NEURAL NETWORK APPROACH TO AUTOMATED WIREBOND DEFECT CLASSIFICATION

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ABSTRACT*:*
This paper discusses the use of an artificial neural network in an automated IC package wirebond inspection defect classification system. A neural network was applied to the inspection of wirebonds in high pin count (>300 pin) IC packages. This study required sample acquisition, image capture, image segmentation, data compression, feature extraction, and training a neural network. Simple image processing algorithms and semi-automated image processing tools were used to analyze the final database of 1404 pad images. The categories with more than 100 samples had a >90% classification accuracy, other categories had 75 to 78% accuracy. Commercially available image processing tools are necessary to make this process manufacturable.

BACKGROUND AND MOTIVATION

This paper discusses the development of a neural network solution for automated IC package wirebond inspection, as a feasible alternative to current visual inspection. Visual inspection of any form is time consuming expensive, and subject to interpretation and fatigue. As the objects being inspected become smaller, denser, and more complex, the inspection process becomes more prone to human error. Traditional machine inspection has been expensive, time consuming, and not as effective as human operator inspection. The result has been continued human inspection or no inspection. Wirebond inspection for high pin count (339 to 600 pins per package), high density devices (>0.75 Million transistors per IC) can be used to rework devices improving yield and profit. Inspection error lowers electrical test yield and can cause non-testable field returns.

Automated inspection in industry has increased in the past 5-10 years, automated areas include: autobody metal and paint, clutch drivers, and PC board solder joint inspection. Automation development is taking place in PC board solder joints, IC wafers, chili-pepper harvesting, IC wirebond inspection, turnkey wirebond and die-attach systems, and 3-D imaging for accept/reject processes [1].

Improvements in lighting systems, microprocessors, image processing systems, and camera technologies have opened the field to replace manual inspection with automated inspection [2]. Specialized lighting systems are required to obtain clean predictable images. Development of high speed, low cost, PC compatible image processing hardware has expanded the automated inspection field [2-3]. Systems incorporate fast specialized image processing hardware to perform the image capture, rotation, region of interest selection, image enhancements, feature extraction, measurements, 3-D mapping, and data compression processes; thus accomplishing precision vision analysis. Software and hardware neural network tools are now available with the high speed image processing boards.

In a comparison with traditional automated vision systems, Huang [2] found that the neural network took longer to train than area calculations, boundary following, or

histogram calculations. However, the accuracy of the neural network and the orientation flexibility made it a more effective classification tool.

IMAGE CAPTURE

Equipment selection and image capture issues include: 1) varied heights between die and package bondpads, 2) high magnification requirements of bond versus low magnification of the wire path, 3) different wire, die bondpad, and package pad reflectivities, 4) specific location lighting and in magnification requirements, 5) varied patterns surrounding each bondpad, 6) different wafer fabrication top metal processes, 7) lot to lot color variation of pads due to residual TiN, 8) two tiers in the package for wirebond attachment.

Images were obtained using a production microscope, a manual low magnification (0.8 to 64x) Zeiss Stemi SV8 stereoscope; a Micro Video Inst. developmental fluorescent ring light; a Javelin Electronics Chromachip 11 Videocamera; a DECstation 325C PC; a PC Matrox framegrabber; and a VT240 monitor. Images were stored in a standard RS232 raw image file, an 8 bit formatted 256 level greyscale, 480x512 pixel image. Using 64X magnification, the resulting pixel dimension was 1 pixel per .0001 inch (2.56 um). The Al wire was 12.5 pixels (1.25 mils) and the bondpad opening was 35.2 x 45.4 pixels (90 x 111 um). The DC244, NVAX memory controller was chosen because of high volume and high complexity. The DC244 die is 0.522 x 0.539 inches, has 336 bond pads (180 lower tier and 176 upper tier), is CMOS3, three metal layer technology. TiN has been stripped off bondpads to allow bonding with the Al/Si wires. Bondpads are 99 x 120 microns with 27 micron spacing for a minimum center to center distance of 126 microns.

Initial image capture was to include the die bondpads, connecting wire, and package bondpads. Problems included: obtaining light capable of distinguishing wires from bondpads, framegrabber software greyscale image file clarity, depth of field for die plus package. Final image capture was confined to die bondpads. Available commercial equipment appears sufficiently sophisticated to accomplish the die bond to wire to package bond trace for an on-line inspection application.

DATA COLLECTION

The population consisted of over 600 pictures of 9 bondpads/picture taken from assembly line rejects. Samples were not available for all defect categories, some defects were created specifically for this study, about 20% of samples were unusable due to pad segmentation difficulties. Some vibration blurred images were included in the study to test the neural network capability under noisy conditions.

A qualified engineer classified each die wirebond according to defect type after segmentation. The defect categories defined and bondpad quantities for this study are listed in Table I. Successful recognition lay in the availability of sufficient sample size of each defect category to enable network convergence.

Table 1: Defect Category Definitions and Quantities:

Defect Codes	Defect Definitions	# Bondpad
Acceptable	No visible reject criteria	815
Long tail	A wirebond tail >2 times the diameter of the wire	53
Offset bond	A wirebond which is <75% on the bondpad metal	131
Missing bond	No wirebond present	261
Broken wire	There is a wirebond but the wire is broken close to the bond	43
Bent wire	Not an actual reject criteria, predicts wires touching	36

	(which does constitute a reject). The wire is bent >70° to the bond.	
Double bonds	Two distinct bonds are made on the same bondpad	65
Total		1404

IMAGE PREPROCESSING AND FEATURE EXTRACTION

Image preprocessing required orienting the image and segmenting single bondpad areas from the irregularly aligned bondpad images. Image data were compressed, edges detected, and edge counts per area computed. Commercially available image processing equipment can perform necessary data manipulation more effectively than the programs written internally for this study.

Pad Segmentation

The pad segmentation process required initial image rotation to align the bondpads at right angles to the image edges. A high pass binary filter was used to standardize lighting thresholds across images. Rotation involved identification of a global maximum pixel gradient change across rows to locate top and bottom bondpad edges. Then template matching was used to define the left and right bondpad edges. Template matching error was 20%, while this is too high for a real-world implementation, it provided sufficient samples to show feasibility.

Data Compression and Edge Detection

[IMAGES NOT AVAILABLE]

(a) Input image (b) Output Segmented Pads

Figure I Input and output of segmentation stages

Individual bondpad image data was compressed to obtain a manageable total pixel count, filter noise, and enhance information. Each segmented pad data record [60x95 pixel greyscale value 5900 pixel/pad count], was far too large to present as input to the network. A reduction routine compressed data and filtered noise via smoothing simultaneously. It performed an n^2 reduction by dividing the total image into 60/n x 95/n cell areas, computing the average greyscale value within a reduced block, and outputting the 60/n x 95/n 2D matrix_of average values. The reduction procedure 1) reduced the overall pixel count, 2) reduced extraneous noise due to lighting variations and vibration, and 3) enhanced features.

Following data reduction, an edge detection algorithm was used to define the edges of the wire, bondpad, and bond. The edge detection procedure scanned the image both vertically and horizontally for changes in adjacent pixel greyscale values. When the greyscale gradient threshold was exceeded, an edge indicator value of 1 replaced the greyscale value of the pixel cell. If the gradient threshold was not exceeded, the cell received a value of 0. The 30x48 pixel average greyscale images was replaced by a 30x48 pixel binary image of outlined shapes. The procedure sensitivity is governed by a combination of 5 parameters: a greyscale gradient threshold, above which, an edge is declared, and 4 adjacent pixel grouping sizes that are compared both horizontally and vertically across the pads.

A find smoothing procedure translated the edge feature information contained in the 30x48 pixel image structure into a 96 cell per pad vector. The 2-D image structure was

reduced by a factor of 4 both horizontally and vertically by averaging the binary values of 4x4 pixel blocks to yield a 16:1 cell reduction.

The front end software developed for this feasibility study was cost effective and sufficient to test a pattern recognition system

PATTERN RECOGNITION CLASSIFICATION

This section contains discussion of the neural network technique applied to the compressed feature data to yield classification of wirebond images by defect category, and the results obtained following training and test on the sample data of 1404 defect classified wirebond samples. For this feasibility study we chose a multilayer perceptron (MLP) neural network to develop a classification algorithm. The MLP used in this study is a 3 layer feed forward neural network which takes input from an information vector and utilizes a network of weights and hidden nodes to compute, in forward fashion, an output classification vector.

The feed forward MLP used to classify wirebond images consisted of 3 layers: the input node, a 96 (8xl2) vector of average edge counts/pad (X_{in}), a 100 node hidden layer ($X_{\sim hid}$), and a 7 node output classification vector (X_{out}). Each input layer is fully interconnected to the successive layer via a weight structure. The value of a hidden node, $X_{hid}(j)$, is the sigmoid transform value of the sum of the product of the input vector ($X_{\sim in}$) and associated weight-vector $W_{\sim in\text{-}hid}(j)$

$$X_{hid}(j)=\text{Sigmoid}\left(\sum_{i=1}^{96} X_{in}(i)W_{in\text{-}hid}(i)(j)\right);\ \text{Sigmoid}(z)=(1.0+e^{-z})^{-1},\ j=1,2,...,100 \quad (1)$$

Similarly, each output classification node ($X_{out}(k)$) is a sigmoid transform of the summed product of a contribution hidden nodes values $\sim X_{hid}$ with the associated weights between the hidden and output vector nodes $W_{\sim hid\text{-}out}(k)$.

$$X_{out}(k)=\text{Sigmoid}\left(\sum_{i=1}^{100} X_{hid}(j)W_{hid\text{-}out}(j)(k)\right);\ \text{Sigmoid}(z)=(1.0+e^{-z})^{-1},\ k=1,2,...,7 \quad (2)$$

The updating of all weights via back propagation of a global error is computed generally as follows: For each input vector $X_{\sim in}$ associated with known (desired) classification vector D_{out}, an observed output vector, X_{out}, is computed by the network. The global error,

$$E=.5\left(\sum_{k=1}^{1404} [X_{out}(k)-D(k)]^2\right), \quad (3)$$

is the sum of the squared error between the observed and desired output vectors. The global error (E) is minimized by finding_the path of greatest descent along all of its vector component pathways. This involves computation of the partial derivatives of E with respect to each node $\sim X_{out}$ in the output vector;

$$e_{out}(k) = -\partial E/\partial X_{out} \quad (4)$$

which is a function of the hidden to output layer weighting structure.

$$e_{out}(k) = f'(X_{out}(k)) \cdot \Sigma e_{hid}(j) \cdot W_{hid\text{-}out} \qquad (5)$$

where $f(X_{out}(k))$ is the derivative at the sigmoid transfer function.

The error term now associated with the hidden layer term $X_{hid}(j)$, $e_{hid}(j)$, can similarly be back propagated to the input layer nodes through the weight vector, $W_{in\text{-}hid}(j)$. Global error is minimized in terms of all network weight values via a least squares steepest descent algorithm. The resulting weight changes required to achieve a steepest descent are applied to the network weights. Following weight adjustment, the next input vector, X_{in}, is fed forward through the network to produce a new global error term. The procedure repeats until some convergence criteria for the global error is met; signaling the completion of the network training (see Zurada [41]).

All MLP with back propagation results listed below were obtained using the Neuralware Neuralworks Professional II/Plus software [5]. The MLP back propagation neural network was trained on all 1404 supervised sample vectors having a sample population breakdown shown in Table 1.

Table 2: MLP Classification Results

Defect Category	Sample Size	% Correct Classification Category vs All Others	 Acceptable vs Rejectable	St Dev. (%)
Acceptable	815	98.4	98A	.4
Long tail	53	73.6	75.5	5.9
Offset Bond	131	91.6	91.6	2.4
Missing Bond	261	99.2	99.2	.6
Broken Wire	43	95.3	100.0	.5
Bent Wire	36	72.2	77.7	6.9
Double Bonds	65	73.8	75.4	53

The final sample sizes in 4 of the defect categories were below 100, considered a minimum number needed to ensure reasonable category discrimination which would generalize correctly on cases never before encountered. The reduced sample sizes resulted from 1) segmentation inefficiency, leading to ~20% deleted sample cases and 2) difficulty in obtaining assembly line rejected parts of a given defect type. Given the small sample sizes in 4 of the 7 categories, we chose to train the neural network on all available data to achieve the highest possible separation between categories. The results of training on the multilayer perceptron are displayed in Table 2.

The 2nd data column of Table 2 lists the % correctly classified by individual categories vs. all others, while column 3 represents the % correctly classified as either defective or acceptable. For example, 95.3% of all broken wires were correctly classified as broken wires, but in all cases (100% of broken wires) a broken wire is rejected as defective. The difference in this case is that network classified 2 of the 43 cases of broken wire, as another defect category (missing wire).

Thus, column 3 represents the rates at which an actual automated inspection station would err: 1.6% of the time the machine would reject an acceptable die (Type I error). The % of time a defective die was accepted as good (Type II error) ranged from 24.6% to 0%, depending on the defective sample population make-up. If one assumes that all defect types listed are equally distributed across the defective bond population, an overall Type II error of 13.6% is calculated, or an average recognition rate of 86.4% over all defect categories.

DISCUSSION

This work demonstrated the feasibility of a neural network solution for automated wirebond defect recognition. The success of each component of automated inspection affects the overall results: from obtaining sufficient numbers of recognizable images, through data compression, feature extraction, and final neural network algorithm training. We used available equipment for image capture and developed all segmentation and feature extraction software, in lieu of purchasing commercially available image processing products for this feasibility stage. Despite the trade off in classification precision, the feasibility of a neural network approach to wirebond defect recognition appears high, with an estimated Type I error of 1.6% and average Type 11 error of 13.6% for an accept versus reject classification.

The MLP network exhibited good to excellent recognition capacity across defect categories in the presence of wide lighting variation and noise during image capture. The good results highlights the capability of the neural network, in general, to filter out noise or non-critical information in a recognition strategy development. Although the network demonstrated the ability to filter noise given sufficient sample size, the appearance of both noise and small sample size simultaneously led to depressed % correct recognition for long tail, bent wire, and double bond defects.

Defect sample size appears to have decreased the % correct recognition in some categories. This resulted from the efficiency of the segmentation routine developed and difficulty in obtaining on-line inspection rejected die containing certain defect types. In an actual on-line application, insufficient samples would not arise: 1) adequate time allocated for obtaining training samples, and 2) higher efficiency segmentation by incorporating a commercially available image processing system; thereby reducing the overall number of images required to adequately train a network.

Commercial image lighting and processing equipment can perform all of the image capture, feature extraction, noise reduction, edge detection, measurement and many additional techniques with greater speed and accuracy than the procedures developed for this study. Additional shape profiling, feature definition, and measurement can be gathered in parallel to feed into a neural network.

In summary, the MLP network trained during this study was able to yield correct recognition in the good to excellent range across all defect categories in the presence of 1) excess noise, 2) insufficient sample sizes, and 3) simplistic edge detection software, by using an average edge count area feature extraction approach. Given the current availability of commercial products on the market which will improve all of the above areas of weakness, we conclude that a customized edge area counting algorithm coupled with a MLP neural network would perform with sufficient precision to be considered as a feasible and desirable alternative to visual inspection of wirebonds.

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