Reclaim Wafer Defect Classification Using Backpropagation Neural Networks

Fang-Chih, Tien, *Te-Hsiu Sun, and Mei-Ling, Liu

***Abstract*—**Silicon wafer is a part of main cost of material in semiconductor manufacturing. Reclaim wafers have been extensively used in the semiconductor industry for many years. Reducing the usage of prime wafers and using reclaim wafers is one of the most cost effective solutions for a manufacturing plant. If any defects such as void, scratches, particles, and contamination found on the surface of reclaim wafers, these wafers will be classified as defective ones (NG). Due to previous study, we found reclaim wafers can be re-polished if its defect is not fatal and its thickness is enough for a repolish. Currently, those NG reclaim wafers must be screened by experienced human inspectors to determine re-usability through its defective mapping. This screening task is tedious, costly, and unreliable.

This study proposed an artificial intelligent system to construct an automated reclaim wafer defect classification system, in which back-propagation (BPN) were used to analyze the pattern of defective mapping, and determined whether reclaim wafers can be re-polished or not. Experiments showed the BPN gave good performance in identifying NG and Good wafers. The proposed method was successfully increase the reusability of RM, and currently serves as important module in the MIS system of case-study company.

***Index Terms*—**Reclaim wafer, wafer defect detection, defect analysis, BPN, digital image process, artificial intelligence.

I. Introduction

Wafer is the most essential and important semiconductor material and thus a main resource in semiconductor industry. It may benefit the profit and increase the competence the competence when utilizing the wafers properly for integrated circuit (IC) foundries. Wafer can be divided into two categories: prime wafers and test wafer. Test wafers are then of two types: control wafer and dummy wafer. The prime wafers are used to manufacture IC and the test wafers are mainly used to monitor parameter and to maintain machines in the manufacturing process. Since the wafer is a limited and precious resource, it is desired to recycle or reclaim the wafers through which a cost down in manufacturing can be achieved. Higher reusability results in higher profit and thus higher competence among IC foundries. The prime wafer has been produced as integrated circuit chips. Consequently, only test wafers can be reclaimed, Categories of wafers as shown in Fig. 1.[1].

To reuse the test wafers, a reclaim wafer process is conducted as in Fig.2. The key processing steps include sorting, stripping, lapping and grinding, polishing, cleaning, and inspection [2]. Since not all processed test wafers can be reclaimed, an inspection system should be sought to classify the test wafers into two types: 'Go (G)' and 'No Go (NG).' For G type, the wafers can be reused in the manufacturing process. For NG type, the wafers are discarded. Among key steps, to determine reusability of reclaim wafers is the most critical task which heavily depends on an inspection system to classify the processed test wafers appropriately.

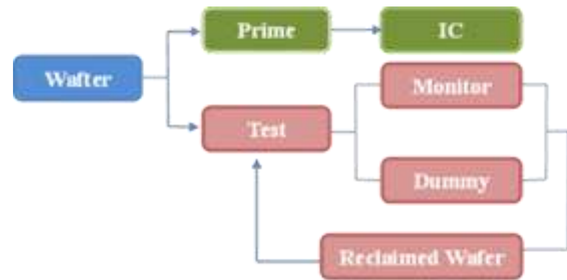

Figure 1: Categories of wafers.

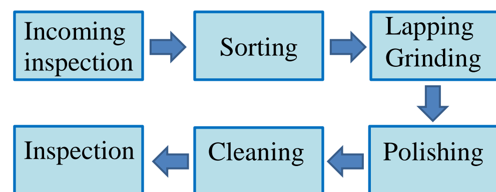

Figure 2 The reclaim wafer processing step.

Since the crucial step in the reclaim wafer process is the inspection, an inspection system with machine vision and automatic inspection will be considered in this paper. The paper is organized as follows: Section 2 gives brief reviews on the automated visual inspection, SVM, and related topics. Then the proposed inspection system with BPN in Section 3 which is followed by experimental results to show the performance of the pro-posed inspection system in Section 4. Finally, Section 5 concludes this paper.

II. Review

Automated visual inspection (AVI) is an image-processing technique for quality control and production automation. It has been widely applied in the production line of manufacturing

Mei-Ling, Liu, Department of Industrial Engineering & Management National Taipei University of Technology (Taipei Tech), Taipei, Taiwan

Te-Hsiu Sun, Industrial Engineering and Management, Chaoyang University of Technology, Taipei, Taiwan, Fang-Chih, Tien, Department of Industrial Engineering & Management
National Taipei University of Technology (Taipei Tech), Taipei, Taiwan

http://dx.doi.org/10.17758/EAP.EAP816013

industries, such as for electronic, electrical and mechanical parts, vehicles, food, and the garment industry. [4]Huang and Pan clearly surveyed the applications of AVI in the semiconductor industry. AVI can be solve the problem of quality engineer require time to training, and instability of inspection quality. Compared to machines, the working hours of quality engineer are relatively short and the cost of labor is a main consideration factor for manufacturers as well.

In practice, using circuit probe test to inspect dies of wafer is the main approach to represent the defect distribution of wafer in bin maps, so called WBM (Wafer Beam Map). However, most of companies heavily rely on experienced human inspectors to analyze WBM[5]. In order to effectively identify the possible candidate of re-polishing, many researches such as [6]-[11]et al. have applied different data mining techniques in this area.

There is very limited reference related to reclaim wafer. Most of the research described the cleaning techniques of reclaim wafers. Besides, the reclaim wafer maps generated by AVI (G-sorter and SP1/SP2) machine, which projects a laser spot on the surface of reclaim wafer and collect height information. This information depicts the defect including: epi spikes, mounds, voids, dislocations, slurry burns, particles, and contamination [16].

Support Vector Machine (SVM) is a popular classification technique, and successfully applied to regression and pattern recognition of the machine learning too[23]-[24]l. It is a good tool for the two classifications, widely to use in various fields as feature selection to hypertension diagnosis [25]. Mohamed et al. classified defects by the SVM method and the principal component analysis. In addition, it has also been applied to handwritten characters and digit recognition, face detection [26] and speaker identification.

Ooi et al. [6] pointed out that there were a variety of different defects on the wafer surface, and the causes of difficulty in detection includes: variations in defect cluster size, shape, location and orientation, on the wafer for the same class of defects, Non-symmetrical geometry, Low signal-to-noise ratio, insufficient quality historical data for training, a-priori unknown best feature sets and/or best classifiers etc. In their study, they used Polar Fourier Transformation and Invariant Moment to obtain invariant characteristics of surface defects, and then applied Bayesian classifier and Top-down induction decision tree for classification. Finally, their system adopted an ADTree classifier that achieves classification accuracy up to 95% for different product types. Hsu and Chien [12] proposed a hybrid data mining approach that integrated spatial statistics and adaptive resonance theory neural networks to quickly extract patterns from WBM. Liu and Chien[13] integrated the geometric information of distributed WBM, and used cellular neural network, adaptive resonance theory (ART) and moment invariant etc. for classification. The proposed system recognized specific failure patterns efficiently and also traced the assignable root causes. Li al et. used wavelet transform techniques in defect inspection of multi-crystalline solar wafer for fingerprint, contamination, saw-mark difficult, and so forth. Li and Tsai developed a machine vision-based scheme to automatically detect saw-mark defects in solar wafer surfaces[14]. First, they used Fourier image reconstruction to remove the multi-grain background of a solar wafer image, and then the Hough transform was used to detect low-contrast saw-mark defects. Sun et al. develop HJPOS algorithm solved MIC problem, and combine vision machine use in wafer re-polish[22]. Wang proposed a spatial defect diagnosis system to identify wafer surface defect[9]. This method used entropy fuzzy means to eliminate noise of wafer map, and then used decision tree in classification according to feature of clusters. Chang et al. used median filter to remove noises, and the defect clustering into blocks, according to the spatial information of blocks[10]. The wafer image was classified into four clusters. Shankar and Zhong developed a template-based vision system for the 100% inspection of wafer die surfaces[18]. Su et al. used BPN, RBFN, and LVQ three kind of neural network in wafer detect of post-sawing[25]. Su and Tong proposed a neural network-based procedure for the process monitoring of clustered defects in integrated circuit fabrication. This method can be effective to reduce warning errors caused by cluster defect[22]. Chang et al. developed an automatic inspection system, which recognizes defective patterns automatically[21]. The Radial Basis Function (RBF) neural network was adopted for inspection processing. The results show the proposed RBF neural network successfully identifies the defective dies on LED wafers images with good performance.

III. Research Method

The objective of this study is to build up an intelligent system to identify the reclaim wafer which can be polished again such that the human inspector can be relieved from the tedious and laborious task.

A. Ten typical defect maps in reclaim wafers

In the reclaim wafer process, defect maps can be divided into ten typical types, by our experiences. Ten types of defect maps are summarized and described in Table I. The related patterns of ten typical defects are listed in Table II. The ten types of defects will be classified as G or NG types for further process.

TABLE I: DESCRIPTION TEN TYPICAL DEFECTS.

Type	Description	G/NG
T1	Surface with line watermarks	G
T2	Surface with scratches	G
T3	Surface with scattered watermarks	G
T4	Surface with over-etched spots	G
T5	Surface with water jet	G
T6	Surface with clustered watermarks	G
T7	Surface with half-sided watermarks	G
T8	Surface with eridite residuals	G
T9	Surface with banded particles	G
T10	Crystal growth defect	NG

TABLE II: TEN TYPICAL DEFECT MAPS.

Type	Maps
T1	
T2	
T3	
T4	

B. Proposed Method

In order to achieve effective use BPN to defect classify, process of research as Fig.3. Process of Research description as following:

Figure 3. Process of Research.

1) AOI Inspection and Data Acquisition

The AOI instrument (G-sorter) were used to derived the 3D information of the reclaim wafer surface. The derived information includes the geometry, flatness, the position of particles etc. However, the amount of acquired data is huge and presented in a digital form, which cannot be perceived by a human inspector.

2) Data Transformation

The purpose of the data transformation is to convert the numerical data into graphical map (Fig. 4) such that a human inspector can classify the reclaim wafer into good and no good based on the distribution of particle. Figure 4 show different maps of defect, in which the different colors represent height of the corresponding location.

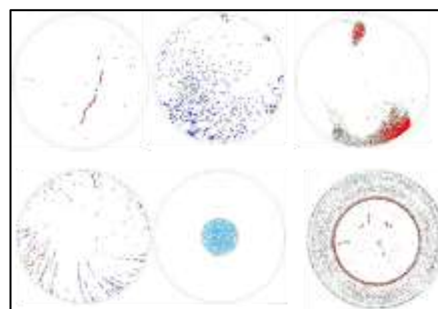

Figure 4. Defect distribution map.

3)Image Preprocessing

Image preprocessing is to remove the unrelated information and enhance the defective area. First, the edge of the defective feature map was removed and the boundary of the image as well. Secondly, the image is converted into a gray scale image and defective blobs are grouped and enhanced through morphological operations such that the scratches, or isolated defects can be visualized easily.

http://dx.doi.org/10.17758/EAP.EAP816013

4) Feature Extraction and Selection

After image preprocessing, the defective feature can be extracted based on the attribute of defects such as the number of particles, position, color, area, distribution and so forth. The feature must be representative for the different types of defective maps described in Table 1. Besides, the extracted feature must be scale, position, and orientation invariant. By using the statistical blob analysis, we obtained the thirteen invariant features, which can be learned by BPN.

5) Classification using BPN

The extracted invariant features were fitted into the BPN. In order to avoid the large scale data dominating the impact of classification process, a normalization of data usually is a necessary process. Usually, a design of experiment is required to determine the structure of BPN. Some parameters such as architecture of BPN (no of input/output neuron, no of layers, no. of hidden nodes), learning rate, momentum, and stopping criteria (error, number of iterations) must be specified.

IV. Experimental Results

The proposed method was implemented using MATLAB Pattern Recognition tool under Windows 8 platform. The number of input/output neurons were determined by the problem such that the 10-x-2 is the general structure of BPN, and the number of hidden nodes were determined by experiment. Sigmoid functions were used as the activation function. The learning process was stopped when the testing MSE running across the training MSE from the lowest point. This stopping criterion overcame the over-trained problem, which was commonly seen during BPN learning. The experiment result is shown in Table III. The BPN's with different numbers of hidden neurons derived different classification results. Most of BPN structures obtained good classification rate up to 94-95% with considerately small MSE. It is much better than the classification rate currently human inspectors conducted.

Table III Experimental Result

# of Hidden Neuron	MSE	Classification result				
		Good		NG		% of Classification
		% of Correct	Type I Error	% of Correct	Type II Error	
2	0.037363	81.8%	3.3%	13.0%	1.9%	94.8%
5	0.040566	82.0%	3.7%	12.6%	1.7%	94.6%
6	0.033587	81.8%	3.5%	12.8%	1.9%	94.6%
7	0.067412	81.8%	3.5%	12.8%	1.9%	94.6%
8	0.035941	81.8%	3.3%	13.0%	1.8%	94.4%
9	0.035518	81.9%	3.8%	12.5%	1.8%	94.4%
10	0.037557	82.1%	4.0%	12.3%	1.6%	94.4%
15	0.037189	82.0%	3.8%	12.5%	1.7%	94.5%
16	0.034656	82.0%	3.3%	13.0%	1.7%	95.0%
17	0.038910	81.9%	3.2%	13.1%	1.8%	95.0%
18	0.032395	82.3%	4.1%	12.2%	1.4%	94.5%
19	0.048697	82.0%	3.4%	12.9%	1.7%	94.6%
20	0.043708	81.9%	3.1%	13.2%	1.8%	95.1%

Note: Using the number of Hidden Neurons = 20, we obtained the highest classification rate, while using 16 hidden neurons had lower classification rate with smaller MSE.

V. Conclusion

Silicon wafer material prices continue to raise. In order to reduce the cost of the control wafer and dummy wafer, reclaim wafer recovery number will be more requested. In this study, we constructed an automatic reclaim wafer defect classification system by using digital image processing and a BPN classifier. Experimental results show that the extracted features were relevant to represent the map of reclaim wafers for further polishing. The trained BPN has excellent performance for classification has up to 95%. The proposed method is currently working on the case study company under their MIS system, and relieve the human inspector from the tedious working environment.

References

[1] Fu-Yi Hong, "*Development and Management of Silicon Wafer Reclaim Industry in Taiwan*", dissertation. National Tsing Hua University.

[2] MT Systems,Inc, "*Wafer Reclaim Processing*", http://www.microtechprocess.com,2008.

[3] Cai-Ding Huang,*"Recycling high-tech industry- wafer reclaim industry"*. Sci-Tech Policy Review, 68-72, 2007.

[4] Szu-Hao Huang *, Ying-Cheng Pan, "*Automated visual inspection in the semiconductor industry: A survey*", Computers in Industry, 66, 1–10, 2015. http://dx.doi.org/10.1016/j.compind.2014.10.006

[5] Liu, Chiao-Wen, Chien, Chen-Fu, "*An intelligent system for wafer bin map defect diagnosis: An empirical study for semiconductor manufacturing*", Engineering Applications of Artificial Intelligence. 26, 1479–1486,2013. http://dx.doi.org/10.1016/j.engappai.2012.11.009

[6] Ooi, M.P.-L., Sok,H.K., Kuang,Y.C., "Demidenko,S.,Chan,C., Defect cluster recognition system for fabricated semiconductor wafers. Engineering Applications of Artificial intelligence",Inpress, http://dx.doi.org/10.1016/j.engappai, 2012.

[7] Chien C.F., Chen,L. "Using rough set theory to recruit and retain high-potential talents for semiconductor manufacturing", IEEE Trans.Semicond.Manuf. 20(4),528–541, 2007. http://dx.doi.org/10.1109/TSM.2007.907630

[8] Chien F., Chen Y., Peng J., "Manufacturing intelligence for semiconductor demand for ecast based on technology diffusion and product life cycle", Int.J.Prod. Econ.128(2),496–509, 2010. http://dx.doi.org/10.1016/j.ijpe.2010.07.022

[9] Wang, C.H., " *Recognition of semiconductor defect patterns using spatial filtering and spectral clustering*". Expert Syst. Appl. 34 (3), 1914–1923.,2008. http://dx.doi.org/10.1016/j.eswa.2007.02.014

[10] Wang, C.H., Wang, S.J., Lee, W.D., 2006. Automatic identification of spatial defect patterns for semiconductor manufacturing. Int. J. Prod. Res. 44 (23), 5169–5185. http://dx.doi.org/10.1080/02772240600610822

[11] Palma, F.D.,Nicolao,G.D.,Miraglia,G.,Pasquinetti,E.,Pic-cinini,F., " Unsupervised spatial pattern classification of electrical-wafer-sorting maps in semiconductor manufacturing", PatternRecognit.Lett.26(12),1857–1865, 2005. http://dx.doi.org/10.1016/j.patrec.2005.03.007

[12] Wei-Chen Li, Du-Ming Tsai,Automatic saw-mark detection in multicrystalline solar wafer images. Solar Energy Materials & Solar Cells. 95, 2206–2220, 2011. http://dx.doi.org/10.1016/j.solmat.2011.03.025

[13] Hsu S.-C., Chien C.F., " *Hybrid data mining approach for pattern extraction from wafer bin map to improve yield in semiconductor manufacturing*". Int. J. Prod. Econ. 107, 88–103 http://dx.doi.org/10.1016/j.ijpe.2006.05.015

[14] Liu, Chiao-Wen, Chien, Chen-Fu., "*An intelligent system for wafer bin map defect diagnosis: An empirical study for semiconductor manufacturing*", Engineering Applications of Artificial Intelligence. 26, 1479–1486, 2013. http://dx.doi.org/10.1016/j.engappai.2012.11.009

[15] Wei-Chen Li, Du-Ming Tsai, "*Wavelet-based defect detection in solar wafer images with inhomogeneous texture*", Pattern Recognition. 45, 742–756, 2012.

[16] Chuan-Yu Chang, ChunHsi Li, Jia-Wei Chang, MuDer Jeng., "*An unsupervised neural network approach for automatic semiconductor*

wafer defect inspection", Expert Systems with Applications. 36, 950–958, 2009.
http://dx.doi.org/10.1016/j.eswa.2007.10.033

[17] Reza Aghaeizadeh Zoroo, Hisashi Taketani, Shinichi Tamura, Yoshinobu Sato, Kazuma Sekiya, "Automated inspection of IC wafer contamination", Pattern Recognition, 1307-1317, 2001.

[18] N.G. Shankar, Z.W. Zhong., "*Defect detection on semiconductor wafer surfaces*", Microelectronic Engineering. 77, 337–346, 2005.
http://dx.doi.org/10.1016/j.mee.2004.12.003

[19] Chao-Ton Su, Taho Yang, and Chir-Mour Ke, "*A Neural-Network Approach for Semiconductor Wafer Post-Sawing Inspection*". IEEE TRANSACTIONS ON SEMICONDUCTOR MANUFACTURING. 15 (2), 260-266, 2002.
http://dx.doi.org/10.1109/66.999602

[20] Chao-Ton Su, Lee-Ing Tong, "*A neural network-based procedure for the process monitoring of clustered defects in integrated circuit fabrication. Computers in Industry*", 34, 285–294, 1997.
http://dx.doi.org/10.1016/S0166-3615(97)00050-X

[21] Chuan-Yu Chang, Yung-Chi Chang, Chun-Hsi Li, and MuDer Jeng, "*Radial Basis Function Neural Networks for LED Wafer Defect Inspection*", IEEE.

[22] Te-Hsiu Sun, Chung-Hao Tang, and Fang-Chih Tien, "*Post-Slicing Inspection of Silicon Wafers Using the HJ-PSO Algorithm Under Machine Vision*", IEEE Transactions on semiconductor manufacturing, 24 (1), 80-88, 2011.
http://dx.doi.org/10.1109/TSM.2010.2088991

[23] Vapnik, V. N., "*Statistical Learning Theory*", Wiley, 1998.

[24] Vapnik, V. N. "*An Overview of Statistical Learning Theory*", IEEE Trans. on Neural.

[25] Chao-Ton Su,Chien-Hsin Yang, "*Feature selection for the SVM: An application to hypertension diagnosis*", Expert Systems with Applications, 34, 754–763, 2008
http://dx.doi.org/10.1016/j.eswa.2006.10.010

[26] Osuna E., Freund R., & Girosi F., "*Training support vector machines: an application to face detection*", In Proceedings of the computer vision and pattern recognition, '97,130–136, 1997.
http://dx.doi.org/10.1109/cvpr.1997.609310