

AOI BASED NEUROFUZZY SYSTEM TO EVALUATE SOLDER JOINT QUALITY

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Abstract: Surface Mount Technology is extensively used in the production of Printed Circuit Boards due to the high level of density in the electronic device integration. In such production process several defects could occur on the final electronic components, compromising their correct working. In this paper a neurofuzzy solution to process information deriving from an automatic optical system is proposed. The designed solution provides a Quality Index of a solder joint, by reproducing the *modus operandi* of an expert and making it automatic. Moreover, the considered solution presents some attractive advantages: a complex acquisition system is not needed, reducing the equipment costs and shifting the assessment of a solder joint on the fuzzy parts. Finally, the typical low computational costs of the fuzzy systems could satisfy urgent time constraints in the in-line detection of some industrial productive processes.

1 INTRODUCTION

Nowadays, Surface Mount Technology (SMT) is extensively used in Printed Circuit Boards (PCBs) electronic production, guaranteeing compact devices, miniature and high density. Nevertheless, in this kind of production different defects can occur. In particular, defects involving solder joints play a critical role, in fact when solder paste is deposited and printed on a board automatically, parameter variations of the printing process may produce faulty solder joints that could lead to failures of the final components (Krippner, 2004). In order to detect the presence of such defects the traditional In-Circuit and Functional Board Test could be unreliable because these might not work correctly if solder joints have faulty connections (Manjeshwar, 2006). Therefore, a reliable inspection technique is required to examine solder joints in a PCB assembly. For this aim, several automated non-destructive inspection techniques like Automated X-ray Inspection (AXI), Automated Laser Inspection (ALI) and Automated Optical Inspection (AOI) have been proposed (Manjeshwar, 2006; Teramoto, 2007; Wu, 2001; Zhang, 2006; Hsu-Nan, 2006).

AXI techniques seem to be the only way to examine solder joints of multilayer or single-layer double-sided PCBs. Nevertheless the X-ray-based techniques are not suitable for in-line inspection

because of their low throughput and the complicated algorithms used for image interpretation (Manjeshwar, 2006; Teramoto, 2007). On the contrary, systems based on ALI methods can be used for 3D reconstruction or vibration analysis (Wu, 2001; Zhang, 2006). Solutions performing the first target showed effective, but slow measurement speed and the need of high-precision motion control are required. If used for the second aim, ALI-based systems achieve a high inspection speed, but it is rather complex to provide a precise alignment between the board and the excitation laser. AOI approaches can perform the inspection of the solder joint quality by making use of a 2D image and are often used to carry out a 3D reconstruction (Hsu-Nan, 2006).

The great part of these techniques showed effective, but rather complex acquisition systems or high computational time are often required. For this reason, they are not suitable for in-line inspection. In order to overcome these drawbacks, AOI solutions are attractive when the evaluation of a product is based on the analysis of 2D images. For this aim, recently, in the field of classification several kinds of inspection algorithms have been developed by using fuzzy/rule-based expert systems (Ko, 2000) and neural approaches (Jagannathan, 1997; Acciani, 2006), transferring the inspection burden to the phase of image processing. In fact, AOI systems

base their classification on visual criteria like a human operator does. Fuzzy systems represent a good tool for reproducing human criteria, offering the advantage of quantifying experts' assessment, whereas neural networks can generalize such assessment by automating operator's classification capabilities.

On the basis of these considerations, in this paper a neurofuzzy system for solder joint quality evaluation is proposed. The target of the present work is to obtain a Quality Index (QI) of a solder joint in a SMT assembled PCB, starting from the knowledge of a human assessment. The proposed system is composed by three modules connected in series: a feature extraction, a supervised neural network-based module and a fuzzy one. The proposed solution offers some interesting advantages: a complex acquisition system is not needed, implying reduced equipment costs; moreover, a low computational time is guaranteed by the fuzzy module.

2 PROPOSED ARCHITECTURE

The proposed architecture is constituted by three fundamental modules connected in series: a Feature Extraction Block, a Neural Module and a Fuzzy one.

The input of the first block is the 256 grey-level image I of a solder joint, extracted from the image of a PCB acquired by a camera. This extraction is conducted by using the procedure described in (Acciani, 2006). The aim of the Feature Extraction Block is to evaluate a vector of 18 features, called *geometric-wavelet features* (GW) and reported in (Acciani, 2006), from the image I of a single pin. Such vector, named GW , revealed efficient in the classification of solder joints. It can be considered as composed by two sub-vectors, codifying the *geometric* and the *wavelet* features, respectively. The former type provides global characteristics of the image under test, the latter takes into account the level of similarity among the image under test and a reference one.

The Feature Extraction Block feeds the subsequent Neural one, constituted by a Multilayer Perceptron (MLP) Neural Network, whose outputs are given by an expert, who is required to provide his evaluation of how much a solder joint belongs to each of the following five classes: "Poor", "Acceptable Poor", "Good", "Acceptable Excessive" and "Excessive". The defined classes are considered as *fuzzy sets*, therefore the expert supplies the degree

of membership of every pin in each set, allowing to construct the target set of the Neural Block.

Let $\mathbf{v} = [v^P, v^{AP}, v^G, v^{AE}, v^E]^T \in [0,1]^{5 \times 1}$ be the membership vector related to each pin, where v^P , v^{AP} , v^G , v^{AE} and v^E represent the degree of membership of the solder joint in the class "Poor", "Acceptable Poor", "Good", "Acceptable Excessive" and "Excessive", respectively. Then, the human operator identifies the class which the solder joint belongs to and assigns a degree of membership $d \in [0,1]$ to the corresponding element of the vector \mathbf{v} . Subsequently, the value $(1-d)/2$ is assigned to the vector components corresponding to the classes which are contiguous to the classified one. If the expert classifies the soldering as belonging to "Poor" (respectively "Excessive"), then the value $1-d$ is assigned to v^{AP} (resp. v^{AE}). The remaining elements of the vector are set to 0. Let $v_i, i = 1, 2, \dots, n$, be the vectors computed for each image of a database of n solder joints, then the matrix $\mathbf{V} = [v_1, v_2, \dots, v_n] \in [0; 1]^{5 \times n}$ can be defined. Let $\mathbf{F} \in \mathcal{R}^{18 \times n}$ be the matrix whose columns are the GW vectors, then the matrices \mathbf{F} and \mathbf{V} provide proper sets for training the MLP network. In this way the designed block is able to reproduce and automate human experts' assessment on which the quality evaluation of soldering is based.

The generic output vector \mathbf{v} constitutes the input for the subsequent Fuzzy Block, whose target consists of supplying an index to express the overall quality of a soldering. In detail, the universe of discourse is divided into the five sets **Poor**, **Acceptable Poor**, **Good**, **Acceptable Excessive** and **Excessive**, whose activation values are given by the components of vector \mathbf{v} . The generic output is constituted by the vector $\mathbf{y} = [y_1, y_2, y_3, y_4]$, whose domain is characterized by four output fuzzy subsets, defined as **Few**, **To Increase**, **To Lower**, **Too Much**, respectively. These sets codify all the possible situations including cases corresponding to good quality. Such fuzzy sets are characterized by four singleton membership functions, centred on the real values $a_0 < a_1 < a_2 < a_3$ in the range $[-1,1]$, as shown in Figure 1.

Values $|a_1| \geq |a_2|$ are chosen, because the case of "acceptable poor" soldering paste is considered less desirable than the case of the "acceptable excessive" one by the experts. The following linguistic rules map the fuzzy input sets into the output ones:

- Rule 1) IF Soldering is **Poor** THEN (y is **Few**)
- Rule 2) IF Soldering is **Acceptable Poor** THEN (y is **Few**) and (y is **To Increase**)

- Rule 3) IF Soldering is **Good** THEN (y is **To Increase**) and (y is **To Lower**)
- Rule 4) IF Soldering is **Acceptable Excessive** THEN (y is **To Lower**) and (y is **Too Much**)
- Rule 5) IF Soldering is **Excessive** THEN (y is **Too Much**).

Subsequently, the elements of the vector y are defuzzified to compute the Quality Index (QI) using the well known method of the “centre of gravity”. The resulting value $QI \in [-1, 1]$ describes the quality of the solder joint under test.

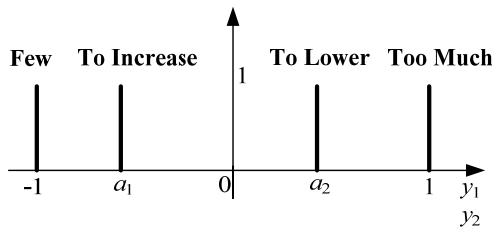


Figure 1: Membership function of output fuzzy sets.

3 EXPERIMENTAL RESULTS

The performances of the proposed neurofuzzy architecture have been investigated by means of a database formed by 480 images. In Figure 2(a) the image of a complete PCB is reported. Figure 2(b)-(f) shows images of pins that an expert classified as belonging to the five defined classes.

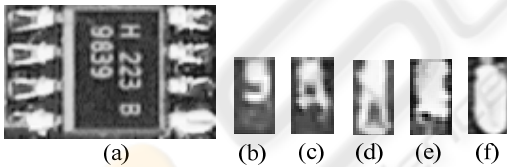


Figure 2: (a) PCB Sample (b)-(f) Solder joints belonging to the defined classes.

The input vectors GW for the MLP network are computed from the images of the database by the Feature Extraction Block. In order to synthesize the architectural parameters of the Neural Module, the Mean Absolute Error (MAE) index is defined as:

$$MAE = \frac{1}{n} \sum_{i=1}^n \|y_i - t_i\|_2$$

being y_i and t_i the output and the target of the network under test, respectively, and n the number of the data samples. The performances of the neural

network have been evaluated by minimizing the mean value of the MAE index computed over $r = 20$ trainings with different initial weights. The designed network has input, hidden and output layers formed by 18, 12 and 5 neurons, whose activation functions are logarithmic-sigmoid. The network has been trained by the Levenberg-Marquardt algorithm, minimizing the Mean Square Error. In order to show the capabilities of the neural network in reproducing the assessment of a human expert, in Figure 3 the values of the target versus the output of the network are reported. It is worth to observe that the more points consolidate on the bisector line the more the network is able to reproduce the assessment of the expert.

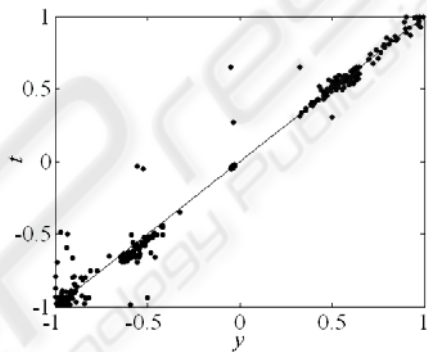


Figure 3: Values of the MLP target vs MLP output.

Subsequently, the output of the network is processed by the Fuzzy Block. In Figure 4 the values of QI, computed for the samples in the considered database and sorted by the membership to each defined class, have been reported.

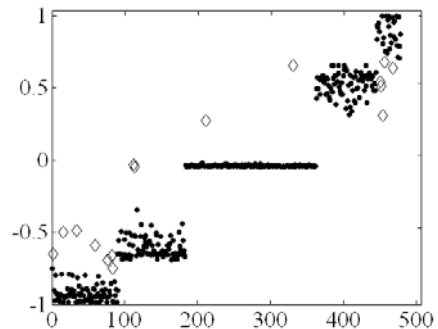


Figure 4: Values of QI computed for the considered samples.

To evaluate the reliability of the outputs provided by the whole neurofuzzy architecture, the values of QI have been partitioned into five hard sets by the four thresholds $th_1, th_2, th_3,$ and th_4 which are computed as:

$$th_1 = (QI_m^P + QI_m^{AP}) / 2 \quad th_2 = (QI_m^{AP} + QI_m^G) / 2$$

$$th_3 = (QI_m^G + QI_m^{AE}) / 2 \quad th_4 = (QI_m^{AE} + QI_m^E) / 2$$

where QI_m^P , QI_m^{AP} , QI_m^G , QI_m^{AE} and QI_m^E are the mean QI value of the elements belonging to the class **Poor**, **Acceptable Poor**, **Good**, **Acceptable Excessive** and **Excessive**, respectively. Such partition of the data can be carried out by using these thresholds as follows: (a) if $QI < th_1$, then soldering is **Poor**; (b) if $th_1 < QI < th_2$, then soldering is **Acceptable Poor**; (c) if $th_2 < QI < th_3$, then soldering is **Good**; (d) if $th_3 < QI < th_4$, then soldering is **Acceptable Excessive**; (e) if $QI > th_4$, then soldering is **Excessive**. The obtained partition is compared to experts' one. In particular, a pin is considered as correctly classified by the system if it belongs to the same set when considering both the former and the latter partition. On the contrary, if this condition is not satisfied, then a misclassification takes place, as it is shown by the diamond marks in Figure 4. The performances of the architecture are measured by defining the *Recognition Rate* index as:

$$RR = \frac{N_C}{N_{TOT}} \times 100$$

being N_C and N_{TOT} the number of correctly classified cases and the number of the considered ones, respectively. Values of *RR* equal to 96.87% and 95.83% concerning training and testing data have been obtained. The results can be considered encouraging, in fact the obtained values show that the designed neurofuzzy system yields a classification similar to that given by the experts, providing a refined evaluation of the solder joints.

4 CONCLUSIONS

In this paper a neurofuzzy architecture for computing a Quality Index of a solder joint in a SMT assembled PCB has been proposed. The system offers some interesting advantages. In particular, the suggested solution does not need a complex illumination and positioning system, implying that the equipment costs could be reduced and the assessment of a solder joint could be shifted on the fuzzy evaluation phase. Moreover, the typical low computational costs of the fuzzy systems could satisfy urgent time constraints in the in-line detection of some industrial productive processes. The

proposed architecture provides a refined evaluation of the solder joints, automating the human expert classification.

Basing on the obtained results, it can be argued that the correct working of the proposed system is due to its capability to reproduce human experts' *modus operandi* properly. Therefore, future developments will be aimed at identifying the characteristics, that a human operator evaluates in order to express the assessments of solder joints. As a consequence, the focus of future works will be constituted by the identification of the features which contain sufficient and useful information to perform a correct diagnosis.

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