference point in the CUT, and from there it can move in sequence over each component, on the basis of the positions schedule. For this task, the template procedure available in the LabView™ library has been used. Such procedure demonstrated to be very fast, especially if the searching area is small. This is the present case, because of the good precision of the mounting process.

b) Template matching, devoted to frame, as precisely as possible, each component, and to correct the offset due to the mounting tolerance. In fact, one image is acquired for each component of the CUT, in order to avoid the parallaxes and to make the images independent by the mounting tolerance. Therefore, the CCD acquires an area larger than the component and then the reference image of the component is used as template in such area.

c) Feature extraction, devoted to reduce the amount of data and to select the meaningful information for the diagnosis. To this purpose, different procedures have been tested. The best results have been obtained with the Wavelets transforms [6], in term of both data reduction and kept information. The number of components of the wavelet transform, which the system uses for the diagnosis, varies, depending on the size of the component image and the number of possible defects that have to be diagnosed on the component. In particular, for small bipolar components, the image is small, and the system has to verify its presence, the position and two solder joints. On the contrary, a multi-terminal integrated component has a larger image, and the correctness of the windowing, the position, and one solder joint for each pin, have to be tested. The operator, which stores a component in the database, can choose the set of defects to diagnose for each component. In such a way, the computational cost for each component can be limited to the real requirements of the process.

d) Training of the neural networks. A Multi Layer Perceptron (MLP) [8] neural network is trained each time a new component is added to the database or new defects are considered for a component already stored. The database stores as many neural networks as the catalogued components and

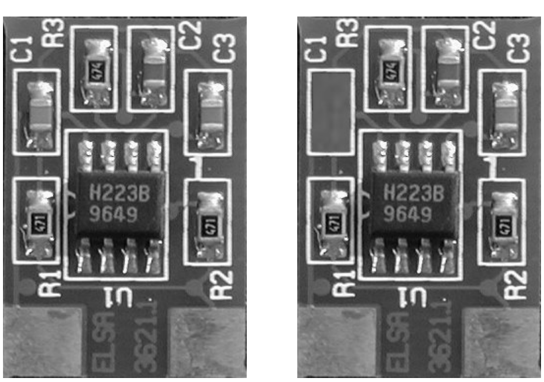


Figure 4 Images for the test of component absence

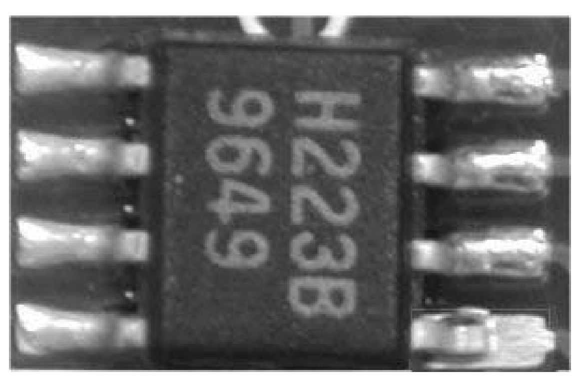
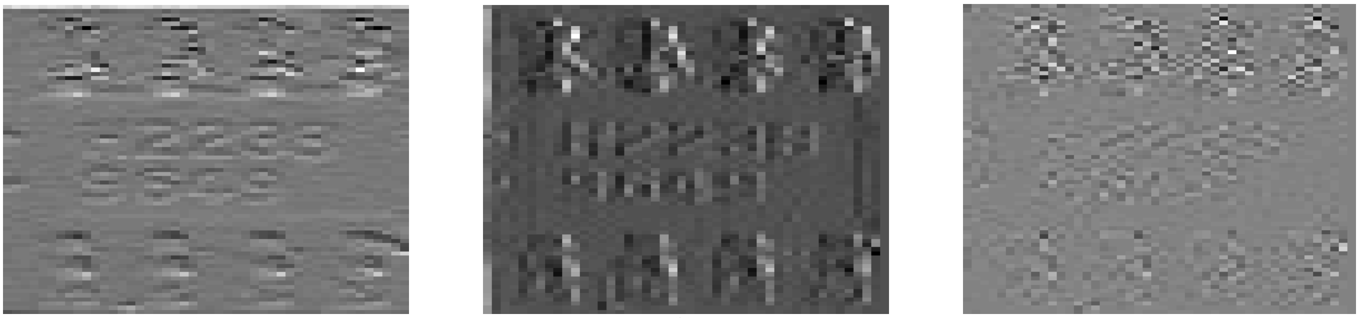


Figure 5 Image for the test of solder joints



(a) (b) (c)

Figure 6 One scale wavelet representation of shot view of the Fig. 5, at three directions

a) horizontal, b) vertical and c) diagonal

regions. The training set is generated by retrieving the images of the components and of the defects from the database and by combining them to obtain the images of all the defects to diagnose. The collection of images is then pre-processed to extract the features by using WVT. Among the computed transform components, the most meaningful are selected to represent the image. Such set of components constitutes the pattern that the neural network uses as input. When the neural network will be recalled, during the diagnosis phase, the same components must be selected from the transform of the test image.

The outputs of the neural network are associated to the possible defects. The sigmoidal activation function has been adopted for the output neurons. For sake of simplicity, an output neuron has been devoted to represent a specific defect. Even if different choices would lead to smaller and easier to train neural networks, the adopted coding has the advantage to make easier to interpret the outputs, especially when they are intermediate between the values used as desired output.

As the training of the neural network has to be automated, it is important to have a criterion both for sizing the hidden layer and to stop the training. The growing approach and the early stopping criterion have been applied to solve these problems. The former technique consists of training a neural network with a few hidden neurons, and on increasing their number until the desired performance is obtained. The early stopping criterion needs two sets of examples, called training set and validation set. During the training, the neural network is trained to recognize the examples of the training set, but, in parallel, the performance on the validation set is evaluated too, by calculating the mean square error (MSE) between the calculated and desired output. Once the MSE on the validation set begins to rise, the training is terminated. The aim of this method is to avoid the overfitting, which occurs when the neural network is able to recognize the examples of the training set, but it is not capable to generalize to examples that do not belong to such set. In order to increase the robustness of the network, a set of fictitious patterns is added to the training set. Such examples do not correspond to actual images, but they are obtained by adding a Gaussian noise to the patterns of the training set. This technique, applied to the present problem, demonstrated that the trained network is more robust with respect to the variability of the patterns, due to environmental conditions, uncertainty of the measurement system, differences between components even belonging to the same class.

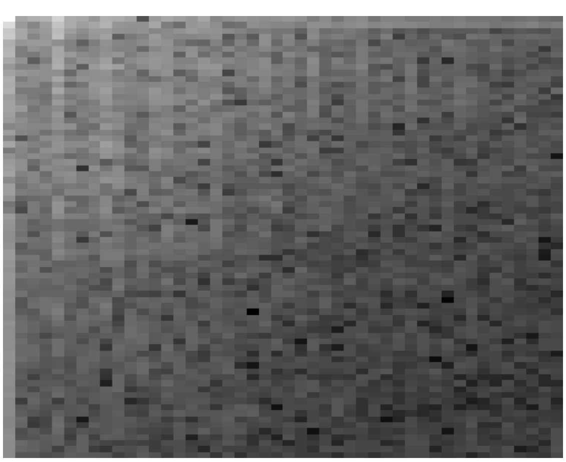


Figure 7 Fourier representation of shot view in Fig. 5

The described procedures to train the network are completely automated, so that the training phase is hidden to the operator, whose task is to select the components and the defects from a list retrieved from the database.

e) Diagnosis of the CUT. The diagnosis consists on recalling the testing path, as settled in the training phase (see Fig. 1). A first shot of the whole board is acquired, to detect the reference point in the board. To this purpose the template matching procedure is performed. Once the reference point is found, the CCD camera moves on it. From there, the CCD moves on the scheduled positions, which have been previously defined on the basis of the circuit layout. Each shot frames an area larger than the region of interest, so that the template matching can correct the tolerance due to the mounting process. The wavelet transform is evaluated for each acquired image. From the wavelet, some components are selected, according to the choice made in the training phase. Then, for each shot, a pattern is obtained, that is given as input to a corresponding, previously trained, neural network. The outputs of the inquired networks are merged in a report, which is presented to the operator throughout the GUI.

IV. The Experimental Results

Fig. 3 represents a blister of electronic keys, used to test the diagnostic system. Fig. 4 represents one sub circuit of the blister shown in Fig. 3, together with the same image modified in such a way it simulates the absence of the component labeled C1. The modified image is different from the image of the circuit where the component is really missing; nevertheless the neural network trained with the synthetic image has been able to recognize the circuits without one component. Fig. 5 shows the image of the component labeled U1. The pin below on the right hand side has a solder lacking in tin. This is a typical example of defect that cannot be detected by means of an electric approach, because the electrical contact is not interrupted. During the training phase, the system retrieves from the database the image of faulty pin, and superposes it to the golden image of the component.

The diagnostic system consists on a set of neural networks, each one being specialized on the diagnosis of a component or a sub-area, and having an independent training set. In order to reduce the amount of data presented to the neural networks, the system applies a feature extraction procedure to the images acquired by the CCD camera. To this purpose, a set of techniques have been experimented and compared in term of compression capability and robustness of the features. Among the experimented techniques, the best performances have been obtained using the Wavelet Transform. In particular, the Mallat method [2] has been used. Fig. 6 shows the wavelet transform of the component depicted in Fig. 5, and Fig. 7 presents the Fourier representation for the same image. It is to note the reduced and localized information on three different bands for the wavelet case than the one with Fourier. This reduction consists of the compact representation of edges at dedicated space. Indeed, edges in images are the important features required for the processing. Among the wavelet components, only the most meaningful are used for the diagnosis. The choice of such components is made during the training phase. On the basis of the training set, one selects the components such that their variance, when they are evaluated on a set of examples, is low for examples of the same class, high for different classes. The number of selected components depends on the size of the images and the number of examples that constitute a single training set. In the studied cases the number of used components has been always less than 30.

The first test regarded the problem of absence of components. In the example shown in Fig. 4, the training set consists of eight configurations related to the case with all the components and seven cases where a component is absent. To obtain the images of the defective circuits we overlapped the component to be made absent with an area having the same color as the background. The neural network gave a correct classification of the cases considered on the validation set, provided that the training set includes the noise patterns as described above.

The second test is related to the component showed in Fig. 5. The training set consists of nine configurations corresponding to the case without defects, and eight cases where one of the solder joints is faulty. The images are obtained by overlapping a defective solder joint image with the image of the component without defects. In this way we can build the training set automatically, without the real images of every defect we want to consider. It is important to ensure repeatability of the acquisition process, otherwise uncertainty due to acquisition can hide a defect we are looking for. We obtained a correct classification of the examined cases. To improve the robustness of the neural network, we enlarge the training set by adding numerical noise to the original patterns.

V. Conclusion

In the present paper, an AOI system for the diagnosis of PCBs, based on neural networks, has been presented. The neural network approach affords diagnostic systems that are very easy to handle in the set up and diagnostic phases. The good results obtained with a low cost prototype point out the robustness of the system and the method's effectiveness.

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