A Novel DBSCAN-Based Defect Pattern Detection and Classification Framework for Wafer Bin Map

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***Abstract*—Defective die on a wafer map tend to cluster in distinguishable patterns, and such defect patterns can provide crucial information to identify equipment problems or process failures in the semiconductor manufacturing. Therefore, it is important to accurately and efficiently classify the defect patterns. In this paper, we propose a novel clustering-based defect pattern detection and classification framework for wafer bin map (WBM). The proposed framework has many advantages. Outlier detection and defect cluster pattern extraction can be done at the same time; arbitrarily shaped cluster patterns can be detected; and there is no need to specify the number of clusters in advance. Based on WBM property, the parameters used in the clustering algorithm are fixed so that parameter sensitivity can be avoided. Since the defect patterns are classified based on extracted features, no labeled data and no supervised classification training are needed and single-type patterns as well as mixed-type patterns can be found. Extensive experiments conducted on a real-world WM-811K dataset has shown the superiority of proposed framework. The proposed framework can also be used in a big data environment to accelerate performance.**

***Index Terms*—Wafer bin map, clustering, defect pattern detection, defect pattern classification, ratio, DBSCAN.**

I. Introduction

SEMICONDUCTOR wafer fabrication is a complex, long, costly process which involves hundreds of chemical steps and requires monitoring a large number of key process parameters. After fabrication, each die on a wafer is classified as functional or defective using a circuit probe test, and the test results are represented in a wafer bin map (WBM). Even well trained process engineers using highly automated and precisely positioned equipment in a nearly particle-free environment cannot avoid defective die [1]. Defective die on a wafer map tend to be in clusters [2], and according to their spatial patterns, defect patterns can be classified into the following typical pattern types: center, donut, edge-loc, edge-ring, loc, near-full, random, scratch, and none. Each of these defect pattern types can provide crucial manufacturing process information to process engineers. For example, center patterns may be caused by a uniformity problem during chemical-mechanical planarization, scratch patterns may result from inappropriate material shipping and wafer handling, edge-ring patterns may be caused by etching problem, and edge-loc pattern may result from thin film deposition. Therefore, accurately and efficiently classifying defect patterns is one of the most important tasks to identify the defect source and improve overall yield and reliability problems.

In this research, we propose a novel defect pattern detection and classification framework for WBM. The proposed framework is based on density-based spatial clustering of applications with noise (DBSCAN) [3] which we call it DBSCANWBM. The main contributions to DBSCANWBM are summarized as follows:

(1) Use of ratio values in the pattern definitions can remove the dependencies associated with various kinds of wafers.
(2) DBSCANWBM inherits all the advantages of DBSCAN.
(3) Based on WBM property, the DBSCAN parameters are fixed so that the influence of parameter settings can be avoided.
(4) Instead of being completely removed, the detected outliers are removed differently according to the different pattern type.
(5) Labeled WBM data is not needed and the disadvantages of a supervised learning approach can be avoided.
(6) Single-type patterns as well as mixed-type patterns can be detected.
(7) Any interesting new pattern type can be embedded into DBSCANWBM for classification.
(8) DBSCANWBM can be parallelizable with both on multicore processors and distributed systems to accelerate the performance, and can also be used for online WBM classification.

To the best of our knowledge, no such framework has been proposed for WBM classification.

The rest of the paper is organized as follows. Section II discusses the related work of WBM classification and

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Section III introduces DBSCANWBM in detail. Extensive experimental results from test of a labeled real-world WM-811K dataset are reported in Section IV. Finally, conclusions and future work are discussed in Section V.

II. Related Work

In this section, we focus on the work related to WBM classification. With rapid advances in integrated circuit design and manufacturing complexity, defect patterns become more and more complex due to different wafer map sizes, die sizes, defect pattern densities, and arbitrarily shaped patterns. This makes defect pattern detection and classification of WBM much more difficult. DBSCANWBM consists of three parts: outlier detection, defect pattern detection, and defect pattern classification. In the following subsections, how each part is used in WBM analysis will be discussed in more detail.

A. Outlier Detection

In most cases, defect patterns coexist with outlier defective die. The presence of outliers masks the underlying defect patterns. In order to remove outliers, connected-path filtering method is applied in [4]. A spatial filter is well known as a smoothing and noise reduction tool in image processing [5] and it has been widely applied in [1], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15]. In order to apply a spatial filter, WBM data needs to be transformed into a binary matrix. Another image processing technique, dilation and erosion, is applied in [16], [17], [18]. Support vector clustering [19] and the nearest-neighbor clutter removal method [20] are respectively used to remove outliers in [21] and [22]. However, as mentioned in [22], results of the aforementioned methods depend highly on the choice of the parameters. For example, Fig. 1 shows some scratch patterns where Fig. 1(a) shows the original scratch pattern and Fig. 1(b) and Fig. 1(c) are respectively the result of applying a 3×3 spatial filer and a 5×5 spatial filter to the scratch pattern shown in Fig. 1(a). As can be seen from Fig. 1(b) and Fig. 1(c), if parameters are not properly set, the spatial filter removes some of the important information which can be used to help to determine the pattern type. Therefore, deciding which outlier detection algorithm to use and how to choose its optimal parameters are challenging tasks.

B. Defect Pattern Detection

The defect patterns in the WBM are not uniformly distributed and not regularly shaped. A lot of unsupervised clustering algorithms have been applied to detect the complex defect patterns such as the adaptive resonance theory network described in [23], [24], a self organizing map in [25], a fuzzy C means in [6], an entropy fuzzy C means with spectral clustering in [8], single-linkage clustering in [1], [11], [12], [14], a similarity-based clustering method in [22], support vector clustering [19] in [9], clustering using representatives in [10], Ordering Points To Identify the Clustering Structure (OPTICS) [26] in [27], and infinite warped mixture model [28] in [4]. However, as with outlier detection, clustering results

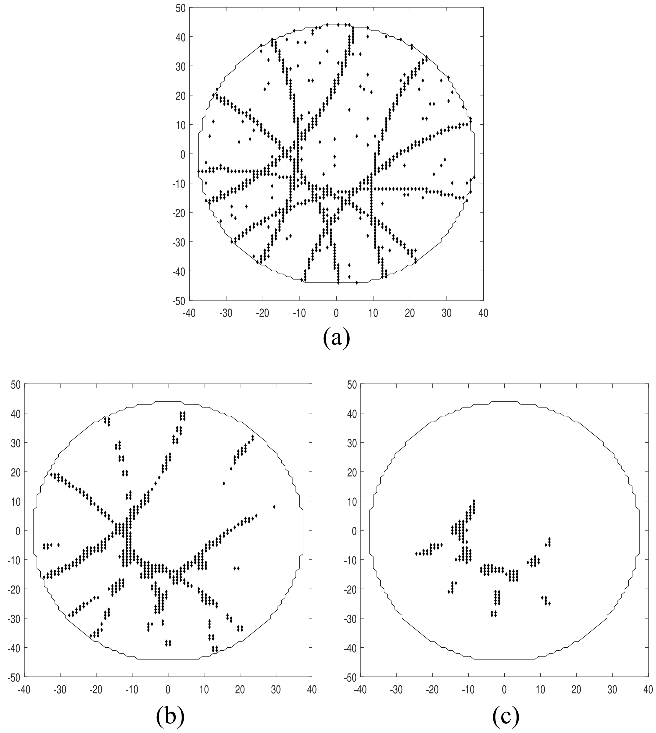

Fig. 1. Scratch pattern and the results of two different sized spatial filters. (a) Scratch. (b) Result of 3×3 size spatial filter. (c) Result of 5×5 size spatial filter.

for each algorithm are highly affected by its parameter settings and the resulting pattern classification results can also be greatly affected. Therefore, deciding which clustering algorithm to choose and how to choose its optimal parameter values are also challenging tasks.

C. Defect Pattern Classification

After detecting the defect patterns, each WBM needs to be classified into the corresponding pattern type(s). Depending on whether or not the class labels of WBMs are available in advance, the work for WBM classification can be categorized into two groups: a supervised learning approach and a feature extraction based approach. Support vector machine [25], [27], [29], joint local and nonlocal linear discriminant analysis (JLNDA)-based Fisher discriminant classification [13], neural network [30], alternating decision tree [31], convolutional neural network [32], randomized general regression network [33], simplified subspaced regression network [34], and ensemble-based method [15], [35] are widely used for WBM classification in a supervised learning approach. Although the test WBMs can be easily labeled with aforementioned classification models, there are three major disadvantages in a supervised learning approach. First, in practice, it is nearly impossible to obtain enough high quality labeled data for training [32], [36]. Second, the classification result is highly affected by training/test set separation, class label distribution, overfitting, and the distinctness of the classes. If the training data is not representative, then the classification result will be poor. Third, if there are mixed-type defect patterns, only

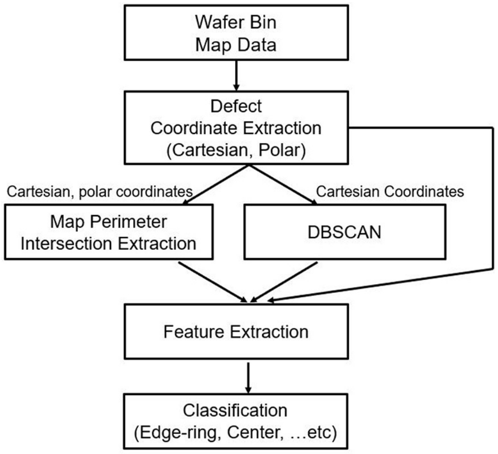

Fig. 2. DBSCANWBM framework.

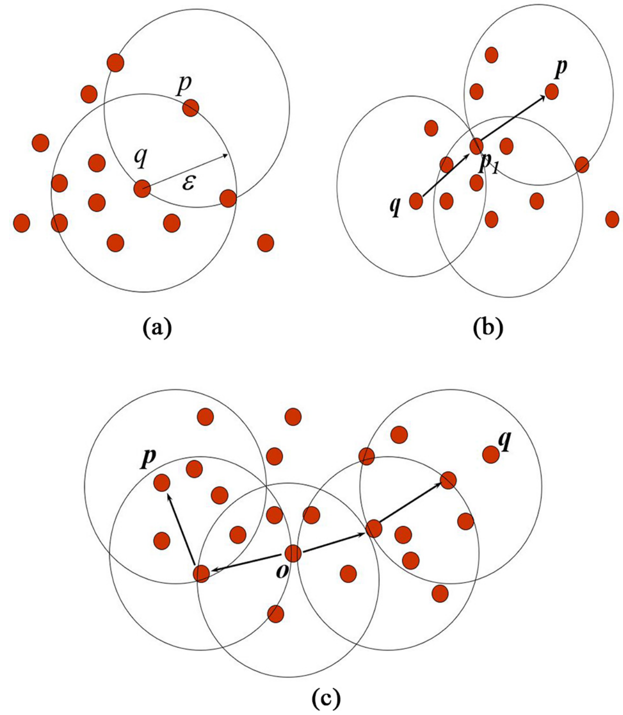

Fig. 3. Concepts of (a) core point, (b) density-reachable, and (c) density-connected in DBSCAN.

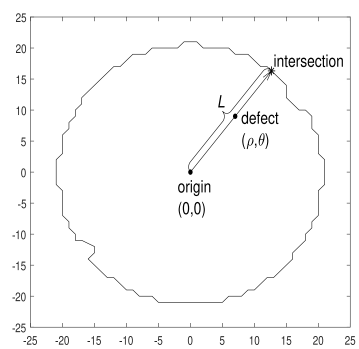

Fig. 4. Intersection between wafer perimeter and line.

one pattern type can be assigned so the classification accuracy can be dramatically decreased [15], [27]. When using the feature extraction based approach, each WBM can be classified purely based on the extracted features [6], [8], [9], [37], [38] so that the aforementioned major issues in a supervised learning approach can be avoided. Some other discriminative features used in a supervised learning approach can be found in [7], [10], [13], [17], [27], [29], [30], [31].

D. Summary of Related Work

Outliers can provide important information to determine the pattern type; however, in all related work detected outliers are removed without being carefully considered with pattern types. While all related work treats outlier detection and defect pattern detection as completely independent tasks, these two tasks can be done at the same time in DBSCANWBN.

Among the numerous studies presented above, the work [27] with OPTICS and the method [4] are closest to DBSCANWBM. OPTICS [26] is a density-based clustering algorithm similar to DBSCAN, however, there are three main limitations in [27]. First, parameters are not properly set. Second, although some outliers may provide much useful information, detected outliers are completely removed in all defect pattern types. Third, although there may be more than one defect pattern type, only one pattern type can be assigned in a supervised learning approach. As with DBSCANWBM, the method [4] can deal with arbitrarily shaped clusters, has no need to specify the number of clusters in advance, and can detect mixed-type patterns. However, detected outliers are completely removed in all defect pattern types.

III. DBSCANWBM

In this section, details of DBSCANWBM are presented and its workflow is shown in Fig. 2.

At first, Cartesian and polar coordinates (ρ, θ) of all defective die and edge die need to be extracted. As shown in Fig. 4, the intersection of wafer perimeter and each line whose direction is from the origin to each defective die can be calculated and then, each defective die will have a corresponding distance of L from the origin to the its perimeter intersection point. However, different WBMs may have different map sizes, different die sizes, and different wafer perimeter locations (valid die locations at the wafer edge). As shown in Fig. 4, each WBM may also not be perfectly symmetrical. Due to such complexities, in this research ratio values are used in pattern definitions to remove the dependencies associated with various kinds of wafers. For example, edge-ring pattern can be defined as most defective die in the edge-ring region (e.g., $\rho >= 0.9 \times L$) which encompass more than four-fifths of the wafer perimeter. The center pattern can be defined as most of defective die are in the center region (e.g., $\rho <= 0.2 \times L$). Other pattern types can be defined in similar ways.

The extracted Cartesian coordinates of defective die are used for DBSCAN clustering. DBSCAN is a density-based clustering algorithm which requires two parameters: radius of the neighborhood of a point ϵ and the minimum number of points in the ϵ-neighborhood *MinPts*. Two points are connected if they are within each other's ϵ-neighborhood and

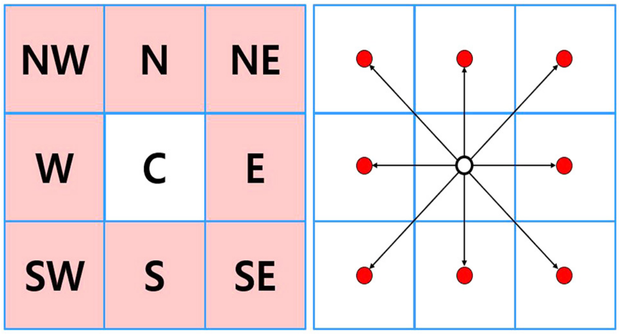

Fig. 5. Moore neighborhood. C: center, E: east, NE: northeast, N: north, NW: northwest, W: west, SW: southeast, S: south, SE: southeast.

a point is a core point if the number of points within ϵ-neighborhood of that point is greater than *MinPts*. Given a core point q and a point p, p is directly density-reachable from q if p is within the ϵ-neighborhood of q. p is density-reachable from q with the transitive closure of direct density-reachability. Two points p and q are called density-connected if there is a third point o from which both p and q are density-reachable. Comprehensive examples related to concepts of core point, density-reachable, and density-connected are presented in Fig. 3. A cluster is defined as a maximal set of density-connected points, and an outlier is defined as every point not contained in any cluster. Interested readers can see DBSCAN [3] for more details. Since DBSCANWBM is based on DBSCAN, it inherits all the advantages of DBSCAN: outlier detection and cluster extraction on the WBM can be done at the same time, arbitrarily shaped cluster patterns can be detected, and there is no need to specify the number of clusters in advance.

As shown in Fig. 5, DBSCAN is applied on the WBM. Each WBM can be seen as a Moore neighborhood structure which is composed of a central die and the eight die surrounding it. The center die is one unit away from each of east, north, west, south die and $\sqrt{2}(\sqrt{2} = \sqrt{1+1})$ units away from each of surrounding die in diagonal directions. We consider that all eight surrounding die are connected to the center die. In this research, we focus on two kinds of outliers in the outlier cluster: one kind is an isolated outlier and the other kind is twin outliers. An isolated outlier is a defective die which is not connected to any other defective die, and twin outliers are two defective die where each defective die is connected to only the other defective die. The reason why we consider these two kinds of outliers is that they are intuitively outliers in some WBMs (e.g., '+' symbol in Fig. 6(a)); however, in some other WBMs (e.g., '+' symbol in Fig. 6(b) and Fig. 6(c)), they play important roles in determining the pattern type. Therefore, it is important to detect them and decide whether or not to remove them. As shown in Fig. 5, the maximum ϵ to form outlier cluster is $\sqrt{2}$ which is the distance between the nearest two connected defective die in the diagonal direction (a kind of twin outliers). If we set the minimum *MinPts* to 3, then both isolated outliers and twin outliers can be directly detected. With these optimal parameter values, the excessive influence of the parameter setting for outlier detection and defect pattern detection can be avoided.

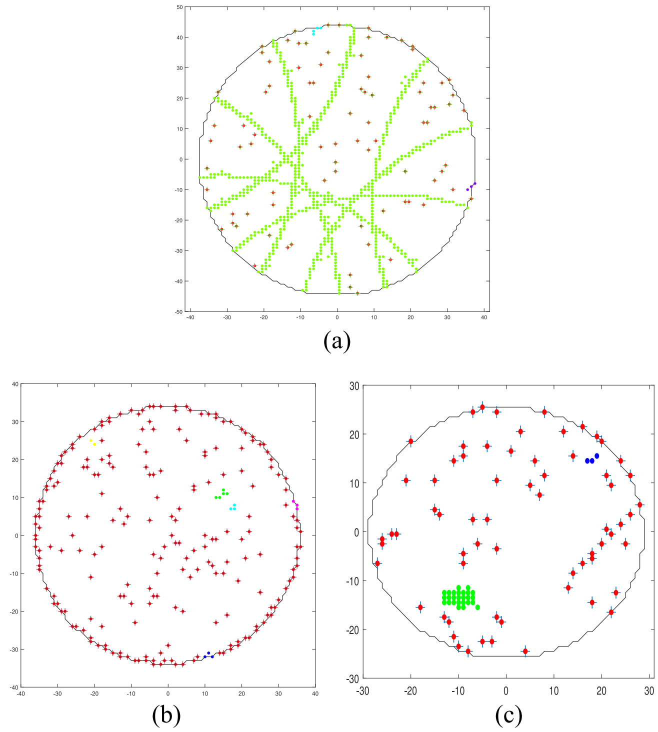

Fig. 6. Outliers in three different WBMs. (a) Scratch. (b) Edge-ring. (c) Mixed-type of loc and scratch.

An outlier is an observation which is very different from other observations so that all detected outliers can be completely removed; however, in some pattern types, outliers can provide the most important information. For example, Fig. 6 shows the clustering results of three completely different WBMs where Fig. 6(a) and Fig. 1(a) are the same WBM. Different colors represent different clusters and the detected outliers are marked with the '+' symbol. Fig. 6(b) shows an edge-ring pattern and Fig. 6(c) shows a mixed-type pattern of scratch and loc patterns. If outliers are completely removed from Fig. 6(b), this WBM would cease to be an edge-ring pattern, while in Fig. 6(c), the scratch pattern will be missed. Therefore, depending on the different pattern type, outliers should be removed differently. For example, when considering the edge-ring pattern, outliers in edge ring region should not be removed and when considering the scratch pattern, outliers should not be removed. Using this approach improves classification accuracy.

Finally, the detected patterns need to be classified into the corresponding pattern types. Supervised classification methods are widely used in most existing defect pattern classification methods. However, there are several disadvantages in the supervised learning approach as presented in Section II-C. In order to address these issues, the discriminative features extracted based on the characteristics of each defect pattern type are used for classification.

Each WBM is iteratively checked for each defect pattern type so that all existing defect pattern types can be detected. With proper pattern definition and corresponding discriminative features, any interesting new pattern type can be easily embedded into DBSCANWBM for classification.

TABLE I
PATTERN TYPE DISTRIBUTION

Type	Count
Center	4294
Donut	555
Edge-loc	5189
Edge-ring	9680
Loc	3593
Near-full	149
Random	866
Scratch	1193
None	147431
Total	172950

Since the classification is executed independently between WBMs, DBSCANWBM not only can be parallelizable with both on multicore processors and distributed systems but also can be used for online WBM classification. This property can greatly accelerate performance.

IV. EXPERIMENTAL RESULTS

The WM-811K [29] dataset consists of 811457 wafer maps and among them, domain experts are recruited to label the pattern type of 172950 wafer maps. There are 9 types of defects (center, donut, edge-loc, edge-ring, loc, near-full, random, scratch, and none) in this labeled WM-811K dataset and the number of wafer maps in each pattern type is shown in Table I.

All WBMs used in this section are from this labeled real-world WM-811K dataset. WBMs which all have different map sizes, different die sizes and different wafer perimeters are chosen to show both the various phenomenons and superiority of DBSCANWBM. In DBSCANWBM, DBSCAN with optimal values of $\epsilon\sqrt{2}$ and *MinPts* 3 are used for clustering. Clustering results of single-type patterns and mixed-type patterns are presented in Fig. 7 and Fig. 8 respectively. Different colors represent different clusters and the detected outliers are marked with the '+' symbol. The clustering result of a near-full pattern is excluded since there is no need to do clustering for this pattern.

As can be seen from Fig. 7 and Fig. 8, both arbitrarily shaped clusters and outliers are accurately detected. In order to improve the classification accuracy, according to each pattern type, outliers should be removed differently for each different defect pattern type. If outliers are removed, not only the pattern type can be made much more dominant but also the computation cost can be reduced. For example, if outliers not in the center part are removed, the center pattern shown in Fig. 7(a) and Fig. 8(b) will be made much more salient. As shown from edge-ring patterns in Fig. 6(b), Fig. 7(d), Fig. 8(a) and Fig. 8(d), if outliers not in the edge ring region are removed, the edge-ring patterns can become much more clear. Outliers in the scratch patterns in Fig. 7(g) and Fig. 8(a) can be completely removed since none of them are key elements in any scratch patterns. In contrast, in Fig. 6(c), some outliers are key elements in the scratch pattern so they cannot be completely removed. From these three scratch patterns, it is worth

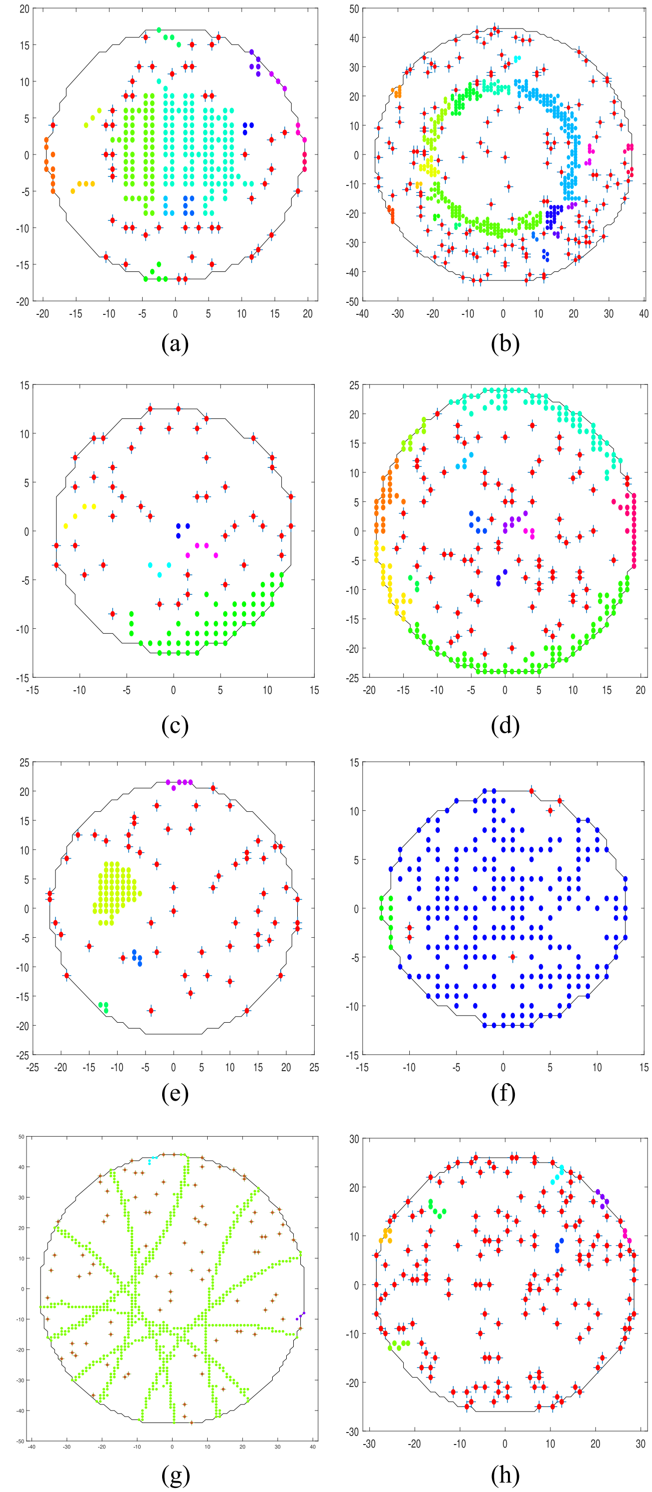

Fig. 7. DBSCAN clustering result of each pattern type. (a) Center. (b) Donut. (c) Edge-loc. (d) Edge-ring. (e) Loc. (f) Random. (g) Scratch. (h) None.

noting that when the scratch pattern is considered, it is better not to completely remove the detected outliers for further classification. Based on careful observations of a large number of WBMs, completely removing the detected outliers for donut, edge-loc, loc, random and none patterns has a minor influence on classification results. Therefore, in order to reduce

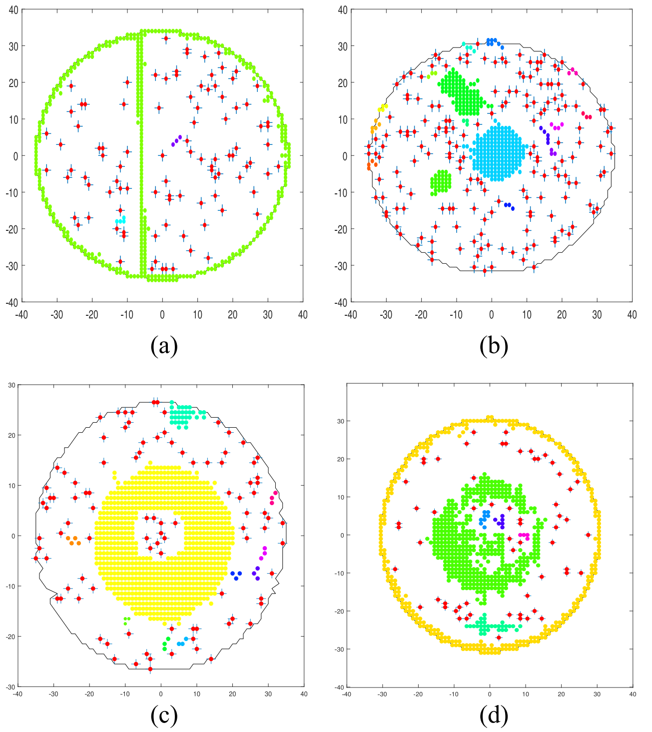

Fig. 8. Mixed-type patterns. (a) Scratch and edge-ring. (b) Center and loc. (c) Donut and edge-loc. (d) Donut and edge-ring.

the computation cost, we recommend completely removing the detected outliers for these type patterns.

After detected outliers are carefully handled, the detected cluster patterns need to be classified. Each of Fig. 7(c), Fig. 7(e), Fig. 7(f) is a single-type pattern and in each WBM, the salient cluster itself is its pattern type. Different from them, multiple pattern types can be included in a salient cluster. For example, Fig. 7(g) shows the clustering result of scratch pattern in Fig. 1(a). Although Fig. 7(g) is a single-type pattern, there are several different scratches in a green colored salient cluster. Take one more example, Fig. 8(a) is a mixed-type pattern where there are two different types of scratch and edge-ring patterns in a green colored salient cluster. From these examples, it seems that for each given WBM, all existing pattern type(s) can be easily detected by using only the salient cluster for every defect pattern type. However, this is not always true since a wafer pattern type(s) may be determined by multiple clusters. For example, each of Fig. 7(a), Fig. 7(d), Fig. 7(b) is a single-type pattern of center, edge-ring, and donut. However, center pattern in Fig. 7(a) is composed of several major clusters near the wafer center, edge-ring pattern in Fig. 7(d) is composed of several clusters along the wafer edge, and donut pattern in Fig. 7(b) is a donut shaped pattern which is located near the wafer center and composed of multiple clusters. Therefore, in these cases, a salient cluster itself cannot be any pattern type at all. Take some mixed-type patterns shown in Fig. 8 as examples. If only the salient cluster is considered, then the other pattern type can be missed. For example, there are center and loc patterns in Fig. 8(b) and the center pattern is the more salient cluster, so loc pattern will be missed. In Fig. 8(c), there are donut and edge-loc patterns and if the donut pattern is the more salient cluster, then the edge-loc pattern will be missed. Mixed-type pattern of donut and edge-ring patterns is shown in Fig. 8(d) and if the edge-ring pattern is the more salient cluster, then the donut pattern will be missed. This is the reason why DBSCANWBM uses the discriminative features of each pattern type for classification not just information obtained from the salient cluster. Although cluster information as well as some other useful features [6], [7], [8], [9], [10], [13], [17], [27], [29], [30], [31], [37] can used for classification, extracting the most discriminative features is a much more time consuming task, and the quality of discriminative features significantly influences classification accuracy. In this research, we present only the classification result for near-full pattern. Our future work will extract discriminative features and obtain much high classification accuracy for the remaining pattern types.

Near-full pattern as the name implies, exhibits a defect coverage where the ratio of defective die to the total number of die is the most discriminative feature. A near-full pattern type can be easily classified if the defect coverage ratio is greater than a certain threshold. A defect coverage ratio of threshold 70% is used to check near-full pattern. With this threshold, all the 149 near-full patterns can be correctly found; however, 26 more wafers are predicted as near-full pattern type. Of these 26 wafers, 17 are from random, 6 from edge-loc, and 3 are from center.

V. Conclusion

In this paper, a novel DBSCAN-based defect pattern detection and classification framework DBSCANWBM is presented. Outlier detection and defect pattern detection are considered independently in most defect pattern recognition analysis; however, thanks to DBSCAN clustering, both tasks can be done at the same time. Based on the characteristics of WBM, optimal parameter values are used so that parameter sensitiveness in outlier detection and defect pattern detection can be avoided. Outliers in each pattern type can provide different useful information so that not all detected outliers are removed (some are carefully removed according to characteristics of each defect pattern). DBSCANWBM is generally applicable to various wafer map sizes and die sizes, is able to detect multiple defect pattern types in each WBM, and can also be parallelizable with both on multicore processors and in distributed systems. We believe that DBSCANWBM will improve the performance of defect pattern classification in terms of accuracy and execution time. For future work, we plan to extract more useful discriminative features for each defect pattern type to improve classification accuracy.

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