

## Reduced Dimensionality Space for Post Placement Quality Inspection of Components based on Neural Networks

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**Abstract** – The emergence of surface mount technology devices has resulted in several important advantages including increased component density and size reduction on the printed circuit board, on the expense of quality inspection. Classical visual inspection techniques require time-consuming image processing to improve the accuracy of the inspected results. In this paper we reduce the computational complexity of classical machine vision approaches by proposing two neural network based techniques. In the first we maintain image information only in the form of edges, whereas the second we preserve the entire content of info but compressed in a single dimension through image projections. Both algorithms are tested on real industrial data. The quality of inspection is preserved while reducing the computational time.

### 1. Introduction

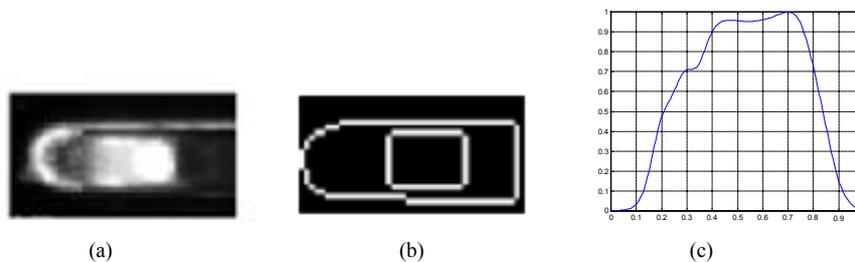
The technology of Surface Mount Devices (SMDs) has been widely used in printed-circuit board (PCB) assemblies, increasing substantially the component density and reducing the size of components on the PCB. These attributes, however, make the quality inspection of SMDs more critical and complicated [1]. Visual inspection techniques require extensive image processing for improving the image quality and deriving characteristic features. The limitation of computer-based tools related to computer time and working space poses a high priority on the objective choice of a limited number of essential characteristics (*feature-space reduction*) but also on the exclusion of redundant observations (*data-space reduction*). Thus, the concept of *approximate processing* [3], has been considered in real-time applications, where there is a necessity for approximating a given algorithm with another that has reduced computational cost. We adopt two different forms of *data-space reduction* [4] directly on the initial image space, affecting: 1) the intensity levels or dynamic range, by transforming the gray-scale image into a binary edge image (referred to as *reduced dynamic-range processing*) and 2) the number of independent variables, by utilizing only specific projections of the data (referred to as *reduced input-dimension processing*).

We employ the abovementioned framework for analyzing SMD images and estimating lead displacements. A novel Bayesian framework for such analysis is proposed in [2]. The paper proceeds in Section 2 with our experimental set up. Section 3 presents the associative memory classifier that implements our reduced dimensionality approach in terms of intensity levels. The concept of reduced dimensionality processing in terms of data dimensions is studied in Section 4. Our methods are applied on SMD post placement quality inspection and the results are

presented in Section 5. Section 6 concludes this study with relevant observations regarding the theoretical development and experimental performance of our algorithms.

## 2. Experimental Set up

A high dynamic range CMOS camera, equipped with a simple led illumination device and a general-purpose processor, performs the acquisition of the component image. For the purpose of presenting our results, QFP (Quad Flat Pack) SMD components with 120 leads (30 leads per side) are employed. Following the image acquisition, the four regions of interest (ROIs) are isolated and all 120 small lead-images are extracted. The density of the CMOS sensor is 1024x1024 pixels, deriving an image resolution of 20x20 $\mu\text{m}$  per pixel. To capture the entire area of interest around each lead, the size of the lead images is set to 35x56 pixels. Each lead image captures information about four areas of interest, namely lead, pad, paste and background. The features are extracted from segmented lead images. For the purposes of estimating other quality measures, only the displacement along the side of the component is essential [2]. Thus, our problem is restated as estimating lead displacement at the direction perpendicular to the lead axis. Essentially, we consider quantized displacement estimations organized at multiples of a pixel displacements. The displacement classes we consider are  $\{-6, -3, 0, +3, +6\}$  and  $\{-6, -4, -2, 0, +2, +4, +6\}$ , in pixel displacements over the lead over its central position. The proposed reduced dimensionality approach overcomes segmentation problems by establishing a macroscopic consideration of features at a higher level of abstraction. More specifically, the image presented for reduced dynamic-range processing preserves only an abstract sketch of the image edges, whereas the data given for reduced input-dimension processing represents a projection of the input image and reflects the abstract structure of interest on a single direction, as illustrated in Figure 1c.



**Figure 1.** Typical images used in data-space reduction approaches.  
(a) original image, (b) reduced dynamic-range image, (c) reduced input-dimension data

## 3 Reduced Dynamic-Range Processing

In our first approach related to data-space reduction, we utilize the edge structure extracted from the input lead image for classification purposes. In most cases, the derived edge structure is partially deformed or destroyed. Thus, the major task is to relate edge patterns so that we can recall a class assignment for each test pattern that may be presented for classification. We exploit the concept of *associative memories* (AMs) as stored patterns representing the desirable classes, and the *Hamming*

*distance* for quantifying the distance between the input pattern and each one of the stored memories (*fundamental memories* or *exemplar patterns*) [5]. For classification of input patterns we use the *Hamming network*, which is a maximum likelihood classifier used to determine the proximity of an input vector to several exemplar vectors or prototype patterns. An input pattern that partially resembles the stimulus of an association invokes the associated response pattern by means of the shortest Hamming distance. The input pattern to the network is a binary edge pattern (as in Fig.1b) obtained from the grayscale input lead image (as in Fig. 1(a) ) through *segmentation* and *edge detection*. The stored AM patterns reflect the edge structure of the “typical” edge image representing each class of lead displacements. Thus, the reduced dimensionality, binary edge image(as in Fig. 1 (b)) is fed to the Hamming network to determine pattern similarities and implement the desirable classifier.

Since we exploit the concept of associative memory, the input pattern must have a structure similar to its closest one of *fundamental memories* (or *exemplar patterns*) [5]. Each fundamental memory comprises the specific characteristics discriminating its class. Moreover, the fundamental memories used in lead displacement must assess the standard characteristics of the problem, such as same image size, uniform lead position, etc. To satisfy these requirements, we first select the memory for one displacement (0 pixels) and then construct the memories associated the other classes by shifting the outside edge structure with respect to the fixed structure of the lead. The basic fundamental memory at shift 0 is selected from a number of test images reflecting exactly this specific case through statistical analysis of the mean pattern in this class. Based on the design of the fundamental memories, we need to train the network so that it recovers the closest stored pattern in response to each test-input. An example of the desirable operation of the associative memory in the case of a test image with +3 pixels lead-shift is illustrated in Fig. 2.



**Figure 2.** Associative memory operation. (a) testing image (b) output response

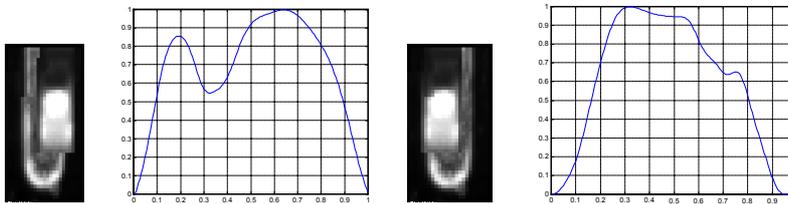
The comparison between the input (edge) pattern and the stored memories requires the use of a distance measure, for example the Euclidean distance or the Hamming distance [5], for quantizing the output to the fundamental memories representing the desirable classes.

#### **4. Reduced Input-Dimension Processing**

In this approach we exploit the structure of the lead image profile (projection ) along one, the most descriptive direction vertical to the lead axis, for extracting meaningful features related to displacement measurements. The important component of this classification scheme is its feature extraction unit. We propose a complete feature extraction and classification approach that consists of three distinct modules. The first module receives the lead projection function at its input and utilizes a nonlinear filter based on a high-order neural network (HONN) [6] for feature extraction. The second module implements feature reduction and de-correlation of the

feature space by using the Karhunen-Loeve transform (KLT). The third module comprised by the Bayes classifier serves as a classifier that assigns each feature vector to one of the predetermined classes.

HONNs are fully interconnected nets, containing high order connections of sigmoid functions in their neurons [6]. The HONN based feature extraction module receives as input a normalized projection function of the tested lead image and updates its weights by stable Lyapunov learning laws as to approximate that input function. Prior to entering the input function is linearly transformed in the range [0,1], as to avoid the appearance of destabilizing mechanisms caused by purely numeric issues, (i.e., large variations on the image projections data). Moreover, for uniformity reasons, the rising point of this function is shifted to the origin. Two displacement examples reflecting  $\pm 3$  pixels lead shift are presented in Figure 3.



*Figure 3. Original lead images and projection functions for  $\pm 3$  pixels lead shift*

A key issue in the design of the feature extraction system is the definition of the feature vector, which is based on relevant parameters employed in modeling the relation  $y = f(x)$ , or on parameters of the approximation  $\hat{y} = \hat{f}(x)$ . In our approach, we take the feature vector  $(\mathbf{F})$  to be  $\mathbf{F} = [\mathbf{W} \ e]^T = [w_1 \ w_2 \ \dots \ w_N \ e]^T$  where  $\mathbf{W} = [w_1 \ w_2 \ \dots \ w_N]^T$  is the HONN weights vector and  $e$  is the approximation error.

## 5. Results

The reduced dynamic-range approach developed in Section 3 is now tested on actual images from four-sided QFP components. A total of 120 lead samples per class of the lead displacement is obtained resulting in totally 1560 samples for the 13 classes. We consider the Hamming network trained and tested for 7 and 5 classes. The first case involves pixel displacements  $\{-6, -4, -2, 0, +2, +4, +6\}$  whereas the second case considers classes  $\{-6, -3, 0, +3, +6\}$ . These two cases study the ability of the classifier to discriminate classes in the feature space separated by 2 and 3 pixels apart, respectively. Our approach is tested on 120 lead samples per type of the lead displacement resulting in totally 840 samples for the 7-class testing set and the 600 samples for the 5-class testing set correspondingly. The testing process follows a jack-knifing scheme [2], where all but one-sample feature vectors are used for training and the last one is used for testing. This process is repeated for all samples, leaving one out in every cycle. The overall classification rates from this jack-knifing process approximate the true classification probabilities of the classifier tested and the results are depicted on Tables 1 and 2, respectively.

**Table 1**

	-6	-4	-2	0	2	4	6
-6	85.00%	14.17%	0.83%	0.00%	0.00%	0.00%	0.00%
-4	0.00%	84.17%	15.83%	0.00%	0.00%	0.00%	0.00%
-2	0.00%	1.67%	77.50%	20.00%	0.00%	0.00%	0.83%
0	0.00%	0.00%	0.00%	92.50%	0.83%	6.67%	0.00%
2	0.00%	0.00%	0.00%	5.00%	82.50%	12.50%	0.00%
4	0.00%	0.00%	0.00%	0.83%	8.33%	82.50%	8.33%
6	0.00%	0.00%	0.00%	1.67%	3.33%	7.50%	88.33%

**Table 2**

	-6	-3	0	3	6
-6	86.67%	10.00%	3.33%	0.00%	0.00%
-3	0.00%	79.17%	20.00%	0.00%	0.83%
0	0.00%	0.83%	95.00%	4.17%	0.00%
3	0.83%	0.00%	5.00%	92.50%	1.67%
6	0.00%	0.00%	1.67%	5.00%	93.33%

The reduced input-dimension processing approach developed in Section 4 is now tested on actual images from four-sided QFP components. Similar to reduce dynamic-range approach, we consider the Bayesian distance classifier trained and tested for 7 and 5 classes. Again, a total of 840 and 600 sample-leads are used for

testing the classifier on seven and five classes, respectively. To approximate the unknown projection function the following HONN structure is used:

$$y = \mathbf{W}^T \mathbf{S}(x) = \sum_{i=1}^3 w_i s_1^i(x) + w_4 s_2^4(x) + \sum_{i=5}^8 w_i s_3^{(i-4)}(x) + \sum_{i=9}^{12} w_i s_4^{(i-8)}(x)$$

with

$$s_1(x) = \frac{0.9571}{1 + e^{-35.703(x-0.076)}} + 0.2245, \quad s_2(x) = \frac{0.3838}{1 + e^{-0.3598(x-1.488)}} - 0.2607$$

$$s_3(x) = \frac{0.9625}{1 + e^{-22.4438(x-0.7927)}} + 0.5625, \quad s_4(x) = \frac{1.2906}{1 + e^{-51.468(x-0.3287)}} - 0.3572$$

The HONN weights are updated according to

$$\dot{w}_i = -0.000534w_i + z s_1^i(x), \quad i=1,2,3, \quad \dot{w}_4 = -0.000756w_4 + z s_2^4(x), \quad i=4$$

$$\dot{w}_i = -0.000825w_i + z s_3^{(i-4)}, \quad i=5,6,7,8, \quad \dot{w}_i = -0.000407w_i + z s_4^{(i-8)}, \quad i=9,10,11,12$$

**Table 3**

	-6	-4	-2	0	2	4	6
-6	85.83%	12.14%	2.03%	0.00%	0.00%	0.00%	0.00%
-4	11.25%	67.83%	16.13%	3.07%	1.23%	0.00%	0.49%
-2	0.26%	8.72%	80.17%	10.21%	0.64%	0.00%	0.00%
0	0.00%	11.31%	0.89%	65.64%	18.92%	3.08%	0.16%
2	1.12%	0.00%	0.00%	16.04%	73.17%	4.60%	5.07%
4	0.00%	0.00%	0.00%	3.03%	4.26%	90.83%	1.88%
6	1.54%	0.00%	0.78%	2.01%	1.78%	1.49%	92.4%

The parameter  $\alpha$  that appears in the abovementioned HONN structure to approximation the unknown projection function is fixed to  $\alpha = 8.0913$ . A genetic algorithm has been used to estimate off-line the optimal constant parameters of the non-linear filter [7]. For the displacement classification task, the Bayesian classifier is implemented. The a priori

class probabilities are set to 1/7 and 1/5 for the seven and five-class assignments, respectively. The KL transform is used to decorrelate the feature vectors by taking the projections of the N-dimensional HONN features to their K most important directions. The classification probabilities resulting from the jack-knife process are illustrated in Tables 3 and 4 respectively.

From the above classification results we conclude that as expected the classification results for the 5-classes assignment are more accurate than these for the 7-classes problem. Notice that the complementary information processed by the two algorithms can be efficiently merged within a Bayesian information fusion scheme [2] to drastically improve the classification probabilities for all classes under consideration. Overall we may conclude that high abstraction features used in approximate processing are generally less descriptive than pixel-based features for classification purposes. With respect, however to computational complexity, the approximate processing can yield appreciable reduction at the cost of slightly inferior results.

**Table 4**

	-6	-3	0	3	6
-6	88.30%	7.67%	4.03%	0.00%	0.00%
-3	3.05%	91.60%	5.35%	0.00%	0.00%
0	8.65%	0.00%	82.40%	6.41%	2.54%
3	0.00%	0.00%	3.42%	90.50%	6.08%
6	0.00%	0.73%	4.82%	3.07%	91.38%

## 6. Conclusion

We have considered two approaches to overcome the computational complexity of classical machine vision quality inspection of SMDs on a PCB. The first employs associative memories to implement the reduced information content in image intensity levels.

The idea is to compare the edge structure of a lead image with that of stored fundamental patterns. The second scheme compresses the data space by considering only an image projection function of the data. A non-linear filter based on high order neural networks is used to encode the characteristics of each projection function. Both methodologies are tested on real industrial PCB images. The quality of inspection slightly deteriorates while the computational time is significantly reduced, when compared to classical visual inspection techniques.

## 7. References

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